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Interim Report on an Inpatient Rehabilitation Facility Prospective Payment System

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PREFACE

This draft is the interim report for a project in support of the Health Care Financing Administration's (HCFA) design, development, implementation, monitoring, and refining a Prospective Payment System (PPS) for inpatient rehabilitation. Such an inpatient rehabilitation facility PPS (IRF PPS) was mandated in the Balanced Budget Act of 1997.

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SUMMARY

In the Balanced Budget Act of 1997, Congress mandated that the Health Care Financing Administration (HCFA) implement a Prospective Payment System (PPS) for inpatient rehabilitation. This interim report describes the research that RAND performed to support HCFA's initial efforts to design and develop such a PPS. It also discusses our plans for further research on the implementation, monitoring, and refinement of such an Inpatient Rehabilitation Facility PPS (IRF PPS).

Data and Methods

In this report, we analyze a variety of options for elements of the IRF PPS including the patient classification system, the methodology for calculating relative weights, the facility payment adjustment factor, and outlier policy. We evaluate these options in terms of: (1) how well payment explains cost at the level of patient and hospital, (2) the Payment to Cost (PTC) ratios for patient groups and hospital groups, and (3) financial risk to hospitals.

We used hospital cost reports, discharge abstracts, and functional independence measure (FIM) data for Medicare discharges in years 1996 and 1997. The FIM data come from the Uniform Data System for medical rehabilitation (UDSmr) and from the Clinical Outcomes Systems (COS) data for medical rehabilitation. Our sample covers about half of all IRF Medicare patients in each of those years. We use the departmental method to estimate the accounting cost of each case in the sample.

Classification System

The unit of payment in the IRF PPS will be the hospital stay, beginning with an admission to the rehabilitation hospital or unit and ending with discharge from that facility. Each stay will be classified into a Case Mix Group or CMG. We define typical cases as cases that are in the hospital for more than 3 days and that are discharged to the community. We use the Function-Related Groups (FRG) methodology, developed by Dr. Margaret Stineman and others to assign typical cases to CMGs. We validated this methodology by showing that the FRGs which we

created in a previous study explain costs in our new data as well as they had in the earlier study.

As the first step in the creation of new FRGs, codes for the impairment that is the primary cause of the hospitalization are grouped into larger categories called Rehabilitation Impairment Categories (RICs). We examined a series of options for defining RICs. We found that most options did not improve on the groupings used in the published definitions for FRGs in their ability to explain costs. Consequently we use RIC definitions that differ from previously published research primarily in the creation of a new RIC for burns.

We use Classification and Regression Trees to iteratively partition patients in each RIC based on their the FIM data and age. Each partition maximizes the variation in the log of case costs that is explained. We explored various stopping rules for the iteration and recommend the use of one which groups typical cases into 92 groups. We show that payment using this set of groups performs just as well as payment using a more detailed set of 143 groups.

Many of these groups have their payment amount modified if the case has one or more of a specified set of comorbidities. We began with the comorbidity model which we developed earlier. We scrubbed this model to eliminate certain diagnoses from certain RICs and added several conditions to the relevant comorbidity list. Finally, the set of ICD-9-CM diagnoses that we found to affect costs were examined to eliminate codes believed to have only a minor effect on resources, codes that were vague enough that they might encourage upcoding, and codes that were for conditions that could be prevented by prudent treatment.

The FRGCs are the basis for the CMGs, but we need to add new groups for the atypical cases or specify rules for paying them. About 21 percent of cases were transferred either to a hospital or to a skilled nursing facility or nursing home. About two-thirds of the transfer cases are short stay transfers--i.e., they stayed less than the average LOS for typical cases in the CMG to which they would be assigned based on their primary impairment, age, FIM, and comorbidities. If short stay transfer cases were to receive a full case payment, most would be substantially overpaid relative to typical cases. The average PTC ratio for short stay transfer cases would be about 1.8. The potential profit from these cases might provide incentives for abuse, with some hospitals transferring cases to reduce their costs and increase Medicare payments, or even admitting patients who are not able to sustain the required therapy. Choosing an appropriate payment policy requires balancing a reduction in these incentives against the need to provide adequate funding for, and access to, all appropriate care. We show that paying short stay transfer cases a per diem amount equal to the per diem for the typical case in the same CMG will result in payments that are only slightly under the cost of the these cases and we recommend this or a similar policy that would add a one-half day per diem.

HCFA might also bundle the payment for more than one hospital stay when the patient returns to the same hospital within a short period of time. We recommend against bundling because such bundled cases would be paid substantially less than their costs.

Less than half of one percent of cases die in the rehabilitation hospital. On average these cases cost substantially less than typical cases in the same CMG, so it is reasonable to create a special group for these cases. Splitting the death group by whether or not the patient was in an orthopedic RIC and whether or not the patient stayed longer than the average death case would further increase the accuracy of the payment system. The remaining atypical cases are the 2.9 percent of cases that stay less than 3 days. We recommend creating a special group for these cases.

Relative Weights

We empirically analyzed the following options for calculating relative weights for the CMGs: cost-based hospital specific relative value (HSRV) weights, cost-based standard weights, and charge-based standard weights. The HSRV weights use each hospital's own costs to standardize costs; the standard method uses the facility payment adjustment to standardize costs.

We found that controlling for hospital costs using individual hospital identity results in estimates of the effect of comorbidity that are more precise than using either standardized cost or standardized charges. The HSRV method appears to result in more accurate estimates of relative cost at the case level. However, the HSRV weights and the standard method cost weights (and probably the standard method charge weights) are compressed at the hospital level--costs increase more quickly than the case mix indices increase.

Hospitals systematically vary in their costliness in ways beyond that which is accounted for in the payment adjustment. Because the HSRV method accounts for these variations in costliness and because it measures the effect of comorbidity better, we believe that its results are more accurate measures of the relative resource use of each CMG. But there are reasons to believe that hospital cost per case averages out certain errors in the patient level cost estimates. We present our plan to improve case cost estimates and to otherwise reduce the compression in the weights. If this is successful, we believe that the HSRV algorithm should be used to calculate weights in the IRF PPS.

Facility Adjustment

We explore facility-level adjustments to the standard payment amounts that may account for cost differences that are beyond the control of facility management and for which it may be appropriate to pay. These include the area wage index, an adjustment for rehabilitation facilities in Alaska and Hawaii, location in a large urban or rural area, the indirect costs of graduate medical education, and serving low-income patients. We explored different formula for some factors and used regression analysis to examine whether each factor explains cost.

We use a pre-reclassification hospital wage index that excludes 100% of wages for services provided by teaching physicians, interns and residents, and non-physician anesthetists under Part B. We found that an adjustment based on the labor-related share for area wage differences explains hospital costs as well as other alternatives.

When cost per case is standardized for case mix and area wage differences, rural hospitals are almost 16 percent more costly than other hospitals. This suggests that an additional payment or special payment protections may be appropriate for rural facilities.

We explored two measures of teaching activity. However, we found that neither significantly explains costs in a payment regression.

We also used 2 measures to describe the extent to which each hospital serves low-income patients--the disproportionate share formula used in the acute PPS and the percentage of patients who are low-income, which seems more logically grounded. However we find that both formula predict costs. There is about a 9 percent increase for each 10 point increase in a facility’s low-income or DSH patient percentage. This suggests an additional payment may be appropriate for hospitals that serve low-income patients.

Outliers

We used simulation to analyze the effect of different levels of outlier payments. The conversion factor for each simulation was set so that average payment per case was within 1 dollar of cost per case.

The amount of outlier payments must be arrived at from a tradeoff between reducing risk and improving fairness in the system against unwanted gaming with charges and/or unnecessary services. We find that outlier payments in the RPPS affect a substantially higher proportion of patients than they do in the acute PPS for the same percentage of outlier payments. This increases the opportunities to benefit from gaming. Further, we found that the rate at which the benefits of outlier policy increased declined with an increasing amount of outlier payments. Thus we recommend limiting the amount of outlier payment to 3 percent of total payments, below the statutory maximum of 5 percent. Input from hospitals on this tradeoff will be very useful.

Simulated Payments Under Recommended System

The simulated payment from the recommended system explains 62.7 percent of the variance in patient level costs (dollar scale). The PTC ratios for groups of patients defined by sex, age, marital status, and RIC are all close to 1--typically within 2 percent of 1.

The log of payment explains 57.8 percent of the variance in log cost at the hospital level. The PTC ratios for most groups of hospitals are close to 1. However, the PTC ratio for the small number of freestanding hospitals with an average daily census of less than 25 is 0.876. The 25 percent of hospitals with the highest case mix index have a payment to cost ratio of 0.966, reflecting compression in the weights.

Future Research

In the remainder of this project, we will address several issues that might affect the initial implementation of the IRF PPS and also work on longer range issues of monitoring and refining the system. We describe our plans for: updating our analyses with later data; investigating and, if possible, eliminating compression; compensating to the extent possible for the non-representativeness of our sample; and comparing the MDS-PAC and FIM data collection instruments.

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An earlier draft of this report was reviewed at a meeting of a Technical Expert Panel (TEP) which was held in Santa Monica, California on May 30 and 31, 2000. The TEP members provided many helpful comments on our work. We thank each of the TEP members who are listed below for their help at the meeting and look forward to working with them more closely during the rest of the project. We revised the future research plans reported in Chapter 8 in response to these comments, and added a few needed qualifications throughout the report. It was not possible, however, to accommodate both our schedule and all their comments. Thus, the deficits in this report are solely the responsibility of the authors.

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1. INTRODUCTION

BACKGROUND

In the Balanced Budget Act of 1997 (BBA), Congress mandated that the Health Care Financing Administration (HCFA) implement a Prospective Payment System (PPS) for inpatient rehabilitation. This interim report describes the research that RAND performed to support HCFA's initial efforts to design and develop such a PPS. It also discusses our plans to update this research and for further research on the implementation, monitoring, and refinement of such a PPS.

This new PPS will apply to rehabilitation hospitals and to distinct rehabilitation units of acute care hospitals that were excluded from the acute PPS. In order to qualify for such an exclusion the rehabilitation facility must meet two conditions. First, Medicare patients must receive intensive therapy (generally at least three hours per day). Second, 75 percent of all patients must have one of 10 specified problems related to neurological or musculoskeletal disorders or burns. We call this PPS the Inpatient Rehabilitation Facility PPS or (IRF PPS).

Payment for inpatient care of Medicare beneficiaries given in a rehabilitation facility is currently made under the Tax Equity and Fiscal Responsibility Act (TEFRA) of 1982. The payment amount depends on a per-case target amount that is calculated from historical costs at the facility trended forward and on the hospital's actual cost per case. Under TEFRA, there is no adjustment for changes in a hospital's case mix and new hospitals were able to obtain larger payments than existing hospitals. The BBA introduced interim changes to the payment system designed to reduce HCFA's costs and to mitigate the advantage that new hospitals had under the TEFRA payment system. In particular, limits were set on the payment rate for new hospitals and separate maximum payment limits for all hospitals were created. In addition, hospitals that were receiving Medicare payments prior to FY 1990 were allowed to request rebasing of their target amounts.

Need to Improve Payment

Technological changes in the process of care, greater availability of post acute care, and financial incentives for acute hospitals to release patients rapidly combined to cause rapid growth in Medicare payments for all forms of post acute care, including rehabilitation. The number of Medicare beneficiaries served by Skilled Nursing Facilities (SNFs) grew by 94 percent from 1990 to 1995, Medicare beneficiaries served by Home Health Agencies by 78 percent, and the number of Medicare discharges from rehabilitation facilities by 67 percent. (MedPAC, July 1998, Charts 4-3, 4-8, and 4-17). Acute hospitals, paid under the acute PPS, find it advantageous to transfer patients to a different setting as soon as possible. Probably affected by both PPS and TEFRA incentives, the number of rehabilitation hospitals and units increased 4.1 percent annually during 1990-1997 (MedPAC, July 1998). By FY 1996, 23 percent of acute PPS discharges used post acute care within one day of discharge and 2.8 percent went to a rehabilitation facility.

Although rehabilitation facility payments from Medicare were substantially less than costs in the early 1990s, the ratio of aggregate Medicare payments to cost increased rapidly during the 1990's. By 1995 payments exceeded costs by 7 percent for free-standing rehabilitation hospitals and by 4 percent in rehabilitation units. (MedPAC, July 1998, Chart 4.17). This improved position was driven, at least in part, by reduced costs associated with a decline in length of stay (LOS) for rehabilitation patients.

In addition to TEFRA’s inability to control costs, it also may hinder access to care. The lack of a case mix adjustment in TEFRA creates incentives for providers to specialize in relatively less expensive cases, which could conceivably limit beneficiary access. Further, TEFRA lacks outlier payments that help to mitigate the acute PPS’s incentives to under serve the most expensive patients and that provide substantial protection to providers against financial risk (Keeler, Carter, and Trude, 1988). Additional distortion of case-level payments occurs when TEFRA counts discharges that do not include a full course of rehabilitation (e.g., short stays for evaluation, transfer cases) as full cases. These distortions may have affected hospital behavior (Chan and Ciol, 2000).

Further, TEFRA is widely perceived to be unfair to older hospitals. Newer hospitals were not subject to the same incentives for efficiency, and indeed were rewarded for incurring higher costs in their base year(s).

Research Enabling an IRF PPS

One of the reasons for the initial exclusion of rehabilitation hospitals from the PPS was that Diagnosis-Related Groups (DRGs) could not predict resource use at these facilities very well. Functional status, measured by activities of daily living and mobility, is more correlated than diagnoses with charges for the patient (Hosek et al., 1986). Restoring functional status is the goal of rehabilitation and thus functional status at admission is one of the primary determinants of resource use.

In the early 1990s Margaret Stineman and colleagues developed Function Related Groups (FRGs) based on the Functional Independence Measure (FIM) as well as on a clinically derived set of rehabilitation impairment categories (RICs) (Stineman, Escarce, et al., 1995). The FIM is an 18-item measure covering six domains: self-care, sphincter control, mobility, locomotion, communication, and social cognition (Stineman, Hamilton, et al., 1994).

Carter, Relles, et al. (1997) evaluated the FIM-FRGs and found that they use the right organizing concepts for a rehabilitation patient classification system--impairment groups subdivided by functional status and age. The study found further that FIM-FRGs are good predictors of resource use. The analysis suggested that the FIM-FRGs could be a suitable basis for a Rehabilitation PPS, but that certain modifications would produce even better groups for payment purposes. In particular they advised using a multiplicative factor to account for the extra costs associated with patients who have at least one of a selected set of major comorbidities and expanded the FRG set to 82 FRGs. In expanding the number of FRGs, they changed the stopping algorithm to limit the number of categories in the classification system.

Carter, Buchanan, et al. (1997) describes the construction of a model of a rehabilitation PPS based on these expanded FRGs and comorbidity weights. They examined the major elements of such a system: case weights, payment arrangements for unusual cases such as transfers and outliers, hospital-level payment adjustments, and a monitoring system. They examined alternative forms of several of these payment elements in payment simulations. They concluded that an PPS based on the FIM-FRGs is feasible and could achieve several goals. They judged that it would (1) provide hospitals with incentives for efficiency because they can keep payments in excess of costs; (2) promote access for all Medicare beneficiaries to high quality and appropriate care because it disadvantages no clinical or demographic group; (3) be fair to hospitals since it distributes Medicare payments according to patient characteristics modified by input prices and covers costs at all groups of hospitals except those who probably have high costs because they have especially high payments under the current payment system.

Survey Instrument for Post Acute Care

In developing a case-based IRF PPS, one must be mindful of the relationship between the PPS and payment for rehabilitation that occurs in other sites—particularly in SNFs and HHAs. The increase in Medicare post acute care costs led to a Congressional mandate to reform all payment for post acute care. The same BBA that mandated a PPS for rehabilitation hospitals, also mandated the use of PPSs for SNFs starting in July 1998 and for HHAs starting in October 1999 (later delayed until October 2000). Further, HCFA must prepare a report to Congress on a PPS for long-term care hospitals.

There is some overlap in the populations seen in these sites (Kramer et al., 1997), and using different payment systems in different sites may lead to inappropriate sorting of patients leading to undesirable clinical and fiscal consequences. Consequently, HCFA has invested in the development of a patient level survey instrument, called the Minimum Data Set-Post Acute Care or MDS-PAC. The intent is that this instrument will be used for all post acute care patients, allowing comparability of case mix and outcomes across settings. This instrument has been pilot tested across all post acute care settings, including inpatient rehabilitation facilities.

PAYMENT

The unit of payment in the IRF PPS will be a Medicare covered hospital stay, beginning with an admission to the rehabilitation hospital or unit and ending with discharge from that facility. Inpatient rehabilitation is inherently episodic: episodes typically begin with a clinical event leading to acute care and the majority end with a return to independent living in the community. Indeed, return to the community is the stated goal of the inpatient rehabilitation process. The Balanced Budget Refinement Act of 1999 (BBRA) mandated that discharges be the unit of payment.

In the first two years of the IRF PPS, the hospital's payment rate will be a blend of the national PPS payment and its TEFRA payment. A fully national prospective payment will be used for all cost report periods beginning in the third year of implementation. The following formula describes the calculation of payment for each case that will be used when the IRF PPS is fully implemented. One-third of this amount will be the PPS payment in the first year of the transition, with two-thirds of the TEFRA payment being added to complete payment. In the second year of the transition, the IRF PPS payment will be two-thirds of the formula and one-third of TEFRA.

Each case will be classified into a Case Mix Group or CMG. The CMGs are based on cause of impairment, functional status as measured by the FIM motor score and FIM cognitive score, and comorbidities. Additional groups are constructed for deaths and atypically short stay cases, whose resource use is not well described by the characteristics used for typical cases. The CMGs will be assigned based on information in the MDS-PAC, with that instrument modified as needed to accommodate the classification rules for CMGs.

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 rate, A_i is the facility payment adjustment, and W_k is the CMG relative weight. R will be chosen to meet the statutory expenditure target, as estimated by the OACT.

This payment may be increased for outlier cases. Also, short stay transfer cases may receive a per diem payment.

OVERVIEW OF INTERIM REPORT

Approach

We have examined a variety of options for the elements of the IRF PPS such as the classification system and the facility payment adjustment. We analyzed the distribution of funds under each payment option. We replicated many of the analyses in our earlier reports with later data from more hospitals and restricting the data to Medicare patients in rehabilitation hospitals. We extended the earlier RAND work by more detailed consideration of several payment elements (notably comorbidities and hospital-level adjustments). Our work is not finished as this is an interim report and we will update the research reported here with newer data and intend further work to include implementation issues, evaluation and monitoring.

The criteria for the design and development of the IRF PPS are similar to those used in Carter, Buchanan, et al. (1997). To insure access to quality care for all Medicare patients, the system must identify patient groups who need different levels of resources and then pay for each group in proportion to cost. The system should be fair to hospitals by paying for costs that are outside the control of hospital administrators, such as area wage levels, or a population that is disproportionately poor. The payment system must allow HCFA to control its budget for post acute care. It must provide incentives for hospitals to provide quality care and limit incentives for "gaming".

Many of the goals of the system conflict. One can attain one goal only at the cost of a lesser attainment of another. Thus the 'optimum' payment system depends on the relative value one places on the criteria. Reasonable people will disagree about what should be done in such a situation and the implementation can and should be derived through a political process that examines alternative points of view and develops a compromise that all can accept. The comments that HCFA receives on its Notice of Proposed Rule Making (NPRM) will help the agency develop such a compromise. We hope this report will inform those making these comments by outlining the major alternatives and describing the feasible tradeoffs so each commenter can figure out what option best meets his or her values. We convened a Technical Expert Panel (TEP) consisting of experts in rehabilitation for the elderly, classification systems, and/or payment systems to review this report, including the project's methods and findings.

The initial design and development of the IRF PPS reported here has been based on a merged file of discharge abstracts from HCFA (the MEDPAR file) and abstracts containing FIM data from both UDSmr and Caredata.com. The data describe discharges in calendar years 1996 and 1997 and are further discussed in Chapter 2. That chapter also describes our major derived variables and the item level completeness of the data files and describes the methods used in our payment simulations.

Payment System Elements

The options for the IRF PPS that we considered were based on varying each of the elements of the payment system. Options for the classification system for typical cases will be discussed in Chapter 3, which also presents an evaluation of the classification system developed in our 1997 report. Chapter 4 discusses the unusual cases that were not used in developing the main classification system. It examines their costs and discusses options for appropriate payments.

The payment will account for patient-level variation in need for rehabilitation resources as measured by weights assigned to each CMG. Options for the method used to calculate these weights are discussed in Chapter 5. Payments will be further adjusted based on hospital characteristics that affect costs. Options for hospital adjustment factors are discussed in Chapter 6.

We used simulations to examine how well each of the payment system elements fit together in a single payment system and to evaluate the likely outcome of the integrated payment system. Simulations were also used to evaluate options for hospital adjustment factors and these simulations are discussed with the other analyses of hospital adjustment factors in Chapter 6. The simulation model is also the primary means that we used to analyze the level of outlier payment as discussed in Chapter 7. In that chapter we also revisit the question of the amount of detail in the classification system.

Implementation Issues and Monitoring

Chapter 8 describes our plans to update and improve the analyses reported here. It also describes our future work on implementation issues and monitoring. We have made recommendations about the information that needs to be collected on the MDS-PAC in order to implement the system as HCFA designed it. We plan further analyses of implementation issues including the reliability of the MDS-PAC as a means of assigning CMG, the costs associated with filling out the instrument, and how the system might be refined to use the additional information that will become available once the MDS-PAC is used uniformly by rehabilitation facilities and by other post acute care providers.

2. DATA AND METHODS

In the first sub-section below, we describe the various data files that we use in our analyses. Our primary data source is a file that provides case mix data on Medicare discharges from facilities that were paid under TEFRA as rehabilitation facilities. We also used annual cost reports from the HCRIS and a file constructed by the Office of the Actuary that projects the HCRIS data into FY 2001. We constructed a file of hospital characteristics which we used to analyze hospital costs and the likely outcome of policy alternatives. We also describe Medicare bills for additional services given to beneficiaries who were inpatient rehabilitation patients. This interim report contains only very preliminary analyses of these bills, but we will discuss our plans for further analyses of them in Chapter 8.

After we discuss our data sources, we define a series of variables that are used throughout the analysis and discuss the frequency of missing data. In the third sub-section, we update our work plan (Carter, Relles, and Wynn, 2000) by describing the samples sizes available for particular analyses and the representativeness of these samples. We conclude this section with a description of the methodology for our simulations. The simulations were used to address various issues throughout the report. Methods used in individual chapters are discussed within those chapters.

DATA SOURCES

Case Mix Data

The information on our case mix file comes from discharge abstracts collected on all Medicare patients by HCFA in the course of administering the program and from additional patient information, including the Functional Independence Measure (FIM), recorded by a subset of rehabilitation hospitals. The case mix file was created prior to this project and is described in more detail in Carter, Relles, and Wynn (2000).

Claim Records. HCFA sent us records of all calendar year 1996 and 1997 discharges from the Medicare Provider Analysis and Review (MEDPAR) file. These provide patient characteristics, the admission and discharge dates, and charges for services rendered during the stay.

We used the provider number in the range 3025 - 3099 to identify free standing rehabilitation hospitals and a value of "T" in the provider code field to identify discharges from rehabilitation units of acute care hospitals that were exempt from the PPS. Such discharges form the universe of 1996 and 1997 rehabilitation cases that we wished to study.

The size of this universe is shown in Table 2.1. There were 359,032 rehabilitation discharges in CY 1997. Freestanding hospitals cared for 33 percent of discharges in each year, but constitute only 19 percent of the hospital universe.

Table 2.1

Number of Rehabilitation Discharges and Facilities

	Number of Discharges			**Number of Facilities**		
Calendar Year	**Total**	**Free-Standing**	**Exempt Units**	**Total**	**Free-Standing**	**Exempt Units**
1996	344,126	114,933	229,193	1,081	204	877
1997	359,032	118,541	240,491	1,123	212	911

Source: MEDPAR

Functional Independence Measure and Related Data. Our FIM data come from the Uniform Data System for medical rehabilitation (UDSmr) and from the Clinical Outcomes Systems (COS) data for medical rehabilitation. UDSmr is operated within the Center for Functional Assessment Research, U. B. Foundation Activities, Inc., in Buffalo, New York. COS is operated by Caredata.com, Inc., a provider of health care data and decision support systems, located in Atlanta Georgia. Participation in either of these databases is entirely a voluntary decision by hospital management. Hospitals that are not participating in either database may be using a different version of the FIM, a different assessment instrument, or not participating in any assessment process.

The data found in both FIM data bases include demographic descriptions of the patient (birth date, gender, zip code, ethnicity, marital status, living setting), clinical descriptions of the patient (condition requiring rehabilitation, ICD-9-CM diagnoses, functional independence measure (FIM) at admission and discharge), and the hospitalization (encrypted hospital identifier, admission date, discharge date, payment source, and discharge destination).

Linking Process. The MEDPAR and FIM files that described the same discharge were linked during an earlier project. The linking process proceeded in two steps. The first step determined the Medicare provider number(s) corresponding to each UDSmr/COS facility code. The second step matched UDSmr/COS and MEDPAR patients within paired facilities using a probabilistic match algorithm. In addition to hospital identity, the variables we used were admission date, discharge date, zip code, age at admission, sex, and race. All these variables are on each of the files, although sometimes in a slightly re-coded form (e.g., birth date).

During the linking process we dealt with a number of complications. Some of the records in our FIM data base were not paid by Medicare. Further, some of the facilities included in our FIM data base were not paid as rehabilitation hospitals under TEFRA (rather they were either SNFs or Long Term Care hospitals). So even their Medicare patients' records did not belong in our data base. In addition, the FIM data do not provide a complete record of activity at these facilities during 1996 and 1997. Many hospitals were joining UDSmr or COS during those years, so may have been present only part of the year, or may not have had their data properly organized to include in the data systems until somewhat later. Also, a few hospitals belonged to both UDSmr and COS and we needed to eliminate duplicate records of the same stay.

Match Quality. We judged the quality of the match, compared to what was possible given our data, in two ways. First, we looked at MEDPAR records for providers that appeared in a FIM data base throughout each year and calculated the fraction of the MEDPAR records that we were able to match to a FIM record. We were able to match 87.6 percent of such MEDPAR records in CY 1996 and 89.4 percent in CY 1997. The second way we judged the quality of the match is the percent of FIM records for which Medicare is listed as the primary payer that we were able to match. In CY 1996 we matched 95.7 percent of such FIM records and in CY 1997 we matched 93.4 percent of such FIM records. Using both measures, the match rate was very similar for each FIM source. Details are in Carter, Relles, and Wynn (2000).

Almost exactly half of all CY 1996 MEDPAR rehabilitation discharges were matched and 57.4 percent of CY 1997 MEDPAR rehabilitation discharges were matched. We will describe the analysis sample in more detail following discussion of other data sources.

HCRIS Data

Hospital cost reports are contained in HCRIS. The cost reports contain information on costs and charges by cost center, facility characteristics, and utilization. Each record covers a hospital fiscal year, and all the hospital fiscal year records that began during a specific federal fiscal year are kept together in the same file. The file is named according to the number of years from the beginning of the acute care Medicare Prospective Payment System (PPS).

In most of the analyses reported here, we used the latest files available in December of 1999 for PPS13 (i.e., hospital fiscal years that began during FY 1996 from 10/1/95 through 9/30/96) and PPS 14 (i.e., hospital fiscal years that began during FY 1997 from 10/1/96 through 9/30/97). We also used an older version of the PPS12 Exempt Hospital and Excluded Units Data Set, which was derived from the HCRIS. Thus, the cost report data coincide well with our MEDPAR file. The cost report data cover the date of discharge of our entire sample except for discharges during the last quarter of CY 1997 for hospitals with a cost report period beginning October 1.

Some of our preliminary analyses were based on earlier cost report data. These cost report data did not include a PPS 14 file and included a PPS 13 file from early 1997.[1] Analyses based on this earlier cost report data include the CART analysis that led to the definition of the CMGs. The weights were created with the newer cost report information. This earlier data was also used for exploratory analyses of most payment elements, but we repeated all analyses with the newer data and report here only the final version of each analysis.

[1] It is this cost report data that was used to calculate case costs on the initial version of the matched MEDPAR-FIM file which was sent to HCFA.

OACT File

This provider level file contains estimates by HCFA's Office of the Actuary (OACT) of TEFRA payments and costs during federal FY 2001. The providers with data in this file are restricted to those for whom HCRIS data were available for PPS 12, 13, and 14. The file contains estimates of total capital costs, operating costs, capital TEFRA payments, operating TEFRA payments, and number of discharges for each provider on the file. The file was received in December of 1999 and reflects the wage adjusted cap on the TEFRA limit that was part of the Balanced Budget Refinement Act. It also reflects revised target rates for hospitals that rebased in their fiscal year that began in FY 1998.

Provider File

This file contains one record for any provider that either had a rehabilitation discharge paid under TEFRA in CY 1996 or CY 1997 or is currently a certified rehabilitation facility as shown on HCFA's OSCAR file. There are 1426 provider numbers on this file.

For each rehabilitation facility we assembled information from HCRIS files and other HCFA sources that we discuss in more detail in Chapter 6. The information includes: (1) a hospital wage index for the area containing the rehabilitation facility, (2) data on the number of medical residents assigned to rehabilitation facilities, (3) data on the percentage of Medicare cases at each rehabilitation facility that are SSI recipients (person level data were not gathered), and (4) information about FY2001 TEFRA payments from the OACT file just discussed. We also took date of certification from the OSCAR file and used it as a surrogate for age of facility, although we found that it frequently lists a date other than the first certification of the facility.

Utilization Data

We received a wide variety of Medicare bills for each beneficiary who was hospitalized in a rehabilitation facility during 1996 and 1997. These bills included all records of hospitalizations, HHA bills, SNF bills, Durable Medical Equipment bills, and institutional outpatient claims.

This interim report contains only very preliminary results from these bills. They will be used in implementation analyses and in the design of the monitoring system as discussed further in Chapter 8.

VARIABLE DEFINITIONS AND DATA QUALITY

Variables Used for Classification

The payment amount for each case in the fully phased-in IRF PPS will be determined in large part by the Case Mix Group (CMG) to which it is assigned. For typical cases--i.e., non-transfers, non-death cases--the CMGs that we have studied are a variant of the Functional Related Groups with Comorbidities (FRGC). The first partition in creating FRGCs is the Rehabilitation Impairment Category or RIC, a grouping of codes that describe the impairment which is the primary cause of the rehabilitation hospitalization.

The codes for the primary impairment are very similar, but not identical in the UDSmr and COS data sets. Most of the differences relate to distinctions within RIC and thus did not affect our analysis. For example, in 1997, UDSmr used codes 8.11 for Status Post Unilateral Hip Fracture and 8.12 for Status Post Bilateral Hip Fracture, while COS used only 8.1 for Status Post Hip Fracture. Although most of the coding differences did not affect our analyses, UDSmr added several new impairment codes related to medically complex conditions in July 1997 while COS used the same codes with an entirely different meaning, viz., to denote cases with multiple impairments. Fewer than 1 percent of COS cases had these codes. We grouped all these cases into the miscellaneous RIC, as there were not enough cases to analyze separately. In addition, there were 328 COS records with impairment codes that could not be assigned to a RIC in 1996 (or 1.26 percent of all COS records in 1996) and 323 such cases in 1997 (0.84 percent of COS records in 1997).

RICs were created based on clinical criteria and, except for the miscellaneous group, do not group patients who are clinically different from one another in the same RIC. In our earlier report (Carter, Relles, et al., 1997), we used the RICs as defined in version 2 of the FRGs (Stineman, et al, 1997). One of the purposes of the analyses reported here was to evaluate these RICs and update them as necessary.

This analysis and the final definition of RIC will be found in Chapter 3.

Each RIC is subdivided based on age and functional status. Age is taken from the MEDPAR and is age in years at the day of admission. Functional status is measured by the Functional Independence Measure or FIM. The FIM is an 18-item measure covering six domains: self-care (six activities of daily living), sphincter control (two items on bowel and bladder management), mobility (three transfer items), locomotion (two items on walking/wheelchair use and stairs), communication (two items on comprehension and expression), and social cognition (three items on social interaction, problem solving, and memory). The first four domains—self-care, sphincter control, mobility, and locomotion—are combined into a single motor scale. Similarly, the last two domains—communication and social cognition—are combined to form a single cognitive scale. All 18 items are scored into one of seven levels of function ranging from complete dependence (1) to complete independence (7) and the motor scale and the cognitive scale are created as the sum of the relevant responses—so the motor scale is in the interval from 13 to 91 and the cognitive scale is in the interval from 5 to 35.

There is a slight difference between our two data sources in the way three FIM items are recorded. In COS separate fields are used to describe independence in walking and in wheelchair use. In UDSmr only a single item covers locomotion in either modality (with a flag saying which is used most frequently or that both are used equally). Similarly, COS uses separate fields for auditory comprehension and visual comprehension and for vocal expression and non-vocal expression, while UDSmr uses a single item for each of comprehension and expression. In the COS data, almost always only one of each of these pairs of items was filled in, so we took whichever one was present. In the few cases when both COS fields for a single FIM item were filled, we averaged them.

The final partition in our classification is comorbidity. We used ICD-9-CM codes from the MEDPAR to analyze the effect of comorbidity. The MEDPAR contains up to nine secondary diagnoses on each discharge record to describe comorbidities and complications. We use only these data fields and do not use the comorbidity data recorded on the FIM instruments.

Chapter 3 describes how we used these elements--impairment code, age, motor score, cognitive score, and ICD-9-CM secondary diagnoses to develop and analyze alternative classification systems and to develop a recommendation for a classification system to be used in the IRF PPS.

Cost Per Case

We used the departmental method to estimate the accounting cost of MEDPAR discharges. This method combines MEDPAR information about charges in each ancillary department with the departmental cost-to-charge ratio (CCR) from the cost report to estimate costs incurred by the patient in the department (see, for example, Newhouse et al., 1989). Separate per diems for routine and special care days are combined with MEDPAR counts of such days to estimate routine and nursing costs. Special care days are days spent in intensive care units or in coronary care units. Fewer than 1 percent of rehabilitation days are spent in such units.

The CCRs and per diems were calculated from the PPS 12, 13 and 14 cost reports. The cost report that includes the date of the discharge was chosen for each case if it was available. The per diems were inflated (or deflated) from the mid-point of the fiscal year to the day of discharge based on the observed rate of increase in hospital per diems between PPS 12 and PPS 13 (1.1 percent annually). In preliminary analysis an earlier version of the PPS 13 cost report was used for discharges in PPS 14. Of necessity this preliminary analysis omitted hospitals that began operation in PPS 14. Other effects of this limitation in our preliminary analysis are likely small. When we compared the cost per case in the sample estimated using the preliminary HCRIS data to that estimated using the latest data, we found that the mean cost of the 1996 cases was 0.4 percent lower with the later data and the mean cost of the 1997 cases was 1.1 percent lower.

Hospitals that are all-inclusive providers[2] were omitted from analyses of case level cost and their data were not used in calculating weights or payment parameters.

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[2] In the PPS13 file only 21 rehabilitation facilities (2 percent) are listed as all inclusive providers.

Some departmental CCRs are missing or were found to be outside a plausible range, probably reflecting an error in the cost report data. We replaced individual CCRs for all departments except anesthesiology when they were either greater than 10, or less than 0.05. For anesthesiology the CCR was replaced only when greater than 10, or less than 0.01. The replacement was calculated as the mean value of the CCR for the same department within the same type of hospital (either freestanding or unit). There were very few replacements. The largest number occurred in the department for supplies with three replacements of the CCR for supplies in PPS 14 out of the 588 hospitals for which we have FIM data and two occurred in PPS 13 out of the 585 hospitals for which we have FIM data. In all other departments combined, there were eight replacements in PPS 14 and a similar number in PPS 13.

Routine care per diem rates were always available and appeared plausible. Special care per diem rates are used relatively rarely for rehabilitation patients, but appeared reasonable for hospitals that have special care days.

Discharge Destination

There are three potential methods of determining where a patient in a rehabilitation facility went after discharge. First, the MEDPAR contains a field called discharge destination which distinguishes discharges to home, acute care hospitals, SNFs, and other destinations. Second, each of the FIM instruments provides information about the living setting or location to which the patient was discharged, distinguishing many of the same settings as MEDPAR and a few additional ones.[3] Third, we can use Medicare bills to determine which patients went to most of the settings that will classify the patient as a transfer: acute care, other hospital, or SNF. Medicare bills cannot identify transfers to non-SNF nursing homes.

Table 2.2 compares the discharge living setting as coded on the FIM instruments with the discharge destination coded on MEDPAR. The categories are not identical on either the MEDPAR or on either of the FIM instruments. Although we grouped only categories that we believed were similar, differences in the definitions of certain categories may be responsible for some of the disagreement between the MEDPAR and the FIM instruments. However, even allowing for slightly different definitions, it is clear that the instruments are recording different outcomes for many cases. For example, there were 6,962 cases that the FIM instrument said went to acute care (either their own or another facility), but the MEDPAR said they were discharged to either home or a home health agency. Similarly, there were over 9,000 cases that the FIM instrument said went to a SNF, but the MEDPAR said they were discharged to either home or a home health agency.

Table 2.2

Number of Matched Discharges in Combinations of MEDPAR Discharge Destinations and FIM Discharge Setting

MEDPAR	Community	Acute Care	Other Hosp.	SNF	Other LTC	Died	Other, Missing	Total
Home and HHA	279729	6962	820	9112	1383	167	2740	300913
Short-term Hospital	2199	17859	199	948	269	118	293	21885
Other Facility	2416	2618	361	1643	528	21	106	7693
SNF	4731	875	296	29458	2505	9	434	38308
ICF	2648	296	52	3138	1017	5	44	7200
Died	55	41	0	6	2	847	17	968
Other, Missing	574	47	2	11	21	4	32	691
Total	292352	28698	1730	44316	5725	1171	3666	377658

Note: For the MEDPAR, we grouped discharge destinations 1, 6, and 8 into Home and HHA and code 7 (left against medical advice) with missing data. For the UDSmr instrument, we grouped codes 1, 2, 3, and 14 into "community;" 6 and 7 into "acute care;" 8 and 9 into "other hospital;" 4, 12, and 13 into "other LTC," and 99 into "other, missing." All discharges that were part of an interrupted stay, except the last discharge, were counted as if sent to acute care. For the MOS instrument, we grouped codes 1, 2, 3, 4, 5, and 11 as discharges to the community; 7 and 8 as "acute care;" 9 and 10 as "other hospital;" 6 as SNF, 12 as "other LTC," and 15, 14, and blank as "other, missing."

Previous examination of the use of the MEDPAR discharge destination to define transfers from acute care showed many errors of omission (Carter and Rumpel, 1993). Further the FIM categories appear to allow one to identify transfers to a nursing home that is not a SNF.

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[3] The setting choices on the two FIM instruments are similar but not identical. Nevertheless, by grouping a few codes on each instrument, one can define settings that are comparable.

Consequently, in the analyses reported here, we used discharge setting on the FIM records to identify transfer cases.

We have recently begun exploring using Medicare bills to help verify discharge destination as recorded on the FIM. Table 2.3 shows that their were 17,768 patients in our 1996 matched MEDPAR-FIM sample for whom we found a Medicare bill for a SNF stay beginning within one day of discharge from their inpatient rehabilitation stay. Of these 68 percent had been recorded as going to a SNF on their MEDPAR record, with an additional 7 percent recorded as going to an intermediate care facility.

Table 2.3

Consistency of MEDPAR and FIM Instrument Discharge to SNF with Medicare Bill for SNF Stay Beginning Within One Day of Discharge

	1996				1997			
	Patients with SNF Bills		Patients with no SNF Bill		Patients with SNF Bills		Patients with no SNF Bill	
	N	%	N	%	N	%	N	%
MEDPAR								
Discharge to SNF	12108	68.14	5288	3.44	16690	66.27	4222	2.33
Discharge to ICF	1271	7.15	2108	1.37	1809	7.18	2012	1.11
Other	4389	24.70	146462	95.19	6686	26.55	174613	96.55
Total	17768	100.00	153858	100.00	25185	100.00	180847	100.00
FIM Instrument								
Discharge to SNF	14500	81.61	6085	3.95	19118	75.91	4613	2.55
Discharge to Other LTC	739	4.16	1146	0.74	2473	9.82	1367	0.76
Other	2529	14.23	146627	95.30	3594	14.27	174867	96.69
Total	17768	100.00	153858	100.00	25185	100.00	180847	100.00

The FIM data appear to be slightly more indicative of actual discharge to SNF, with 81.6 percent of 1996 patients with SNF bills being shown as discharged to SNFs. The decline in 1997 is due to the introduction by UDSmr of a code for 'sub-acute setting', which we classify as 'other long term care'--although 84 percent of patients with this code actually had a SNF bill.

Another thing to notice in Table 2.3 is that there are a substantial number of cases that are shown by both MEDPAR and FIM to be going to a SNF and, yet, no bill is received. These cases outnumber the cases where a bill was found but the FIM did not indicate a discharge to a SNF or other LTC facility. Some of the apparent overestimate of the number of transfers to SNFs by the FIM data may instead be accurate counts--patients who have exhausted their Part A benefits or patients who otherwise choose to enter the SNF as private pay patients.[4] Another part of the overestimate of the transfer rate may be due to transfers to non-SNF nursing homes. As shown in the 'other LTC' row many of the cases which the FIM recorded as discharged to non-SNF, non-hospital LTC facilities actually went to SNFs. We expect there are similar errors in the opposite direction--i.e., cases that went to non-SNF, non-hospital facilities being classified as discharged to a SNF.

Table 2.4 compares the discharge destination codes to MEDPAR bills for hospitalizations that begin within a day of discharge. Again the FIM data appear to correspond better to the bill data than the MEDPAR. Adding the codes for other hospitals and acute care, we can use the FIM to identify 82 percent of the 1996 cases with bills from receiving hospitals. Errors of omission are largely matched by errors of commission leaving hospital transfer rates calculated from the FIM (7.99 percent in 1996 and 8.11 percent in 1997) being roughly equal to hospital transfer rates calculated from the bills (8.04 percent in 1996 and 8.18 percent in 1997). Transfers to hospitals would be slightly underestimated using the MEDPAR discharge destination (7.71 percent in 1996 and 7.94 percent in 1997).

Based on these data we conclude that the FIM discharge destination is more accurate than the MEDPAR data, but that neither is completely accurate. In addition, we will typically group together discharges to SNF with other discharges to long term care using the definitions shown in the Note to Table 2.2. When the discharge location on the FIM instrument was missing,[5] we used the MEDPAR discharge destination information. We also allowed the Social Security Administration's definition of date of death to override discharge destination. When the MEDPAR provided a verified date of death equal to the date of discharge or the preceding day, we counted the patient as dying in the rehabilitation hospital.

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[4] Some of the error may also be due to simple miscoding of dates.

[5] In the UDSmr, the missing code is 99; in the COS, the missing code is a blank.

Table 2.4

Consistency of MEDPAR and FIM Instrument Discharge to Hospital with MEDPAR Bill for the Receiving Hospitalization

	1996					1997				
		Patients with Receiving Hospital Bills		Patients with no Receiving Hospital Bill			Patients with Receiving Hospital Bills		Patients with no Receiving Hospital Bill	
	All Patients	N	%	N	%	All Patients	N	%	N	%
MEDPAR										
To Acute Care	9864	8730	63.27	1134	0.72	12021	10456	62.08	1565	0.83
Other Hosp	3363	1417	10.27	1946	1.23	4330	1702	10.10	2628	1.39
Other	158399	3650	26.46	154749	98.05	189681	4686	27.82	184995	97.78
Total	171626	13797	100.00	157829	100.00	206032	16844	100.00	189188	100.00
FIM Instrument										
To Acute Care	12876	11129	80.66	1747	1.11	15822	13500	80.15	2322	1.23
Other Hosp	837	157	1.14	680	0.43	893	171	1.02	722	0.38
Other	157913	2511	18.20	155402	98.46	189317	3173	18.84	186144	98.39
Total	171626	13797	100.00	157829	100.00	206032	16844	100.00	189188	100.00

ANALYSIS SAMPLE

Here we update our work plan by describing the completeness of the case mix records and the cost data, and therefore the sample sizes available for various analyses. Then we describe how representative the data is of the entire set of rehabilitation discharges paid under TEFRA in CY 1996 and CY 1997.

Sample Size

Table 2.5 shows the size of the sample available for various analyses. The population is the count of MEDPAR records paid under TEFRA in each year. We matched FIM data with 49.9 percent of the 1996 records and 57.4 percent of the 1997 records. The fraction of hospitals is roughly similar to the fraction of cases. There were several hundred cases in our file from each year that had incomplete data for either the impairment that is the primary cause of the hospitalization or the motor score or the cognitive score and the remaining cases are counted in the table as being "Good FIM". In each year there were several thousand cases for which we could not estimate a case cost and which could not be used in most of our analyses. Most of these were from all-inclusive providers for whom we lost all cases.[6] The remaining records with good FIM and cost data are shown in the table in the first row labeled 'Case Cost and FIM.' The next row is the preliminary sample which consists of the subset of records for which at least one cost report was available at the beginning of the project and which were not from all-inclusive providers. The lack of current data in our preliminary analyses deprived us of 431 1996 records and 4,289 1997 records.[7] We repeated most, but not all, analyses with the most complete data available.

Our classification analyses used data from all available hospitals. However, hospitals in Maryland will not be included in the IRF PPS and consequently, we eliminated data from the single Maryland hospital that was in our data set when we calculated parameters of the IRF PPS such as weights. We will call the subset of non-Maryland discharges with good FIM data and case costs our analysis sample. Many of our parameter estimations (such as case weights) and our simulations are based on the CY 1997 analysis sample: 201,164 cases from 618 hospitals (55 percent of the population).

Table 2.5

Analysis Sample Size

	Discharges				Hospitals			
	1996		1997		1996		1997	
	N	%	N	%	N	%	N	%
Population	344,126	100.0	359,032	100.0	1,081	100.0	1,123	100.0
Matched Records	171,626	49.9	206,032	57.4	565	52.3	631	56.2
Good FIM	171,206	49.8	205,375	57.2	565	52.3	631	56.2
Case Cost and FIM	167,473	48.7	201,653	56.2	556	51.4	619	55.1
Preliminary Sample	167,042	48.5	197,364	55.0	552	51.1	599	53.3
Exclude Maryland	171,298	49.8	205,542	57.2	564	52.2	630	56.1
Good FIM	170,878	49.7	204,886	57.1	564	52.2	630	56.1
Case Cost and FIM	167,145	48.6	201,164	56.0	555	51.3	618	55.0
In OACT File	147,685	42.9	172,104	47.9	471	43.6	511	45.5
Good FIM	147,376	42.8	171,559	47.8	471	43.6	511	45.5
Case Cost and FIM	144,359	41.9	168,337	46.9	465	43.0	505	45.0

For simulations of FY2001 payments, we are restricted to the hospitals for which OACT predicted costs and TEFRA payments. The size

[6] There were also several cases with no charges and therefore no way to estimate ancillary costs.

of the sample with all required data is shown in the last row of the table. In the following section, we will examine the representativeness of this OACT sample and of our full analysis sample. (The representativeness of all matched cases is addressed in Carter, Relles and Wynn, 2000.)

Table 2.6

Percent of Inpatient Rehabilitation Discharge Universe in Samples, by Patient Characteristics

	1996			1997		
Patient Characteristics	**N**	**% Analysis Sample**	**% OACT Sample**	**N**	**% Analysis Sample**	**% OACT Sample**
Total	344,126	49	42	359,032	56	47
Sex						
Male	129,399	49	42	135,781	56	47
Female	214,727	48	42	223,251	56	47
Race						
White	296,894	49	42	309,026	57	47
Black	35,090	46	39	37,491	53	43
Other	12,142	48	42	12,515	52	46
Age						
<65	27,215	48	41	29,667	56	46
65-69	48,413	50	43	48,570	57	47
70-74	68,219	50	43	70,529	57	47
75-79	78,885	49	43	82,851	57	48
80-84	65,683	48	42	68,854	56	47
85-89	39,217	47	41	41,123	55	46
90-94	13,549	45	39	14,390	52	44
95+	2,765	42	37	3,048	49	42
Beneficiary Status						
Aged without ESRD	312,482	49	42	325,114	56	47
Aged with ESRD	3,424	43	36	3,097	46	38
Disabled without ESRD	24,836	48	41	27,176	56	46
Disabled with ESRD	2,035	50	42	2,144	57	46
ESRD only	1,359	46	39	1,501	55	46

Representativeness of Sample

Table 2.6 shows how well our samples represent the patient characteristics found in the universe of all inpatient rehabilitation cases paid under TEFRA. The analysis sample describes 49 percent of all 1996 rehabilitation discharges and 56 percent for 1997. The OACT sample

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[7] Other data quality problems with age and LOS reduced the sample in the classification analyses by 2 records from 1996 and 5 records from 1997.

is somewhat smaller, but still we have good FIM data and cost data for almost half the universe. Both samples contain a reasonable representation of all demographic groups, although they slightly underestimate minorities, those 95 or older, and the aged with ESRD.

Table 2.7

Percent of Inpatient Rehabilitation Discharge Universe in Samples, by Hospital Characteristics

	1996			1997		
Hospital Characteristics	**N**	**% Analysis Sample**	**% OACT Sample**	**N**	**% Analysis Sample**	**% OACT Sample**
Total	344,126	49	42	359,032	56	47
Unit	239,193	45	39	240,491	50	42
Freestanding	114,933	55	48	118,541	68	56
Location Type						
Large Urban	163,564	45	37	168,036	52	42
Other Urban	148,316	56	51	158,439	64	56
Rural	29,411	34	28	31,878	39	31
Location						
New England	38,828	32	30	40,635	43	38
Middle Atlantic	48,223	52	49	46,783	59	54
South Atlantic	57,893	57	49	61,876	68	57
East North Central	58,847	60	53	61,611	63	54
East South Central	25,736	56	39	27,793	63	45
West North Central	21,436	40	36	22,206	47	42
West South Central	55,762	39	32	60,599	46	38
Mountain	15,841	33	30	15,860	48	36
Pacific	21,560	51	42	21,669	52	42
Percent Low-Income (LIP)						
LIP < .1	144,076	50	46	148,259	57	52
.1 <= LIP < .2	106,022	53	46	112,757	61	50
.2 <= LIP < .3	38,780	40	30	42,220	45	32
.3 <= LIP	20,186	46	29	21,271	42	34
Average Daily Census (ADC)						
Free, ADC < 25	8,932	49	38	9,383	54	38
Free, 25 <= ADC < 50	36,950	52	42	39,800	64	49
Free, 50 <= ADC	68,605	58	53	68,978	73	63
Unit, ADC < 10	39,032	35	31	40,493	38	32
Unit, 10 <= ADC < 25	117,104	44	37	124,765	49	42
Unit, 25 <= ADC	71,591	55	46	73,267	59	50
Interns and Residents to ADC (TCH)						
0 = TCH	265,745	51	43	273,943	57	49
0 < TCH < .05	48,618	48	47	48,774	59	54
.05 <= TCH < .15	15,864	50	44	15,555	53	47
.15 <= TCH	5,042	28	15	4,560	37	30

Table 2.8

Percent of Inpatient Rehabilitation Hospital Universe in Samples, by Hospital Characteristics

	1996			1997		
Hospital Characteristics	**N**	**% Analysis Sample**	**% OACT Sample**	**N**	**% Analysis Sample**	**% OACT Sample**
Total	1,081	56	47	1,123	55	45
Unit	877	54	46	911	53	44
Freestanding	204	65	52	212	65	50
Location Type						
Large Urban	478	55	46	506	54	43
Other Urban	428	66	56	451	64	53
Rural	143	43	36	152	41	34
Location						
New England	98	43	38	105	42	35
Middle Atlantic	89	58	52	91	58	51
South Atlantic	144	67	56	148	67	54
East North Central	209	67	57	221	65	54
East South Central	54	69	48	54	67	48
West North Central	96	49	46	54	67	48
West South Central	199	46	37	210	46	35
Mountain	72	44	35	73	42	34
Pacific	120	57	48	121	57	47
Percent Low-Income (LIP)						
LIP < .1	366	60	54	382	59	52
.1 <= LIP < .2	336	65	57	351	64	54
.2 <= LIP < .3	154	51	38	164	50	36
.3 <= LIP	104	39	32	108	39	31
Average Daily Census (ADC)						
Free, ADC < 25	54	48	33	58	47	31
Free, 25 <= ADC < 50	77	69	52	77	71	52
Free, 50 <= ADC	67	81	73	68	82	72
Unit, ADC < 10	295	43	35	306	42	34
Unit, 10 <= ADC < 25	433	58	49	446	58	48
Unit, 25 <= ADC	137	71	62	138	70	62
Interns and Residents to ADC (TCH)						
0 = TCH	857	58	48	890	58	46
0 < TCH < .05	95	73	71	98	72	68
.05 <= TCH < .15	41	56	49	42	55	48
.15 <= TCH	25	56	44	26	58	42

Tables 2.7 and 2.8 shows how well our samples represent the hospital characteristics in the Medicare universe. In Table 2.7, we count sample discharges while in Table 2.8 we count each hospital equally and count a hospital in the sample if it had any discharges in the sample. The differences between sample and universe in hospital characteristics are somewhat larger than the differences in patient characteristics. In particular, our sample under represents units,

rural hospitals, hospitals in New England, and hospitals with a high proportion of low-income patients. On average, free standing facilities are larger than exempt units. Within each group our sample is drawn slightly more from the larger facilities.[8] Although there are only a total 25 hospitals with more than 0.15 interns and residents per average daily census, this small group is also underrepresented in the sample.

SIMULATIONS

We simulated a variety of alternative designs for the IRF PPS. Most of the simulations were based solely on the CY 1997 data and were designed to test individual features of an IRF PPS such as options for the classification system, the amount of outlier payments, or facility adjustments. We also simulated a small number of options to examine the impact of the design of the IRF PPS relative to projected costs in FY 2001 and relative to projected TEFRA payments in FY 2001. Each simulation was based on the assumption that changes in details of the payment method would not affect behavior.

Each of the CY 1997 simulations that were used to analyze options for the design of the PPS expended exactly the same amount of funds (to within one dollar per case). For these CY 1997 simulations, total payments were designed to equal total costs. We achieved a value of payment per case that is within one dollar of cost per case in each simulation by adjusting the conversion factor and the outlier threshold.

The impact simulation payment rate for FY 2001 was determined so that total PPS payments would equal 94 percent of estimated FY2001 payments under TEFRA. Thus, in the FY 2001 simulation only, one-third of the IRF PPS payment plus two-thirds of the TEFRA payment should equal the mandated 98 percent of estimated TEFRA payment. As in the CY 1997 simulations, we achieved a value of payment per case that is within one dollar of the target payment by adjusting the conversion factor and the outlier threshold.

The CY 1997 discharges in the merged MEDPAR-FIM analysis file were used in the simulation after selected interrupted stays were bundled as

[8] The reason why the larger proportion of larger hospitals in our sample does not lead to a higher proportion of discharges in our sample than of hospitals is that some of the hospitals are in the sample for only part of the year.

described in Chapter 5.[9] The impact simulation was based on the OACT sample, also with bundled interrupted stays. Each case was weighted equally.

We evaluated each simulation with respect to a variety of outcomes which are described below.

Payment for Groups of Hospitals

For the simulations of options for the IRF PPS, we calculated the payment to cost ratio using the simulated payment and the estimated cost of the case using the departmental method described above. For the FY2001 simulation we used the actuary's estimate of FY2001 cost per case as the denominator. For the FY2001 simulations we also calculate the ratio of the IRF PPS payment per case to the TEFRA payment per case from the OACT file.

The aim of the IRF PPS is to pay each rehabilitation facility in proportion to the costs of efficiently producing the care required by its set of Medicare patients. We would not want to pay hospitals for inefficiency or even for a greater intensity of care than is received typically by patients with similar clinical characteristics and social support level. We follow Gianfrancesco (1990) and others in using the relationship between reimbursement and costs for groups of hospitals as one way of detecting systematic unfairness in a payment system. A finding of a higher ratio of payment to cost in one group than another would suggest unfairness in the payment mechanism unless there was a good reason to believe that efficiency differed between the groups.

We present payment to cost ratios and a comparison of PPS payments and TEFRA payments for groups of hospitals defined by: (1) rural, urban, and large urban location; (2) census region; (3) free-standing versus exempt unit; (4) size of the low-income population; (5) teaching status; (6) size of rehabilitation program; and (7) age of facility. We sum payments and costs for all cases in the group in order to calculate the ratio. Thus all ratios are 'case-weighted' rather than 'hospital weighted.'

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[9] Some policy recommendations were actually made based on simulations using preliminary data. However, in this report we present the final analyses which show that the policy recommendations are consistent with our best data and with other policy decisions.

Payment for Groups of Patients

We examined the payment to cost ratio for groups of patients defined by demographic characteristics such as age, sex, and marital status to ensure that the needs of each group of patients are adequately covered. We believe that providing payment that approximates cost is the best way to provide incentives for hospitals to ensure access and quality care for all patients who need inpatient rehabilitation services.

We also examined special categories of patients such as transfers and deaths to ensure that payment matches the intended policy after accounting for the interaction of the policy with other payment elements. We described the kinds of cases and hospitals that receive outlier payments and the effect of high cost outlier payments on reducing risk.

Accuracy at the Case Level

The accuracy with which the IRF PPS matches payment to cost at the patient level is measured by a univariate regression of the cost of each case on the payment amount for the case (including special payments such as outlier and transfer payments). The statistics from this regression that will be reported for each simulation include the R-squares and the coefficients and their standard deviation. The coefficient on the payment should be close to 1 if payment rises with cost.

Accuracy at the Hospital Level

The accuracy with which the IRF PPS matches payment to cost at the hospital level was measured by the mean absolute value of the difference between each hospital's average cost per case and its average payment per case. We also report the root mean square error (RMSE) of payment as a prediction of cost. This measure gives greater weight to larger errors. One minus the ratio of MSE to the variance of average cost per case is the Efron R-square for a prediction of cost from payment, and can be interpreted as the percent of variance in cost that is explained by payment.

Financial Risk

Rehabilitation hospitals are typically much smaller than acute care hospitals. The median freestanding rehabilitation hospital discharges only 477 Medicare cases per year and the median exempt unit discharges only 222 Medicare cases per year.[10] The median acute care PPS hospital discharged over 1200 patients in the same time frame. The smaller size of rehabilitation facilities suggests that they would be at higher financial risk from a PPS than acute hospitals, i.e., there would be a higher likelihood that their costs would exceed revenues by a substantial amount. However, the higher risk from their small size is partially offset by the greater homogeneity of the cost of cases within FRGCs than within DRGs. Our previous study (Carter, Buchanan, et al., 1997, Table 5.6) showed that, in the absence of outlier payments, the financial risk faced by the typical freestanding rehabilitation hospital under an acute IRF PPS would be quite similar to the amount of risk faced by the typical acute care PPS hospital in the absence of outlier payments. Because exempt units are quite a bit smaller, their risk is larger--close to that of rural hospitals under the acute care PPS.

To assess the extent of financial risk from an IRF PPS, we will use the following measure of financial risk under a PPS for a particular hospital. Risk is defined to be the standard deviation of annual profit around its expected value expressed as a percentage of annual revenues (Keeler et al., 1988). Profit is defined as Medicare revenues minus Medicare costs. We estimate this quantity by assuming that each hospital has its own population of cases that might appear for admission and that actual cases are drawn independently from this distribution. Let

s_i = an estimate of the standard deviation of profit per case at hospital i,

n_i = number of annual cases at hospital i, and

r_i = average revenue per case at hospital i.

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[10] Calculated from the calendar year 1997 MEDPAR file. Averages rather than medians are 559 and 264, respectively.

Then, under our assumption of a random draw of cases,

$$Risk_i = s_i/(sqrt(n_i)r_i).$$

Actual year-to-year variation in profits in the acute care PPS has been shown to be somewhat higher than the variation estimated from this model (Carter and Farley, 1993). At least in part, this was due to management actions that affect costs or revenues.

This risk measure has several characteristics that make sense. Risk decreases with hospital size for hospitals with similar case mix. And the greater the variability of profit among cases, the greater the risk, since variability increases the chance that the hospital will receive so many unprofitable cases that it cannot offset its losses with gains.

In implementing the risk measure we use the simulated payment data on matched MEDPAR-FIM cases in the analysis sample to estimate s_i and r_i, but use all discharges in the entire 1997 MEDPAR file to estimate n_i.

3. CASE CLASSIFICATION SYSTEM

INTRODUCTION

This section describes the case classification system developed for the Inpatient Rehabilitation Facility Prospective Payment System (IRF PPS). We expect to update this classification system with more recent data and invite feedback and criticism before final revisions.

Typical cases (i.e., cases that complete the course of rehabilitation) will ultimately be compensated according to a formula which depends primarily on their assigned class, adjusted by area wage rates and other hospital characteristics. In this chapter, we classify only these typical cases which we will define more precisely in the Methods subsection below. In Chapter 4, we will discuss payment rules for unusual cases, including interrupted stays. Here we use discharge as the unit of classification--a case and a discharge are the same thing for typical cases.

Case classification is a major step in developing a payment formula for a PPS. We build on the Function Related Group (FRG) classification methodology developed in Stineman et al (1994) and extended to incorporate comorbidities in Carter, Relles, et. al. (1997). The latter paper used data from calendar year 1994 (CY94). This report applies essentially the same methods to update the groupings based on more recent (CY96 and CY97) and more voluminous data, and also examines alternative stopping rules. We also try to give insight into the stability of the groupings by examining how well the old FRG groupings and availability lists perform on the more recent data.

We want to group cases that are medically similar and that have similar expected resource needs. The case classification system will be based on the structure of the FRGs enhanced with information about comorbidities (FRGCs). Creation of FRGCs requires three steps.

1. Group cases that are clinically similar. Here we start by using the 20 rehabilitation impairment categories (RICs) defined by Stineman et al. (1997) and examine a variety of changes that Dr. Stineman suggested might improve either clinical or resource homogeneity.

2. Group cases that have similar resource needs. A statistical method called CART (Classification and Regression Trees, Breiman et al., 1984) is used within RICs to partition the population of cases into groups that are homogeneous with respect to resource use and functional impairment.
3. Determine which comorbidities affect the cost of rehabilitation cases by RIC. In Carter et al. (1997), we developed a list of major comorbidities so that any person with a secondary diagnosis appearing on this list had an expected cost that was higher than the expected cost of persons in the same FRG without a major comorbidity. The magnitude of the proposed payment adjustment varied by RIC. We consider modifying that list here.

In the Methods section immediately below, we discuss the methods we employ to develop/update the FRGC case classification system. We then evaluate the old FRGs with our new data. The next two sub-sections analyze the clinical partitioning step and show how we accomplished the resource-based partitioning. The Comorbidities section covers the addition of comorbidity effects, which gives us the preliminary FRGCs that we recommended to HCFA as the basis of the classification system.

DATA AND METHODS

We used the merged MEDPAR/FIM data for calendar years 1996 and 1997 which contain one record for each hospital discharge. MEDPAR data describe all in-patient stays (including rehabilitation stays) paid for by Medicare. FIM data describe the functional status of patients cared for in rehabilitation facilities. Data set construction is documented in the project work plan (Carter, Relles, and Wynn, 2000) and summarized in Chapter 2.

To develop the partitions, we first obtained clinical input about potential modifications to the RIC structure. We then used CART to divide the clinical groups into FRGs based on resource use and analyzed alternative stopping rules for the CART algorithm. This produced the case classification system. As a final step, we defined dummy variables to reflect the new set of FRGs and potential definitions of relevant comorbidities, and determined the recommended comorbidity lists and multipliers through regression methods.

Data Description

The merged MEDPAR/FIM data contained several variables we would need for the classification. Table 3.1 identifies these variables, and indicates at which stages of the process they were used.

Table 3.1

MEDPAR/FIM Variables and Stages of Use

Purpose	Variable	Source	Description
Selection	AGE	MEDPAR	age
	DISSTAY	FIM	discharge stay indicator
	LOS	MEDPAR	length of stay
	IMPCD	FIM	rehabilitation impairment codes
	PROVCODE	MEDPAR	provider code
	PROVNO	MEDPAR	provider number
	TCOST	MEDPAR	total cost estimates, based on cost to charge ratios (*)
Clinical partitioning	IMPCD	FIM	impairment code
Resource use	TCOST	MEDPAR	total cost estimates, based on cost to charge ratios (*)
	ACOG	FIM	cognitive score (*)
	AMOT	FIM	motor score (*)
	AGE	MEDPAR	age

(*) See Chapter 2 for an explanation of how these variables were derived.

The selection variables define what we think of as the typical case. We exclude transfers to hospitals and long term care settings, deaths, cases of three days or less duration, and statistical outliers. Also, the clinical partitioning and resource use variables needed to be present and in range. Selection was based on the intersection of the following rules:

Variable	**Selection Requirement**
AGE	between 16 and 105.
DISSTAY	indicates discharged to the community. (See note to Table 2.2 for specific codes)[11].
LOS	more than three days, less than one year.
IMPCD, TCOST	we excluded cases with log(cost) more than three standard deviations from the average within old RIC (see Table 3.4)
PROVNO, PROVCODE	4-digit rehabilitation provider number between 3025 and 3099, or provider code = "T".
IMPCD	contained in impairment list for assignment to rehabilitation categories (see Table 3.4).
TCOST, AMOT, ACOG	greater than zero.

Table 3.2 shows the amount of data we had to work with, before and after selection, by FIM source. Most of the reduction in cases is for ineligibility: deaths, interrupted stays, or transfers to other forms of post-acute care. The last column indicates how many cases were kept with full information. Overall, the reductions due to missing cost data and data quality (present and in-range, exclude cost outliers) are small: about 3 percent in 1996, 4 percent in 1997. Fortunately, the additional reduction due to cost outliers is especially small--0.3 percent--so we do not believe we are contaminating our results by the cost outlier exclusions.

We felt that there was a sufficient number of cases to support our identifying analysis versus evaluation half-samples. We planned to use the analysis sample to develop our models while holding out a sample to be used initially only for checking. This would enable us to get true estimates of how well our models were performing (it is well known that goodness of fit gets exaggerated in cases where the same data are used to estimate parameters and characterize goodness of fit). After the checking, we combined both halves of the sample to obtain estimates with full precision.

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[11] At the time at which these analyses were done, we did not have the post acute care utilization records and we had not analyzed the transfer cases. Consequently, we incorrectly coded UDSmr cases listed as 'discharged to intermediate care' (code 4) as if they were discharged to the community. These constitute approximately one-half of one percent of the sample and will be omitted in future work. Also, we used the FIM discharge setting to identify death cases.

Table 3.2

Number of Linked MEDPAR/FIM Records

Calendar Year	Source	Initial Number of Records	Rehab Facility	Present and In-Range	Eligible	Exclude Cost Outliers
1996	UDSmr	162,692	145,613	141,811	108,380	108,121
1996	MOS	26,197	26,013	25,229	19,484	19,423
1996	Total	188,889	171,626	167,040	127,864	127,544
1997	UDSmr	183,960	167,608	160,078	121,636	121,335
1997	MOS	38,722	38,424	37,281	27,914	27,830
1997	Total	222,682	206,032	197,359	149,550	149,165

Modeling Methods

We wanted first to establish that the classification process was stable enough to model. We planned to use essentially the same methods we used in 1997. Thus, it seemed prudent to ask whether prediction accuracy is roughly the same, along with whether the 1997 FRG groups do a reasonable job of distinguishing among cases based on their costs.

The first step in developing new FRGs is to identify rehabilitation impairment categories (RICs), which distinguish types of care by the impairment that is the primary cause of the hospitalization. We want to ensure that patients with clinically distinct problems (e.g., stroke versus orthopedic conditions) are treated separately. In previous work, that had been done exogenously: a specification was made primarily on clinical grounds. However, there were sub-categories whose placement was difficult to determine a priori. Here, we consider alternative assignments of some of the "miscellaneous categories," and we seek to choose from alternative specifications according to how much they affect both the mean and variance of cost.

Given a candidate set of RICs, we develop FRGs within RIC using CART, which is a well-known technique for building classification models (Breiman et al., 1984). CART requires a dependent variable (here, log(cost)), and it seeks to develop predictors of the dependent variable through a series of binary splits from a candidate set of independent variables (here, age, FIM motor score, and FIM cognitive score). Each split creates 2 groups of cases that differ on the dependent variable. In effect, CART creates a series of dummy variables for least squares regression. It decides how many dummy variables to use (i.e., how many groups to create) based on statistical significance criteria. Provided the number of dummy variables is not large, the CART models offer the advantage of being quite interpretable.

However, we are working with fairly large data sets, even with the half samples, and it turns out that CART produces models with far too many splits. We needed to introduce "practical" considerations into the stopping criteria. We felt that our ultimate classification system should have fewer than 100 categories, and we take several steps to get within that goal.

EVALUATION OF OLD FRGS

Before proceeding with the modeling, we wanted to see how log cost varies by RIC and by FRG, for the "old" FRG rules developed in Carter et al. (1997). We want the old FRGs to explain average cost, ideally with as much precision as occurred in the data set upon which the FRGs were first developed. The more stability we see, the more confidence we have that the models we derive now will apply in the future. We regressed log(cost) on the old FRG dummy variables, which depended only on ACOG, AMOT, and AGE. Table 3.3 shows how the R-squares from those regressions held up.

There are two things to note in this table. First, results on 1996 and 1997 are quite close to each other. Second, most of the time, the R-squares on the new data are comparable to the old values, the notable exceptions being amputation (other) and cardiac. The amputation RIC had a small sample size in 1994 (258 cases), so we do not view this as a serious problem. For the cardiac RIC, it turns out that there was a large increase in volume between our 1994 data and our current data (more than a doubling in 1997). The reason for the growth in cases is not clear. There may be new clinical subgroups which require rehabilitation and which have differential costs. However, because the cardiac RIC does not have multiple impairment codes, determining whether there are different clinical subgroups will require additional data. Therefore, this is an issue for longer term refinement of the FRGs. In the longer term refinement analysis, we might look at the rate of cardiac rehabilitation cases by intermediary, using short LOS as a surrogate for normal recovery path.

Table 3.3

R-squares for New and Old Data

	Sample Sizes			R-squares			
RIC	**1994**	**1996**	**1997**	**1994**	**1996**	**1997**	**RIC Description**
1	28322	33078	35431	22	28	29	Stroke
2	1134	1403	1653	19	20	19	Brain dysfunction, traumatic
3	1898	2549	2885	21	23	23	Brain dysfunction, nontraumatic
4	618	747	812	27	22	23	Spinal cord dys-function, traumatic
5	2521	3812	4361	29	27	30	Spinal cord dys-function, nontraumatic
6	4014	4775	5769	12	14	16	Neurological conditions
7	13746	16824	18116	11	13	15	Orthopedic--lower extremity fracture
8	16934	31237	37462	15	14	16	Orthopedic--lower extremity joint repl
9	3868	5325	6594	7	13	13	Orthopedic other
10	3495	4831	5454	8	8	8	Amputation, lower extremity
11	258	357	479	15	5	5	Amputation, other (*)
12	1193	2347	2864	10	10	9	Osteoarthritis
13	1270	1173	1527	18	12	13	Rheumatoid and other arthritis
14	2220	4110	5680	24	15	15	Cardiac (**)
15	1779	2451	3571	12	11	11	Pulmonary
16	1156	1329	1890	7	7	7	Pain syndrome
17	321	562	540	0	0	0	Major mult trauma, wo/inj to brain or spinal cord
18	4886	10233	13575	15	16	15	Other disabling impairments
19	231	241	278	37	41	41	Guillain-Barre
20	112	160	224	0	0	0	Major mult trauma, w/inj to brain or spinal cord
Total	89976	127544	149165				

(*) small sample sizes
(**) requires further explanation: see below

Figures 3.1 through 3.3 show how the mean values vary by FRG, for 1994, 1996, and 1997 cost data. The scaling is a little different, the maximum going to $40,000 now versus $50,000 before. But we see the patterns for 1996 and 1997 are quite similar to those of 1994. There is a steep ascent within RIC as the means vary across FRGs, and except for the cardiac RIC, the ascents are steepest for the same RICs as before

(4, 5, and 19). This shows a continuing ability of the old FRGs to explain variation in average costs.

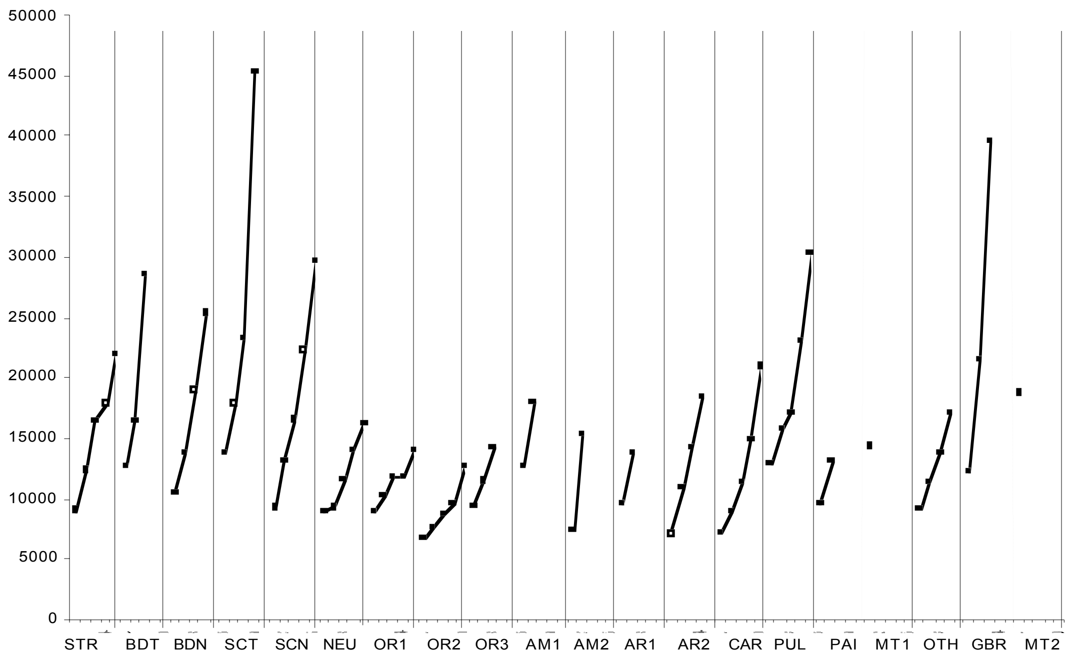

Figure 3.1--Average Cost in 1994 FRGs, 1994 Data

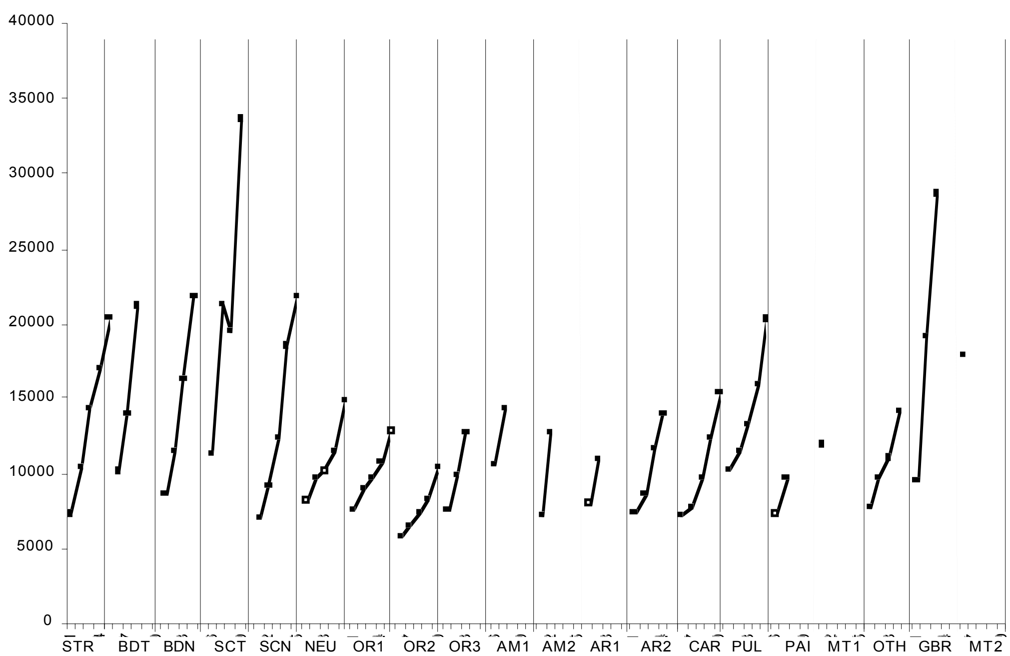

Figure 3.2--Average Cost in 1994 FRGs, 1996 Data

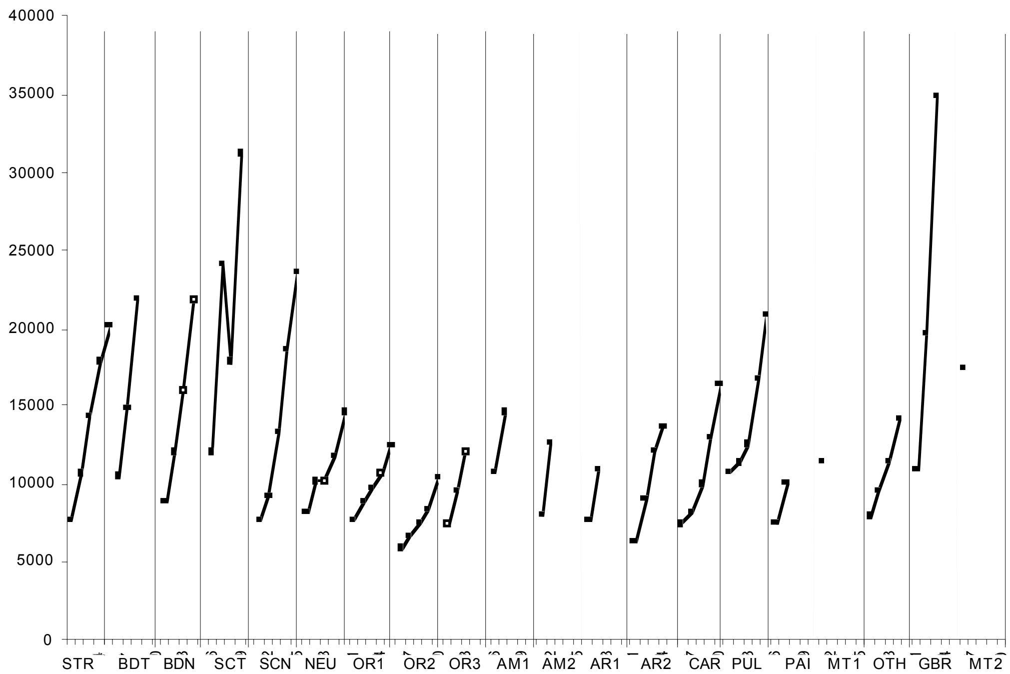

Figure 3.3--Average Cost in 1994 FRGs, 1997 Data

In summary, the old FRGs fit the new data about as well as they had fit the 1994 data. In almost all RICs: the R-square was similar in 1996 and 1997 to what it had been in 1994, and there are large differences in average cost among the FRGs. Thus, the new FRGs that we fit on the 1997 data should be stable over time. Also, we were able to use the old FRGs to analyze other payment elements, while we simultaneously updated the FRGs and the comorbidity list.

REHABILITATION IMPAIRMENT CATEGORIES

FIM data contain an "impairment" code which gives the reason for the rehabilitation stay. Stineman et al. (1994) mapped these codes into rehabilitation impairment categories (RICs). The 1997 study by Carter convened a panel of rehabilitation experts, who generally approved the RIC definitions, but who nevertheless offered some suggestions to try if sample sizes became larger. Further, Dr. Stineman wished to explore some modifications to the definition of RIC in a larger sample. The impairment code to RIC mapping that we used in our 1997 study of 1994 data is shown in Table 3.4.

Table 3.4

Initial Grouping of Impairment Group Codes into Rehabilitation Impairment Categories

Rehabilitation Impairment Category			Impairment Groups
1	STR	Stroke	1.1 through 1.9
2	BDT	Traumatic brain injury	2.2, 2.21, 2.22
3	BDN	Nontraumatic brain injury	2.1, 2.9
4	SCT	Traumatic spinal cord	4.2, 4.21 through 4.23
5	SCN	Nontraumatic spinal cord	4.1, 4.11 through 4.13
6	NEU	Neurological	3.1, 3.2, 3.3, 3.5, 3.8, 3.9
7	OR1	Hip fracture	8.11 through 8.4
8	OR2	Replacement of LE joint	8.51 through 8.72
9	OR3	Other orthopedic	8.9
10	AM1	Amputation, lower extremity	5.3 through 5.7
11	AM2	Amputation, other	5.1, 5.2, 5.9
12	AR1	Osteoarthritis	6.2
13	AR2	Rheumatoid, other arthritis	6.1, 6.9
14	CAR	Cardiac	9
15	PUL	Pulmonary	10.1, 10.9
16	PAI	Pain Syndrome	7.1 through 7.9
17	MT1	Major multiple trauma, no brain or spinal cord injury	14.9
18	OTH	Miscellaneous	11, 12.1, 12.9, 13, 15, 16, 17 through 17.9
19	GBR	Guillain-Barre	3.4
20	MT2	Major multiple trauma, with brain or spinal cord injury	14.1, 14.2, 14.3

These partitions were reconsidered for the present study. We felt that, because there was more data than were available when the earlier set of RICs was generated, we should examine different alternatives. We redefined RICs based on clinician judgment of the clinical homogeneity of the patients, backed up by analyses of resource costs. The specific suggestions from Margaret Stineman and the earlier clinical panel were as follows.

1. Within the otherwise not classified RIC (18, OTH), determine if debility or congenital deformities are statistically different from the remaining cases in that category. If so, one or two new RICs might be defined, with the remaining cases in RIC OTH placed in a redefined 'other' category. This is change proposal 1 in Table 3.5. The specific impairment codes that would appear in each new RIC are shown in Table A.1 in the Appendix.

2. See if new RICs should be defined for burns and multiple sclerosis with the more recent data.
3. To simplify the RIC structure, see if one can statistically support placing Guillain-Barre syndrome under the non-traumatic spinal cord RIC 5. Guillain-Barre syndrome is a non-traumatic condition that impairs spinal cord function. The analyses leading to the original definition of RIC, however, indicated that its LOS was more prolonged than other forms of non-traumatic spinal cord injury. This may have changed.
4. To simplify the RIC structure see if patients classified in the major multiple trauma (MMT) with brain or spinal cord RIC 20 (MT2) might be appropriately classified in with traumatic brain injury (RIC 2) or traumatic spinal cord injury (RIC 4). A new MMT RIC might be explicitly defined as containing those MMT patients with BOTH brain and spinal cord involvement.
5. Try to reduce heterogeneity of the neurology RIC 6. It currently combines certain conditions associated with central nervous system disorders with those involving the peripheral nervous system. Multiple sclerosis, Parkinson's disease, and cerebral palsy are degenerative disorders of the central nervous system, whereas polyneuropathy is a peripheral nervous system disorder. See if multiple sclerosis and Parkinson's disease fit better in the BDN RIC 3. See if the coefficient of variation of the neurological category is reduced once those conditions are removed. It would be logical to eventually redefine the neurological category to include conditions involving the peripheral nervous system and muscle (myopathies) only leaving BDN, BDT, and STR to cover central nervous system impairments and SCN and SCT to cover spinal cord impairments.
6. The OR1 RIC might be designated as hip fracture and other lower extremity fractures (not involving hip) classified elsewhere.
7. Major multiple fracture (UDSmr impairment code 8.4) was grouped with lower extremity fracture (RIC 7) in our previous work. On clinical grounds it would be better grouped with Major multiple trauma

without brain or spinal cord injury (MMT-no B/SC), RIC 17. An alternative would be to group 8.4 to the 'other orthopedic' RIC 9.

New RICs were created which either split, combined, or rearranged existing RIC groupings. The formal definitions rely on impairment code assignments, which are shown in Table A.1. The criterion for whether an additional grouping would be desirable is whether it leads to more accurate predictions. We evaluated this by fitting models within alternative candidate RICs, then seeing if the prediction error was decreased by a significant amount in the new RICs. We leaned toward accepting the old RICs if the improvements were only minor. Table 3.5 shows the twelve alternative groupings we tried. In all cases, we attempted to split or combine one or two RICs into at most three new RICs.

Table 3.5

Candidate RIC Alternatives

Change Proposal	**Old RIC**	**New RIC**	**New RIC Description**	**Old RIC Description**
1. split	18	21	Debility	Other disabling impairments
	18	22	Congenital deformities	Other disabling impairments
	18	23	Other disabling impairments	Other disabling impairments
2. split	18	24	Burns	Other disabling impairments
	18	25	Other disabling impairments	Other disabling impairments
3. split	06	26	Multiple sclerosis	Neurological conditions
	06	27	Other neurological conditions	Neurological conditions
4. combine	05	28	Spinal cord dysfunction, nontraumatic	Spinal cord dysfunction, nontraumatic
	19	28	Spinal cord dysfunction, nontraumatic	Guillain-Barre
5. rearrange	02	29	Brain dysfunction, traumatic	Brain dysfunction, traumatic
	20	29	Brain dysfunction, traumatic	Major mult trauma, w/inj to brain or spinal cord
	20	30	Major multiple trauma	Major mult trauma, w/inj to brain or spinal cord
	04	31	Traumatic spinal chord dysfunction	Spinal cord dysfunction, traumatic
	20	31	Traumatic spinal chord dysfunction	Major mult trauma, w/inj to brain or spinal cord

Table 3.5 (cont.)

6. rearrange	03	32	Multiple sclerosis or Parkinson's	Brain dysfunction, nontraumatic
	06	32	Multiple sclerosis or Parkinson's	Neurological conditions
	06	33	Other neurological conditions	Neurological conditions
7. rearrange	07	34	Orthopedic hip fracture	Orthopedic, lower extremity fracture
	07	35	Orthopedic upper leg	Orthopedic, lower extremity fracture
	09	35	Orthopedic upper leg	Orthopedic other
8. rearrange	15	36	Pulmonary and ventilator	Pulmonary
	18	36	Other disabling impairments	Other disabling impairments
	18	37	Other disabling impairments	Other disabling impairments
9. rearrange	02	38	Brain dysfunction, traumatic	Brain dysfunction, traumatic
	20	38	Brain dysfunction, traumatic	Major mult trauma, w/inj to brain or spinal cord
	04	39	Traumatic spinal chord dysfunction	Spinal cord dysfunction, traumatic
	20	39	Traumatic spinal chord dysfunction	Major mult trauma, w/inj to brain or spinal cord
10. rearrange	02	40	Brain dysfunction, traumatic	Brain dysfunction, traumatic
	20	40	Brain dysfunction, traumatic	Major mult trauma, w/inj to brain or spinal cord
	04	41	Traumatic spinal chord dysfunction	Spinal cord dysfunction, traumatic
	20	41	Traumatic spinal chord dysfunction	Major mult trauma, w/inj to brain or spinal cord
11. rearrange	07	42	Orthopedic, upper leg	Orthopedic, lower extremity fracture
	07	43	Orthopedic other	Orthopedic, lower extremity fracture
	09	43	Orthopedic other	Orthopedic other
12. rearrange	07	44	Major mult trauma, wo/inj to brain or spinal cord	Orthopedic, lower extremity fracture
	17	44	Major mult trauma, wo/inj to brain or spinal cord	Major mult trauma, wo/inj to brain or spinal cord
	07	45	Orthopedic, lower extremity fracture	Orthopedic, lower extremity fracture

Judging a set of candidate RICs depends on how well they help to predict the cost of a case. To do this, we need the prediction methodology for deriving FRGs, which is provided in the next section. Our method is to carry along every candidate set of RICs, within each RIC to fit the best model we can using those methods, and to base the choice of RICs on clinical simplicity as well as bias in average payments and root mean square prediction error for cases in RICs affected by the partitioning.

RESOURCE-BASED PARTITIONS

Given candidate clinical partitions (RICs), the next step is to split each RIC into groups that reflect resource use. FRGs have traditionally been obtained by running binary partitioning algorithms on data within RIC. Here, our measure of resource use is log(cost). As in earlier work, we have FIM scores and age to use in explaining log(cost).

There are certain other independent variables we might consider using, such as marital status, sex, and race. However, to use these variables would be to raise issues concerning equity. Our approach here is to develop models without these variables, then to see if an analysis of potential payment inequities shows a bias: e.g., how far off are predicted costs for males versus females in a model that does not attempt to adjust for sex? Chapter 7 will address this question.

Minimum Prediction Error Fits Using CART

The alternative models are based on the CART recursive partitioning algorithm. This algorithm was used in the initial development of the FRGs (Stineman et al., 1994). The CART algorithm examines a set of independent variables and searches for a partition that (it thinks) appropriately explains variation in the dependent variable. The algorithm is recursive. At each step, CART searches for the optimal two-way split of any existing group, the criterion being to maximize R-square for that step. CART stops splitting when it thinks it is introducing just noise.

We used CART's "10-fold cross-validation method" to determine the optimal number of splits in the final classification tree. This method divides the data into ten mutually exclusive sets of equal size, chosen at random. For each set, a tree with k nodes is fit on the other 90 percent of the data, and the squared error of the predictions for the other 10 percent is computed and summed over the ten sets. CART then chooses the k with the minimum sum of squares error (equivalently, the maximum R-square), and it fits a tree on the entire data set with k nodes.

Because this method resulted in many splits in large RICs, we also trace the values of R-square as we increase the number of nodes within each RIC. These traces show that the gain in R-square per node is rather low as you get beyond 10, also that by the time you get to 20 you are already very close to the CART maximum. We use this to justify restricting consideration to fewer than 20 node models in all cases.

Half-Sample Results

All of our initial modeling was based on half of the sample. We did this in order to get true estimates of how well our models were performing. We obtained only results for the old RICs. We limit examination here to old RICs because we do not make our final recommendation on which RIC definitions to use until we use the entire data set (not just half of it). We present detailed results only for splits producing 20 or fewer categories within each RIC, and we required a minimum of 50 cases in each FRG.

CART provides a trace of its cross-validated estimate of R-square versus the number of nodes. This trace is shown in Table 3.6. In most cases, it attains its maximum below 20; but in a few cases, it is willing to go well beyond where the fits seem to be making a difference (see especially RIC 8). In those cases, there is so little effect as the number of nodes approaches 20 that we decided to bound the number of nodes at 20.

Table 3.7 shows the variation in R-square and root mean square prediction error within RIC produced by the bounded models. We see that the R-square for the evaluation sample is usually lower than for the fitting sample. This seems especially true when the number of parameters fit is large. Figure 3.4, which plots FRG minus RIC means for the evaluation sample against the corresponding means for the fitting sample, shows a regression to the mean phenomenon: FRG means for the evaluation sample are more compressed than for the fitting sample. It appears we are over-fitting to cases at the extremes, and hence have too many nodes. Breiman et al. (1984, 78-80) recommended a more aggressive number of nodes stopping rule to correct this situation: put confidence bands around estimates of prediction error, and choose the first node where prediction error is within one standard error of the minimum. The right half of Table 3.7 shows how this rule performs. The

R-square and prediction errors vary much less between fitting and evaluation samples than before, without much increase in prediction root mean square error (RMSE). This confirms that we should be more aggressive than the CART default about cutting back on the number of parameters for our final model fits.

Table 3.6

How R-square Grows as the Number of Nodes Increases, Half-Sample Results

		Number of Nodes																			
RIC	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**29**	**20**	**Max-imum**	**# Nodes**
1	.226	.264	.287	.289	.295	.297	.306	.308	.309	.310	.310	.311	.312	.312	.313	.313	.314	.315	.315	.316	21
2	.147	.194	.212	.219	.215	.230	.235	.235	.233	.234	.236	.237								.237	13
3	.175	.195	.189	.192	.201	.205														.205	7
4	.110	.138	.153	.152	.157															.157	6
5	.197	.253	.256	.278	.282	.282	.282	.281	.280	.282	.286									.286	12
6	.114	.138	.163	.169																.169	5
7	.112	.134	.143	.144	.147	.149	.153	.153	.153	.153	.154	.154	.155	.155	.155	.156	.156	.157	.157	.159	25
8	.101	.115	.136	.140	.142	.145	.151	.155	.156	.156	.156	.156	.157	.157	.157	.157	.157	.157	.157	.163	57
9	.104	.127	.134	.135	.141	.143	.144	.146												.146	9
10	.095	.092	.115																	.115	4
11	.125	.133																		.133	3
12	.073	.091	.092	.114	.120															.120	6
13	.154	.152	.182																	.182	4
14	.104	.126	.133	.138	.138	.140	.139	.139	.139	.139	.141	.143								.143	13
15	.088	.100	.109	.123	.121	.121	.123	.125	.129	.129	.130									.130	12
16	.056	.080	.087	.071	.072	.072	.072	.083	.091											.091	10
17	.066	.084	.074	.114																.114	5
18	.105	.131	.142	.141	.146	.151	.151	.151	.152	.153	.153	.153	.153	.154	.154	.154	.154	.154	.154	.155	24
19	.367																			.367	2
20																				.000	1

Note: These R-squares are the 10-fold cross-validated estimates produced by CART.

Table 3.7

R-squares on Fitting and Evaluation Samples, Established RICs

RIC	Sample Sizes		CART Minimum Prediction Error					CART Minimum + 1 Standard Deviation Prediction Error				
			# CART Nodes	R-square		RMSE		# CART Nodes	R-square		RMSE	
	Fitting	Eval		Fitting	Eval	Fitting	Eval		Fitting	Eval	Fitting	Eval
1	17676	17755	20	0.329	0.312	0.487	0.494	20	0.329	0.312	0.487	0.494
2	824	829	13	0.305	0.196	0.499	0.527	4	0.257	0.165	0.516	0.537
3	1465	1420	7	0.244	0.264	0.535	0.517	3	0.215	0.231	0.545	0.528
4	413	399	6	0.254	0.258	0.614	0.634	3	0.208	0.257	0.632	0.634
5	2194	2167	12	0.334	0.296	0.516	0.535	5	0.306	0.299	0.526	0.534
6	2837	2932	5	0.177	0.150	0.513	0.508	4	0.171	0.150	0.515	0.508
7	9042	9074	20	0.179	0.165	0.441	0.450	8	0.165	0.161	0.445	0.451
8	18711	18751	20	0.180	0.175	0.429	0.430	20	0.180	0.175	0.429	0.430
9	3283	3311	9	0.170	0.140	0.498	0.498	4	0.150	0.137	0.504	0.499
10	2770	2684	4	0.122	0.086	0.520	0.530	4	0.122	0.086	0.520	0.530
11	240	239	3	0.169	0.143	0.504	0.574	2	0.154	0.102	0.509	0.587
12	1433	1431	6	0.146	0.119	0.500	0.531	5	0.138	0.115	0.502	0.532
13	744	783	4	0.208	0.103	0.486	0.519	4	0.208	0.103	0.486	0.519
14	2887	2793	13	0.172	0.165	0.480	0.492	4	0.145	0.156	0.488	0.495
15	1765	1806	12	0.165	0.105	0.522	0.517	5	0.138	0.102	0.530	0.518
16	929	961	10	0.151	0.126	0.495	0.508	3	0.104	0.125	0.509	0.509
17	274	266	5	0.220	0.129	0.506	0.523	3	0.176	0.092	0.520	0.534
18	6845	6730	20	0.193	0.177	0.497	0.502	6	0.169	0.164	0.505	0.506
19	138	140	2	0.402	0.308	0.563	0.571	2	0.402	0.308	0.563	0.571
20	98	126	1	0.000	0.000	0.674	0.724	1	0.000	0.000	0.674	0.724
Total	74568	74597	192					110				

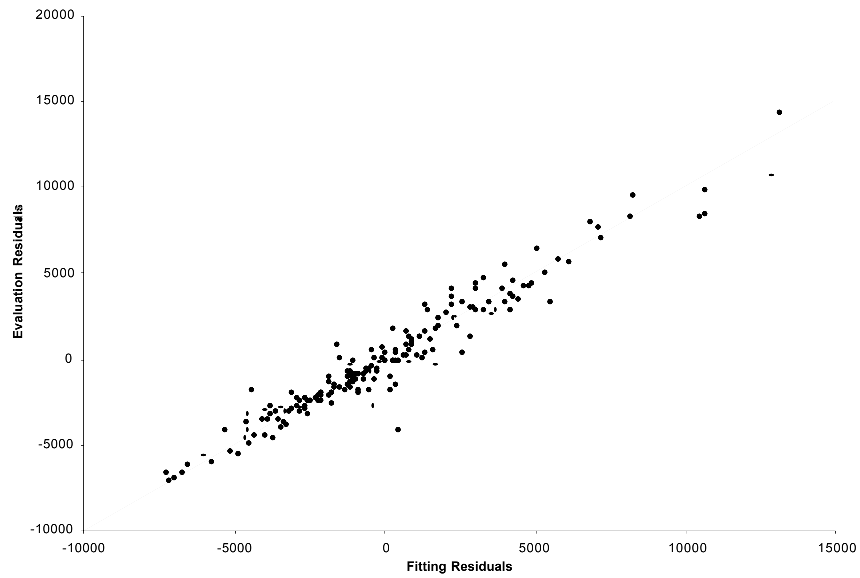

Figure 3.4--Average FRG Cost Comparison, Analysis vs. Evaluation Samples

Full-Sample Results: Final Selection of RICs

It was at this stage of the process that we were able to determine a final set of RICs. Table 3.8 shows the types of information we examined. We restricted ourselves just to 1997 data. For all cases affected by a RIC change, we computed means and root mean square errors, both for cost and log(cost).

Table 3.8

Performance of Suggested Alternative RICs: Old and New Values for Reclassified Cases, 1997 Data

			Thousands of Dollars						Logarithms of Dollars					
RICs				Predictions		RMSE		Drop RMSE		Predictions		RMSE		Drop RMSE
Old	New	N	TCOST	Old	New	Old	New		TCOST	Old	New	Old	New	
18	21	9565	10.79	10.93	10.79	5.60	5.61	-0.01	9.14	9.15	9.14	0.49	0.49	0.00
18	22	45	13.52	12.25	13.52	7.44	7.73	-0.29	9.35	9.27	9.35	0.55	0.58	-0.03
18	23	4357	11.18	10.90	11.18	6.18	6.17	0.01	9.16	9.14	9.16	0.51	0.51	0.00
18	24	110	14.10	11.63	14.10	7.32	7.79	-0.46	9.39	9.21	9.39	0.55	0.58	-0.03
18	25	13857	10.90	10.92	10.90	5.78	5.78	0.00	9.14	9.15	9.14	0.50	0.50	0.00
06	26	974	12.52	12.54	12.52	6.96	6.97	-0.01	9.27	9.28	9.27	0.54	0.54	0.00
06	27	4996	11.50	11.50	11.50	6.26	6.26	0.00	9.20	9.19	9.20	0.50	0.50	0.00
05	28	4561	11.58	11.58	11.77	7.06	7.00	0.06	9.15	9.15	9.16	0.53	0.52	0.00
19	28	302	16.31	16.31	13.35	9.25	9.60	-0.35	9.45	9.45	9.27	0.54	0.56	-0.03
02	29	1759	14.22	14.22	14.40	7.82	7.62	0.20	9.39	9.39	9.39	0.52	0.51	0.01
20	29	167	17.99	18.04	16.04	10.65	10.82	-0.17	9.57	9.55	9.49	0.58	0.56	0.01
20	30	51	16.22	15.93	16.22	11.29	13.49	-2.20	9.44	9.45	9.44	0.53	0.63	-0.10
04	31	864	16.51	16.51	16.51	11.39	11.40	-0.01	9.44	9.44	9.44	0.61	0.61	0.00
20	31	32	17.36	17.53	17.33	12.78	11.19	1.59	9.49	9.54	9.50	0.62	0.55	0.07
03	32	3034	13.46	13.46	12.83	7.50	7.75	-0.25	9.32	9.32	9.29	0.52	0.53	-0.01
06	32	2321	11.85	12.24	12.67	6.30	6.42	-0.12	9.23	9.26	9.28	0.51	0.51	-0.01
06	33	3649	11.55	11.30	11.55	6.43	6.33	0.11	9.19	9.18	9.19	0.51	0.50	0.01
07	34	14427	10.49	10.52	10.49	4.87	4.88	0.00	9.14	9.14	9.14	0.44	0.44	0.00
07	35	4259	10.63	10.53	10.35	5.17	5.16	0.01	9.15	9.14	9.11	0.47	0.47	0.00
09	35	6830	9.60	9.60	9.78	5.08	5.05	0.04	9.02	9.02	9.05	0.50	0.50	0.00
15	36	3647	12.22	12.22	12.16	6.78	6.83	-0.06	9.25	9.25	9.25	0.52	0.52	0.00
18	36	131	11.63	11.20	13.20	7.07	7.08	-0.01	9.18	9.17	9.32	0.55	0.57	-0.01
18	37	13836	10.92	10.92	10.92	5.78	5.78	0.00	9.15	9.15	9.15	0.50	0.50	0.00
02	38	1759	14.22	14.22	14.40	7.82	7.62	0.20	9.39	9.39	9.39	0.52	0.51	0.01
20	38	167	17.99	18.04	16.04	10.65	10.82	-0.17	9.57	9.55	9.49	0.58	0.56	0.01
04	39	864	16.51	16.51	16.53	11.39	11.33	0.06	9.44	9.44	9.44	0.61	0.61	0.00
20	39	83	16.66	16.55	16.54	11.88	10.46	1.43	9.46	9.48	9.43	0.57	0.51	0.06
02	40	1759	14.22	14.22	14.44	7.82	7.72	0.10	9.39	9.39	9.39	0.52	0.51	0.01
20	40	218	17.57	17.55	15.74	10.80	10.97	-0.17	9.54	9.53	9.47	0.57	0.56	0.01
04	41	864	16.51	16.51	16.51	11.39	11.40	-0.01	9.44	9.44	9.44	0.61	0.61	0.00
20	41	32	17.36	17.53	17.33	12.78	11.19	1.59	9.49	9.54	9.50	0.62	0.55	0.07
07	42	17873	10.47	10.51	10.47	4.90	4.90	0.00	9.14	9.14	9.14	0.45	0.45	0.00
07	43	813	11.54	10.78	10.60	5.81	5.83	-0.03	9.22	9.16	9.12	0.47	0.48	-0.01
09	43	6830	9.60	9.60	9.71	5.08	5.08	0.01	9.02	9.02	9.03	0.50	0.50	0.00
07	44	813	11.54	10.78	11.64	5.81	5.76	0.05	9.22	9.16	9.22	0.47	0.47	0.00
17	44	611	11.84	11.84	11.71	6.30	6.48	-0.18	9.22	9.22	9.22	0.50	0.52	-0.01
07	45	17873	10.47	10.51	10.47	4.90	4.90	0.00	9.14	9.14	9.14	0.45	0.45	0.00

Note: Variance dominates in the root mean square error calculations for cost. For example, the Guillain-Barre cases have a predicted mean of about $3,000 less when paired with nontraumatic spinal chord cases, but their standard deviation is about $9,000, so there is not much change in prediction accuracy.

We looked simultaneously for situations where the new assignment improved the mean prediction of cost for some cases and there was a simultaneous drop in root mean square error. The options that were evaluated were clinically derived and therefore deemed to be clinically acceptable. In most cases, we saw very little change in performance, and in view of the already broad acceptance in the rehabilitation community of the existing RICs, we chose to leave those RICs alone. For example, in the first change examined, the mean prediction for the new RIC 21 (debility) declined by only $140 and the root MSE is actually .01 worse. Several of the larger drops in root MSE in the dollar scale disappeared in the log scale indicating the effect of a small number of cases with large changes. There were also several cases where the new groupings performed substantially worse than the older grouping. For example, when Guillain-Barre is grouped with RIC 5, into the new RIC 28, the average cost of the Guillain-Barre cases ($16,310) is estimated at $13,335--an underestimate of almost $3,000.

There were two areas where positive changes seemed large enough to be important. First, we defined a new RIC for burns (RIC 24 in Table 3.8). As the data show, the average cost of burn cases is underestimated by $2,470 (=1000*(14.10-11.63)) when they are grouped with RIC 18. However, because the small sample size allows at most two FRGs when burns are put in a separate RIC, the average error in the prediction of the cost of an individual burn case is actually worse for a separate RIC than for a pooled RIC. Because there are so few burn cases, eliminating them from RIC 18 as in the new RIC 25 has only the tiniest effect on the predictions for the remaining 'misc' cases. We believe that the average prediction for burns is probably more important than the individual error and so we propose a separate RIC for burn cases. Access is probably more affected by the payment to cost of the typical burn case through the decision to have such a program than by the harder to implement decision to detect the expensive cases prior to admission and refuse admission. Also, hospitals with burn programs may have substantial numbers of cases and provider equity argues for paying for the expected cost of such programs.

The second area where change seemed desirable is to move the group "Status post major multiple fractures" from RIC 07 (orthopedic--lower extremity fracture) to group it with other cases in RIC 17 (major multiple trauma without brain or spinal cord injury). The data are shown in the table as the new RICs 44 and 45. The costs of the cases moving from RIC 7 to RIC 44 were noticeably underestimated in the old RIC, and are only very slightly overestimated in the new RIC assignment. Because the costs of multiple fracture cases are close to the costs of the MMT-noB/SC group (RIC 17), the new assignment has only a small effect on these cases. There are few multiple fracture cases relative to all lower extremity fractures and so removing them results in only a very small improvement in the mean prediction for the cases in the new RIC 45.

Table 3.9

Final Grouping of Impairment Group Codes into Rehabilitation Impairment Categories

Rehabilitation Impairment Category		**Impairment Groups**
1	Stroke	1.1 through 1.9
2	Traumatic brain injury	2.2, 2.21, 2.22
3	Nontraumatic brain injury	2.1, 2.9
4	Traumatic spinal cord	4.2, 4.21 through 4.23
5	Nontraumatic spinal cord	4.1, 4.11 through 4.13
6	Neurological	3.1, 3.2, 3.3, 3.5, 3.8, 3.9
7	Hip fracture	8.11 through 8.3
8	Replacement of LE joint	8.51 through 8.72
9	Other orthopedic	8.9
10	Amputation, lower extremity	5.3 through 5.7
11	Amputation, other	5.1, 5.2, 5.9
12	Osteoarthritis	6.2
13	Rheumatoid, other arthritis	6.1, 6.9
14	Cardiac	9
15	Pulmonary	10.1, 10.9
16	Pain Syndrome	7.1 through 7.9
17	Major multiple trauma, no brain or spinal cord injury	8.4, 14.9
18	Major multiple trauma, with brain or spinal cord injury	14.1, 14.2, 14.3
19	Guillain-Barre	3.4
20	Miscellaneous	12.1, 12.9, 13, 15, 16, 17 through 17.9
21	Burns	11

After deciding on these changes and discussing them with HCFA, we renumbered the new burn RIC to be RIC 21. We retained numbers 7 and 17 for the newly redefined Fracture of the LE, and MMT without brain or spinal cord injury. We made one other cosmetic change at this time: switching RICs 20 (major multiple trauma with injury to brain or spinal cord) and RIC 18 (other), which enabled us to put the major multiple trauma RICs together.

The final definition of impairment code is shown in Table 3.9 and reflected in Tables 3.10 and beyond.

Full-Sample Results: Final Selection of FRGs

Using all of our 1997 data, we asked CART to provide the best fit for what were at times very large samples. We required a minimum of 100 cases in each FRG. Raw CART fits produced a total of 359 nodes. This is not too surprising: CART fits nodes where it sees statistical significance, and with this large a sample, even minor differences are statistically significant.

For administrative simplicity, we did not wish to create such a large number of groups. In addition, we did not want to create groups characterized by very small intervals of motor or cognitive scales for fear it would encourage upcoding. It would not be enough to simply fit what CART thought was the "best" model.

Our strategy was to produce some reduced-size models according to their perceived statistical power and practical importance. Ultimately, we justify the reduced-size models in a simulation exercise that assesses prediction bias for various combinations of demographic and hospital factors.

First, we look at the R-square trace produced by CART (Table 3.10), which confirms that there is very little to gain in going beyond 20 (yielding 232 nodes). We therefore bounded the number of nodes at 20, and considered further reductions with respect to these bounded models.

Table 3.10

How R-square Grows as the Number of Nodes Increases, Full Sample Results

	Number of Nodes																				
RIC	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**Max-imum**	**# Nodes**
1	.226	.265	.288	.289	.296	.304	.304	.304	.304	.304	.305	.305	.305	.306	.306	.306	.307	.307	.307	.320	61
2	.134	.177	.182	.201	.220	.224	.222	.225	.230											.230	10
3	.178	.194	.226	.226	.229	.236	.237	.236	.235	.236	.237	.238	.239	.240	.241	.242	.243			.243	18
4	.209	.197	.235	.222	.239	.244														.244	7
5	.220	.259	.287	.286	.305	.303	.302	.303	.303	.304	.305	.307	.308							.308	14
6	.117	.134	.155	.155	.157	.155	.156	.156	.157	.157	.157	.157	.157	.157	.157	.157	.158	.158	.158	.160	45
7	.109	.135	.148	.148	.153	.155	.156	.160	.162	.162	.162	.163	.163	.163	.163	.163	.164	.164	.164	.166	30
8	.111	.112	.150	.157	.157	.160	.166	.167	.168	.168	.168	.169	.169	.169	.169	.170	.170	.170	.170	.178	55
9	.091	.118	.135	.136	.144	.145	.147	.147	.148											.148	10
10	.077	.093	.103	.102	.101	.102	.103													.103	8
11	.132	.117	.159																	.159	4
12	.086	.100	.103	.101	.104	.119	.118	.121												.121	9
13	.122	.138	.137	.147																.147	5
14	.107	.138	.149	.152	.153	.154	.155	.155	.155	.156	.156	.157	.157	.157	.158	.158	.158	.159	.159	.162	28
15	.071	.101	.101	.115	.121	.125	.126													.126	8
16	.083	.111	.115	.117	.132															.132	6
17	.116	.131	.146	.148																.148	5
18	.115	.141	.154	.154	.163	.165	.167	.167	.168	.169	.169	.170	.170	.171	.171	.172	.172	.173	.174	.178	28
19	.289	.394	.412																	.412	4
20	.258	.274																		.274	3
21																				.000	1

Notes: This table uses the new RIC numbering system. These R-squares are the 10-fold cross-validated estimates produced by CART.

Second, based on our split sample analysis, we decided to use a stopping rule based on one prediction standard error (the rule recommended by Breiman et al., 1984). This gets us down to 143 nodes total.

Third, we try stopping when R-square is within .01 of the R-square for the one standard error models. For timing and computational reasons, we used the actual R-squares, not the cross-validated ones shown in the table. We do not believe it affects our results much, but we will use the cross-validated ones in future revisions of our work. This gets us to 104 nodes.

Fourth, we look at the FRG category definitions from the 104-node models, and noticed that predicted costs were sometimes quite close (within $1,500) among lower branches of the same part of the tree. We tried combining these categories, thereby reducing our model size to 92 total nodes.

Table 3.11 shows the progression of each of these steps to reducing R-squares. The table points to two candidate models for simulation evaluation: the 143-node model arising from CART, and the 92-node reduced model arising from considering the R-square trace and the pairing/tripling up of adjacent branches of the classification tree where predicted costs are close.

Table 3.12 shows the 92-node model, arranged in a way that describes the classification tree and what branches have been combined. (The 143-node model appears as Table A.2.) For example, the first split in RIC 1 was between those with a motor score greater than 45.5 and those with a motor score less than 45.5. The group with a motor score greater than 45.5 was then split into those greater than and less than 56.5. The higher functioning group was then split into those greater than or less than 61.5. So the first FRG, 0101, can simply be described as those with motor score greater than 61.5, but the table shows the tree that led to that node. The splits that we recombined because the difference in cost between the groups was too small occur in RICs 7,8, 9, 12, 14, 16, and 20.

Table 3.11

Number of Nodes in Various CART Alternatives RIC Definitions, Sample Sizes, and Number of Nodes (1997 Data)

		Number of Nodes					
RIC	**1997 Sample**	**(0)**	**(1)**	**(2)**	**(3)**	**(4)**	**Description**
01	35431	61	20	20	11	11	Stroke
02	1653	10	10	6	6	6	Brain dysfunction, traumatic
03	2885	18	18	6	5	5	Brain dysfunction, nontraumatic
04	812	7	7	4	4	4	Spinal cord dysfunction, traumatic
05	4361	14	14	6	5	5	Spinal cord dysfunction, nontraumatic
06	5769	45	20	4	4	4	Neurological conditions
07	17995	30	20	10	6	4	Orthopedic--lower extremity fracture
08	37462	55	20	20	10	6	Orthopedic--lower extremity joint repl
09	6594	10	10	6	5	4	Orthopedic other
10	5454	8	8	4	3	3	Amputation, lower extremity
11	479	4	4	4	4	4	Amputation, other
12	2864	9	9	7	6	4	Osteoarthritis
13	1527	5	5	3	3	3	Rheumatoid and other arthritis
14	5680	28	20	5	4	3	Cardiac
15	3571	8	8	5	4	4	Pulmonary
16	1890	6	6	5	4	3	Pain syndrome
17	661	5	5	2	2	2	Major mult trauma, wo/inj to brain or spinal cord
18	224	3	3	2	2	2	Major mult trauma, w/inj to brain or spinal cord
19	278	4	4	3	3	3	Guillain-Barre
20	13472	28	20	20	12	11	Other disabling impairments
21	103	1	1	1	1	1	Burns
Total	149165	359	232	143	104	92	

Notes: This table uses the new RIC numbering system
(0) = raw CART fits
(1) = raw CART, number of nodes bounded at 20
(2) = CART model that gets within 1 stdev of minimum prediction error (bounded models)
(3) = CART model that gets within .01 of maximum R-square (bounded models)
(4) = CART model which combines terminal nodes less than $1500 different (bounded models)

Table 3.12

Recommended FRG Models: 92 Node Models Resulting from Recombination

RIC	FRG	Condition	Average Cost	N	Additional Grouping
01	01	M>45.5 & M>56.5 & M>61.5	7475	3030	
01	02	M>45.5 & M>56.5 & M<61.5 & C>26.5	8483	1763	
01	04	M>45.5 & M>56.5 & M<61.5 & C<26.5	10481	1277	
01	03	M>45.5 & M<56.5 & M>50.5 & C>27.5	10137	2590	
01	05	M>45.5 & M<56.5 & M>50.5 & C<27.5	11728	3088	
01	06	M>45.5 & M<56.5 & M<50.5	12859	4889	
01	07	M<45.5 & M>35.5 & M>41.5	14948	3914	
01	08	M<45.5 & M>35.5 & M<41.5	16885	4962	
01	09	M<45.5 & M<35.5 & A>83.5	17709	1603	
01	10	M<45.5 & M<35.5 & A<83.5 & M>30.5	19425	2831	
01	11	M<45.5 & M<35.5 & A<83.5 & M<30.5	22625	5484	
02	01	M>40.5 & M>57.5 & C>29.5	6717	90	
02	02	M>40.5 & M>57.5 & C<29.5	10202	234	
02	03	M>40.5 & M<57.5 & C>21.5	11553	362	
02	04	M>40.5 & M<57.5 & C<21.5	13940	368	
02	05	M<40.5 & M>24.5	16994	412	
02	06	M<40.5 & M<24.5	23288	187	
03	01	M>44.5 & M>57.5 & C>21.5	7940	454	
03	02	M>44.5 & M>57.5 & C<21.5	10350	149	
03	03	M>44.5 & M<57.5	11348	992	
03	04	M<44.5 & M>34.5	14921	585	
03	05	M<44.5 & M<34.5	20089	705	
04	01	M>33.5 & M>54.5	9123	164	
04	02	M>33.5 & M<54.5	12883	328	
04	03	M<33.5 & M>16.5	20652	234	
04	04	M<33.5 & M<16.5	33571	86	
05	01	M>45.5 & M>54.5 & M>67.5	5474	174	
05	02	M>45.5 & M>54.5 & M<67.5	7386	1089	
05	03	M>45.5 & M<54.5	9502	1279	
05	04	M<45.5 & M>33.5	13342	1102	
05	05	M<45.5 & M<33.5	20232	717	
06	01	M>45.5 & M>55.5	8491	1436	
06	02	M>45.5 & M<55.5	10540	1757	
06	03	M<45.5 & M>37.5	12389	1114	
06	04	M<45.5 & M<37.5	15786	1462	
07	01	M>45.5 & M>54.5 & M>60.5	7029	959	1
07	01	M>45.5 & M>54.5 & M<60.5	8086	2474	1
07	02	M>45.5 & M<54.5 & C>33.5	9052	2832	2
07	02	M>45.5 & M<54.5 & C<33.5	10036	3784	2
07	03	M<45.5 & M>39.5	11452	3727	
07	04	M<45.5 & M<39.5	13430	4219	

Table 3.12 (cont.)

08	01	M>49.5 & M>58.5 & M>68.5	4927	969	3
08	01	M>49.5 & M>58.5 & M<68.5	5886	7922	3
08	02	M>49.5 & M<58.5 & C>33.5 & M>51.5	6476	8265	4
08	02	M>49.5 & M<58.5 & C>33.5 & M<51.5	7117	2082	4
08	02	M>49.5 & M<58.5 & C<33.5	7421	5502	4
08	03	M<49.5 & M>42.5 & C>33.5	7866	4205	5
08	03	M<49.5 & M>42.5 & C<33.5	8829	3840	5
08	04	M<49.5 & M<42.5 & C>33.5	9610	1786	
08	05	M<49.5 & M<42.5 & C<33.5 & M>35.5	10430	1833	
08	06	M<49.5 & M<42.5 & C<33.5 & M<35.5	12391	1058	
09	01	M>46.5 & M>58.5	6794	1082	
09	02	M>46.5 & M<58.5 & C>31.5	8471	1926	6
09	02	M>46.5 & M<58.5 & C<31.5	9478	1090	6
09	03	M<46.5 & M>37.5	10942	1643	
09	04	M<46.5 & M<37.5	13427	853	
10	01	M>52.5	10424	2257	
10	02	M<52.5 & M>42.5	12962	1719	
10	03	M<52.5 & M<42.5	15669	1478	
11	01	M>46.5 & M>60.5	7324	60	
11	02	M>46.5 & M<60.5 & A>67.5	9498	174	
11	01	M>46.5 & M<60.5 & A<67.5	13487	60	
11	04	M<46.5	16140	185	
12	01	M>48.5 & C>33.5 & M>54.5	7213	645	7
12	01	M>48.5 & C>33.5 & M<54.5	8467	353	7
12	02	M>48.5 & C<33.5 & M>56.5	8200	340	8
12	02	M>48.5 & C<33.5 & M<56.5	9537	517	8
12	03	M<48.5 & M>36.5	10812	754	
12	04	M<48.5 & M<36.5	13777	255	
13	01	M>48.5 & M>60.5	7227	243	
13	02	M>48.5 & M<60.5	8874	628	
13	03	M<48.5	12387	656	
14	01	M>53.5 & M>58.5	7505	1756	9
14	01	M>53.5 & M<58.5	8742	1009	9
14	02	M<53.5 & M>40.5	10483	2115	
14	03	M<53.5 & M<40.5	14368	800	
15	01	M>50.5 & A>77.5	9366	717	
15	02	M>50.5 & A<77.5	11107	1537	
15	03	M<50.5 & M>27.5	14097	1173	
15	04	M<50.5 & M<27.5	23292	144	
16	01	M>49.5 & C>32.5 & M>57.5	6447	412	10
16	01	M>49.5 & C>32.5 & M<57.5	7740	300	10
16	02	M>49.5 & C<32.5	9079	464	
16	03	M<49.5	10782	714	
17	01	M>42.5	9996	394	
17	02	M<42.5	15749	267	
18	01	M>34.5	12069	127	
18	02	M<34.5	25747	97	
19	01	M>43.5 & M>54.5	8086	77	
19	02	M>43.5 & M<54.5	12684	69	
19	03	M<43.5	24214	132	

Table 3.12 (cont.)

20	01	M>47.5 & M>59.5 & M>69.5 & A>58.5	6093	358	
20	04	M>47.5 & M>59.5 & M>69.5 & A<58.5	9432	55	
20	02	M>47.5 & M>59.5 & M<69.5	7770	1774	
20	03	M>47.5 & M<59.5 & M>54.5	8921	1932	
20	05	M>47.5 & M<59.5 & M<54.5 & A>64.5 & C>33.5	9207	831	11
20	05	M>47.5 & M<59.5 & M<54.5 & A>64.5 & C<33.5	10209	2115	11
20	07	M>47.5 & M<59.5 & M<54.5 & A<64.5	12023	339	
20	06	M<47.5 & M>38.5 & A>64.5	11534	2895	
20	10	M<47.5 & M>38.5 & A<64.5	14563	375	
20	08	M<47.5 & M<38.5 & A>83.5	12557	675	
20	09	M<47.5 & M<38.5 & A<83.5 & M>31.5	14513	1097	
20	11	M<47.5 & M<38.5 & A<83.5 & M<31.5	16519	1026	
21	01	1.00	14849	103	

(1) M stands for motor score, C for cognitive score, and A for age.
(2) The FRG numbers were assigned in increasing order of average cost.
(3) For RIC 20, CART produced splits at an awkward age: 65 and below, or 66 and above. We overrode these definitions to 64 and below, or 65 and above, to be consistent with standard Medicare eligibility requirements.

We used the simulation model to compare the alternatives and found that the 143-node model had only a very small effect on overall accuracy and no noticeable effect on payment for any group of hospitals. This preliminary simulation used data that were incomplete and several of the assumptions about payment for unusual cases and hospital adjustments were incorrect. Rather than present these preliminary simulations here, we wait until we have discussed the other elements of the payment system and present more accurate simulations in Chapter 7. The conclusion will be the same: the 143 node model does not noticeably improve payments.

COMORBIDITIES

We next discuss the adding of comorbidities to the classification system. We began by validating the comorbidity model which we developed in our 1997 report on FRGs (Carter, Relles, Buchanan, et al., 1997). We then scrubbed this model to eliminate certain diagnoses from certain RICs. We also reviewed the other conditions that the clinical participants in our earlier study hypothesized would affect costs and found that, in our larger data base, more of these conditions are positively correlated with cost. In the last step, the set of ICD-9-CM diagnoses that we found to affect costs were examined by Dr. Laurie

Fineberg of HCFA to eliminate (1) codes believed to have only a minor effect on resources, (2) codes that were vague enough that they might encourage upcoding, and (3) codes that were for conditions that could be prevented by prudent treatment.

All the analyses to be presented here were performed with the same data used to develop the FRG structure--i.e., preliminary estimates of the cost of cases were used and the sample excluded cases with a LOS of three days or less, transfers, and deaths.

Major Comorbidity Variable

The major comorbidities were defined as those diagnoses that were found in a study of refined DRGs to have major effects on the costs of acute stays. In our 1997 study, using 1994 discharges, we determined that these comorbidities also increased the cost of rehabilitation. We found that the effect of comorbidities varied across RICs, significantly increasing the cost of patients in some RICs while having no effect in others. We further found that, in RICs where comorbidities affect cost, the amount of the increase in cost was well modeled as the same percent increase in the cost of each FRG.

This major comorbidity list was coded using the ICD-9-CM diagnoses in use in FY 1994 (October 1, 1993). We added new codes that are now used to code patients that would have received a diagnosis on the old major comorbidity list. We examined all the newly created codes published in the federal register for Sept 1994, 95, 96, and 97. For each code that was a CC in one of the tables, we determined whether it was a further specification of a code that was a major comorbidity in the initial list and therefore would have been coded as a major comorbidity prior to the new code creation.[12] A dummy variable was created which was 1 if the patient had any secondary diagnosis on the major comorbidity list and 0 otherwise.

Table 3.13 shows the effect of the major comorbidities on log cost in our current data in the columns headed 'Major Comorbidity'. The regressions controlled for dummy variables for each value of FRG in the 92 node FRG model. As in our earlier work, substantial effects of the

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[12] The codes thus added to the list of major comorbidities are given in Carter, Relles, and Wynn (2000).

major comorbidities on cost are found in many, but not all RICs. As before, he effects are quite large in the orthopedic RICs (7,8,9) and essentially 0 in stroke (RIC 1). After we describe how we improved our comorbidity variable so it is more appropriate for an RPPS, we will describe tests that show that the model structure--a multiplicative model with the same coefficient for all FRGs in the same RIC--still holds in our new data.

Improving the Comorbidity Variable

One of the shortcomings our earlier study was that exactly the same set of diagnoses was evaluated in each RIC. But, clearly what is a comorbidity in one RIC might be a typical condition of the patients in another RIC. For example, stroke is clearly a complication in most RICs, but will be present for all patients in RIC 1 whether coded or not. Similarly, cardiac conditions might complicate management in all RICs but should not be viewed as a comorbidity in the Cardiac RIC 14.

We asked Dr. Margaret Stineman to review the list of ICD-9-CM codes in the major comorbidity list and determine which diagnoses should not be counted as a comorbidity in each RIC. Many diagnoses, including most infections, were not excluded from any RIC. A single diagnoses was excluded from two RICs. The remaining diagnoses were excluded from only one RIC. The exclusions are listed in Appendix Table B.3. Nevertheless there were dramatic declines in the frequency of our major comorbidity variable within two RICs: In RIC 1, 37 percent of cases had at least one of the major comorbidities; after RIC exclusions were enforced only 5.5 percent of cases had a major comorbidity. Also, in the pulmonary RIC 15, the incidence of a major comorbidity went from 26.8 percent of cases to 7.1 percent of cases. Predominantly due to the large number of stroke cases, the percent of cases with comorbidity in all RICs combined declined from 16.0 percent to 7.3 percent when RIC exclusions were implemented.

The implementation of comorbidity exclusions specific to stroke substantially improved the ability of the remaining major comorbidities to predict cost in RIC 1. As may be seen in the columns headed 'With RIC exclusions' in Table 3.13, cases in RIC 1 with one of the non-excluded comorbidities cost about 6.2 percent more than cases in the same FRG2 without such a comorbidity (p<0.0001). The coefficient on RIC

15 is also larger after the exclusions but does not reach statistical significance here (p=0.09 in 1997). The exclusions have little effect on the estimated effect of comorbidity on other RICs.

Table 3.13

Regression of Log of Cost on Comorbidity Variables, Controlling for FRG2

	Major Comorbidity		With RIC Exclusion		Final Comorbidity	
RIC	**Coef**	**t-stat**	**Coef**	**t-stat**	**Coef**	**t-stat**
1996 data						
1	0.0065	1.17	0.0561	4.70 *	0.0614	5.24 *
2	0.0325	0.81	0.0325	0.81	0.0124	0.31
3	0.0737	3.07 *	0.0640	2.39	0.0776	2.93 *
4	0.1110	1.84	0.1110	1.84	0.3087	3.78 *
5	0.2251	7.14 *	0.2218	7.03 *	0.2109	6.38 *
6	0.1048	4.57 *	0.1048	4.57 *	0.0688	2.90 *
7	0.1445	10.02 *	0.1445	10.02 *	0.1368	8.28 *
8	0.1969	13.99 *	0.1885	12.84 *	0.1855	13.26 *
9	0.2536	8.21 *	0.2485	8.03 *	0.2479	8.34 *
10	0.1576	7.01 *	0.1353	5.50 *	0.0772	3.81 *
11	0.2860	3.71 *	0.2958	3.71 *	0.0285	0.42
12	0.2053	4.46 *	0.2053	4.46 *	0.1484	3.40 *
13	0.1533	2.87 *	0.1533	2.87 *	0.1573	2.98 *
14	0.1264	5.85 *	0.1700	7.15 *	0.1707	7.53 *
15	-0.0130	0.52	0.0639	1.53	0.0253	0.75
16	0.2833	3.46 *	0.2833	3.46 *	0.2704	4.11 *
17	0.1654	2.16	0.1654	2.16	0.2038	2.70 *
18	-0.0267	0.18	-0.0267	0.18	0.2471	1.87
19	0.1790	1.23	0.1790	1.23	0.0483	0.34
20	0.0993	7.90 *	0.0993	7.90 *	0.0995	8.18 *
21	0.2232	0.98	0.2232	0.98	0.3409	1.58
1997 data						
1	-0.0074	1.36	0.0622	5.42 *	0.0623	5.42 *
2	-0.0059	0.16	-0.0059	0.16	0.0164	0.46
3	0.1238	5.31 *	0.1252	4.87 *	0.1077	4.19 *
4	0.0925	1.60	0.0925	1.60	0.1384	1.86
5	0.2227	7.41 *	0.2227	7.41 *	0.2203	6.65 *
6	0.0958	4.48 *	0.0958	4.48 *	0.1033	4.87 *
7	0.1313	9.49 *	0.1313	9.49 *	0.1322	8.23 *
8	0.2019	15.33 *	0.2027	14.76 *	0.1828	13.72 *
9	0.1876	6.83 *	0.1855	6.71 *	0.1736	6.57 *
10	0.1571	7.50 *	0.1501	6.72 *	0.0742	3.98 *
11	0.1386	2.02	0.1331	1.87	0.1190	1.97
12	0.1323	3.26 *	0.1323	3.26 *	0.1311	3.41 *
13	0.1223	2.38	0.1223	2.38	0.1248	2.60 *
14	0.1275	7.21 *	0.1470	7.39 *	0.1301	6.72 *
15	0.0034	0.17	0.0537	1.54	0.0464	1.70
16	0.1820	3.44 *	0.1820	3.44 *	0.1683	3.12 *
17	0.2373	3.06 *	0.2373	3.06 *	0.1565	2.03
18	0.1198	1.06	0.1198	1.06	0.1572	1.41
19	0.1306	1.14	0.1306	1.14	0.1640	1.49
20	0.0878	7.92 *	0.0878	7.92 *	0.0999	9.32 *
21	-0.1071	0.74	-0.1071	0.74	-0.0298	0.20

*p < 0.01.

Our clinical consultants to our 1997 study had hypothesized that certain other comorbidities would also increase costs. We asked Drs. Stineman and Zingmond to review these hypotheses and suggest changes and additions. They suggested adding a group of infections (particularly HIV which was not coded in our earlier data) and certain additions and deletions of codes in other groups. We evaluated the revised hypotheses using the split sample and our original FRGs.

A report of our current evaluation of additional comorbidities is found in Appendix B. In our 1997 study, we had found that variables for selected infections, deep vein thrombosis, and tracheotomy predicted cost in our 1994 data while other conditions that had been hypothesized by our clinical consultants did not.[13] We verified that these three conditions (as modified by our clinical consultants) also increase costs in our current data. However we also found that, in the larger data set available here, renal dialysis and malnutrition also had significant positive effects on cost. Each of these are very infrequent conditions and had not been significant in the smaller 1994 data set.

A final review of the codes found to affect costs was undertaken to ensure policy acceptability. A series of codes was eliminate because either (1) they were believed to have only a minor effect on resources, (2) they were vague enough that they might encourage upcoding, or (3) they were for conditions that could be prevented by prudent treatment. These codes are also listed in Appendix B. This review also suggested a small number of codes that were for conditions similar to those already included.

After implementing these additional exclusions, the rough magnitude of each of the six effects: major comorbidities, infections, DVT, tracheotomy, renal disease, and malnutrition were quite similar. Table 3.14 shows the coefficients on each comorbidity variable in a regression that is pooled across RICs and controls for each of the 92 recommended FRGs. The coefficients appear to be reasonably similar except for the tracheotomy cases, so combining them into a single

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[13] Ventilator patients were also singled out as more costly. However, these patients are already counted as having a major comorbidity and thus are not an additional category.

variable should fit the data as well as separate variables.[14] There are fewer than 200 cases per year in the tracheotomy group, so it is hard to measure their costs precisely. Also the few number of cases here means their excess costs can not significantly affect the coefficient on a pooled variable. In view of the simplicity of a single pooled variable, we recommended such a single comorbidity variable to HCFA.

Table 3.14

Effect of Individual Comorbidity Variables on Log Cost, Controlling for FRG2

	1996 Data		1997 Data	
	Coef.	**t-Stat**	**Coef.**	**t-Stat**
Major Comorbidity	0.1093	18.85 *	0.1067	20.41 *
DVT	0.1506	5.92 *	0.0819	3.10 *
Infection	0.1224	19.24 *	0.1061	18.01 *
Malnutrition	0.1488	3.12 *	0.1882	4.37 *
Renal Disease	0.1604	7.43 *	0.2161	11.34 *
Tracheotomy	0.3290	12.58 *	0.2937	11.95 *

*p < 0.002.

Note: These regressions include all cases paid a full FRG payment in the final system.

Thus we merged the diagnoses associated with any of these conditions into a single set of comorbidities with certain RICs excluded from each diagnosis. This list is given in Table B.3 in Appendix B. Any patient with a secondary diagnosis in this list, who is not in an excluded RIC, was classified as 'with comorbidity'. The columns in Table 3.13 labeled 'Final comorbidity variable' shows the comorbidity coefficient of regressions within each RIC and year, of log cost on FRG2 and this final comorbidity variable.

We have shown that comorbidities significantly increase cost, at least in most RICs. There are two questions left for our classification model. First, are the differences between the RICs in the comorbidity important? To answer this question, we pooled the data from all the RICs and regressed log of cost on dummies for all of the FRGs, a single comorbidity coefficient and then separate comorbidity coefficients for

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[14] The 95 percent confidence intervals around the coefficient of the major comorbidities, infections, DVT, and malnutrition overlap in both years. The renal coefficient confidence interval also overlaps in 1996, but is somewhat higher in 1997 than the other four.

each of the remaining 20 RICs. The coefficients vary across RICs by much more than can be explained by chance: $F = 6.79$ and 4.45 in 96 and 97, respectively, with 20 degrees of freedom ($p< 0.0001$ in each year). Further, in the large RICs where the comorbidity effects are measured very precisely, the differences are large enough that we believe they may be of policy significance. For example, in RIC 1 comorbidity increases costs by a little more than 6 percent. In RIC 8, it increases cost by more than 18 percent. Pooling the comorbidity effect across RICs would substantially over pay cases with comorbidity in RIC 1 and underpay cases with comorbidity in RIC 8.

The second remaining question is whether the comorbidity effect varies among FRGs within the same RIC. Again we fit another regression model, this time within each RIC and year. The independent variables were dummy variables for each of the selected FRGs in the 92 node model (Table 3.11), comorbidity, and the interaction of FRG and comorbidity. The interaction terms were significant in only two RICs in 1997 (RICs 1 and 14). Even in RIC 1 where there was substantial data, the effects of comorbidity are not measured very precisely and do not vary consistently with average resource use in the FRG. In 1996 there was no interaction of comorbidity with FRG in RIC 1 ($p=0.66$), but instead interactions were found in RICs 20, 14, and 15 ($p< 0.01$).

Thus we believe that the best treatment of comorbidity in our classification is a simple partition of each FRG based on comorbidity, with a multiplier specific to the RIC used to determine relative weights.

In the next three chapters of this report we will use the selected set of Function-Related Groups with Comorbidities as the basis of our analyses of unusual cases, weighting methodology, and hospital adjustment factors. In Chapter 7, we will return to the question of the value of using a more detailed FRG system as the basis of classification for typical cases. In particular, we will compare payments using the selected FRGC system with those based on the more detailed FRGC system.

4. UNUSUAL CASES

The classification system discussed in the previous chapter was designed by analyzing more than three-fourths of all rehabilitation cases. However, in its design we deliberately omitted cases that might distort the analysis, viz., discharges to health care facilities, in-hospital deaths, and very short stay cases. Here we consider how we should classify these unusual cases.

ISSUES RELATED TO PAYING FOR UNUSUAL CASES

Which Cases are Candidates for Special Payment

Some cases are transferred to another health care institution before the patient has received the full course of rehabilitation therapy. Many of these transfers are to acute care facilities and occur because the patient has encountered a medical condition or event requiring acute care management. A small number of transfers are from one rehabilitation facility to another, and they are often at the patient's request. There are also a small number of transfers to a chronic care hospital. These and transfers to a Skilled Nursing Facility (SNF) indicate that the patient has not recovered adequately to return to independent living. In some cases the patient was not able to tolerate the intense therapy required in an inpatient rehabilitation setting and the discharge occurs very quickly.

Other patients that are also of concern are those transferred to a subacute unit, a nursing home, or a long term care home which does not receive Medicare payment. One might be concerned that these transfers could occur to increase reimbursement from non-Medicare sources. However, before acting on this concern, it is important to define which institutions should be labeled a 'nursing home' rather than a form of community living. There is now a continuum of living arrangements from assisted living through various stages of dependence and some nursing services are provided at all levels. For many families, the decision to move a senior into a nursing home or other group residence is greatly influenced by many things beyond the condition of the patient (and thereby beyond the control of the rehabilitation hospital and its discharge process). These factors include the patient's tastes, the amount of time that family caregivers are available, and family finances. Thus one can't use just the presence of nursing services to determine which institutions should qualify as receiving a transfer. HCFA has suggested that the right criteria be that the institution qualify to receive either Medicare or Medicaid payment as a nursing home. This is a sensible criterion for defining a transfer if it is possible to distinguish Medicaid payment as a nursing home from Medicaid payments to residential facilities such as group homes for the disabled and assisted living facilities that receive payments under Medicaid Home and Community Waivers.

For a transfer to a hospital, SNF, or Medicaid nursing home, it may be appropriate to not provide the full case payment when the patient receives less than the typical amount of treatment. A reduced payment that reflects the actual cost of the case is more appropriate and should reduce financial incentives to increase reimbursement by providing care in multiple settings. It also will make available funds that can be used to increase payment for other cases.

It is worth noting that we do not include transfers to home health or to the outpatient department of the hospital as cases that do not receive the full course of inpatient rehabilitation treatment. When patients are functioning well enough to return to the community and no longer need the intense therapy provided in the inpatient rehabilitation setting, they will often still need some lesser amount of therapy or medical care that can be provided efficiently either in the home or in an ambulatory setting. Based on data from our earlier study, the majority of rehabilitation hospitalizations end with a transfer to home health.[15] Indeed, it is much less efficient to keep the patient in the costly inpatient rehabilitation setting than to provide the therapy in an alternate site. The payment systems for the HHA, hospital outpatient department, and Part B therapy should recognize how the needs of patients who are discharged from inpatient rehabilitation differ from the needs of those who are discharged directly from acute care, but these payment systems are outside the bounds of this study.

[15] Our preliminary analysis of HHA bills for 1996 and 1997 suggests that this remained true in these years.

Although we believe that most patients who receive HHA or other outpatient services should be treated as a discharge to the community rather than as a transfer, it is possible that some hospitals could abuse the system by discharging patients to a course of outpatient therapy that substitutes for what would normally be provided during the inpatient stay. In future work, we will examine the distribution of the amount of outpatient services received per patient as a function of patient characteristics and hospital to determine if it might be reasonable to consider setting a threshold that says that the combination of inpatient resource use and outpatient resource use exceeds normal bounds. There has not been time to investigate this issue adequately for this interim report.

In studying transfers from rehabilitation hospitals to institutional care, we distinguish those who go to hospitals from those who go to SNFs and other long term care facilities. We use a single hospital group that includes transfers to acute care, to long term care hospitals, and to other rehabilitation hospitals. Transfers to hospitals were almost entirely transfers to acute care (94 percent of hospital transfers in each year). Transfers to other rehabilitation hospitals were very rare--less than 5 percent of hospital transfers and less than four tenths of one percent of discharges. Chronic hospitals received the other 1.1 percent of transfers to hospitals (0.09 percent of discharges were transfers to chronic hospitals). We also use a single group for SNF and other LTC non-hospital institutional settings. As discussed earlier (Chapter 2), our data do not distinguish well between these SNFs and other LTC, and so we cannot say with precision which fraction of the transfers to SNF/NH actually go to SNFs.

We shall also distinguish short stay transfers--i.e., transfers that occur before the (arithmetic) mean length of stay for non-transfer patients in the same FRGC. We choose to use a FRGC specific cutoff for short stays because of the wide variance across FRGCs in average LOS. We use our recommended definition of FRG from Table 3.12, and split the FRGs by the presence of comorbidities in the RICs where comorbidity was shown to increase cost (see Table B.3 in Appendix B for the definition of relevant comorbidities).

Two other groups of patients that are of concern because they have not received the full course of therapy are those who die in the rehabilitation hospital and those who stay in the hospital a very short time. There are relatively few cases in either group and we discuss them after we finish our discussion of transfer cases.

Payment Amount and Method

If transfer cases and very short stay cases were to receive a full FRGC payment, there are several ways in which it might be possible for hospitals to game the system. Some hospitals might transfer cases to reduce their costs or to increase Medicare payments. Some cases might be admitted to rehabilitation even when there was a high likelihood that the patient would not be able to sustain the demands of therapy and would need to return to acute care. These incentives will be greater if potential profit from these cases is greater, so one wants to avoid overpaying for such cases. Just as it is possible to pay too much for transfer cases and very short stay cases, it is possible to pay too little. Reductions much below cost might have the unwanted effects of providing disincentives for appropriate transfers and/or might reduce access to inpatient rehabilitation for patients with a good, but not certain, chance to complete inpatient rehabilitation and return to the community. Thus our main analyses examine the costs of transfers and other unusual cases.

A transfer payment policy could be implemented by either specifying payment for each transfer discharge or by bundling the payment for more than one hospital stay or for care provided by more than one provider. Thus, in addition to examining the cost of unusual discharges, we will also examine the bundled cost of interrupted stays. We will discuss payment options after we present our analyses of the data.

DESCRIPTIVE STATISTICS FOR TRANSFER CASES

Table 4.1 provides the rate of each kind of transfer by whether the hospital was freestanding or an exempt unit. In each year, about 21 percent of cases were transfers, and about 14 percent were short stay transfers. The majority of transfers to hospitals were short stay transfers. Transfers to SNFs and non-hospital long term care settings were more likely to stay longer than average for the FRGC than transfers to hospitals.

Table 4.1

Percent of Cases that are Transfers and Short Stay Transfers by Destination Type, Year, and Type of Rehabilitation Facility

			Percent of Cases					
			All Transfers			Short Stay Transfers		
Year	Type of Hospital	N Cases	To Hosp	To SNF/NH	Both Dest.	To Hosp	To SNF/NH	Both Dest.
96	Unit	103628	7.1	14.0	21.1	5.8	9.2	15.0
96	Free-standing	63517	9.0	11.6	20.6	6.7	5.5	12.2
96	All	167145	7.8	13.1	20.9	6.2	7.8	14.0
97	Unit	120629	7.1	14.2	21.3	5.9	9.5	15.4
97	Free-standing	80535	9.3	12.4	21.8	6.9	5.6	12.5
97	All	201164	8.0	13.5	21.5	6.3	7.9	14.2

Freestanding hospitals were more likely than units to transfer cases to acute care. This probably reflects the ability of a unit that is part of an acute care hospital to keep an ill patient in a rehabilitation bed because, should acute care be required, it would be immediately available. If this is the correct interpretation, it reflects the valuing of patient care standards over financial incentives, since the same acute care hospital would receive the acute PPS DRG payment. On the other hand, units are more likely to transfer cases to SNFs and nursing homes than are freestanding hospitals. They are particularly more likely to have short stay transfers to SNF/NHs. This may reflect the easy transmission of behavior from acute unit to TEFRA unit, since this cost-reducing strategy was widely used under the acute PPS.

Table 4.2 provides the rate of each kind of transfer by RIC. The rates vary substantially across RIC. The large RIC 8, lower extremity joint replacement, has very few transfers which reflects the relative health and strength of this population. On the other hand strokes (RIC 1), brain injuries (RICs 2,3, and 18), traumatic spinal cord injury (RIC 4) and the small burn RIC (21), have relatively large transfer rates. These findings are consistent across year.

Although we do not show in detail, cases with at least one of the comorbidities in our classification recommendation are more likely to be transferred (32 percent vs. 20 percent in 1997), and also more likely to transfer after a short stay (23 percent vs. 13 percent). Further, after controlling for the presence of comorbidity, cases in FRGCs with higher weight or longer LOS are much more likely to be transferred than cases in FRGCs with lower weight or LOS. Thus the pattern of transfers is consistent with sicker patients being less likely to be able to complete the full course of rehabilitation (or needing subsequent institutional care in a SNF or nursing home).

There are substantial differences in resource use between cases transferred to a hospital and cases transferred to SNFs and nursing homes. Table 4.3 shows that the average LOS of cases transferred to a hospital in 1997 was 12.35 days, while the average LOS of cases transferred to SNFs or NHs was 20.12 days. For comparison, we also show the average LOS of typical cases (i.e., non-transfer, non-death) cases[16] with the same distribution of FRGC as the transfer cases. So, the average LOS of non-transfer cases in the same FRGCs as transfers to hospital was 19.26 days in 1997. The next column of the table shows the ratio of the LOS of average cases to the LOS of transfer cases, after controlling for FRG. For the average transfer to hospital in 1997, a typical case in the same FRGC has a LOS that is 1.56 times (=19.26/12.35) the LOS of the transfer. On the other hand, transfers to SNFs have an average LOS similar to that of non-transfer cases in the same FRGC. As described above, transfer cases tend to be in FRGCs with higher weights. These FRGCs also have longer LOS. The average LOS for non-transfer, non-death cases was only 15.4 in 1997 (15.9 in 1996), substantially smaller than the average LOS for non-transfers with the same FRGC distribution as transfer cases.

Typical cases have a LOS that is 1.77 times that of short stay transfers in the same FRGC. The LOS of typical cases is more than double that of comparable short stay transfers to hospitals and over 50 percent more than the LOS of short stay transfers to SNFs and nursing homes.

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[16] This table and discussion includes cases with LOS <=3 as if they were typical.

Table 4.2

Percent of Cases that are Transfers and Short Stay Transfers by Destination Type, Year, and RIC

			Percent of Cases					
			All Transfers			Short Stay Transfers		
Year	RIC	N Cases	To Hosp	To SNF/NH	Both Dest.	To Hosp	To SNF/NH	Both Dest.
96	1	47353	8.6	19.4	28.0	7.1	12.5	19.7
96	2	2066	11.2	18.5	29.8	8.7	11.3	19.9
96	3	3748	11.5	17.7	29.3	9.0	11.2	20.2
96	4	1090	11.9	17.3	29.3	8.8	10.5	19.3
96	5	5074	9.7	11.9	21.6	7.6	6.5	14.1
96	6	6269	8.8	13.0	21.8	6.6	7.2	13.8
96	7	22438	6.2	17.4	23.6	5.0	10.4	15.4
96	8	35554	3.5	4.4	7.9	2.4	2.2	4.6
96	9	6819	6.4	12.9	19.3	4.9	6.7	11.6
96	10	6451	11.4	11.2	22.6	8.6	6.1	14.7
96	11	522	18.0	11.3	29.3	13.2	6.1	19.3
96	12	2878	6.5	6.8	13.3	4.9	3.2	8.1
96	13	1429	7.6	8.5	16.0	5.9	4.3	10.2
96	14	5208	11.4	6.9	18.3	8.9	3.7	12.5
96	15	3270	13.6	8.4	22.0	10.4	4.5	14.9
96	16	1652	7.3	8.7	16.0	5.5	4.1	9.6
96	17	819	7.4	13.3	20.8	5.6	7.7	13.3
96	18	239	10.5	18.4	28.9	8.8	11.7	20.5
96	19	324	11.7	10.5	22.2	10.2	8.0	18.2
96	20	13825	12.1	11.8	23.9	9.7	6.2	15.9
96	21	117	15.4	20.5	35.9	8.5	6.8	15.4
97	1	52769	8.7	20.5	29.2	7.3	12.9	20.2
97	2	2592	11.5	19.8	31.2	9.1	11.3	20.4
97	3	4454	12.7	17.9	30.6	10.4	10.1	20.4
97	4	1250	13.4	16.9	30.2	10.6	9.6	20.2
97	5	6055	10.1	12.1	22.2	7.6	6.2	13.8
97	6	7932	9.4	13.7	23.1	7.2	7.7	15
97	7	25059	6.6	18.4	24.9	5.1	11.2	16.3
97	8	43267	3.4	4.7	8.1	2.5	2.4	4.9
97	9	8722	6.3	14.2	20.6	4.5	7.8	12.3
97	10	7500	11.2	11.7	22.9	8.2	6.8	15
97	11	673	14.9	9.5	24.4	11.0	4.5	15.5
97	12	3591	6.1	7.7	13.8	4.9	3.8	8.8
97	13	1933	7.7	8.5	16.2	5.8	3.8	9.6
97	14	7325	11.9	7.0	18.8	9.5	3.7	13.2
97	15	4867	12.8	9.0	21.8	10.2	4.8	15
97	16	2419	7.2	9.6	16.9	5.7	5.0	10.7
97	17	920	8.7	16.3	25.0	7.0	9.8	16.7
97	18	334	14.1	15.6	29.6	10.8	9.0	19.8
97	19	395	11.4	12.4	23.8	9.1	9.1	18.2
97	20	18944	11.8	11.9	23.8	9.2	6.3	15.4
97	21	163	9.8	22.1	31.9	4.9	11.7	16.6

Table 4.3

Average LOS and Standardized Cost of Transfer Cases Compared to Typical Cases in the Same FRGC by Destination of Transfer Cases and Year

Year	Type of Transfer	Number of Cases	Average LOS	LOS of Typicals in Same FRGC	Ratio	Average Standard Cost	Standard Cost of Typicals in Same FRGC	Ratio
96	SNF/NH	21926	20.42	21.20	1.04	15077	15646	1.04
96	Hospital	13080	12.79	19.84	1.55	9760	14682	1.50
96	Both Dest	35006	17.57	20.69	1.18	13091	15286	1.17
96	Short Stay SNF/NH	13049	14.29	21.95	1.54	10989	16269	1.48
96	Short Stay Hospital	10288	9.12	20.32	2.23	7198	15084	2.10
96	Both Short Stay	23337	12.01	21.23	1.77	9318	15746	1.69
97	SNF/NH	27147	20.12	20.60	1.02	14901	15353	1.03
97	Hospital	16056	12.35	19.26	1.56	9560	14386	1.50
97	Both Dest	43203	17.23	20.10	1.17	12916	14993	1.16
97	Short Stay SNF/NH	15942	13.83	21.32	1.54	10730	15947	1.49
97	Short Stay Hospital	12630	8.82	19.70	2.23	7123	14764	2.07
97	Both Short Stay	28572	11.61	20.60	1.77	9135	15424	1.69

Note: Costs were standardized using only the hospital wage index.

Table 4.3 also shows the standardized cost of each type of transfer and compares it to the standardized cost of typical cases. We standardized costs using the hospital wage index[17] and a 0.705 labor market share (i.e., standardized cost = cost/(0.295+0.705*wi)). Because transfer cases tend to fall into more expensive FRGCs, the average standardized cost of typical patients with the same FRGC distribution as all transfer cases ($14,993 in CY 1997) is 35 percent higher than the average standardized cost of all typical patients ($11,068 in FY 1997; $11,330 in CY 1996). If typical patients were paid equal to the average cost of a case in their FRGC and transfer payments were given the full FRGC payment, then the ratio in the last column would give the payment to cost ratio for transfer cases. The lower LOS of transfer cases is translated directly into a reduction in the cost of transfer cases. Consistent with the LOS data, we find that short stay transfers cost

[17] The wage index used here is prior to reclassification and reflects the teaching adjustment as will be discussed in Chapter 5.

substantially less than typical cases. The magnitude of the overpayment of short stay transfers to either hospitals or NHs would appear to be large enough to be of concern if these cases were to be paid the full FRGC payment--short stay transfers to SNFs would be overpaid by 50 percent of costs and transfers to hospitals would be overpaid by 100 percent of costs.

ANALYSES OF THE COST OF TRANSFER CASES

One possible payment system would be a single payment for all short stay transfer cases. Because short stay transfers to SNF/NHs cost 50 percent more than short stay transfers to hospitals ($10,730 vs. $7,123 in 1997, Table 4.3), one might have two transfer payment amounts, depending on destination. For either policy, the standard deviation of standardized cost is a reasonable proxy measure of the typical difference between cost and payment under such a policy. For all short stay transfers, the standard deviation in 1997 was 5,582 or 61 percent of the mean. For short stay transfers to hospitals only, the standard deviation in 1997 was 5,108 or 72 percent of the mean; for SNF/NHs, it was 5,425 or 51 percent of the mean. So, any system with only one or two standardized payments for transfer cases would allow substantial overpayment for many cases and underpayment for others.

Part of the reason for variation in standardized costs across transfer cases is the FRGC of the case, but the larger reason is the variation in LOS. The inter-quartile range of LOS for short stay transfers is from seven to 15 days. Almost 10 percent of such cases have LOS of three days or less and 10 percent have a LOS of 20 days or more. Consequently, we have explored the relationship between the cost of short stay transfers and per diem cost in the FRGC.

We used simple regression models which capture the major variation across both LOS and FRGC group, and, if necessary, transfer destination. This analysis is similar to the payment model developed in our earlier work on the model RPPS which, in turn, built on earlier analyses of the costs of transfer cases in the acute care PPS (Carter and Rumpel, 1993). The models build on the fact that the costs of hospitalizations are well modeled as per diem cost times LOS plus an extra cost for the first day to cover costs that occur only once in the stay.

We present two models. In Model 1 we show how the per diem cost of transfer cases relates to the per diem cost of typical cases. In particular, we regress standardized cost of each transfer case on two variables: (1) The per diem standardized cost in the FRGC (average standardized cost of a non-transfer, non-death case in the FRGC divided by the average length of stay for the same set of cases), (2) per diem cost for the all days beyond the first, i.e., the LOS of the transfer case minus one multiplied by the per diem standardized cost. The model has no intercept term, so per case costs, if any, are loaded onto the first day per diem. If we wished the relative payment for transfer cases to match their relative cost, we could use this equation to develop a payment model by substituting per diem payment of typical cases for the per diem cost.

Model 2 asks whether transfers to hospitals have substantially different costs from transfers to SNFs and nursing homes. It does so by adding the interaction of the two variables in Model 1 with a dummy variable that is one if and only if the transfer was to a hospital (rather than to a nursing facility).

In each year and in each model, the cost of the first day of each stay appears to be a little more than one and a half times the cost of a typical day in the same FRGC (see Table 4.4). The coefficient on the per diem pay is very close to one. The standard error of the estimate of the coefficient on the cost of subsequent days is 0.0034 in each year, and therefore the coefficient is statistically indistinguishable from 1 ($t < 1$, $p > 0.2$). So additional days in the transfer stay cause an average increase in cost identical to the average cost of a typical day in the FRGC.

The results from model 2 show that, after controlling for FRGC and LOS, the cost of cases transferred to hospitals is very similar to the cost of cases transferred to SNFs. The coefficient on first day pay interacted with transfer to a hospital is not significant in either year. Although the coefficient on the interaction of hospital transfer and subsequent per diem is significant, the magnitude of the effect is very small and is in an opposite direction to the effect of the constant term. Thus we believe a single per diem payment rule could closely approximate cost for both types of transfers.

The note in Table 4.4 gives the standard error of the predictions from each of the models. The SEEs are roughly half of the standard deviation of the cost of short stay transfer cases. Thus using a per diem payment rule greatly improves accuracy compared to either using a single payment for transfer cases or using payments that depend only on transfer destination.

Table 4.4

Regressions of Cost of Short Stay Transfer Cases on Per Diem Payment and First Day Payment

	1996		1997	
	Coef.	**t-stat**	**Coef.**	**t-stat**
Model 1				
First Day Cost	1.630	35.82	1.65	38.58
Each Subsequent Day Cost	0.997	285.01	0.998	292.87
Model 2				
First Day Cost	1.688	22.31	1.67	23.6
Each Subsequent Day Cost	0.991	194.46	0.989	200.67
Transfer to Hospital and				
First Day Cost	-0.129	1.34	-0.138	1.53
Each Subsequent Day Cost	0.018	2.35	0.038	5.04

Note: R-square for model 1 in 1996: 0.791, for model 2 in 1996: 0.791.
R-square for model 1 in 1997: 0.764, for model 2 in 1997: 0.765.
Root MSE for model 1 in 1996: 2564, for model 2 in 1996: 2564.
Root MSE for model 1 in 1997: 2711, for model 2 in 1997: 2708.

INTERRUPTED STAYS

One possibility would be to bundle the two rehabilitation stays when a rehabilitation case returns to the same rehabilitation hospital within a fixed period of time. Here we consider what would happen if a single payment were to cover these two rehabilitation discharges. Note, that, unlike the UDSmr definition of an interrupted stay, we do not restrict the interruption to cases transferred to acute care.

We used beneficiary identifier and provider number on the MEDPAR to identify all discharges in our sample hospitals where the patient returned to rehabilitation at the same hospital within 10 days. In 2.6 percent of all discharges, the patient returned to their rehabilitation program within 10 days. Eighty-eight percent of these returns had been discharged as a transfer to a hospital; 10 percent were discharged home and 2 percent discharged to a SNF or NH. Twenty-nine percent of all transfers to hospitals returned to the same rehabilitation hospital within 10 days to continue their rehabilitation.

To explore a possible bundled payment, we analyzed the cost of these interrupted stays as a function of the length of the interruption to the rehabilitation program. We also compared that cost to payment under both a bundled payment system and one that would pay separately for each discharge. For simplicity, we consider only the first two rehabilitation discharges for each interrupted stay. We used only stays for which both discharges were in our analysis sample. We added the standardized cost and LOS of these two parts and give the average value of the sum in the first columns of Table 4.5. The first line covers all the interrupted stays that returned within 10 days and for which we have data on both parts of the stay. The average case spent 26.5 days in rehabilitation in the first two parts of its interrupted stay and that rehabilitation cost an average of $19,746.

We then estimated what the sum of standard payments for these two discharges would be by assuming the standardized case payment for each typical discharge and long stay transfer would be set at the average standardized cost of a typical case in the FRGC and assuming short stay transfers would be paid the FRGC per diem times the LOS of the case. We show the result in the column headed discharge payment.

Table 4.5

LOS, Standardized Cost and Payment, Under Bundled and Non-bundled Policies for First Two Parts of Interrupted Stay, as a Function of Length of Interruption (combined 1996 and 1997 data)

						Payment to Cost Ratio	
Days	N Cases	Total LOS	Total Cost	Discharge Payment	Bundled Payment	Discharge Payment	Bundled Payment
All	10440	26.5	19746	19127	12824	0.97	0.65
0	252	23.3	18954	19726	11884	1.05	0.63
1	788	24.4	19031	19053	12622	1.01	0.66
2	1145	25.6	19087	18841	12724	0.99	0.67
3	1349	25.9	19475	18926	12795	0.98	0.66
4	1398	26.3	19889	19088	12684	0.96	0.64
5	1326	26.4	19522	18950	12902	0.97	0.66
6	1218	27.2	20316	19639	13118	0.97	0.65
7	1036	27.7	19716	19016	12844	0.97	0.65
8	833	27.3	20345	19091	12579	0.94	0.62
9	596	28.5	20314	19638	13311	0.97	0.66
10	499	27.2	20253	19324	13170	0.96	0.65

We also estimated a bundled payment in which the case receives a single payment for the two parts of the stay. The payment is a per case payment if the case is discharged to the community following the second stay and uses the same transfer payment rule as the discharge payment if the case is transferred either to SNF or hospital at the end of the second discharge. These bundled payments are also shown in Table 4.3 along with the payment to cost ratio for each of the two payment policies. Each payment amount used for the bundled payment is 1.6 percent higher than the similar payment amount used for the per discharge policy, reflecting the spreading of the savings from using the bundled payment policy across all cases. Note that if the bundled payment were to be used only for shorter interruptions, then the savings from the bundled payment would be reduced and the bundled payments would be slightly smaller (less than 1.6 percent smaller) and the PTC ratio for the bundled payment also slightly smaller. For example if we bundled only interruptions of two days or less, the savings in standardized payment would be only 0.34 percent rather than 1.6 percent and so the payments would be about 1.26 percent lower than shown in the table.

Interrupted stays have substantially longer LOS than other discharges (25.6 vs. about 16 days) and cost two-thirds more than the average discharge (almost $20,000 rather than under $12,000). The discharge payment policy, without bundling, overpays the discharges that return on the same day they were discharged by 5 percent, but then matches average payment to average cost almost exactly. On average the bundled payment pays only 65 percent of cost. There is only a weak relationship between the length of time spent in acute care and cost or payment to cost ratios. In general the cost increases with the length of the interruption, but the amount of the increase is small.

We performed a similar analysis using the data for interrupted stays as coded by UDSmr instead of all returns. This analysis was restricted to our preliminary cost data and to 1997 cases. We got very similar results in terms of cost and payments, so we do not present the details here. However, the matching of the parts of the interrupted stay to a MEDPAR record showed one interesting anomaly. For 91 percent of the interruptions recorded on the UDSmr FIM, we matched both the rehabilitation stay preceding the interruption and the rehabilitation stay following the interruption to an acute stay to a MEDPAR record--this is very close to the match rate for non-interrupted stay cases. This matching rate was independent of the length of the acute interval except for the small number of cases transferred to acute care and returned the same day. We matched both stays for only 28 of 52 (54 percent) of such interruptions. This raises the issue of exactly how a discharge is defined for payment because it may be that some of the non-matched discharges were not actually counted by Medicare as discharges. The definition of a discharge used in practice may vary across the country. Was the patient really discharged when he returned to his rehabilitation program the same day that he left? It would seem prudent to be explicit about defining a discharge. For example, if the case returns to the hospital within 12 or 24 hours, or on the same day, one might deem it to be not a discharge. This would affect very few current cases and prevent unwarranted future gaming.

VERY SHORT STAY CASES

Another group of cases who are unlikely to receive the full course of rehabilitation are those who stay in the hospital a very short time. We show in Table 4.6 the number of cases with each LOS up to five, and then group all cases with LOS of six days or more. In order to describe these cases further we grouped them by information about their discharge destination. Because of the small number of cases per cell, we add the data for both years together. The first half of the table covers our analysis sample for whom we have good cost and FIM data and could assign an FRGC. The second half of the table includes the small number of cases that leave the rehabilitation hospital prior to completion of their initial assessment. UDSmr (but not Caredata.com) indicates these cases in their admission class data field with a 4 for an "unplanned discharge without assessment." According to the coding instructions "This is a stay that lasts less than 72 hours because of an unplanned discharge. An admission FIM assessment has not been completed." All the UDSmr cases with missing FIM score were classified as 'Unplanned discharge without assessment,' although many stayed more than three days. Although Caredata.com does not explicitly classify patients in this manner, it does have cases which were not assigned answers to all the FIM questions.[18]

Table 4.6

Number and Percent of Cases With and Without FIM Assessment and With Each Discharge Destination, by LOS (1996 and 1997 data)

	Number of Cases						
	LOS = 1	**LOS = 2**	**LOS = 3**	**LOS = 4**	**LOS = 5**	**LOS = 6**	**All**
FIM Known							
SNF/NH	56	132	338	418	477	47652	49073
Hospital	1293	1407	1501	1501	1549	21885	29136
AMA	55	45	34	57	47	345	583
Died	61	83	88	112	106	1205	1655
Community	383	1399	3664	6984	7970	267462	287862
Subtotal	(1848)	(3066)	(5625)	(9072)	(10149)	(338549)	(368309)
FIM Missing							
SNF	4	5	3	3	2	156	173
Hospital	44	30	21	5	5	112	217
AMA	4	4	1	1	0	0	10
Died	1	1	0	0	0	4	6
Community	28	24	16	16	25	546	655
Subtotal	(81)	(64)	(41)	(25)	(32)	(818)	(1061)
Total	1929	3130	5666	9097	10181	339367	369370
	Percent of Cases						
	LOS = 1	**LOS = 2**	**LOS = 3**	**LOS = 4**	**LOS = 5**	**LOS = 6**	**All**
FIM Known							
SNF/NH	2.9	4.2	6.0	4.6	4.7	14.0	13.3
Hospital	67.0	45.0	26.5	16.5	15.2	6.4	7.9
AMA	2.9	1.4	0.6	0.6	0.5	0.1	0.2
Died	3.2	2.7	1.6	1.2	1.0	0.4	0.4
Community	19.9	44.7	64.7	76.8	78.3	78.8	77.9
Subtotal	(95.8)	(98.0)	(99.3)	(99.7)	(99.7)	(99.8)	(99.7)
FIM Missing							
SNF	0.2	0.2	0.1	0.0	0.0	0.0	0.0
Hospital	2.3	1.0	0.4	0.1	0.0	0.0	0.1
AMA	0.2	0.1	0.0	0.0	0.0	0.0	0.0
Died	0.1	0.0	0.0	0.0	0.0	0.0	0.0
Community	1.5	0.8	0.3	0.2	0.2	0.2	0.2
Subtotal	(4.2)	(2.0)	(0.7)	(0.3)	(0.3)	(0.2)	(0.3)
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Two-thirds of the cases with only a one-day stay were transferred to the hospital and about 3 percent each went to a nursing home, died, or left against medical advice. However, a little over 20 percent are

[18] Insofar as cases with missing FIM data did not actually miss assessment, we may have overestimated the extent of the missing assessment problem. However, we expect the overestimate is modest since 80 percent of the data come from UDSmr and these hospitals explicitly noted the lack of assessment.

shown as being discharged to the community. The fraction of each LOS that are discharged to the community rises quickly with LOS and is similar for all cases with a LOS greater than 3. Thus, although we can distinguish the reason why some patients have very short stays, there are others whose cause is not discernible from our data. But it seems unlikely that a LOS of two or three days can be viewed as a typical course of inpatient rehabilitation, even when the patient returns home.

We next ask how much very short stay cases cost and how this varies by LOS and by the apparent reason for the very short stay case. We restrict the analysis to cases that stay three days or less. Because we have already analyzed transfer cases, we also exclude those cases from the data in Table 4.7. We have grouped 'left against medical advice' with those discharged to the community, because we believe that this distinction may be ambiguous in some cases. These short stay cases have an average standardized cost of only $2,088, or 18.6 percent of the cost of a typical case that is discharged home.

Table 4.7

Average and Standard Deviation of Standardized Cost of Selected Very Short Stay Cases

	LOS = 1			LOS = 2			LOS = 3			All LOS <= 3		
	N of Cases	Avg. Cost	Std. Dev. Cost	N of Cases	Avg. Cost	Std. Dev. Cost	N of Cases	Avg. Cost	Std. Dev. Cost	N of Cases	Avg. Cost	Std. Dev. Cost
Discharged prior to assessment	81	941	514	64	1831	780	41	2371	755	186	1562	885
Discharged to home or AMA	438	882	394	1444	1699	514	3698	2419	718	5580	2112	805
Died	61	944	330	83	1844	593	88	2712	905	232	1937	977
Any of above	580	897	407	1591	1712	533	3827	2426	725	5998	2088	821

Within each LOS, the three groups have similar costs. Because of the different distribution of LOS, the group discharged prior to assessment costs somewhat less than those discharged to home. Although the death cases also cost less than those discharged to home, ($p < 0.05$), the difference in cost is only $175 per case.

IN-HOSPITAL DEATH CASES

Table 4.8 shows the death rate by RIC and comorbidity. Although the death rate is small in all RICs, it is very small in RIC 8, joint replacement of the LE. The death rate is also noticeably lower than average in the other orthopedic RICs (7 and 9) and in the Pain RIC (16). Although the death rate is also numerically low in RIC 18 (MMT with brain or spinal cord injury), the sample size is too small to ensure that the actual death rate is lower than average. Patients in RIC 15 (Pulmonary disorders) have the highest death rate. Patients with one of the relevant comorbidities are more than six times more likely to die in the hospital than those without (1.88 percent vs. 0.28 percent).

Table 4.8

Death Rate by RIC and Comorbidity

	Death Rate (percent)			Sample Size		
RIC	**Whole RIC**	**No Comorbidity**	**With Comorbidity**	**Whole RIC**	**No Comorbidity**	**With Comorbidity**
1	0.59	0.41	2.82	100122	92879	7243
2	0.69	0.50	1.56	4658	3825	833
3	0.74	0.60	1.33	8202	6542	1660
4	0.60	0.29	2.80	2340	2054	286
5	0.42	0.33	1.32	11129	10065	1064
6	0.48	0.35	1.35	14201	12424	1777
7	0.29	0.15	2.64	47497	44804	2693
8	0.07	0.04	0.98	78821	75969	2852
9	0.21	0.13	1.38	15541	14528	1013
10	0.62	0.35	1.74	13951	11249	2702
11	0.75	0.75	0.76	1195	932	263
12	0.31	0.27	0.85	6469	6001	468
13	0.33	0.16	2.01	3362	3063	299
14	0.74	0.60	1.53	12533	10640	1893
15	1.51	1.33	2.72	8137	7069	1068
16	0.15	0.08	1.21	4071	3824	247
17	0.52	0.38	1.97	1739	1587	152
18	0.17	0.21	0.00	573	482	91
19	0.70	0.47	2.60	719	642	77
20	0.78	0.54	1.65	32769	25609	7160
21	0.36	0.44	0.00	280	225	55
Total	0.45	0.30	1.89	368309	334413	33896

Note: Based on pooled 1996 and 1997 analysis sample.

The cases that died in hospital had significantly shorter LOS and lower cost than typical cases in the same FRGCs, as may be seen in the first row of Table 4.9. If each death case were to receive a payment equal to that of a typical case in the FRGC, these cases would be overpaid relative to their costs by 72 percent. In the previous subsection, we found that the cost of death cases with a LOS of three days or less was very similar to the cost of other cases with similar length stays. Thus one might choose to pay these very short stay cases with other atypically short stay cases. As shown in the second row of Table 4.9, the overpayment for the remaining death cases is lower, but still they would be paid over 50 percent more than typical patients relative to their costs.

Table 4.9

LOS and Standardized Cost of In-Hospital Deaths Compared to Typical Cases in the Same FRGC

Type of Death Case	N of Cases	Avg. LOS	LOS of Typicals in Same FRGC	Ratio	Average Cost	Cost of Typicals in Same FRGC	Ratio
All	1655	12.17	21.78	1.79	9696	16710	1.72
Exclude LOS <= 3	1423	13.80	21.69	1.57	10961	16620	1.52

Note: Based on pooled 1996 and 1997 cases in analysis sample. Costs were standardized using only the hospital wage index.

The size of the overpayment suggests it is desirable to provide a special payment for death cases. One possibility would be to pay each death case the same amount, with the amount set to be proportional to the cost of the death cases. This would result in fair payment for these cases and free up some money to be paid to other cases. As before, we use the standard deviation of standardized cost as a proxy measure for the typical difference between cost and payment under such a policy. As shown in Table 4.10, the standard deviation is $9,189 or 95 percent of the mean cost. Clearly such a single payment would result in payments substantially above or below cost for many cases.

As is shown in the next two lines of the table, death cases in the orthopedic RIC have almost 20 percent lower costs than death cases in the non-orthopedic RICs. Setting two payment rates rather than one, would decrease the average overpayment of orthopedic cases that die in the hospital, but would have only a little effect on the degree of overpayment and underpayment as measured by the root mean square error.

Akin to the transfer cases, we also consider a policy which defines short stay death cases depending on whether the death occurred before the average LOS of typical cases in the FRGC. This is shown in the third section of the table which maintains the subdivision into the orthopedic deaths and the non-orthopedic deaths. Not surprisingly, this plan results in a significant improvement in payment accuracy.[19] All three of the above payment plans for death cases (one payment, different payments for orthopedic and non-orthopedic cases, and a further split into short stay cases) are replicated in the table under the assumption that death cases that stay three days or less are paid in a different manner.

Table 4.10

Standardized Cost of In-Hospital Deaths for Selected Partitions of Death Cases

Type of Death Case	Number of Cases	Average Cost	Std. Dev. Cost	Group RMSE	Ratio of RMSE to Avg. Cost
All	1655	9696	9189	9189	0.95
Orthopedic RIC	226	8060	7208	9168	0.95
Non-Orthopedic RIC	1429	9954	9441		
Short Stay Orthopedic	187	5982	3914	7287	0.75
Short Stay Non-Orthopedic	1218	7573	5302		
Long Stay Orthopedic	39	18027	10461		
Long Stay Non-Orthopedic	211	23703	14846		
All LOS > 3	1423	10961	9308	9308	0.85
Orthopedic RIC, LOS > 3	193	9154	7248	9283	0.85
Non-Orthopedic RIC, LOS > 3	1230	11244	9563		
Short Stay Orthopedic, LOS > 3	154	6907	3685	7481	0.68
Short Stay Non-Orthopedic, LOS > 3	1019	8664	5110		
Long Stay Orthopedic	39	18027	10461		
Long Stay Non-Orthopedic	212	23703	14846		
Orthopedic, 3 < LOS <= 12	122	5523	2420	7251	0.66
Non-Orthopedic, 3 < LOS <= 14	794	6837	3217		
Orthopedic, LOS >= 13	71	15394	8454		
Non-Orthopedic, LOS >= 15	436	19270	11810		

Note: Based on pooled 1996 and 1997 cases in analysis sample. Costs were standardized using only the hospital wage index.

The just discussed division into short stay and long stay cases has a problem in that there is a substantial variation in average LOS across FRGCs and, and therefore in the LOS of death cases that are classified as short stay, and the payment system is not accounting for the resulting variation in costs (as it does for transfers and typicals). An alternative way to define short stay death cases would be based on the average LOS of the relevant death cases rather than the

[19] Even greater improvement in accuracy could be obtained by using a per diem payment policy for short stay death cases just like the

average LOS of typical cases in the FRGC to which the case would have been assigned if the patient had not died. Payment under such a system, with the omission of death cases of three days or less, is shown in the last section of the table.

IMPLICATIONS FOR PAYMENT

Payment for Transfer Cases

If short stay transfer cases were to receive a full FRGC payment, most of these cases would be substantially overpaid relative to typical cases. We have shown that the average payment to cost ratio for short stay transfer cases would be about 1.8. The payment to cost ratio for transfers to hospitals would be greater than 2.

Abuse might occur if hospitals transferred cases to reduce their costs or to increase Medicare payments or if patients were admitted who had a high likelihood that they would not be able to tolerate the therapy and would need to return to acute care. The TEFRA incentives were apparently sufficient to cause an increase in some transfers (Chan and Ciol, 2000). The PPS incentives to transfer will be stronger because the hospital will retain all the cost savings rather than sharing it with HCFA. In order to reduce these incentives, it seems prudent to implement a reduced payment for short stay transfers, defined as cases transferred before the mean LOS for their FRGC to hospitals, SNFs, or nursing homes which receive Medicaid payment.

It would not be prudent to reduce the payment for such cases to be much below expected cost. We do not want to discourage appropriate transfers that provide beneficiaries with needed services. Further, too low payments for transfer cases or very short stay cases might have the unwanted effect of reducing access to inpatient rehabilitation for patients with a good, but not certain, chance to complete inpatient rehabilitation and return to the community.

Thus choosing an appropriate payment policy for short stay cases and transfers requires balancing a reduction in incentives to provide unneeded care or to obtain unjustifiable payments against the need to provide adequate funding for, and access to, all appropriate care.

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transfer policy. But this might not conform to the BBRA.

Using a per diem payment system for short stay transfer cases would closely match payments to cost. Indeed, it would reduce the error in payment by more than half compared to a single per case transfer payment. The greater accuracy would reduce opportunities for profitable gaming and be fairer to hospitals that, just by chance, receive many patients that require a transfer.

Based on our model of the cost of transfer cases, the payment system that would best match payments to cost would pay a per diem payment equal to the average payment for a day in the FRGC2 plus an additional one-half per diem. Elimination of the one-half-day per diem would provide a small penalty for each transfer case that might discourage hospitals from developing a care policy based on frequent transfers while having only a small effect on access.

Because marginal cost can be less than average cost, it is important that the rate of transfer cases be monitored on a hospital specific basis to ensure that gaming does not occur.

We recommend that long stay transfer cases receive the FRGC payment, and that this payment reflect, in addition to the cost of typical cases, both the full cost of long stay transfer cases and the fact that short stay transfer cases are not paid as full cases. Each of these factors will increase the relative weight of FRGCs with a higher than average proportion of transfers so that the relative weight of a typical or long stay transfer case is proportional to the average cost of such cases in the FRGC. Thus, although transfer cases will lose money on average,[20] cases with any specified mix of impairment group, comorbidity, and function will be paid in proportion to costs.

Bundling

Our analysis above addresses the possibility of bundling the two rehabilitation stays when a rehabilitation case is sent to acute care and then returns within a short period of time. Using any length of time in excess of one day would result in substantial underpayments for these cases. Typically they would be paid only two-thirds of relative

[20] All cases that stay longer than average for their group lose money, so almost all long stay transfer cases will lose money. If short stay transfers are paid at costs, then transfers on average lose money.

costs. Using a per discharge payment, including a per diem payment for transfer cases, accurately matches payments to cost.

In general, we believe that matching payments to expected costs as closely as possible is the best way to reduce opportunities for profitable gaming and to reduce the effect of financial considerations in clinical decisions. If discharges that returned in a short period of time were bundled, it might discourage necessary readmissions or increase acute care costs. We recommend that these discharges not be bundled. However, we do recommend that a discharge be clearly defined, perhaps excluding cases that return to the same rehabilitation hospital within 24 hours as not having received a discharge from the program in the first place.

There are other possibilities for bundling. One is for the small number of cases, 0.34 percent in our 1997 data, that are transferred from one rehab facility to another rehab facility. One might consider paying a single payment to cover both facilities and letting the hospitals work out the split. This is actually the transfer policy that was proposed in FY 1983 for the acute care PPS. It raised serious objections in the field due to the administrative implications and we expect that it would raise similar objections here. The expert panel on our previous study said that rehabilitation facility to rehabilitation facility transfers were essentially always at the request of the patient. This increases the administrative problem of the facility under such a policy, because the sending hospital has no control over, and likely no financial arrangement with, the receiving hospital. The only concern here would be if some pairs of hospitals were to look on this as an opportunity to game the system. Thus we recommend active monitoring of the source and destination of such transfers, with action taken only if abuse is detected. In the meantime, the same transfer policy should be used for transfers to a rehabilitation facility as for transfers to acute care, chronic care, and SNFs.

Transfers to LTC hospitals (i.e., chronic hospitals) were only 0.10 percent of cases in FY 1997 according to the FIM instrument. When we tried to find a long term care hospitalization for the same beneficiary that began on the day of discharge or one day earlier or later, we found only 0.07 percent of cases had such a transfer. We would recommend using the same transfer payment policy for the rehabilitation stay as for transfers to acute care, another rehabilitation facility, and SNFs rather than implementing a special payment policy. We would also recommend monitoring such transfers to ensure that they do not increase.

Finally, the bundling of payment across all post acute providers and/or with the acute stay provider is certainly a desirable long term goal. We believe that it should be considered in the refinement section of this project rather than make any attempt to implement such a policy in the upcoming fiscal year. Authority to change the payment for acute care and other post-acute providers due to the patients' use of a rehabilitation facility may not be supported by current legislation.

Payment for Deaths and Atypical Short Stay Cases

In rehabilitation facilities, 2.9 percent of cases stay less than three days. It makes sense to reduce their payment so that it is based on their relative cost. This can be done by creating a special group for these cases. The variance in the cost of all three day cases is only 39 percent of the mean, so there is no need to split these cases further. However, the creation of a group for such cases provides a strong incentive to keep the patient for four days. Thus it may result in a decrease in the number of cases with LOS <=3 and a corresponding increase in the number of cases with LOS of four or five days. This should be monitored at both the hospital and national levels.

There are even fewer cases that die in the hospital--less than half of one percent. On average these cases cost substantially less than typical cases in the same FRGC, so it is reasonable to pay these cases closer to costs and thereby free up funds to pay other cases more accurately. There is a large variation in the cost of such cases. Splitting the death group by whether or not the patient was in an orthopedic RIC and whether or not the patient stayed longer than the average death case would further increase the accuracy of the payment system. Because of the large variation in relative costs across FRGCs, any grouping of death cases into a small number of death-only categories will result in some cases that are paid more if they die in the hospital than if the same patient were discharged alive.

5. RELATIVE CASE WEIGHTS

In Chapters 3 and 4 we reported our analyses of issues related to case classification--using FRGCs for typical cases and exploring options for classification of unusual cases. Based in part on these analyses, but also on HCFA's understanding of the incentives inherent in aspects of the payment system, HCFA made some preliminary decisions about case classification that we used to explore further options for the IRF PPS, including choice of an algorithm to calculate relative weights.

Since relative weights depend on the underlying case classification system, we report these decisions in the first sub-section described below. Because these decisions go beyond the FRGC system to include classification of atypical cases, we will call the resulting classification system the Case Mix Groups (CMGs). The second sub-section describes policy options for calculating relative weights for the CMGs. We then describe the data and methods that we use to calculate several alternative sets of weights. After we empirically compare the options for the development of case weights, we discuss the implications of our findings.

The average of the relative weights for a set of cases is called the case mix index or CMI. The CMIs for cases at different hospitals can be compared to describe the relative costliness of each hospital’s case mix.

ASSUMPTIONS ABOUT CASE CLASSIFICATION

Typical Cases

Typical cases are defined as discharges to the community that spent more than three days in the rehabilitation facility. These cases are classified according to the FRGC methodology discussed in Chapter 3. In particular, in this chapter we analyze weights where typical cases are classified into FRGs according to the rules found in Tables 3.9 and 3.12. The weights include a multiplicative effect of comorbidity on costs where comorbidity is defined based on the presence of any one of the relevant comorbidities shown in Table B.3 and applying the RIC exclusions also shown in that table.

Atypical Cases

Other assumptions about case classification are as follows:

(1) A single group contains all non-transfer cases that stay in the hospital for three days or less, including death cases.

(2) Death cases that stay for four days or more are placed in one of four groups based on LOS and whether or not they are orthopedic. Orthopedic cases are defined as those with a primary impairment that causes assignment to one of the orthopedic RICs (7,8, or 9). Each of the sets of orthopedic and non-orthopedic death cases are then subdivided based on whether they stay less than the mean LOS for that set of death cases.

(3) Cases transferred from one rehabilitation facility to another rehabilitation facility that has certain financial ties to the sending facility will be paid only a single case payment. Because we do not have data on financial ties, we omit this rule in our analyses. In view of the very small number of such cases, we believe that this has no substantial effect on our analyses.[21]

(4) Cases transferred to a hospital (except as in (3) above) or to a SNF or NH that is paid under either Medicare or Medicaid and that stay less than the mean LOS of typical cases assigned to the same FRGC are paid a per diem equal to the average daily payment for a typical case in the same FRGC. We call these cases short stay transfers.

(5) Transfer cases that are not short stay transfers (defined as in (4) above) will be classified with typical cases in the FRGC.

Bundling

HCFA decided, at least provisionally, that discharges where the patient returns to the same rehabilitation facility on the day of discharge or on either of the two following days should be bundled with the subsequent discharge for purposes of case classification and payment.

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[21] We mean only that applying the rule to past data would not affect analyses. The rule could affect behavior in the future.

In order to develop relative weights consistent with this provisional decision, we preceded as follows. We began by identifying all MEDPAR discharges for all hospitals with at least one discharge in our matched FIM-MEDPAR data set (including both matched and unmatched discharges). We then matched up every set of MEDPAR records where the same person returned to the same rehabilitation facility within two days of discharge.

We used the following rules to classify the interrupted stays. We used the impairment code and FIM scores from the FIM record matching the first discharge. When there was no FIM record matching the first discharge, and the FIM record that matched the second discharge recorded an admission within one day of the first discharge, we used that FIM data. This occurred in about 10 percent of the interrupted stays with any match and we believe that it was usually due to FIM records that covered multiple discharges (i.e., the admission date on the FIM record matched the admission date on the first MEDPAR discharge and the discharge date on the FIM record matched the discharge date on the last discharge, yet the FIM record did not note an interrupted stay). We used the last discharge in the interrupted stay to code transfers and deaths. We set the flag for the relevant comorbidity as 1 if a relevant comorbidity appeared on any matched MEDPAR discharge in the stay. Finally, we summed days and cost across each discharge to assign the LOS and cost for the interrupted stays.

Table 5.1 counts the number of stays that had good information for case classification and for cost, by number of discharges per stay. In 1996 there were 922 interrupted stays made up of 1865 discharges--with 903 stays made up of exactly two discharges each, 17 made up of exactly three discharges and two made up of four discharges. The other 165,385 discharges did not return to their rehabilitation program within two days of the day of discharge and were not bundled. The last row in the table shows that there are an average of 0.62 percent more discharges than cases in our sample. This is somewhat lower than the 0.83 percent more discharges than cases among all discharges at the sample hospitals, perhaps reflecting the greater difficulty of matching FIM records and discharges for this kind of case.

Table 5.1

Sample Counts for Interrupted Stays (return within two days following discharge)

Row	Interrupted Stays	1996	1997	Total
	2 discharges	903	1261	2164
	3 discharges	17	38	55
	4 discharges	2	0	2
(a)	Total interrupted stays	922	1299	2221
(b)	Total discharges	1865	2636	4501
(c)	Non-interrupted stays	165385	198740	364125
	Total cases = (a) + (c)	166307	200039	366346
	Total discharges = (b) + (c)	167250	201376	368626
	Ratio of discharges to cases	(1.0057)	(1.0067)	(1.0062)

OPTIONS FOR CALCULATION OF RELATIVE WEIGHTS

For any particular hospital, the payment for each case will be proportional to the relative weight assigned to the patient's CMG. To ensure that beneficiaries in all CMGs will have access to care and to encourage efficiency, we will calculate weights that are proportional to the resources needed by a typical case in the CMG. So, for example, cases in a CMG with weight of 2 will typically cost twice as much as cases in a CMG with a weight of 1.

There are a variety of ways in which relative weights could be calculated. In this section, we review these methods and select several for empirical analyses in subsequent sub-sections.

In previous work, we examined alternatives that differed in the measure of resource use (charge vs. cost), the method used to control for variations in costs across facilities (hospital specific standardization vs. payment factors) and whether the weight algorithm should account for the proportion of outlier payments in the payment group. We found only modest differences among the various types of weights with respect to (1) their ability to explain costs at the case level, (2) their ability to explain costs at the hospital level, (3) associated hospital payment factors, and (4) payment to cost ratios for groups of hospitals (Carter, Buchanan, et al., 1997). Consequently, we believe that theoretical advantages and disadvantages of the options could play a role in the policy decision and present these next.

Resource Measure

Cost-based weights were used in the initial acute care PPS implementation, but charge-based weights have been used since FY 1986. Cotterill et al. (1986) found charge- and cost-based weights for the acute care PPS to be quite similar. Similarly, we found cost and charge weights to be quite similar in our model of a rehabilitation RPPS.

One of our major analytic goals was to determine whether cases with comorbidities require additional resources. The distribution of patients with these comorbidities varies across rehabilitation facilities. Thus our criteria of access and provider fairness require that we measure additional costs associated with comorbidities as accurately as possible.

As shown in Chapter 3, comorbidities have a measurable effect on cost per case, and we expect that is because of the additional non-therapy ancillary services required by these patients. As shown in Table 5.2, the cost-to-charge ratios of several of the major ancillary departments, namely laboratory, pharmacy, supplies, and respiratory therapy are substantially lower than those of the major therapy departments. Thus using charges would overestimate the costs of cases that use more than average of these services. On the other hand the cost-to-charge ratio of the dialysis department is unusually high so that charge-based weights would underestimate the cost of cases needing dialysis. These same patterns were seen in the PPS 13 cost reports (See Carter, Relles, and Wynn, 2000).

Charge-based weights can be updated more quickly than cost-based weights because they do not require the filing and auditing of cost reports, a process that may take up to two years. Charge-based weights can be updated based on discharge data that are typically available after only six months. In addition, some exploratory analyses on the early acute care PPS found charge based weights to estimate cost better for hospitals with a high case mix index.

Table 5.2

Mean Cost to Charge Ratios for Ancillary Departments in Rehabilitation Facilities

Department	Number of Facilities	Cost to Charge Ratio
Laboratory	1010	0.38
Pharmacy	1011	0.35
Respiratory therapy	983	0.32
Supplies	994	0.43
Radiology	1011	0.45
Physical therapy	994	0.59
Occupational therapy	669	0.56
Speech therapy	650	0.61
Dialysis	468	0.73
Blood products/administration	514	0.74
Other	970	0.76

Note: Based on PPS 14 cost reports for rehabilitation facilities reporting good data. The department 'other' excludes surgery and anesthesiology departments which are rarely used by rehabilitation inpatients.

Controlling for Hospital Costs

Both charges and costs are affected by hospital characteristics for which the IRF PPS could adjust payment — i.e., the factors that go into the calculation of the facility payment factor. In the standard method used to calculate DRG weights, charges are first standardized by the hospital’s payment factor.

The payment factors capture only a small part of the variation across hospitals in costs for any specific DRG. A method that accounts for more of the cross-hospital variation in costs than the standard method is the hospital specific relative value (HSRV) method. The HSRV method differs from the standard method in that a hospital’s costs are not standardized using its payment factor, but instead are standardized using hospital-specific costs and the hospital’s case mix index. The HSRV method should be superior to the standard method because it produces weights that reflect relative accounting costs. However, because within department pricing rules vary and are unknown, there is no guarantee that, after averaging across hospitals, the HSRV method will yield relative weights closer to relative actual costs (rather than accounting costs).

In our earlier study, we evaluated both methods of controlling for hospital costs. Using the standard method and the facility payment factor to standardize charges provides similarity to the acute care PPS. However, Hosek et al. (1986) found substantial correlation in resource use (charges and length of stay) for patients treated at the same facility even after controlling for impairment group, functional status, and facility characteristics. Further, the TEFRA rules have allowed newly certified units to recover larger costs. Thus, on a priori grounds, one might prefer the HSRV method in this circumstance.

We also might control for hospital costliness in calculating the multiplicative effect of comorbidity. The multiplicative model analogous to the HSRV method would include a dummy variable for each provider. We could also standardize costs or charges for payment factors and use these standardized costs or charges as the dependent variable in the regressions.

One problem with the standard method of calculating weights is that one must know the weights in order to calculate the payment factor and one must know the payment factor to calculate the weights. The HSRV method can be used to get initial weights which could be used to obtain payment factors which could be then used to obtain standard weights and then a refined payment factor.

Fair Weights

The term ‘fair weights’ has been given to the result of weight calculations that adjust for outlier case costs because these cases receive additional reimbursement. Under the acute care PPS, DRG weights are calculated to be proportional to the resources used by the average case in the DRG. Fair weights could be calculated so that, instead, total PPS standardized reimbursement (including outlier payment) would be proportional to the resources used by the average case in the DRG. Such fair weights have been considered by ProPAC (1994) and are sometimes known as 'DRG Specific Outlier Funding' or DSOF.

Outlier payments will be a higher percentage of RPPS payments in some FRGs than in others. This is appropriate insofar as it provides more outlier payment for the cases that would otherwise cause the highest losses.

Options Selected for Empirical Exploration

Based on the above considerations we decided to explore cost-based HSRV weights, cost-based standard weights, and charge-based standard weights. We present two versions of the HSRV weights, one where hospital costliness is controlled in estimating the comorbidity effects and one where it is not. The latter model is included because it was used in subsequent analyses. Although the former model is theoretically better, the weights from the two models are very similar.

We do not present here results for fair weights. In Chapter 7, we will show that outlier payments improve the accuracy of the payment system at both the case and hospital level. If fair weights were implemented initially, these advantages would be lost. We will discuss this further under future research in Chapter 8.

ALGORITHMS

The first step in the calculation of CMG weights is to estimate the effect of comorbidities. The second step is to adjust the costs or charges of each discharge for these effects. These adjusted resource use values for each discharge are then used to calculate “relative adjusted weights” in each CMG--either by the 'standard' method or by the HSRV method. The final steps are to calculate the weight by modifying the “relative adjusted weight” with the effects of comorbidity and normalize the weights to 1.

Estimating the Effect of Comorbidity

As we saw in Chapter 3, the presence of one of the relevant comorbidities multiplies the expected resource use of a case by the same amount for each FRG in the same RIC. Thus, we use the log transform and regression to calculate the comorbidity weight for each case.

The data we use in the regressions differs from that used in Chapter 3, because we now group long stay transfers with typical cases in the same CMG so that these cases will affect the weight for the CMG. The data also reflect the bundling of discharges into cases as discussed above, although this causes a much smaller difference than that due to the inclusion of long stay transfers. We report only 1997 data.

We performed four sets of regressions, each with the case as the unit of analysis. The dependent variables were the log of cost of the case for two regressions and the log of the standardized cost of the case and the log of the standardized charge of the case for the other two regressions. The standardized cost and charge of the case was calculating by dividing the cost and charge by the hospital payment adjustment factor. We used the following payment adjustment factor (based on Model 5.B of Table 6.9):

A_i = (.295+.705WI)(1+.1547*rural)((.0001+LIP)** .0893),

where WI is hospital i's wage index, rural = 1 if hospital i is in a rural area and 0 other wise and LIP is the hospital's fraction of patients that are low-income.

Regressions were performed within each RIC from 1 to 21 for all but the HSRV regression that controlled for hospital identity. The independent variables were dummies for each CMG in that RIC (except 1) and an indicator of whether the patient had one of the relevant comorbidities. Because in many RICs we did not have enough cases to accurately estimate each hospital dummy variable, we pooled the data across RICs 1 to 21, added dummy variables for all hospitals and for all CMG's (except 1), and separate dummy variables for each RIC that were 1 if the case was in that RIC and had a relevant comorbidity and 0 otherwise.

If the coefficient, a, for the RIC containing CMG k is positive and significant, then the weight for a case in CMG k is given by

$$W(k,x) = \exp(ax)*w_k, \qquad (5.1)$$

where :

x = 1 if the patient had at least one of the relevant comorbidities,

= 0 otherwise, and

w_k is the comorbidity adjusted weight for the FRG that is the basis of the CMG.

If the coefficient for the RIC containing CMG k is not positive and significant, then a will be set to 0. Then exp(ax)=1 and the weight will be just w_k.

Adjustment for Comorbidity

The second step in the calculation of weights is to adjust the resource use for each case to eliminate the effect of comorbidities. For each dependent variable, the adjusted resource use for a discharge, with value x for comorbidity is:

$$A = \text{resource\_use}/\exp(ax), \qquad (5.2)$$

where resource_use is either cost, standardized cost, or standardized charge, and the coefficient a comes from the relevant regression.

The adjusted resource use values for each case are then used to calculate the relative adjusted weight in each CMG k, w_k, by either the HSRV method or the standard method. All cases are used in these calculations. The adjusted resource use for cases from RICs 50 and 51 are their actual resource use. Short stay transfer cases are counted as a fraction of a case with the fraction equal to the ratio of the LOS of the transfer case to the average LOS for a typical case with the same CMG comorbidity combination. This is the same method used by HCFA in the acute care PPS. Their adjusted resource use is calculated according to formula (5.2), just as for other cases.

HSRV Method for Relative Adjusted Weights

In the HSRV method, the adjusted costs are standardized at the hospital level using hospital-specific costs--so costs for a patient at a hospital with high average costs for its patient mix are counted as less resource use than costs at a hospital with low average costs. The average weight or CMI is used to account for the variation in patients across hospitals.

In the HSRV method, the total adjusted cost for each case is divided by the average adjusted cost for the hospital in which the case occurred. The resulting ratio is then multiplied by the hospital’s CMI to produce a hospital-specific, relative value. This relative value can be viewed as a cost that has been standardized by the hospital’s own costliness, in contrast to the standard method where the cost estimate is standardized by the payment factor.

The process of calculating the weights is iterative. Initial values are chosen for the CMI of each hospital. CMG adjusted weights are then set in proportion to the average value of the hospital-specific, relative value. These result in a new CMI for each hospital and therefore new hospital-specific, relative values. The process is continued until there is convergence between the weights produced at adjacent steps, for instance when the maximum difference is less than 0.0001. Earlier work showed that the algorithm is not sensitive to starting values of the CMI (Rogowski and Byrne 1990; Carter and Rogowski, 1992).

After the first iteration, we eliminated statistical outliers defined as cases with HSRV standardized costs that differ from the CMG mean by more than three standard deviations in the log scale.

Standard Method for Relative Adjusted Weights

In the standard method, we merely average the adjusted resource use for all cases within each CMG. Then we divide by the overall average adjusted resource use. Statistical outliers, defined as cases with adjusted resource use that differs from the CMG mean by more than three standard deviations in the log scale, were excluded.

Relative Weights for CMG-Comorbidity Combinations

The next step in the algorithm is to calculate a relative weight for each relevant combination of CMG and comorbidity, using equation 5.1. The final step of the algorithm is to multiply by the normalizing constant so that the average weight per case is 1.

Measuring Compression

The term 'weight compression' is used to indicate that a set of weights has the property that high weighted cases have weights that are too low--i.e., high weighted cases are under valued relative to resource needs and low weighted cases are over valued relative to resource needs. Similarly, CMI compression indicates that hospitals with high case mix indices have costs that are higher relative to their CMI than hospitals with lower CMIs. We'll use decompression to indicate the opposite of compression.

Weight compression is one of the possible causes of CMI compression, but not the only one. Hospitals with high CMIs could, on average, spend more resources on low weight cases than hospitals with a low CMI. If so, the relative weights could be exactly proportional to resource use, but the weights would still exhibit CMI compression.

In order to measure CMI compression, it is usual to regress the log of average cost at a hospital on the log of the CMI. The coefficient on the CMI shows how much cost increases with increasing CMI. If the weights are neither compressed nor decompressed, the coefficient will be 1. A value greater than 1 would indicate CMI compression--hospitals with a high CMI (i.e., patients that need more than average amounts of resources) have higher costs relative to their CMI than hospitals with lower CMIs. For example, if the coefficient is 1.2, then a hospital with a CMI that is 10 percent higher than another will on average cost 12 percent more. If the coefficient is less than one the weights would have CMI decompression.

If one assumes that there is no correlation between hospital case mix and either efficiency or output, a finding of CMI compression can allow one to infer weight compression. If one had a good measure of resource cost for each patient, one can directly assess weight compression with a regression of the log of resource use on the log of the weight for the case. The coefficient on the weight shows how much resource use increases with increasing weight. As for the CMI, if the coefficient on the weight is greater than 1 the weights are compressed; if less than 1 they are decompressed.

If the findings from the hospital level analyses and the case level analyses agree, one can be confident in the interpretation. If they disagree, the analysis is inconclusive. Judgement must be used to determine whether there is more error in the case estimate of resource use than in the hospital estimate of resource use and about whether there is any relationship between case mix and either efficiency or output.

RESULTS

Effect of Comorbidity

Table 5.3 summarizes the four regressions that we ran in order to measure comorbidity effects. The first regression in the table has no control for hospital costliness. The coefficients are slightly larger than those in Table 3.13 reflecting the inclusion of long stay transfer cases. The pattern is, however, similar. Among the larger RICs, the comorbidity effects are smaller than average in RICs 1 and 15 and larger than average in RICs 5 and 8.

Table 5.3

Effect of Comorbidity in Each RIC by Method of Control for Hospital Costliness

		Log (cost) Regression		Log (cost) Single Regression		Log (stan-dardized cost)		Log (standardized charges)	
		No Hospital Control		Hospital Dummies		Standardization		Standardization	
RIC	N	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
1	40964	0.0877	8.87 *	0.0845	9.74 *	0.0788	8.08 *	0.0849	6.91 *
2	1986	0.0302	0.93	0.0439	1.63	0.0364	1.13	0.0326	0.84
3	3434	0.1195	5.24 *	0.1284	7.04 *	0.1176	5.26 *	0.1467	5.28 *
4	967	0.1817	2.74 *	0.2190	4.93 *	0.1886	2.89 *	0.1412	1.88
5	5033	0.2152	7.29 *	0.2378	10.36 *	0.2134	7.30 *	0.2498	6.94 *
6	6546	0.1339	6.82 *	0.1630	10.18 *	0.1186	6.13 *	0.1644	6.89 *
7	20588	0.1531	10.49 *	0.1610	11.94 *	0.1541	10.77 *	0.1538	8.31 *
8	39623	0.2053	16.38 *	0.2038	17.06 *	0.2039	16.64 *	0.2423	13.96 *
9	7404	0.1844	7.56 *	0.1646	8.16 *	0.1679	7.00 *	0.1891	6.19 *
10	6165	0.0888	5.13 *	0.0955	6.96 *	0.0858	5.04 *	0.0410	1.89
11	551	0.2064	3.77 *	0.1703	3.95 *	0.1991	3.65 *	0.1660	2.23
12	3122	0.1381	3.82 *	0.1188	4.07 *	0.1172	3.23 *	0.1978	4.42 *
13	1696	0.1463	3.25 *	0.1491	4.03 *	0.1362	3.08 *	0.1277	2.26
14	6158	0.1566	8.54 *	0.1719	11.07 *	0.1701	9.69 *	0.1387	5.68 *
15	3959	0.0730	2.84 *	0.0972	4.87 *	0.0766	3.03 *	0.0400	1.20
16	2084	0.1730	3.33 *	0.1884	4.58 *	0.1592	3.10 *	0.1699	2.38
17	751	0.2161	3.03 *	0.1939	3.48 *	0.2048	2.89 *	0.2297	2.86 *
18	260	0.2335	2.50	0.2044	2.88 *	0.2363	2.54	0.2515	2.13
19	313	0.1690	1.63	0.1672	2.17	0.1637	1.62	0.2238	1.97
20	15455	0.1124	11.25 *	0.1186	14.35 *	0.1065	10.81 *	0.1087	8.67 *
21	127	-0.0188	0.14	-0.0067	0.08	-0.0174	0.13	-0.0965	0.66

* $p < 0.01$

Note: All regressions included dummy variables for each FRG in the RIC. Based on 1997 analysis sample after bundling and excluding short stay transfers.

The second regression in the table shows the effect of controlling for hospital costliness using dummy variables for each hospital. The 617 hospital dummies are very significant: f=129.83, $p < 0.0001$.[22] Thus hospital identity predicts cost even after controlling for FRG and comorbidity. When one compares the comorbidity coefficients in this regression to those from the first regression there is little pattern: 13 of the 21 regressions have larger coefficients, eight have smaller.

[22] In preliminary analyses, separate regressions were run in each RIC and the set of hospital dummies was significant at $p < 0.0001$ in all RICs except RIC 21.

However the t-statistics are substantially larger in all RICs except 21 with its negative coefficient. We can measure comorbidity effects more precisely after controlling for hospital identity.

The dependent variable for the third regression in the table is standardized cost. Using the standardization process to control for hospital costliness results in measured comorbidity effects and t-statistics closer to the no control regression than to the regression that controls for hospital identity.[23] The t-statistics for all RICs but 21 are larger in the regression with hospital identity dummies than in the regression using the standardization. Thus we infer that hospitals systematically vary in their costliness in ways beyond that which is accounted for in the payment adjustment and that the HSRV method results in more precise estimates of the effects of comorbidities on costs than the standardization method.[24]

The last regression in the table uses standardized charges as the dependent variable. The coefficients appear to differ more than those of the three cost based regressions (See e.g., RICs 3,4, 8 and 12). The t-statistics are typically the lowest of any one of the regressions--the comorbidity effect is not even statistically significant in RICs 4, 10, 11, 13 and 15. We believe that this lack of precision in the effects of comorbidity occurs because the large variation across hospitals in charging behavior adds a random component to the data.

Weights

Figure 5.1 is a scattergram of the two HSRV weights. Each point represents a CMG, with the HSRV weight that used hospital dummies in the comorbidity regression plotted on the horizontal axis and the HSRV weight with no hospital control plotted on the vertical axis. The scattergram is almost a perfect 45-degree line. Less than 3 percent of the 1997 cases are in CMGs where weights by the two methods differ by more than 0.01; less than 0.15 of one percent of cases are in CMGs where weights differ by more than 0.05. The two points on the graph that are

---

[23] The average absolute difference in coefficients between the first and third regressions is about half (0.0076) the difference between the second and third regressions (0.0146).

[24] In Chapter 6 we will explore other hospital characteristics that affect cost.

visibly below the line are both CMGs in RIC 18 with comorbidity (fewer than 50 total cases). The comorbidity effect could not be measured without the hospital control, but is found with the hospital dummies.

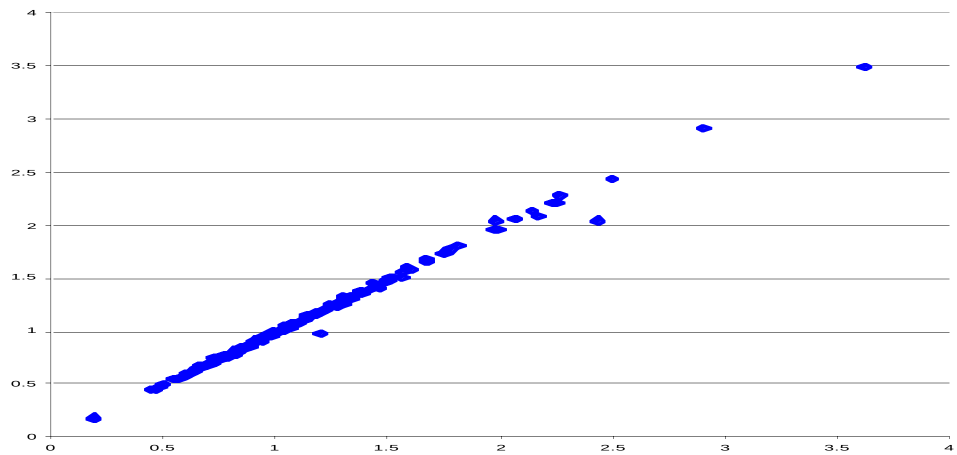

Figure 5.1—HSRV Weights, With and Without Hospital Control in Comorbidity Regression

Figure 5.2 is a scattergram of the standardized cost weight against the HSRV weight. There is more deviation from the 45 degree line than in Figure 5.1. Thirteen percent of cases have HSRV weights that differ from the standardized cost weight by 0.10 or more. These cases are scattered throughout the line so no relationship between the magnitude of the weight and the difference between the two weights is apparent.

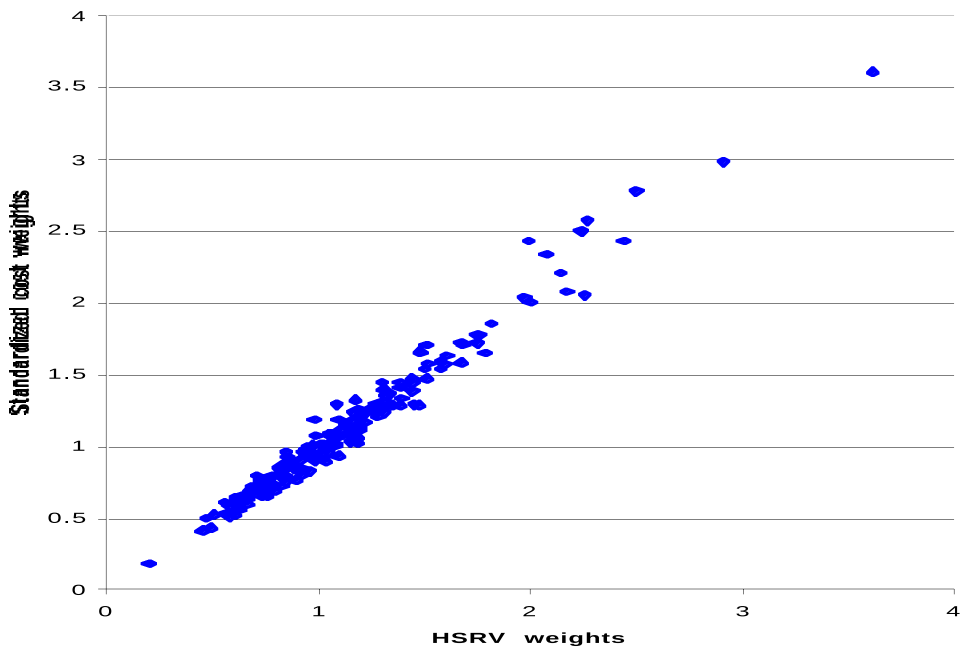

Figure 5.2—Standardized Cost Weights vs. HSRV Weights (With Hospital Control in Comorbidity Regression)

Figure 5.3 is a scattergram of the standardized charge weights against the HSRV weight. There is noticeably more scatter from the 45 degree line than in either of the previous plots. Twenty-one percent of cases have HSRV weights that differ from the standardized charge weight by 0.10 or more. Further, when the weights are above 2 (in either scale), the charge weight is frequently substantially larger than the HSRV weight.

Accuracy at the Case Level

We want the weights for each CMG to be proportional to the typical cost of a case in that CMG. Excluding short stay outliers, the payment for each case will be:

$R*A_i*W(k,x)$

where A_i is the hospital payment factor and W(k,x) is the relative weight for a case in CMG k with comorbidity x (either 0 or 1). Thus we want the cost of the case divided by A_i to be directly proportional to the weight for the case.

We examine the extent to which each of our sets of weights accomplishes this goal by regressing the log of the standardized cost of the case on the log of the weight for the case. The coefficient on the weight shows how much cost increases with increasing weight. Because, by design, short stay transfers are slightly underpaid, we omit short stay transfers from this analysis.

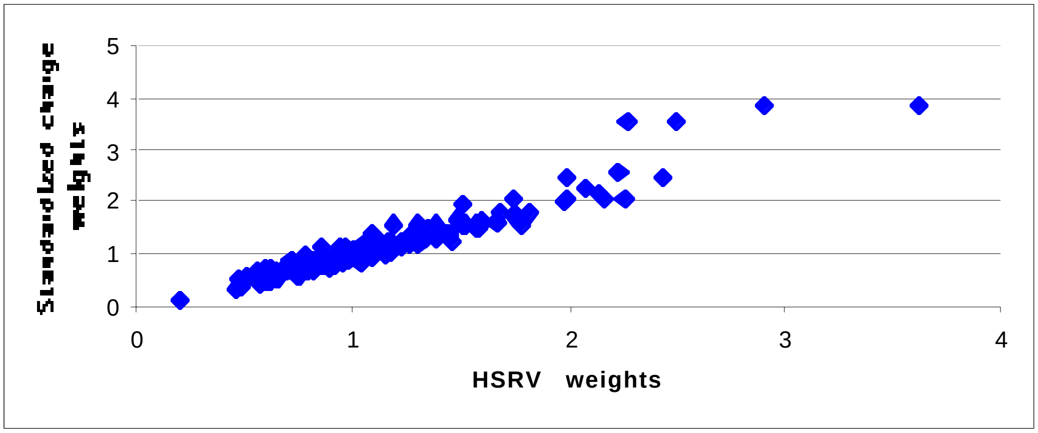

Figure 5.3—Standardized Charge Weights vs. HSRV Weights (With Hospital Control in Comorbidity Regression)

Table 5.4 shows the results. The usual t-statistic tests the hypothesis that the coefficient is really 0. In these regressions this is not interesting because we really want to know whether the coefficient is 1.[25] Consequently we present the standard error of the coefficient and the t-statistic for the hypothesis that the coefficient is 1. The first two rows are for our two HSRV weights--the first being the weights that used the comorbidity regression with hospital dummies. These are very similar and the data are completely consistent with cost moving in direct proportion to weight.

Costs increase at a lower rate than the standardized cost weights, thus indicating that low weight cases are under-weighted. It is most unlikely that this is due to chance. This is somewhat surprising in that these weights were designed to equal average standardized costs. What this appears to be saying is that there is consistent variation

[25] For the record, the t-statistics for the for the first four regressions in the table, respectively, are:367.90, 367.90, 363.20, and 356.13. All are p<0.0001.

across hospitals in costs which distorts the relative weights. The charge weights perform even worse than the cost weights. In addition to the apparent bias in the weights, the R-square is slightly lower than for the HSRV weights, especially for the standardized charge weight indicating an increased randomness in the weights.

Table 5.4

Regression of Log of Standardized Cost of a Case on Log of Weight, by Weight Calculation Method

Dependent Variable and Type of Weight	R-square	Intercept	Coef.	Standard Error	t Statistic for Coef. = 1
Log (standard cost)					
HSRV	0.4402	9.2891	0.9981	0.0027	-0.68
HSRV (no control)	0.4402	9.2890	0.9984	0.0027	-0.59
Standard cost	0.4339	9.2942	0.9242	0.0025	-29.79 *
Standard charges	0.4243	9.2960	0.8810	0.0025	-48.12 *
Log (wage adjusted cost)					
HSRV	0.4527	9.4961	0.9972	0.0027	-1.03
HSRV (no control)	0.4527	9.4961	0.9975	0.0027	-0.94
Standard cost	0.4464	9.4906	0.9239	0.0026	-29.81 *
Standard charges	0.4370	9.4954	0.8804	0.0025	-48.16 *
*p < 0.0001					

Note: based on 172,103 cases from 1997, excluding short stay transfer cases. Regression wage adjusted cost also controls for rural location and low-income percentage.

One might ask whether the results just reported occur because we used a formula for standardization that was developed using the HSRV weights. The formula for the wage adjustment is based on the proportion of costs that are wages and is not based in anyway on the weights. However, the effects of location and low-income percent that were used to standardize the costs were derived from the HSRV weights. In order to find out if tailoring the hospital adjustment to the weights would improve the performance of the standard method weights, we repeated these regressions with two changes. First, we changed the dependent variable to log of wage adjusted costs (i.e., costs divided by the wage adjustment). Second, we added a dummy variable to indicate patients cared for in rural hospitals and the percent low-income at the hospital in the same form as used to derive the payment adjustment. The last four lines of Table 5.1 show that allowing the payment adjustment to be based on the weights does not affect our conclusion at all.

In another sensitivity analysis that we do not report in detail, we removed all cases with standardized cost outside three standard deviations of the CMG mean in the log scale and repeated all eight regressions. All the R-squares went up, of course, but the relationships among the eight regressions remain as shown in the table. Neither the coefficients nor the t-statistic for the hypothesis that the coefficient was 1 changed appreciably.

Accuracy at the Hospital Level

The weights are intended to adjust payments for differences across hospitals in case mix. If one assumes that there is little correlation between average case mix and hospital inefficiency, then one would want average hospital costs to be directly proportional to the average case weight (CMI or case mix index) at the hospital. As in the model of individual case costs which was just discussed, we will regress the log of costs on the log of the CMI and want the coefficient on the CMI to be 1. A value more than 1 would indicate CMI compression--hospitals with a high CMI (i.e., patients that need more than average amounts of resources) have higher costs relative to their CMI than hospitals with lower CMIs. As before, we eliminate short stay transfer cases in order to avoid having our analysis confused by their weights which are slightly lower than would be expected from their costs.

We present the results from regressions that use the log of average wage adjusted cost as the dependent variable and that also control for rural location and the percent of low-income patients at the hospital. Results from regressions of standardized costs are very similar. We weight each hospital in proportion to the number of cases in our sample at the hospital.[26]

Table 5.5 shows that, unlike the case level analysis, increases in the weights underestimate the magnitude of increases in costs. The HSRV weights are more compressed than the standard weights, although the standard cost weight is also compressed. The t-statistic for the charge-based weight is marginally significant (p=0.012).

[26] In hospital weighted regressions all the coefficients move toward 1, and none are significantly different from 1 at the 0.01 level. However, we believe this is due to the imprecision in the estimate which results from hospitals with few cases in our sample.

Table 5.5

Regression of Each Hospital's Log (average wage adjusted cost) on Log (case mix index)

Weight for CMI	R-square	Intercept	CMI Coef.	Standard Error	t for Coef. = 1
HSRV-V4	0.3946	9.5504	1.2669	0.0766	3.48*
HSRV-V3	0.3950	9.5504	1.2681	0.0766	3.50*
Cost	0.4130	9.5377	1.1850	0.0683	2.71*
Charges	0.4178	9.5385	1.1669	0.0664	2.51
* p<0.01					

Note: based on 1997 data at 618 hospitals. Average cost and case mix excluded short stay transfer cases. Regressions were weighted by number of cases.

Regression also included an indicator for rural location and hospital's low-income percentage.

IMPLICATIONS FOR POLICY AND RECOMMENDATIONS

Our empirical findings are as follows: First, controlling for hospital costs using individual hospital identity results in estimates of the effect of comorbidity that are more precise than using either standardized cost or standardized charges. Second, the HSRV method appears to result in more accurate estimates of relative cost at the case level. Third, the HSRV weights, and indeed the standard method cost weights, and probably the standard method charge weights, are compressed at the hospital level--costs increase more quickly than the case mix indices increase.

What are we to make of this? In the next chapter, we will show that hospitals systematically vary in their costliness in ways beyond that which is accounted for in the payment adjustment. Because the HSRV method accounts for these variations in costliness and because it measures the effect of comorbidity better, we believe that its results are more accurate measures of the relative resource use of groups of cases. This is consistent with the case level accuracy analyses found here and important to insure access for all groups of patients.

But, the weights will be a major determinant of hospital payment, so the finding of hospital level compression is important and the HSRV method results in more compression than either of the other methods. There are some reasons to believe that the hospital cost per case estimates average out certain errors in the patient level cost estimates. If so, it would cast doubt on the findings of the case level analyses here. In Chapter 8, we will present our plan to improve case cost estimates and to otherwise reduce the compression in the weights. If this is successful, we believe that the HSRV algorithm should be used to calculate weights in the IRF PPS.

Table 5.6 shows the HSRV relative weights for each combination of CMG and comorbidity. It is these weights that we used in the analyses reported in the rest of this paper. The table also shows the average length of stay for typical cases that we use to calculate the weights for transfer cases.

If we are not successful in eliminating compression, and if the refinement activity results in a comparative evaluation of HSRV and standardized cost weights such as we see today, the tradeoff will require thought. The decision should rest, at least in part, on the extent to which one believes the case cost estimates are worse than the hospital cost estimates. If one believes the case cost estimates are wholly accurate, then the HSRV method would appear superior. Otherwise one might opt for the standardized cost weights. Our analyses should shed light on this issue.

We believe that the case cost estimates that we use are substantially more accurate than charges. We believe the variation across departments in CCRs shows the greater accuracy of costs. The lack of ability to estimate the cost of comorbidities is further evidence. In addition, hospitals can manipulate charges more easily than accounting costs. Consequently, we believe that using charge weights would introduce substantial error, both random and systematic, into the weights.

Table 5.6

Typical LOS and Relative Weights for CMGs

			Los		Relative Weight	
FRG	**Definition (M = motor, C = cognitive, A = age)**	**Split by Com.?**	**No Com.**	**W Com.**	**No Com.**	**W Com.**
101	M in (62,91)	Y	10.4	9.6	0.6058	0.6613
102	M in (57,61) and C in (27,35)	Y	12.0	11.4	0.7095	0.7746
103	M in (51,56) and C in (28,35)	Y	14.3	15.2	0.8605	0.9394
104	M in (57,61) and C in (5,26)	Y	14.2	16.7	0.8560	0.9344
105	M in (51,56) and C in (5,27)	Y	15.9	16.7	0.9620	1.0501
106	M in (46,50)	Y	17.7	17.2	1.0944	1.1947
107	M in (42,45)	Y	20.1	20.7	1.2630	1.3787
108	M in (36,41)	Y	22.7	21.2	1.4365	1.5682
109	M in (13,35) and A >= 84	Y	24.0	24.9	1.5989	1.7455
110	M in (31,35) and A <= 83	Y	25.9	23.4	1.6616	1.8139
111	M in (13,30) and A <= 83	Y	29.5	29.6	1.9626	2.1425
201	M in (58,91) and C in (30,35)	N	9.4	9.4	0.5504	0.5504
202	M in (58,91) and C in (5,29)	N	13.3	13.3	0.8325	0.8325
203	M in (41,57) and C in (22,35)	N	16.0	16.0	0.9777	0.9777
204	M in (41,57) and C in (5,21)	N	18.3	18.3	1.1640	1.1640
205	M in (25,40)	N	22.3	22.3	1.4739	1.4739
206	M in (13,24)	N	31.6	31.6	2.2179	2.2179
301	M in (58,91) C in (22,35)	Y	10.6	10.4	0.6399	0.7208
302	M in (58,91) C in (5,21)	Y	13.5	13.3	0.8393	0.9454
303	M in (45,57)	Y	14.8	15.3	0.9467	1.0664
304	M in (35,44)	Y	19.2	19.3	1.2605	1.4198
305	M in (13,34)	Y	24.8	26.9	1.7517	1.9731
401	M in (55,91)	Y	12.6	10.3	0.7135	0.8560
402	M in (34,54)	Y	17.5	18.6	1.0506	1.2603
403	M in (17,33)	Y	26.6	25.5	1.7459	2.0944
404	M in (13,16)	Y	39.3	48.6	2.9252	3.5092
501	M in (68,91)	Y	8.4	8.2	0.4459	0.5528
502	M in (55,67)	Y	10.6	12.8	0.6197	0.7683
503	M in (46,54)	Y	13.5	15.7	0.8152	1.0107
504	M in (34,45)	Y	18.2	18.8	1.1515	1.4277
505	M in (13,33)	Y	25.9	30.2	1.7816	2.2089
601	M in (56,91)	Y	12.3	12.5	0.6971	0.7970
602	M in (46,55)	Y	15.2	15.6	0.9086	1.0389
603	M in (38,45)	Y	17.7	18.2	1.0833	1.2387
604	M in (13,37)	Y	21.4	22.6	1.3375	1.5292
701	M in (55,91)	Y	11.7	12.1	0.6525	0.7604
702	M in (46,54)	Y	14.3	15.5	0.8337	0.9716
703	M in (40,45)	Y	17.1	17.5	1.0129	1.1803
704	M in (13,39)	Y	19.6	20.9	1.1794	1.3743

Table 5.6 (cont.)

801	M in (59,91)	Y	8.6	9.6	0.4822	0.5920
802	M in (50,58)	Y	10.1	11.3	0.5984	0.7346
803	M in (43,49)	Y	12.2	14.3	0.7464	0.9162
804	M in (13,42) and C in (34,35)	Y	13.5	16.8	0.8835	1.0845
805	M in (36,42) and C in (5,33)	Y	15.3	16.7	0.9540	1.1710
806	M in (13,35) and C in (5,33)	Y	18.4	21.2	1.1765	1.4441
901	M in (59,91)	Y	10.4	11.0	0.5587	0.6716
902	M in (47,58)	Y	13.3	14.5	0.7641	0.9185
903	M in (38,46)	Y	16.4	17.0	0.9685	1.1642
904	M in (13,37)	Y	20.0	19.7	1.2144	1.4597
1001	M in (53,91)	Y	15.0	14.1	0.8488	0.9278
1002	M in (43,52)	Y	18.2	17.5	1.1178	1.2219
1003	M in (13,42)	Y	21.4	21.0	1.3785	1.5068
1101	M in (61,91)	Y	10.6	9.6	0.6095	0.7489
1102	M in (47,60) and A >= 68	Y	13.4	13.5	0.8278	1.0171
1103	M in (47,60) and A <= 67	Y	17.4	17.8	1.0894	1.3386
1104	M in (13,46)	Y	20.7	20.8	1.3232	1.6258
1201	M in (49,91) and C in (34,35)	Y	10.7	12.1	0.5965	0.6847
1202	M in (49,91) and C in (5,33)	Y	13.3	13.9	0.7181	0.8244
1203	M in (37,48)	Y	16.4	17.0	0.9181	1.0540
1204	M in (13,36)	Y	20.8	22.4	1.1492	1.3192
1301	M in (61,91)	Y	11.3	11.2	0.5927	0.6859
1302	M in (49,60)	Y	13.3	14.2	0.7116	0.8234
1303	M in (13,48)	Y	18.0	19.1	1.0450	1.2093
1401	M in (54,91)	Y	12.4	12.1	0.6511	0.7618
1402	M in (41,53)	Y	15.4	16.4	0.9006	1.0537
1403	M in (13,40)	Y	19.7	24.3	1.2689	1.4846
1501	M in (51,91) and A >= 78	Y	14.0	12.7	0.7741	0.8327
1502	M in (51,91) and A <= 77	Y	15.0	15.3	0.8529	0.9175
1503	M in (28,50)	Y	19.2	19.6	1.1875	1.2774
1504	M in (13,27)	Y	29.6	32.6	2.2797	2.4524
1601	M in (50,91) and C in (33,35)	Y	11.0	10.6	0.6151	0.7313
1602	M in (50,91) and C in (5,32)	Y	12.8	15.1	0.7257	0.8628
1603	M in (13,49)	Y	15.9	16.0	0.9725	1.1562
1701	M in (43,91)	Y	14.8	15.5	0.8513	1.0565
1702	M in (13,42)	Y	22.5	24.9	1.3677	1.6974
1801	M in (35,91)	N	16.7	16.7	0.9935	0.9935
1802	M in (13,34)	N	29.5	29.5	2.0563	2.0563
1901	M in (55,91)	N	11.5	11.5	0.7048	0.7048
1902	M in (44,54)	N	18.0	18.0	1.0883	1.0883
1903	M in (13,43)	N	31.4	31.4	2.0648	2.0648

Table 5.6 (cont.)

2001	M in (70,91) and A >= 59	Y	9.2	8.8	0.5010	0.5604
2002	M in (60,69)	Y	11.5	11.5	0.6435	0.7198
2003	M in (55,59)	Y	13.0	13.0	0.7468	0.8353
2004	M in (70,91) and A <= 58	Y	13.9	11.2	0.7131	0.7977
2005	M in (48,54) and A >= 65	Y	14.4	14.4	0.8549	0.9562
2006	M in (39,47) and A >= 65	Y	16.5	17.0	1.0145	1.1348
2007	M in (48,54) and A < 65	Y	16.0	15.7	0.9998	1.1183
2008	M in (13,38) and A >= 84	Y	18.2	20.2	1.1359	1.2705
2009	M in (32,38) and A < 84	Y	19.8	19.9	1.2481	1.3960
2010	M in (39,47) and A < 65	Y	18.1	18.6	1.1570	1.2941
2011	M in (13,31) and A < 84	Y	23.2	24.3	1.4898	1.6664
2101	All	N	18.5	18.5	1.2863	1.2863
5001	Atypical low cost case (LOS <= 3)	N	2.6	2.6	0.1908	0.1908
5101	Orthopedic, died (3 < LOS <= 12)	N	7.1	7.1	0.4657	0.4657
5102	Orthopedic, died (LOS < 12)	N	20.0	20.0	1.0777	1.0777
5103	Not orthopedic, died (3 < LOS <= 14)	N	8.4	8.4	0.5485	0.5485
5104	Not orthopedic, died (LOS > 14)	N	25.1	25.1	1.5027	1.5027

6. FACILITY LEVEL ADJUSTMENTS

OVERVIEW OF METHODOLOGY AND FINDINGS

In Chapter 5, we report on relative weights that are intended as case-level adjustments to the standard payments that would account for case mix differences across hospitals. In this section, we explore potential facility-level adjustments to the standard payments. These are factors that may account for systematic cost differences that are beyond the control of facility management and may be appropriate to recognize in the payment system. The statutory provision establishing IRF PPS requires an area wage adjustment. In addition, the statute gives the Secretary discretionary authority to take into account the unique circumstances of rehabilitation hospitals located in Alaska and Hawaii and to make other adjustments necessary to properly reflect variations in necessary costs of treatment among rehabilitation facilities.

Our methodology for evaluating the effects of various factors on a facility’s costs per case consists of three parts. First, we identify and develop the explanatory variables that we will use in our analysis. Second, we perform multivariate regression analyses to measure the effects of the factors on facility costs and establish potential payment adjustments. Third, we confirm the adjustments indicated by the regression analyses through payment simulations.

Our analysis file consists of 624 facilities for which we have case mix and cost data. For most facilities, we use the PPS 13 and 14 cost reports to establish the facility-level variables for our regression analyses and payment simulations.[27] Nine facilities in our sample are no longer listed as participating in the Medicare program. We include these facilities because we believe that their cases are likely to be treated in other participating facilities.

[27] For 26 facilities, we are missing PPS 14 cost reports and use PPS 12 and 13 data. We have PPS 12 data only for four facilities.

In the first subsection below, we describe the variables that we use in our regression analyses. In developing the variable measures, we review the adjustments that have been used in other prospective payment systems. Our review is intended to identify potential payment adjustments for the IRF PPS and to provide the rationale for our choice of specific variables for analysis. We also draw on analyses used to support the payment adjustments in other prospective payment systems to assure that we investigate a full range of options. We establish measures for the statutorily-required area wage adjustment, for location in a large urban or rural area, the indirect costs of graduate medical education (IME) and for serving low-income patients.

We also establish measures for other factors that may explain costs such as the date of certification, type of facility, and type of ownership. Evaluating the impact of these factors on facility costs helps us understand the likely impact of the IRF PPS on different classes of facilities.

In the second subsection, we describe our methodology for evaluating the effect of the explanatory variables on facility costs. Our primary tool is multivariate regression. The dependent variable is the average cost per case at a particular facility. The general specification is that:

$$C = f(CMI, WI, X)$$

Where:

C = average cost per case at the facility

CMI = the case mix index, a measure of the relative resources required to treat cases at the facility

WI = the hospital wage index for the facility, a measure of relative differences in input prices

X = a vector of additional explanatory variables that affect a hospital’s costs per case, such as its teaching activities, proportion of low-income patients, etc.

We perform the regressions in several steps. First, we perform a number of preliminary regressions to identify the most promising set of alternatives. Second, we use fully specified regressions to understand the various factors affecting costs and to identify which potential payment variables are significant. Third, we perform a set of regressions using only the potential payment variables that are significant. We use the coefficients from the payment regressions to determine the adjustment factors for potential payment variables. We then simulate payments using the 1997 cases in our analysis file and determine the payment-to-cost ratios for different classes of hospitals for specific combinations of payment policies.

In the third subsection, we present our results. Key findings include the following:

1. In the fully specified regressions using all explanatory variables, the following are significant in explaining variation in cost per case: case mix, wage index, teaching, low-income patient percentage, type of facility (free-standing hospital or unit), type of ownership, size and geographic location.
2. When only potential payment variables are included in the regression, teaching is no longer significant.
3. The wage index coefficient approximates the labor-related portion of cost per case.
4. When cost per case is standardized for case mix and area wage differences, rural hospitals are almost 16 percent more costly than other hospitals.
5. There is about a 9 percent increase in costs for each 10 percentage point increase in a facility’s low-income or DSH patient percentage.

In the final subsection, we discuss the implications of our findings for policy and our recommendations. In addition to the statutorily-mandated wage index, we recommend using the regression coefficients to establish an adjustment for serving low-income patients and an additional adjustment for rural facilities.

ESTABLISHING THE VARIABLES USED IN THE ANALYSES

Cost Per Case

A case is defined in the same way as in Chapter 5. In particular, short-stay transfers to another hospital, NF or SNF are counted as a partial discharge and interrupted stays are bundled together into a single discharge. A short-stay transfer case's equivalence to a full case is determined by the ratio of the length of stay for the transfer to the average length of stay for non-transfer cases in the same CMG. Two or more discharges count as a single case when a patient is discharged from the rehabilitation facility and returns to the same facility on either the day of discharge or one of the next two calendar days.

Our method for estimating the cost for each case is described in Chapter 2. We determine the facility's average cost per case by summing the costs for all cases in the analysis sample and dividing by the number of equivalent full cases. When we have cost per case data for both 1996 and 1997, we pool the number of cases and total costs. The pooled data should provide more stability in the payment adjustments than using data for a single year. We do not adjust for cost differences between the years when we pool the data. This is because price inflation between 1996 and 1997 was more than offset by a reduction in the average length of stay. The case–weighted average change in cost per case between 1996 and 1997 was relatively small (-1.76 percent). When data for only one year are available, we use the costs and number of equivalent cases for that year in order to have the maximum number of facilities in our analysis.

We use the cost per case calculated from the analysis file rather than the cost per discharge from the cost report. This provides 1) a match between the cases for which we have case mix data and the costs of those cases and 2) accounts for transfer cases and interrupted stays. By treating short-stay transfers as a partial discharge and bundling interrupted stays, the dependent variable is consistent with our payment policy recommendations.[28]

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[28] We explored using cost per discharge (no transfer or interrupted stay policies) instead of cost per case using preliminary data. We found that the r-squares were consistently higher in the regressions using cost per case (.47 vs. .44).

Case Mix Index

The case mix index is the average of the CMG relative weights derived by the HSRV method for each facility. We discuss our method for constructing the HSRV relative weights in Chapter 5. We normalize the case mix index to 1.0 for complete cases. We give short-stay transfers a partial weight based on the ratio of the length of stay for the transfer to the average length of stay for non-transfer cases. If we have cases for both 1996 and 1997, we base the case mix index on the cases for both years.

Wage Index Value

The statute establishing the IRF PPS requires the Secretary to adjust the labor-related portion of the PPS rates for area differences in wage levels. The adjustment factor is to reflect the relative hospital wage level in the geographic area of the rehabilitation facility compared to the national average wage level for such facilities. The wage index adjustment is to be budget neutral.

The wage index adjustment is intended to account for systematic differences in wage levels across labor market areas. The current hospital prospective payment systems use different approaches to specifying an adjustment for geographic differences in costs.

- In the acute care hospital operating PPS, the labor-related portion of the standardized amount (71.1 percent) is adjusted by the wage index. The labor-related portion is determined from cost report data and is established in conjunction with the hospital market basket.
- In the acute care hospital capital PPS, the geographic adjustment was determined through regression analysis using total costs (operating and capital) per case as the dependent variable. The geographic adjustment factor is expressed in exponential form and applies to the entire payment. Payment increases approximately 6.8 percent for each 10 percent increase in the hospital wage index (DHHHS, 1991). Carter Buchanan et al. (1997) used a similar approach in their earlier work on IRF PPS.

- In the hospital outpatient PPS, regression analysis was used to estimate the percentage change in total costs attributable to a .01 point increase in the wage index. Depending on the regression model, the coefficient varied from .51 to .68. The labor-related portion was set at 60 percent of the standard payment amount (DHHS, 1998).

Based on this review, we examine three alternative specifications for the wage index variable. The alternatives are to 1) use a pre-determined labor-related share (acute operating PPS), 2) use a non-logged form of the wage index as an independent variable (acute capital PPS and Carter, Buchanan et al. (1997)), and 3) use a logged form of the wage index as an independent variable (hospital outpatient PPS). HCFA’s Office of the Actuary determined that for TEFRA hospitals in FY1998 the labor-related share was 70.5 percent when capital and operating costs are combined. We use the 70.5 labor-related share in evaluating the first alternative. We define the wage index variable as (.705*WI + .295). This is consistent with the way the wage index would be applied in an IRF PPS using a 70.5 percent labor-related share.[29]

Acute care hospitals report wage information annually on Worksheet S-3 of the cost report. This worksheet was designed to support annual updates to the acute care hospital wage index. No identifiable wage data specific to rehabilitation facilities is currently reported that can be used to construct a rehabilitation facility-specific wage index. Wages attributable to ancillary services provided to rehabilitation inpatients are combined with the wages for ancillary services provided to acute care inpatients and outpatients. The wages and hours attributable to routine (room and board) services provided in the rehabilitation units are not reported as a separate line item but are combined with wages for services provided in other sub-provider components of the hospital complex (except SNF services are reported separately).

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[29] Based on intervening increases in the various components of the hospital market basket, HCFA OACT estimates the FY2001 labor-related share at 71.103. We use the 70.5 percent in these analyses since it matches our cost report data.

We use a HCFA-furnished wage index based on the FY1996 audited hospital wage data, that is, wage data for cost reporting periods beginning on or after October 1, 1995 and before October 1, 1996. The labor market areas are consistent with other prospective payment systems (i.e., MSAs and non-MSA areas of States). The labor market areas are determined without regard to geographic reclassification under section 1866(d)(8) or (d)(10) of the Medicare law.[30] The pre-reclassification wage index is consistent with the wage index used in setting the TEFRA limits established by the Balanced Budget Act of 1997 (BBA) and Balanced Budget Refinement Act of 1999 (BBRA) and in the payment systems for SNFs and HHAs.

The wage index is based on data that excludes 100 percent of wages for services provided by teaching physicians, interns and residents, and non-physician anesthetists under Part B. HCFA is phasing out over a five-year period the inclusion of these wages in the hospital wage index. The services of teaching physicians, residents and interns, and non-physician anesthetists are not covered under IRF PPS. Unlike the PPS for acute care hospitals, a transition is unnecessary for IRF PPS because payment for inpatient rehabilitation services has never been based on a wage index that includes these services.[31]

Geographic Location

The current hospital prospective payment systems recognize geographic cost differences that are not accounted for by the wage index.

- Under the acute care operating PPS, the law provides for a 1.6 percent add-on for large urban hospitals (hospitals located in

[30] In the provider universe, we determined 104 acute care hospitals with rehabilitation facilities were reclassified for FY2000. All but 20 of these are rural hospitals. The mean difference between the non-reclassified and reclassified wage index values is 12.4 percent for the reclassified hospitals.

[31] We compared the wage index values that we are using with the pre-reclassification transition wage index. With one exception, the differences across geographic areas between a wage index is less that 2 percent. The difference for Albany, Georgia is so great (1.0372 vs. 1.6055) and the value so high that the data are probably aberrant. We use the transition wage index value for the rehabilitation unit located in Albany, GA MSA in our analyses.

MSAs with 1 million population or NECMAs with 970,000 population or more).

- Through regression analysis, a 3 percent add-on was established for large urban hospitals under acute care capital PPS (DHHS, 1991).
- No large urban add-on was provided in hospital outpatient PPS because HCFA concluded large urban hospitals were not significantly different from other urban hospitals. Analysis indicated rural hospitals have higher costs under the hospital outpatient prospective payment system. (DHHHS, 1998). To protect rural hospitals with less than 100 beds, the BBRA provides a 5-year hold-harmless period.

Carter, Buchanan et al. (1997) found the large urban effect was not significant in explaining total costs per case for inpatient rehabilitation facilities. The rural effect was not evaluated. We examine both the large urban and rural effect on costs per case in our analyses. We define the variables consistent with acute care PPS.

The legislation establishing IRF PPS specifically authorizes a cost of living adjustment for rehabilitation facilities in Alaska and Hawaii. A cost of living adjustment is made under the acute care PPS for hospitals located in Hawaii and Alaska. The adjustments (currently 1.25 for Alaska and 1.225 for Hawaii) are applied to the non-labor related portion of the rate. There are three rehabilitation facilities in Hawaii and one in Alaska. However, we have only one of the Hawaii facilities and the Alaskan hospital in our sample. We examine the impact of IRF PPS on these hospitals in our payment simulations.

Indirect Teaching Costs

Separate payments will be made under the IRF PPS for the direct costs of medical education consistent with current Medicare policies. The direct costs of graduate medical education (that is, resident salaries and fringe benefits, teaching physician compensation, and associated overhead costs) will continue to be paid based on a hospital-specific per-resident amount. Additional payments will be made for the allowable costs of provider-operated nursing and allied health education programs recognized under current Medicare policies.

In the prospective payment systems for acute care hospitals, adjustments are also made in the payment to account for higher costs indirectly associated with graduate medical education. These are higher costs attributable to teaching activity that are not captured as direct graduate medical costs. Consistent with the acute care prospective payment systems (which derive from Medicare policies on allowable patient care costs), we confine our analysis to exploring the indirect effect of graduate medical education on patient care costs. We note, however, that while the measure is based on the number of residents at the hospital, it implicitly accounts for higher patient care costs associated with other missions typically provided in conjunction with graduate medical education (e.g., undergraduate medical education , nursing and allied health education, research, and specialized care for complex patients that is not accounted for by the patient classification system). Different approaches have been used to examine the teaching effect on costs.

- Early regressions looking at this issue for the acute care operating PPS used the ratio of residents-to-beds. This methodology was incorporated into the payment formula specified in the law. The FTE count includes resident time spent in all areas of the hospital subject to the prospective payment system, outpatient areas, and non-hospital settings where the hospital incurs substantially all of the training costs in those settings. The bed count includes all beds staffed and maintained to provide inpatient care covered under the PPS system.
- For the acute care capital PPS, the teaching adjustment was determined through regression analysis using total costs per case as the dependent variable and residents-to-average daily census as the independent variable. The resident count is the same as under operating PPS. Average daily census was considered an improved measure of patient load subject to less manipulation (DHHS, 1991).

- In analyzing potential payment adjustments for the hospital outpatient PPS, HCFA modified the resident-to-average daily census variable to reflect the ratio of residents to combined inpatient and outpatient utilization. The ratio of inpatient costs per day to outpatient costs per unit for each hospital was used to convert outpatient services into inpatient day equivalents(DHHS, 1998). The final payment system does not include a teaching adjustment.
- In its March 2000 report, the Medicare Payment Advisory Commission (MEDPAC) re-examined the indirect teaching adjustment for acute care inpatient services using the ratio of residents assigned to the inpatient area only to beds. MEDPAC estimated resident time in ancillary areas spent on inpatient care using a ratio of inpatient charges to total charges for the department(MEDPAC,2000).

Carter, Buchanan et al. (1997) used the capital-PPS teaching intensity measure and found no teaching effect on cost for rehabilitation stays. They suggested one reason might have been some data errors. Another reason may have been inconsistencies in the resident count (resident time spent in the inpatient routine area only for units versus time spent in inpatient and outpatient areas of freestanding hospitals). Ideally, the resident count should be consistent with the utilization measure. Determining the appropriate resident count for IRF PPS is complicated by the way all resident time in ancillary areas of the hospital is counted for acute care PPS under current law. An FTE count using resident time associated with both the inpatient routine and ancillary services provided rehabilitation inpatients would involve counting the residents in ancillary areas of acute care hospitals twice: once under acute care PPS and again under IRF PPS. The ratio of FTE resident time in the inpatient routine area to average daily census is the most direct measure of inpatient teaching intensity and does not result in double counting. However, using this measure in the payment formula could have the unintended consequence of discouraging training in ambulatory settings.

Based on this review, we used two measures of teaching intensity in preliminary analyses: the ratio of (1) the total time residents spend working throughout the hospital complex to an adjusted average daily census that takes into account outpatient services, and (2) the time residents spend in the inpatient rehabilitation unit to average daily census. However, the first measure was never significant and so we present here only results with the second measure.

The time residents spend in the inpatient rehabilitation unit excludes the time residents spend in outpatient clinics or ancillary service areas of the hospital. HCFA provided a special HCRIS 14 file containing information on how resident salaries were apportioned to excluded units.[32] To estimate the number of residents assigned to the rehabilitation inpatient units, we multiply the total number of residents in the hospital complex by the ratio of resident salaries assigned to the rehabilitation unit to total resident salaries. We compute the average daily census by dividing the total number of inpatient days in the rehabilitation facility reported on the HCRIS 14 cost report by the number of days in the cost reporting period.[33] We then compute the ratio of residents to average daily census and use this variable in our regression analysis.

Low-Income Patients

The adjustment provided in acute care operating PPS for hospitals that serve a disproportionate share of low-income patients(DSH) is specified in the Medicare law. The adjustment takes into account:

- The percentage of Medicare inpatients who are entitled to Supplemental Security Income (SSI), and
- The percentage of total patients who are entitled to Medicaid but are not entitled to Medicare.

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[32] Resident time assigned to the rehabilitation unit was not available. Also, the file does not have the data necessary to determine the time residents spend in ancillary areas caring for rehabilitation facility inpatients.

[33] We use HCRIS 13 if no data are available for HCRIS 14 and we use HCRIS 12 if neither 13 nor 14 are available.

The formula is intended to achieve a geographic balance between States that have relatively generous Medicaid eligibility and low-income States with more restrictive programs. The patient percentage criteria for DSH payment vary for urban hospitals and for rural hospitals by bed size categories, and for sole community hospitals and rural referral centers.

HCFA has generally maintained that the DSH adjustment is intended to cover only the higher costs associated with the care of Medicare beneficiaries in hospitals serving a disproportionate share of low-income patients. For example, the DSH adjustment in the acute care capital PPS was determined through multivariate regression analysis based solely on the relationship of the DSH variables to hospital costs per case. On the other hand, MEDPAC (and its predecessor ProPAC) views the DSH adjustment as a policy adjustment independent of hospital cost. MEDPAC views the DSH payment as a Medicare subsidy to assist hospitals in assuring access to quality care for low-income Medicare beneficiaries.

The Balanced Budget Act required the Secretary to report to Congress with recommendations for a revised formula for DSH payments. Drawing on work by ProPAC, the formula is to:

- Establish a single threshold for hospitals serving low-income patients;
- Consider the costs incurred by hospitals in serving Medicare patients who are entitled to SSI; and,
- Consider the costs incurred by hospitals in serving Medicaid patients who are not entitled to Medicare.

The Secretary’s report to Congress has not been released. We limit our analysis to the effects of serving low-income patients on costs per case. We believe the issue of using DSH payments as a subsidy for uncompensated care is a broader issue that requires resolution in a larger context than IRF PPS.

Carter, Buchanan et al. (1997) found the percentage of Medicare patients who were entitled to Medicaid was a significant variable in explaining cost per case. Given the BBA mandate, we evaluate a facility-level adjustment that takes into account the both the percentage of Medicare patients who are on SSI and the percentage of Medicaid patients who are not entitled to Medicare. We explore using the current method for defining the DSH patient percentage. Under the current method, however, a hospital’s DSH patient percentage does not measure the percentage of low-income patients within the facility. This is because it is the sum of the percent of Medicare patients who are on SSI and the percent of total patients who are Medicaid (non-Medicare) patients. We also examine an alternative measure of low-income patient share. This measure equals the sum of Medicare SSI days and non-Medicare Medicaid days as a percent of total inpatient days.

The examples in Table 6.1 demonstrate the difference between the two measures.

The examples illustrate that two facilities with the same number of low-income patients can have different DSH percentages. In facilities where the number of Medicare cases is small relative to the Medicaid (non-Medicare) cases, the DSH percentage can exceed 100. If a hospital has a high percentage of Medicare patients, the effect of Medicaid on the DSH percentage may be minimal even though a high percentage of the non-Medicare patients are on Medicaid. This is because the denominator includes the Medicare patients.

Table 6.1

Comparison of DSH Ratio and Low-Income Ratio

	Hospital A	**Hospital B**
Medicare Days	1000	700
Medicare SSI Days	600	420
Medicaid Non-Medicare Days	100	280
Total Days	1200	1200
DSH Ratio	$\frac{600}{1000} + \frac{100}{1200} = .60 + .08 = .68$	$\frac{420}{700} + \frac{280}{1200} = .60 + .23 = .83$
Low-Income Ratio	$\frac{600 + 100}{1200} = \frac{700}{1200} = .58$	$\frac{420 + 280}{1200} = \frac{700}{1200} = .58$

We develop measures of DSH and low-income patient percentages in several steps. We obtain the percentage of patients on SSI from one of two sources.

- Our preferred source was a file obtained from HCFA providing information on SSI days and total Medicare days. For rehabilitation units, the resulting SSI percentage is based on all Medicare inpatient stays (both acute care and excluded units).[34]
- The second source is the provider-specific public use file used to develop the final FY2000 acute care PPS rates. The file contains both the percentage of Medicare patients who are on SSI and the percentage of total patients who are on Medicaid and not entitled to Medicare.

Our preferred source for Medicaid days in the rehabilitation facility is the cost report. If this information is not available, we use the Medicaid ratio on the provider-specific public use file. When we use the public use file, we are applying the acute care Medicaid and SSI ratios to total inpatient days in the rehabilitation facility. Similarly, the HCFA-provided SSI file includes acute care days. Further investigation is needed to explore whether it is reasonable to assume that the SSI percentages are comparable across the acute care and rehabilitation units. Even with these data sources, we are missing the data needed to construct low-income patient measures for 47 facilities. We impute the low-income variable values for these facilities by assigning the State average for large urban and other facilities as appropriate.

Other Factors Affecting Cost

In addition to examining factors that may be appropriate to incorporate into IRF PPS, we explore the effect of other factors on rehabilitation facility costs. This analysis helps us to understand the likely impact of IRF PPS on different types of facilities.

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[34] Information on a patient's entitlement to SSI benefits is confidential and is not available on the inpatient bill. HCFA periodically sends all MEDPAR bills to the Social Security Administration for a match with SSI eligibility files. The percentage of Medicare inpatients entitled to SSI is returned to HCFA and the intermediary. For this report, we were unable to obtain the SSI percentage for inpatient stays specific to rehabilitation facilities.

Type of facility. Carter, Buchanan et al. (1997) found freestanding hospitals were significantly more expensive than rehabilitation units of acute care hospitals. There are 138 freestanding hospitals and 486 rehabilitation units of acute care hospitals in our sample. We use a dummy variable to evaluate whether there are systematic differences in costs between freestanding rehabilitation hospitals and rehabilitation units of acute care hospitals.

Size. Carter, Buchanan et al. (1997) used number of Medicare rehabilitation cases as the size variable and found no effect on costs per case. We use average daily census (ADC) as the size variable and control for type of facility. We use dummy variables for the size categories shown in Table 6.2.

Table 6.2

Size Categories Used in Regression Analysis

	Freestanding Hospitals	**Rehabilitation Units**
Size Variable	**ADC**	**ADC**
Small	< 25	< 10
Medium	=>25 and <50	=>10 and <25
Large	=>50	=>25

Time period for certification. Carter, Buchanan et al. (1997) found facilities certified in recent years were more expensive than facilities in existence since the early years of PPS. Older facilities have been operating under the TEFRA limits for a number of years. We expect this would constrain their cost increases and cost per case relative to newer facilities. In this regard, we note that the initial TEFRA base year carries over when there is a change of ownership.

We use the OSCAR certification date to develop three categories for certification: before 1985, 1985-90, and 1991 or later. We find that there may be problems with the certification dates, which frequently are different from the certification dates reported on the HCRIS 12 cost report. (Certification date is not reported on HCRIS 13 or 14). The OSCAR certification date may not be an appropriate indicator of the

TEFRA base year. A new certification date may be assigned each time a new provider agreement is signed.

Type of control. Carter, Buchanan et al. (1997) found that proprietary facilities were more costly than other facilities. Relative to facilities owned by governmental or non-profit entities, a higher proportion of proprietary hospitals is freestanding.

We use a dummy variable to explore whether proprietary facilities are more costly than non-profit or governmental institutions after controlling for other factors affecting costs.

METHODS: MULTIVARIATE REGRESSION ANALYSES AND PAYMENT SIMULATIONS

General Specification Issues

We use multivariate regression to examine factors that may explain variation in costs per case. Our dependent variable is each facility's average total (operating and capital) cost per case. We use the natural logarithm to transform cost and examine different specifications.

In preliminary analyses, we examine whether the payment coefficients are sensitive to whether the payment regression is facility-weighted or case-weighted. Facility-weighted regressions have been used in acute care PPS; however, case-weighted regressions should be more efficient. They account for the fact that there is more random variation in data from small facilities. They produce minimum variance unbiased estimates of the coefficients. Carter, Buchanan et al. (1997) found case-weighted and hospital-weighted regressions produced similar empirical results.

The values for teaching and low-income patient ratios can be zero.[35] Since the log of zero cannot be taken, the customary practice has been to add 1.0 to the teaching and low-income patient variables (for example, log (1+resident-to-ADC ratio). This specification for the logged form of the variable is used in acute care operating PPS and was used to examine teaching and DSH effects in the proposed rule for hospital outpatient PPS. Rogowski and Newhouse (1992) found that, if

[35] This occurs with the teaching variable for all non-teaching facilities. It rarely occurs with the low-income patient variable since at least one patient is likely to be entitled to SSI and/or Medicaid.

the true specification is log-log, then adding 1.0 to the measure of teaching intensity biases the teaching coefficient substantially. This is because the variable values are quite small. To reduce the distortion to less than 1 percent, they added .0001 to the teaching ratio instead of 1.0.

To avoid the distortion created by adding 1.0 to the teaching and low-income patient ratios, HCFA used non-logged forms of teaching and DSH variables in capital-PPS (O'Dougherty, Cotterill et al., 1991). Carter, Buchanan et al. (1997) also used the non-logged form to explore the effects of Medicaid on costs per case. We examine the effects of using the two different forms of the logged variables (for example, log (1+low-income patient percentage) and log (.0001+low-income patient percentage)) and non-logged variable forms for teaching and low-income patients.

Fully Specified Regression

We perform an evaluation regression to understand the various factors affecting cost per case. Our dependent variable is the log of cost per case. We perform one regression using the log of the CMI (average CMG weight per case) and log (.705*WI +.295) on the right-hand side of the equation as well as the log of .0001 + the teaching and low-income patient ratios. We perform a second regression using the log of the CMI and non-logged versions of the teaching and low-income patient ratio variables and the wage index value. In both regressions, we add dummy variables to indicate: those facilities for which we imputed the low-income patient ratio, freestanding units, date of certification category, size category and geographic location.

Payment Regressions

We also perform a set of payment regressions using only those variables that measure factors that have been used as payment parameters and that were significant in the fully specified regression. We move CMI to the left hand-side of the equation since payment will be proportional to the CMI. We also move the WI to the left-hand side by standardizing the labor-related share of each facility's CMI-adjusted cost per case for the WI. This is consistent with the way these adjustments would be applied in IRF PPS. We regress the CMI and WI-adjusted cost per case on the potential payment variables that were found to be significant in our fully specified regressions. We explore alternative specifications that might be used in the payment formula.

Payment Simulations

We assess the appropriateness of the adjustments indicated by the payment regressions by simulating payments using coefficients from the regressions to determine the payment adjustment factors. For this purpose, we use 1997 claims data from 618 facilities in our analysis file. In each simulation, total payments equal total costs for the cases in the sample. We assume a 3-percent outlier policy consistent with our recommendation for an outlier policy in Chapter 7. We compare payments for selected models relative to a base model that includes a wage adjustment only.

ANALYSIS RESULTS

Characteristics of Facilities in Analysis File

Table 6.3 summarizes key characteristics of the 624 facilities in our analysis file. There are 109 facilities with teaching programs in our sample, most of which are units of acute care hospitals. Only 38 facilities have a resident-to-average daily census ratio equal to or greater than .10. As is the case with acute care teaching hospitals, the facilities with major teaching programs tend to be located in large urban areas, and have a higher case mix and a higher proportion of low-income patients.

For the facilities for which we have actual data on SSI and Medicaid ratios, 78.5 percent have a low-income patient ratio below .20. There are 82 facilities with a low-income patient ratio between .20 and .30 percent and 42 facilities with a low-income patient ratio of .30 or more.

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Table 6.3

Variable Means by Facility Characteristics

Type of Facility	N Facilities	Average Annual Cases	Case Weighted: Cost Per Case	CMI	Low - Income Patient Ratio	Resident to ADC	WI	Facility Weighted: Percent Large urban	Percent Rural	Percent Free-standing	ADC
All Facilities	624	178857	12063	0.999	0.117	0.014	0.971	43	10	22	25
By Geographic Area											
Urban	561	167682	12019	0.998	0.115	0.015	0.980	48	0	23	26
Large Urban	271	77966	12343	0.994	0.120	0.022	1.037	100	0	21	27
Other Urban	290	89716	11737	1.001	0.111	0.010	0.930	0	0	25	25
Rural	63	11175	12725	1.024	0.138	0.001	0.835	0	100	13	14
By Region											
East North Central	144	35407	12395	1.023	0.116	0.022	0.987	40	11	7	19
East South Central	37	15415	11721	1.039	0.121	0.015	0.879	22	11	32	37
Middle Atlantic	53	25741	10617	0.912	0.074	0.022	1.008	58	6	40	42
Mountain	32	6678	11010	0.956	0.094	0.005	0.945	31	9	31	17
New England	44	15390	12110	0.944	0.089	0.017	1.101	64	2	30	36
Pacific	69	10283	16802	1.163	0.144	0.010	1.170	59	7	19	15
South Atlantic	99	36546	11300	1.012	0.130	0.006	0.938	42	11	25	31
West North Central	50	9273	11364	1.009	0.111	0.012	0.899	30	20	10	16
West South Central	96	24123	13002	0.987	0.155	0.011	0.882	40	10	30	23
Units of Acute Care Hospitals	486	108719	11968	1.005	0.138	0.017	0.971	44	11	0	18
Average daily census <10	131	13952	12669	0.995	0.123	0.004	0.963	37	24	0	7
Average daily census = >10 and <25	258	55403	11793	0.998	0.141	0.019	0.971	43	9	0	16
Average daily census =>25	97	39364	11966	1.019	0.139	0.020	0.974	54	0	0	37
Freestanding Hospitals	138	70137	12209	0.990	0.084	0.010	0.970	42	6	100	50
Average daily census <25	27	4487	15892	1.080	0.087	0.000	0.992	41	11	100	16
Average daily census =>25 and <50	55	21392	12830	1.000	0.071	0.004	0.946	42	4	100	39
Average daily census =>50	56	44258	11536	0.976	0.089	0.013	0.980	43	5	100	77

Table 6.3 (cont.)

Variable Means by Facility Characteristic

			Case Weighted					Facility Weighted			
	N Facilities	Average Annual Cases	Cost Per Case	CMI	Low - Income Patient Ratio	Resident to ADC	WI	Percent Large urban	Percent Rural	Percent Free-standing	ADC
Low-Income Patient Ratio											
<.10	227	75691	11009	0.962	0.066	0.010	0.981	44	11	20	26
=>.10 and <.20	226	60854	12573	1.029	0.139	0.017	0.971	41	9	17	24
=>.20 and <.30	82	17194	13061	1.036	0.249	0.035	0.975	49	11	12	22
=>.30	42	7818	14075	1.069	0.401	0.020	0.939	52	14	12	20
Missing	47	17300	12978	0.994		0.001	0.937	34	6	83	35
Teaching Status											
No teaching	515	142861	12016	1.001	0.112	0.000	0.957	39	12	23	23
Resident-to-avg. daily census <.1	71	26587	11469	0.967	0.118	0.034	1.020	66	4	24	37
Resident-to-avg. daily census =>.1 & <.2	23	7645	14304	1.057	0.188	0.138	1.043	65	0	17	38
Resident-to-avg. daily census =>.2	15	1763	15109	1.080	0.188	0.341	1.010	60	0	7	21
Type of Ownership											
Voluntary	402	109315	11717	0.996	0.118	0.018	0.984	45	9	13	22
Proprietary	143	50510	12358	0.998	0.098	0.002	0.935	39	8	55	33
Government	49	11515	13381	1.040	0.187	0.022	0.983	39	18	8	25
Missing	30	7517	13081	0.995	0.119	0.035	0.994	53	17	17	20
Medicare Days as Percent of Inpatient Days											
0-49	105	19390	14940	1.080	0.169	0.046	1.059	66	1	25	27
50-64	134	37312	12877	1.018	0.136	0.024	1.007	46	7	22	27
65-79	240	79799	11356	0.984	0.102	0.008	0.953	38	12	23	25
80 and over	145	42356	11361	0.975	0.102	0.003	0.932	34	17	19	21
Total Costs per Case											
25th percentile and below	152	57830	8628	0.925	0.098	0.009	0.954	46	9	18	25
26 -50th percentile	158	53345	11250	0.984	0.110	0.013	0.957	38	13	25	28
51 -75th percentile	156	41429	13856	1.051	0.123	0.013	0.974	46	10	23	25
Above 75th percentile	158	26252	18453	1.112	0.160	0.031	1.030	44	9	23	21

The case-weighted CMI for rural hospitals is 2.4 percent higher than the national average. On average, rural facilities tend to have fewer cases and a higher average cost per case. Table 6.4 provides additional comparative information on case-weighted data for the 618 facilities for which we have 1997 case mix data. The cost differences between rural and urban facilities become more evident when the average cost per case is standardized for the CMI and the wage index. The standardized cost per case for rural hospitals is 15 percent higher than the national average. Both routine costs and therapy costs in rural hospitals are higher than the national average.

We compare the case-weighted length of stay in each geographic area to the national average length of stay for cases in the same CMG. We find that the length of stay in rural hospitals is 2 percent higher than expected for non-transfer cases. The rural facility transfer rates are slightly lower than the transfer rates for urban hospitals.

Table 6.4

Cost and Utilization by Geographic Location

	Large Urban Areas	**Other Urban Areas**	**Rural Areas**
Mean CMI per case	.9967	1.0026	1.0205
Mean cost per case	$12,236	$11,671	$12,745
Standardized for CMI and WI	$11,894	$12,195	$14,102
Mean routine cost per day	$448	$413	$443
Standardized for WI	$437	$433	$501
Mean therapy cost per case	$2,889	$2,829	$3,287
Standardized for WI	$2,819	$2,989	$3,734
Mean therapy cost per day	$183	$179	$205
Standardized for WI	$179	$189	$233
LOS- Non-Transfer Cases	15.02 days	15.57 days	16.04 days
Ratio LOS to expected ALOS	.98	1.01	1.02
Percent hospital transfers- all	8	7	6
Percent hospital transfers - short stay	6	6	5
Percent SNF/NH transfers- all	14	13	13
Percent SNF/NH transfers - short stay	8	8	8
Percent discharged to home health	27	25	22

Note: Discharge status taken from MEDPAR; Percent discharged to home health is understated.

Preliminary Regressions

We examine whether the payment coefficients are sensitive to whether the payment regression is facility-weighted or case-weighted. We find that the case-weighted regressions perform slightly better.[36] We discuss the results of the case-weighted regressions in this report.

Preliminary regression results indicate that the wage index alternative using the pre-determined labor-related share performs as well as specifications using the coefficient of the logged or non-logged wage index variable to establish the wage adjustment. Since HCFA expressed a preference for this alternative in the IRF PPS, we use it in the regressions in this report.

We also perform preliminary regressions to explore the three different specification alternatives for teaching and serving low-income patients. The R-squares for the three forms are comparable. The coefficients are quite different since the scale is different. We find through residual analysis that either logged form would be appropriate to use but that the specification adding .0001 to the low-income patient variable is a slightly better fit. We present the results of using a logged specification adding .0001 to the variable and the non-logged form in this report.

Fully Specified Regressions

We present in Table 6.5 the results of two fully specified regressions using a full set of explanatory variables. The first regression uses the non-logged form of WI, teaching and LIP. The second uses logged forms of these variables.

The CMI, WI, low-income patient ratio and small size are highly significant. The coefficient for the CMI (1.2835 and 1.2775 for the non-logged and logged regressions, respectively) is consistent with the compressed weights (i.e., weights that undervalue high cost CMGs and overvalue low cost CMGs) discussed in Chapter 5. The coefficient for WI is statistically indistinguishable from the expected value of 1.0. In

[36] The analysis was based on 604 facilities for which we had case mix data and HCRIS 12 and/or 13 cost reports. The r-square for the fully-specified case-weighted regression on cost per case was .4739 compared to .4700 for the facility-weighted regression.

both regressions, the coefficient for the low-income patient variable is highly significant while the dummy variable for imputed low-income patient ratios is not significant. This indicates that the facilities with imputed values are not significantly different from other facilities after controlling for other factors that affect costs.

Table 6.5

Fully Specified Regression on Case-weighted Cost Per Case

	Non-logged WI, Teaching, and LIP		**Logged WI, Teaching, and LIP**	
Variable	**Coefficient**	**t-statistic**	**Coefficient**	**t-statistic**
Log of CMI	**1.2835**	**18.1420**	**1.2775**	**17.7830**
Wage index	**1.0435**	**9.5280**	**1.0608**	**9.3150**
Teaching	**0.4275**	**2.3040**	0.0040	1.0890
Low-income patient ratio	**0.4501**	**4.4590**	**0.0733**	**5.0440**
Low-income patient dummy	0.0360	1.1470	0.0286	0.8970
Large urban area	-0.0219	-1.1470	-0.0190	-0.9810
Rural area	**0.1083**	**2.9520**	**0.1143**	**3.0870**
Freestanding	**0.0504**	**2.4190**	**0.0484**	**2.3150**
Proprietary	**0.0496**	**2.2810**	**0.0505**	**2.2990**
Certification before 1985	-0.0290	-1.2910	-0.0281	-1.2420
Certification after 1990	0.0252	1.2610	0.0250	1.2500
Large size	-0.0117	-0.6340	-0.0116	-0.6220
Small size	**0.0743**	**2.5520**	**0.0790**	**2.6910**
Intercept	**8.2394**	**76.2000**	**9.5469**	**202.4950**
R-square	0.4869		.4822	

Note: Based on 624 facilities. Variables with coefficients in bold have significance at the .05 level or less.

Rural location, type of facility, type of ownership and size are also significant factors in explaining cost per case. Teaching is significant only in the non-logged regression. After controlling for other factors affecting cost per case, each 10 percentage point increase in the resident-to-ADC ratio results in 4.3 percent increase in cost per case. Facilities located in rural areas are about 11 percent more costly than urban hospitals, freestanding hospitals are about 5 percent more costly than rehabilitation units of acute care hospitals, and proprietary facilities are about 5 percent more costly than other facilities after controlling for other factors affecting costs. Consistent with the findings by Carter, Buchanan et al. (1997), location in a large urban area is not significant. In contrast to that study, we find that the date of certification is not significant.

Payment Regressions

In the payment regressions, we retain only those explanatory variables that are potential payment factors. The R-squares drop from the .48 range in the fully specified regressions to the .07-.11 range in the payment regressions. This is primarily because we account for the variables with the greatest explanatory powers (CMI and WI) on the left side of the equation.

The regression results that we present in this report focus on three issues:

- using the low inpatient patient ratio or the DSH patient percentage as a measure for serving low-income patients (Models 1 and 2 vs. 3 and 4);
- using logged or non-logged variables for serving low-income patients and for teaching (Models A vs. Models B); and,
- including the rural dummy variable in the payment regressions (Model 1 vs. Model 2; Model 3 vs. Model 4). Including the variable is consistent with an adjustment for facilities located in rural areas. Leaving the rural dummy variable out of the regression is more consistent with special protections for certain classes of rural hospitals or an exceptions policy.

We explore the effects of using the logged vs. non-logged forms of the teaching and low-income patient ratio variables in Models 1 and 2. We display the results in Table 6.6.[37] We find that the logged forms have a slightly higher R-square than the non-logged forms. This is a

[37] The independent variables that we used in each model are as follows:

1A	Residents to ADC; low-income patient ratio; low-income imputed value dummy; rural dummy
1B	Log(.0001+residents to ADC); log(.0001+low-income patient ratio); low-income imputed value dummy; rural dummy
2A	Residents to ADC; low-income patient ratio; low-income imputed value dummy
2B	Log(.0001+residents to ADC); log(.0001+low-income patient ratio); low-income imputed value dummy

consistent pattern across all the payment regressions and differs from our finding in the fully specified regressions.

Table 6.6

Results of Regression Models 1 and 2

Variable	Model 1A		Model 1B		Model 2A		Model 2B	
	Non-logged; LIP, TCH, rural		Logged; LIP, TCH, rural		Non-logged; LIP, TCH		Logged; LIP, TCH	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Intercept	**9.291**	**600.99**	**9.565**	**234.01**	**9.300**	**598.72**	**9.567**	**231.24**
Low-income patient ratio	**0.570**	**5.896**	**0.089**	**6.543**	**0.590**	**6.029**	**0.092**	**6.621**
Residents-to-ADC	0.265	1.420	-0.001	-0.191	0.199	1.057	-0.002	-0.639
Low-income patient impute value dummy	**0.092**	**3.112**	**0.077**	**2.574**	**0.085**	**2.857**	**0.069**	**2.303**
Rural area	**0.147**	**4.134**	**0.143**	**4.027**	.	.	.	.
R-square	0.1051		0.1091		0.0804		0.0858	

We find that when only the potential payment variables are used in the regression, teaching is no longer significant. We explore through additional regression analysis whether there is a teaching threshold and whether the presence or absence of teaching has a significant effect on costs. In each specification, we do not find teaching to be significant.[38]

We explore the effect of using the DSH patient ratio in Models 3 and 4, and summarize the results in Table 6.7.[39] Compared to Models 1 and 2, we find that the R-square for the regressions using the DSH variable is slightly higher than the regressions using the low-income patient ratio when the logged form of the variables are used. The opposite is the case when the non-logged version is used. Teaching is still not significant. The coefficient for the DSH ratio is lower than

[38] In our preliminary analyses, we found teaching to be significant in the payment regression only when facility-weighted regressions were used.

[39] The independent variables that we used in each model are as follows:

- 3A Residents to ADC; DSH patient ratio; DSH imputed value dummy; rural dummy
- 3B Log (.0001+residents to ADC); log (.0001+DSH patient ratio); DSH imputed value dummy; rural dummy
- 4A Residents to ADC; DSH patient ratio; DSH imputed value dummy
- 4B Log (.0001+residents to ADC); log(.0001+DSH patient ratio); DSH imputed value dummy

the coefficient for low-income patient ratio in the non-logged form, but not in the logged form.

Table 6.7

Results for Regression Models 3 and 4

Variable	Model 3A		Model 3B		Model 4A		Model 4B	
	Non-logged; DSH,TCH, rural		Logged; DSH,TCH, rural		Non-logged; DSH, TCH		Logged; DSH,TCH	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Intercept	**9.2900**	**591.99**	**9.5477**	**246.55**	**9.2994**	**590.42**	**9.5473**	**243.43**
DSH patient ratio	**0.4856**	**5.870**	**0.0910**	**6.649**	**0.4958**	**5.914**	**0.0924**	**6.666**
Residents-to-ADC	0.2307	1.231	-0.001	-0.348	0.1645	0.869	-0.003	-0.802
DSH patient imputed value dummy	**0.0848**	**2.849**	**0.0674**	**2.238**	**0.0783**	**2.599**	**0.0601**	**1.972**
Rural	**0.1511**	**4.257**	**0.1461**	**4.120**	.	.	.	.
R-square	0.1047		0.1110		0.0784		0.0866	

We perform additional regressions using only the payment variables that are significant. In Table 6.8, we compare the results using the logged and non-logged forms of the low-income patient ratio (Models A vs. B) and the effects of including the rural dummy. In Table 6.9, we compare the results using the disproportionate share patient percentage in place of the low-income patient ratio. [40] The R-squares are slightly higher with the logged formulations than the non-logged.

The R-squares using the logged DSH patient ratio are slightly higher than the formulations using the low-income patient ratio. The non-logged and logged formulations of the low-income patient ratio and DSH patient ratio affect the payment adjustment for different patient percentages. The non-logged formulation increases payments to hospitals

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[40] The independent variables that we use in each model are as follows:

5A	Low-income patient ratio; low-income imputed value dummy; rural dummy
5B	Log (.0001+low-income patient ratio);low-income imputed value dummy; rural dummy
6A	Low-income patient ratio; low-income imputed value dummy
6B	Log (.0001+low-income patient ratio);low-income imputed value dummy
7A	DSH patient ratio; DSH imputed value dummy; rural dummy
7B	Log (.0001+DSH patient ratio); DSH imputed value dummy; rural dummy
8A	DSH patient ratio; DSH imputed value dummy
8B	Log (.0001+DSH patient ratio); DSH imputed value dummy

at both extremes of relatively high and low ratios relative to the logged form. It lowers payments to hospitals with mid range values relative to the logged form. To illustrate, we compare the adjustments using the coefficients from Models 6A and 6B at different low-income patient percentages in Table 6.10. We normalize the adjustment to the adjustment for the average low-income patient ratio ((0.117). The formulations are very similar for the great majority of hospitals that are found in the mid-range of low-income percent and differ only for the few hospitals at the extreme (LIP <=0.05 or LIP >= 0.3). We use the range from 0.02 to 0.50 because it covers the first to the 99th percentile of the low-income patient ratios in our analysis sample.

Table 6.8

Results of Regression Models 5 and 6

Variable	**Model 5A**		**Model 5B**		**Model 6A**		**Model 6B**	
	Non-logged; LIP, rural		**Logged; LIP, rural**		**Non-logged; LIP**		**Logged; LIP**	
	Coeff	**t-stat**	**Coeff**	**t-stat**	**Coeff**	**t-stat**	**Coeff**	**t-stat**
Intercept	**9.2934**	**603.09**	**9.5702**	**298.41**	**9.3009**	**600.69**	**9.5834**	**296.63**
Low-income patient ratio	**0.5895**	**6.153**	**0.0893**	**6.553**	**0.6040**	**6.233**	**0.0909**	**6.595**
Low-income patient imputed value dummy	**0.0869**	**2.960**	**0.0778**	**2.645**	**0.0817**	**2.752**	**0.0726**	**2.439**
Rural	**0.1425**	**4.024**	**0.1438**	**4.078**	.	.	.	.
R-square	0.1022		0.1091		0.0787		0.0852	

Table 6.9

Results of Regression Models 7 and 8

Variable	**Model 7A**		**Model 7B**		**Model 8A**		**Model 8B**	
	Non-logged; DSH, rural		**Logged; DSH, rural**		**Non-logged; DSH**		**Logged; DSH**	
	Coeff	**t-stat**	**Coeff**	**t-stat**	**Coeff**	**t-stat**	**Coeff**	**t-stat**
Intercept	**9.2912**	**592.93**	**9.5563**	**322.40**	**9.3001**	**591.32**	**9.5676**	**319.89**
DSH patient ratio	**0.5031**	**6.170**	**0.0905**	**6.651**	**0.5081**	**6.152**	**0.0913**	**6.622**
DSH patient imputed value dummy	**0.0800**	**2.709**	**0.0693**	**2.336**	**0.0750**	**2.509**	**0.0642**	**2.138**
Rural	**0.1475**	**4.167**	**0.1475**	**4.188**	.	.	.	.
R-square	0.1025		0.1108		0.0773		0.0857	

Table 6.10

Comparison of Non-logged and Logged Payment Adjustment

Low-Income Patient Ratio	Model 6A Non-logged Adj=k*e**(lip*.6040)	Model 6B Logged Adj=k*(.0001+lip)**.0909
0.020	0.9433	0.8522
0.050	0.9605	0.9260
0.100	0.9900	0.9861
0.150	1.0203	1.0231
0.200	1.0516	1.0502
0.300	1.1171	1.0896
0.400	1.1867	1.1185
0.500	1.2605	1.1414

Payment Simulations

We use payment simulations to confirm the results of the regression analysis. The coefficients from the regressions are used to establish the payment parameters.[41] In Table 6.11 we summarize the payment-to-cost ratios resulting from selected payment simulations by key facility characteristics. We present more detailed simulation results in Tables 6.13-6.17 at the end of this section. In Table 6.11, we include results from a preliminary simulation using only the wage index as a facility-level adjustment.[42] We use Model 5B as a reference model. It uses the logged form of the LIP ratio as the measure of low-income patients and includes an adjustment for rural facilities.

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[41] We note that the number of cases and facilities differ somewhat from the analysis file used in the payment regressions. The payment simulations use 1997 claims, whereas the regression analyses were based on pooled data for 1996 and 1997. We apply the following facility level payment adjustments to the individually priced cases in the preliminary payment simulations:

Base Model: (.295+.705WI)
Model 5A: (.295+.705WI)(1+.1532*rural)(e**.5895*lip)
Model 5B: (.295+.705WI)(1+.1547*rural)((.0001+lip)** .0893)
Model 6B: (.295+.705WI)((.0001+ lip)**.0909)
Model 7B: (.295+.705WI)(1+.1589*rural)((.0001+DSH)** .0905)
Note: The exponentiated form of the rural adjustment is shown in the formula (e.g., (e**.1425)-1=0.1532), where e is the natural antilog of 1).

Table 6.11

Payment Simulation Results for Selected Models
Case-Weighted Payment-to-Cost Ratios

	N Facilities	N Cases	Base Model	Model 5B	Model 5A	Model 6B	Model 7B
Type of Facility			WI only	Logged; LIP, rural	Non-logged; LIP, rural	Logged; LIP	Logged; DSH, rural
All Facilities	618	200,039	1.000	1.000	1.000	1.000	1.000
Large Urban	269	86,390	1.016	1.005	1.008	1.012	1.007
Other Urban	288	101,230	1.000	0.996	0.994	1.003	0.995
Rural	61	12,419	0.893	0.995	0.992	0.900	0.994
Freestanding	138	80,084	0.979	0.975	0.9730	0.997	0.976
Units	480	119,955	1.015	1.017	1.019	1.016	1.017
Low-Income Patient							
<.10	226	83,364	1.044	1.000	1.009	1.000	0.998
=>.10 and <.20	226	68,606	1.000	1.013	1.001	1.013	1.013
=>.20 and <.30	80	18,827	0.964	1.015	1.013	1.016	1.015
=>.30	41	8,784	0.904	0.992	1.027	.983	0.992
Missing	45	20,458	0.925	0.948	0939	0.9541	0.954
Residents-to-ADC							
No Teaching	509	161,040	0.995	0.997	0.997	0.996	0.997
<.1	71	28,916	1.044	1.030	1.031	1.035	1.029
=>.1 and <.2	23	8,164	0.952	0.984	0.974	0.990	0.989
=>.2	15	1,899	0.898	0.912	0.918	0.917	0.914

- Comparing the results to Model 5A confirms whether the logged form performs at least as well as the non-logged form.
- Comparing the results to Model 6B confirms whether a rural adjustment results in cost-to-charge ratios closer to 1.0 across geographic locations.
- Comparing the results to Model 7B shows the payment implications of using low-income ratio versus the DSH ratio.

The base model indicates that if the payment rate were adjusted by the wage index only, the average payment-to-cost ratio for rural hospitals would be .893. Large urban hospitals would have a slightly higher than average payment-to-cost ratio of 1.016. On average, hospitals with low-income patient ratios of .20 or greater and teaching hospitals with a resident-to-average daily census ratio of .10 or greater would have a payment-to-cost ratio of less than 1.0. Hospitals with low-income ratios of less than .20 and teaching hospitals with resident-to-average daily census ratios of less than .10 would have an average payment-to-cost ratio greater than 1.0.

The payment-to-cost ratios are very similar across geographic areas in the models using a rural adjustment. In Model 6B, which does not include a rural adjustment, rural hospitals on average receive 90 percent of their cost while large urban hospitals receive slightly more than cost (1.012 payment-to-cost ratio).

The pattern of payment-to-cost ratios is as expected for the two specifications of the low-income patient variable in Models 5A and 5B. The ratios are slightly higher for hospitals at the low and high end of the low-income patient ratios using the non-logged form and slightly higher for hospitals with a mid-range value for low-income patient ratios using the logged form. The differences are quite small except for hospitals with low-income patient ratios of at least .30. The non-logged specification results in a 1.027 payment-to-cost ratio for this group of 41 hospitals.

The average payment-to-cost ratios are nearly identical when the DSH patient ratio is used instead of the low-income patient ratio. While there are distributional differences for individual providers, average payments are essentially the same for each provider group. When we look at the more detailed simulations, we find that there are payment effects of less than 1 percent across urban and rural regions. Although the differences are small, a comparison of the average payment-to-cost ratio for each geographic area indicates the ratio tends to be closer to 1.00 about twice as often when the low-income patient ratio is used relative to the DSH ratio.

Table 6.12

Payment Impact by Low-Income Patient Ratio

Low-Income Patient Ratio	Payment-to-cost Ratio		Winners				Losers			
			% Cases		Avg. Profit		% Cases		Avg. Loss	
	5B	7B	5B	7B	5B	7B	5B	7B	5B	7B
<.10	1.000	0.998	53.9	52.4	1470	1536	46.1	47.6	1723	1686
=>.10 and <.20	1.013	1.013	58.2	58.7	1722	1726	41.8	41.3	2033	2100
=>.20 and <.30	1.016	1.015	58.0	59.2	1916	1907	42.0	40.8	2194	2280
=>.30	0.992	0.992	43.8	37.2	2341	2649	56.2	62.8	2012	1918

Table 6.12 compares payments within the low-income patient categories. With the exception of hospitals with the highest low-income patient category, the patterns are quite similar. In the last category, two additional hospitals would lose using DSH. The average loss per case, however, is almost $200 lower using DSH than the low-income patient ratio.

IMPLICATIONS FOR POLICY AND RECOMMENDATIONS

Our main empirical findings and their import for the design of the IRF PPS facility-level adjustments are:

If only the statutorily-mandated wage adjustment were established, the classes of hospitals that would have an average payment to cost ratio of less than 1.0 include: rural hospitals (.893), teaching hospitals with a resident-to-average daily census of .20 or greater (.898) and hospitals with a low-income patient percentage of .30 or higher (.904). To improve payment equity, we believe additional facility-level adjustments are needed.

The wage index coefficient approximates the labor-related portion of cost per case. We believe this finding confirms that it would be appropriate to use the labor-related share determined by HCFA's Office of the Actuary.

When only potential payment variables are included in the regression, teaching is no longer significant. However, the payment simulations indicate major teaching hospitals (resident- to-average daily census of .20 or higher) will receive on average only 91 percent of costs. While there are only 1899 cases at 15 hospitals in this category, this is an area of concern that warrants further investigation.

When cost per case is standardized for case mix and area wage differences, rural hospitals are almost 16 percent more costly than other hospitals. We find the adjustment based on the regression coefficient works well. The payment-to-cost ratios across large urban, other urban and rural hospitals using the payment regression coefficients as an adjustment are all close to 1.0.

There is about a 9 percent increase in costs for each 10 percentage point increase in a facility's low-income or DSH patient percentage. We discuss our recommendations for this adjustment below.

The simulation results are inconclusive regarding whether a cost-of-living adjustment would improve payment equity for facilities in Alaska and Hawaii. In the absence of a cost-of-living adjustment, the facility in Hawaii would still have a profit and the Alaskan facility would have a loss. The average profit per case for the Hawaiian facility (982 cases) in Model 5B is $1226. The average loss per case for the Alaskan facility (117 cases) is $979.

The regression analyses and payment simulations that we present in this section focus on three issues. The first issue is whether the logged or non-logged form of the low-income patient variable is more appropriate as a payment parameter. We find that the while the differences are slight, the logged formulation provides a better fit. For example, the R-squares are slightly higher and the payment-to-cost ratios are slightly closer to 1.0 for most classes of hospitals in Model 5B relative to Model 5A. Hospitals with a low-income patient ratio of .30 or higher would be paid close to costs in the logged formulation (Model 5B) and slightly overpaid if the non-logged formulation were used.

The second issue is whether the low-income patient ratio or the DSH patient percentage is a better measure of serving low-income patients. Based on the payment simulations, we conclude that one variable for low-income patient population does not appear to work better than the other. However, we believe the low-income patient ratio is a better technical measure of low-income patient load than the DSH patient percentage. We are concerned, however, that in constructing both measures, we needed to assume that the SSI percentage for the total facility is representative of the SSI percentage for the rehabilitation unit. Also, the Technical Expert Panel noted that there may be differences in Medicaid coverage of rehabilitation services across states that could affect the reliability of both measures. These issues need to be investigated further before establishing the final payment parameters for IRF PPS.

We are also concerned that the facilities where we impute the low-income percentage appear to be underpaid using the state average low-income patient ratios. It is not clear if this is due to their actually having a larger low-income patient ratio or if they differ is some way from other hospitals. (We note that the imputed variable was not significant in the fully specified regressions but was in the remaining regressions). This needs to be investigated further if it is not possible to replace the imputation with actual SSI and Medicaid data for these hospitals before establishing final payment parameters.

Third, we explore the issue of whether rural hospitals should have an add-on and conclude that these hospitals will be significantly underpaid unless there is an adjustment or some other form of special payments. We try to see why rural hospitals cost more. One factor may be the hospital wage index. If there is less variation in therapist wages across geographic areas relative to hospital wages in general, the acute care hospital wage index may overstate the differences in wage levels in rehabilitation hospitals. The wage index will tend to underpay low wage areas, which are predominately rural areas, and overpay high wage areas, which are predominately large urban areas.

In addition, we find rural hospitals have a slightly lower transfer rate and higher length of stay. The lower transfer rate may reflect the high proportion of rural facilities (87 percent) that are units in acute care hospitals. The units may be able to address some acute care needs without transferring the patient. The lower rural discharge rates to home health may reflect less availability of HHAs in rural areas and potential access problems. Relatively fewer HHAs and other community support services may affect the length of stay in the rural rehabilitation facilities.

A final area of concern is that teaching hospitals with a resident-to-bed ratio of .2 or greater are paid about 91.5 percent of costs. While this is slightly higher than the base model, alternate specifications do not help. Although we cannot be sure, the deficit of payment to these hospitals is probably related at least in part to case mix compression. In addition, our measure of teaching activity may require further refinement before establishing the final payment parameters. The Technical Expert Panel noted that the ratio of residents-to-average daily census for some facilities is not consistent with Residency Review Committee accreditation requirements for programs in rehabilitation and physical medicine and suggested there may be reporting errors. In addition, we did not obtain the data needed to construct a measure of teaching activity that includes the time residents spend in ancillary areas for this interim report. While the additional resident time is likely to be small, it may have an impact on whether teaching has a significant effect on costs and warrants further investigation.

Table 6.13

Base Model Payment Simulation Results
FY 1997 Cases

Type of Facility	N Hospitals	N Cases	Avg. Cost Per Case	Avg. Payment Per Case	Percent Outlier Cases	Avg. Outlier Payment	Avg. Payment to Cost Ratio	Adjusted Cost per Case
All Facilities	618	200039	11257	11257	5.2	337	1.000	11522
By Geographic Area								
Large Urban	269	86390	11477	11657	4.8	340	1.016	11186
Other Urban	288	101230	10970	10975	5.0	311	1.000	11545
Rural	61	12419	12060	10774	9.0	533	0.893	13677
By Region								
New England	44	17402	11528	11738	4.1	339	1.018	10573
Middle Atlantic	53	27451	10168	10679	3.9	331	1.050	10185
South Atlantic	98	41730	10541	11074	3.9	233	1.051	11084
East North Central	143	38850	11350	11405	4.6	277	1.005	11481
East South Central	36	17577	11001	11031	5.1	260	1.003	12045
West North Central	50	10337	10472	10635	4.2	246	1.016	11226
West South Central	96	27932	12178	10815	9.4	585	0.888	13307
Mountain	31	7604	10249	10540	5.3	432	1.028	10676
Pacific	67	11156	15379	14622	7.2	465	0.951	13638
Units of Acute Care Hospitals	480	119955	11085	11250	4.8	307	1.015	11315
Average daily census<10	128	15405	11590	11021	6.6	362	0.951	11919
Average daily census=>10 and <25	255	61331	10884	11104	4.4	275	1.020	11089
Average daily census=>25	97	43219	11190	11539	4.8	333	1.031	11421
Freestanding Hospital	138	80084	11514	11268	5.7	383	0.979	11832
Average daily census<25	27	4994	14657	12823	13.2	1017	0.875	14695
Average daily census=>25 and <50	55	25299	11981	11268	7.1	465	0.940	12506
Average daily census=>50	56	49791	10962	11112	4.2	277	1.014	11203
Low-Income Patient Ratio								
<.10	226	83364	10420	10875	3.7	242	1.044	10603
=>.10 and <.2	226	68606	11517	11518	5.5	365	1.000	11779
=>.20 and <.3	80	18827	12191	11756	5.9	405	0.964	12427
=>.30	41	8784	13170	11901	8.0	452	0.904	13591
Missing	45	20458	12114	11203	8.0	521	0.925	12688

Table 6.13 (cont.)

Base Model Payment Simulation Results

Type of Facility	N Hospitals	N Cases	Avg. Cost Per Case	Avg. Payment Per Case	Percent Outlier Cases	Avg. Outlier Payment	Avg. Payment to Cost Ratio	Adjusted Cost per Case
Teaching Status								
Non-teaching	491	154871	11222	11165	5.4	342	0.995	11621
Resident to ADC <.10	70	28821	10759	11234	3.3	241	1.044	10624
Resident to ADC =>.10 & <.20	22	8107	13351	12716	6.9	557	0.952	12777
Resident to ADC =>.20	14	1653	14741	13237	7.8	822	0.898	14327
Missing	21	6587	10814	11235	4.4	248	1.039	10890
Type of Ownership								
Government	49	12990	12389	11808	6.1	427	0.953	12615
Proprietary	141	58862	11588	11152	6.5	423	0.962	12169
Voluntary	401	119838	10942	11256	4.3	283	1.029	11068
Missing	27	8349						
Medicare Days as Percent of Total Days								
0-49	105	20791	13816	12926	6.9	533	0.936	13231
50-64	134	41335	11985	11735	5.7	432	0.979	11984
65-79	237	89049	10671	10938	4.5	279	1.025	11071
80 and above	142	48864	10619	10723	5.2	279	1.010	11226
Alaska and Hawaii	2	1099	12159	13141	1.9	81	1.081	10810
Total Costs Per Case								
25^{th} percentile and below	156	64067	8086	10080	1.3	75	1.247	8388
26^{th}-50^{th} percentile	155	60254	10524	10898	3.3	175	1.036	10935
51^{st}-75^{th} percentile	152	46334	12925	11885	6.5	422	0.919	13230
Above 75^{th} percentile	155	29384	17044	13571	15.3	1108	0.796	16869
Capital Costs Per Case								
25^{th} percentile and below	148	54705	9179	10581	2.5	164	1.153	9255
26^{th}-50^{th} percentile	148	44178	11186	11237	4.2	258	1.005	11409
51^{st}-75^{th} percentile	145	43430	11398	11378	4.5	261	0.998	11600
Above 75^{th} percentile	148	49874	13387	11820	9.3	652	0.883	13923

Table 6.13 (cont.)

Base Model Payment Simulation Results

	Winners				Losers			
Type of Facility	N Hospitals	N Cases	Percent of Cases	Avg. Profit Per Case	N Hospitals	N Cases	Percent of Cases	Avg. Loss Per Case
All Facilities	293	113119	56.5	1581	325	86920	43.5	2058
By Geographic Area								
Large Urban	139	52161	60.4	1818	130	34229	39.6	2317
Other Urban	135	56354	55.7	1403	153	44876	44.3	1751
Rural	19	4604	37.1	1088	42	7815	62.9	2684
By Region								
New England	23	10903	62.7	1425	21	6499	37.3	1828
Middle Atlantic	33	17744	64.6	1635	20	9707	35.4	1543
South Atlantic	59	29298	70.2	1520	39	12432	29.8	1793
East North Central	64	20186	52.0	1890	79	18664	48.0	1929
East South Central	21	10859	61.8	1322	15	6718	38.2	2057
West North Central	21	5581	54.0	1511	29	4756	46.0	1419
West South Central	28	8764	31.4	1397	68	19168	68.6	2625
Mountain	15	4424	58.2	1671	16	3180	41.8	1629
Pacific	29	5360	48.0	1724	38	5796	52.0	3051
Units of Acute Care Hospitals	235	70080	58.4	1853	245	49875	41.6	2207
Average daily census<10	46	6446	41.8	2054	82	8959	58.2	2456
Average daily census=>10 and <25	135	36715	59.9	1880	120	24616	40.1	2258
Average daily census=>25	54	26919	62.3	1767	43	16300	37.7	1994
Freestanding Hospital	58	43039	53.7	1140	80	37045	46.3	1857
Average daily census<25	7	1614	32.3	1343	20	3380	67.7	3350
Average daily census=>25 and <50	17	9012	35.6	1367	38	16287	64.4	1865
Average daily census=>50	34	32413	65.1	1066	22	17378	34.9	1560
Low-Income Patient Ratio								
<.10	123	52611	63.1	1647	103	30753	36.9	1585
=>.10 and <.2	111	39843	58.1	1626	115	28763	41.9	2250
=>.20 and <.3	35	9940	52.8	1389	45	8887	47.2	2475
=>.30	13	2973	33.8	1636	28	5811	66.2	2755
Missing	11	7752	37.9	1134	34	12706	62.1	2159

Table 6.13 (cont.)

Base Model Payment Simulation Results

	Winners				Losers			
Type of Facility	N Hospitals	N Cases	Percent of Cases	Avg. Profit Per Case	N Hospitals	N Cases	Percent of Cases	Avg. Loss Per Case
Teaching Status								
Non-teaching	231	83282	53.8	1598	260	71589	46.2	1983
Resident to ADC <.10	38	19934	69.2	1469	32	8887	30.8	1752
Resident to ADC =>.10 & <.20	11	4928	60.8	1270	11	3179	39.2	3587
Resident to ADC =>.20	4	627	37.9	1372	10	1026	62.1	3261
Missing	9	4348	66.0	2157	12	2239	34.0	2950
Type of Ownership								
Government	18	6016	46.3	1371	31	6974	53.7	2264
Proprietary	55	29802	50.6	1105	86	29060	49.4	2016
Voluntary	211	72839	60.8	1786	190	46999	39.2	1968
Missing	9	4462			18	3887		
Medicare Days as Percent of Total Days								
0-49	37	7242	34.8	1705	68	13549	65.2	2277
50-64	61	22959	55.5	1372	73	18376	44.5	2277
65-79	124	56339	63.3	1556	113	32710	36.7	1954
80 and above	71	26579	54.4	1783	71	22285	45.6	1897
Alaska and Hawaii	1	982	89.4	1232	1	117	10.6	1116
Total Costs Per Case								
25th percentile and below	145	61422	95.9	2113	11	2645	4.1	780
26th-50th percentile	98	38784	64.4	1030	57	21470	35.6	811
51st-75th percentile	41	11641	25.1	724	111	34693	74.9	1633
Above 75th percentile	9	1272	4.3	572	146	28112	95.7	3656
Capital Costs Per Case								
25th percentile and below	113	46378	84.8	1981	35	8327	15.2	1819
26th-50th percentile	72	22665	51.3	1577	76	21513	48.7	1557
51st-75th percentile	62	23933	55.1	1328	83	19497	44.9	1674
Above 75th percentile	34	15068	30.2	797	114	34806	69.8	2590

Table 6.14

Model 5B Payment Simulation Results
FY 1997 Cases

Type of Facility	N Hospitals	N Cases	Avg. Cost Per Case	Avg. Payment Per Case	Percent Outlier Cases	Avg. Outlier Payment	Avg. Payment to Cost Ratio	Adjusted Cost per Case
All Facilities	618	200039	11257	11257	5.5	337	1.000	6081
By Geographic Area								
Large Urban	269	86390	11477	11537	5.5	363	1.005	5976
Other Urban	288	101230	10970	10927	5.5	317	0.996	6143
Rural	61	12419	12060	11999	5.9	331	0.995	6309
By Region								
New England	44	17402	11528	11447	4.7	355	0.993	5776
Middle Atlantic	53	27451	10168	10495	4.3	347	1.032	5622
South Atlantic	98	41730	10541	11265	3.8	216	1.069	5757
East North Central	143	38850	11350	11138	5.7	315	0.981	6149
East South Central	36	17577	11001	11326	4.3	213	1.030	6198
West North Central	50	10337	10472	10246	5.5	270	0.978	5935
West South Central	96	27932	12178	11154	8.7	520	0.916	6786
Mountain	31	7604	10249	10385	6.2	461	1.013	5769
Pacific	67	11156	15379	14895	8.5	537	0.969	7062
Units of Acute Care Hospitals	480	119955	11085	11275	5.5	323	1.017	5951
Average daily census<10	128	15405	11590	11159	7.3	389	0.963	6227
Average daily census=>10 and <25	255	61331	10884	11176	5.1	292	1.027	5811
Average daily census=>25	97	43219	11190	11456	5.3	342	1.024	6051
Freestanding Hospital	138	80084	11514	11231	5.6	360	0.975	6277
Average daily census<25	27	4994	14657	12693	13.2	952	0.866	7583
Average daily census=>25 and <50	55	25299	11981	11383	6.6	416	0.950	6512
Average daily census=>50	56	49791	10962	11007	4.3	271	1.004	6027
Low-Income Patient Ratio								
<.10	226	83364	10420	10418	5.0	284	1.000	5913
=>.10 and <.2	226	68606	11517	11668	5.7	363	1.013	6111
=>.20 and <.3	80	18827	12191	12380	5.3	362	1.016	6131
=>.30	41	8784	13170	13065	6.0	358	0.992	6372
Missing	45	20458	12114	11489	6.9	436	0.948	6498

Table 6.14 (cont.)

Model 5B Payment Simulation Results

Type of Facility	N Hospitals	N Cases	Avg. Cost Per Case	Avg. Payment Per Case	Percent Outlier Cases	Avg. Outlier Payment	Avg. Payment to Cost Ratio	Adjusted Cost per Case
Teaching Status								
Non-teaching	509	161040	11200	11168	5.7	334	0.997	6110
Resident to ADC <.10	71	28916	10800	11119	4.0	260	1.030	5712
Resident to ADC =>.10 & <.20	23	8184	13335	13119	6.9	566	0.984	6553
Resident to ADC =>.20	15	1899	14105	12862	8.8	805	0.912	7199
Type of Ownership								
Government	49	12990	12389	12270	5.8	397	0.990	6367
Proprietary	141	58862	11588	11218	6.2	397	0.968	6396
Voluntary	401	119838	10942	11169	5.1	301	1.021	5897
Missing	27	8349						
Medicare Days as Percent of Total Days								
0-49	142	48864	10619	10796	4.9	254	1.017	5884
50-64	105	20791	13816	13041	7.8	557	0.944	6862
65-79	134	41335	11985	11735	6.4	450	0.979	6310
80 and above	237	89049	10671	10872	4.9	280	1.019	5901
Alaska and Hawaii	2	1099	12159	13150	2.5	100	1.082	5770
Total Costs Per Case								
25th percentile and below	147	60897	8024	9905	1.5	78	1.234	4508
26th-50th percentile	160	61927	10451	10899	3.4	171	1.043	5763
51st-75th percentile	150	45101	12783	11786	7.3	426	0.922	6977
Above 75th percentile	161	32114	16797	13768	14.6	1024	0.820	8420
Capital Costs Per Case								
25th percentile and below	145	54308	9180	10471	2.7	160	1.141	4952
26th-50th percentile	145	43541	11143	11198	4.8	269	1.005	6011
51st-75th percentile	149	44308	11396	11364	4.9	266	0.997	6130
Above 75th percentile	150	50030	13398	11920	9.5	643	0.890	7288

Table 6.14 (cont.)

Model 5B Payment Simulation Results

	Winners				Losers			
Type of Facility	N Hospitals	N Cases	Percent of Cases	Avg. Profit Per Case	N Hospitals	N Cases	Percent of Cases	Avg. Loss Per Case
All Facilities	288	108721	0.543	1613	330	91318	0.457	1920
By Geographic Area								
Large Urban	129	47402	0.549	1883	140	38988	0.451	2157
Other Urban	131	54804	0.541	1351	157	46426	0.459	1690
Rural	28	6515	0.525	1846	33	5904	0.475	2166
By Region								
New England	18	8364	0.481	1567	26	9038	0.519	1606
Middle Atlantic	33	17002	0.619	1601	20	10449	0.381	1744
South Atlantic	60	29306	0.702	1621	38	12424	0.298	1392
East North Central	59	18338	0.472	1684	84	20512	0.528	1906
East South Central	22	11305	0.643	1512	14	6272	0.357	1813
West North Central	20	4691	0.454	1477	30	5646	0.546	1640
West South Central	33	9886	0.354	1517	63	18046	0.646	2417
Mountain	15	4466	0.587	1394	16	3138	0.413	1654
Pacific	28	5363	0.481	2123	39	5793	0.519	2897
Units of Acute Care Hospitals	234	68956	0.575	1897	246	50999	0.425	2120
Average daily census<10	52	7209	0.468	1906	76	8196	0.532	2487
Average daily census=>10 and <25	128	35228	0.574	2002	127	26103	0.426	2017
Average daily census=>25	54	26519	0.614	1756	43	16700	0.386	2101
Freestanding Hospital	54	39765	0.497	1120	84	40319	0.503	1667
Average daily census<25	6	1359	0.272	1263	21	3635	0.728	3170
Average daily census=>25 and <50	18	9863	0.390	1167	37	15436	0.610	1727
Average daily census=>50	30	28543	0.573	1096	26	21248	0.427	1367
Low-Income Patient Ratio								
<.10	104	44937	0.539	1470	122	38427	0.461	1724
=>.10 and <.2	115	39900	0.582	1722	111	28706	0.418	2034
=>.20 and <.3	39	10916	0.580	1916	41	7911	0.420	2194
=>.30	17	3849	0.438	2341	24	4935	0.562	2013
Missing	13	9119	0.446	1168	32	11339	0.554	2066

Table 6.14 (cont.)

Model 5B Payment Simulation Results

	Winners				Losers			
Type of Facility	N Hospitals	N Cases	Percent of Cases	Avg. Profit Per Case	N Hospitals	N Cases	Percent of Cases	Avg. Loss Per Case
Teaching Status								
Non-teaching	238	85181	0.529	1633	271	75859	0.471	1900
Resident to ADC <.10	34	17908	0.619	1528	37	11008	0.381	1648
Resident to ADC =>.10 & <.20	12	5005	0.612	1546	11	3179	0.388	2990
Resident to ADC =>.20	4	627	0.330	1867	11	1272	0.670	2777
Type of Ownership								
Government	19	6032	0.464	1855	30	6958	0.536	1830
Proprietary	59	30346	0.516	1022	82	28516	0.484	1850
Voluntary	199	67425	0.563	1868	202	52413	0.437	1883
Missing	11	498			16	3431		
Medicare Days as Percent of Total Days								
0-49	74	28069	0.574	1613	68	20795	0.426	1762
50-64	37	7456	0.359	1794	68	13335	0.641	2212
65-79	52	18549	0.449	1841	82	22786	0.551	1953
80 and above	125	54647	0.614	1511	112	34402	0.386	1881
Alaska and Hawaii	1	982	0.894	1226	1	117	0.106	979
Total Costs Per Case								
25th percentile and below	133	57342	0.942	2035	14	3555	0.058	603
26th-50th percentile	105	39298	0.635	1200	55	22629	0.365	860
51st-75th percentile	39	10306	0.229	890	111	34795	0.771	1556
Above 75th percentile	11	1775	0.055	1314	150	30339	0.945	3283
Capital Costs Per Case								
25th percentile and below	105	42859	0.789	1985	40	11449	0.211	1307
26th-50th percentile	68	21736	0.499	1730	77	21805	0.501	1615
51st-75th percentile	73	26739	0.603	1162	76	17569	0.397	1849
Above 75th percentile	31	12943	0.259	903	119	37087	0.741	2308

Table 6.15

Model 5A Payment Simulation Results
FY 1997 Cases

Type of Facility	N Hospitals	N Cases	Avg. Cost Per Case	Avg. Payment Per Case	Percent Outlier Cases	Avg. Outlier Payment	Avg. Payment to Cost Ratio	Adjusted Avg. Cost per Case
All Facilities	618	200039	11257	11257	5.3	337	1.0000	10508
By Geographic Area								
Large Urban	269	86390	11477	11566	5.1	352	1.0077	10307
Other Urban	288	101230	10970	10906	5.3	324	0.9942	10634
Rural	61	12419	12060	11961	5.8	345	0.9918	10885
By Region								
New England	44	17402	11528	11435	4.7	372	0.9919	9982
Middle Atlantic	53	27451	10168	10399	4.5	363	1.0228	9646
South Atlantic	98	41730	10541	11210	3.8	219	1.0634	9964
East North Central	143	38850	11350	11288	4.9	291	0.9945	10590
East South Central	36	17577	11001	11179	4.9	250	1.0162	10842
West North Central	50	10337	10472	10558	4.5	256	1.0082	10285
West South Central	96	27932	12178	11139	8.7	541	0.9147	11724
Mountain	31	7604	10249	10411	5.7	463	1.0158	9929
Pacific	67	11156	15379	14796	7.0	445	0.9621	12234
Units of Acute Care Hospitals	480	119955	11085	11293	4.9	307	1.0187	10271
Average daily census<10	128	15405	11590	11151	6.4	354	0.9621	10704
Average daily census=>10 and <25	255	61331	10884	11186	4.4	270	1.0277	10020
Average daily census=>25	97	43219	11190	11494	5.0	343	1.0271	10473
Freestanding Hospital	138	80084	11514	11203	5.8	383	0.9730	10864
Average daily census<25	27	4994	14657	12892	12.0	905	0.8796	13014
Average daily census=>25 and <50	55	25299	11981	11315	6.9	455	0.9444	11338
Average daily census=>50	56	49791	10962	10977	4.7	295	1.0014	10407
Low-Income Patient Ratio								
<.10	226	83364	10420	10518	4.6	282	1.0094	10101
=>.10 and <.2	226	68606	11517	11529	5.6	368	1.0010	10727
=>.20 and <.3	80	18827	12191	12348	4.9	347	1.0129	10638
=>.30	41	8784	13170	13529	4.4	277	1.0272	10510
Missing	45	20458	12114	11376	7.4	479	0.9391	11311

Table 6.15 (cont.)

Model 5A Payment Simulation Results

Type of Facility	N Hospitals	N Cases	Avg. Cost Per Case	Avg. Payment Per Case	Percent Outlier Cases	Avg. Outlier Payment	Avg. Payment to Cost Ratio	Adjusted Avg. Cost per Case
Teaching Status								
Non-teaching	509	161040	11200	11170	5.4	338	0.9973	10560
Resident to ADC <.10	71	28916	10800	11139	3.7	254	1.0314	9844
Resident to ADC =>.10 & <.20	23	8184	13335	12989	6.7	538	0.9741	11373
Resident to ADC =>.20	15	1899	14105	12942	7.6	731	0.9175	12507
Type of Ownership								
Government	49	12990	12389	12149	5.5	388	0.9807	11085
Proprietary	141	58862	11588	11211	6.5	419	0.9675	11045
Voluntary	401	119838	10942	11180	4.6	291	1.0218	10182
Missing	27	8489						
Medicare Days as Percent of Total Days								
0-49	142	48864	10619	10795	4.9	267	1.0166	10139
50-64	105	20791	13816	13064	6.8	525	0.9456	11910
65-79	134	41335	11985	11744	5.9	437	0.9799	10932
80 and above	237	89049	10671	10862	4.8	287	1.0178	10187
Alaska and Hawaii	2	1099	12159	12880	2.3	95	1.0593	10110
Total Costs Per Case								
25th percentile and below	147	60897	8024	9886	1.5	81	1.2320	7759
26th-50th percentile	160	61927	10451	10848	3.5	183	1.0379	9962
51st-75th percentile	150	45101	12783	11827	6.9	432	0.9252	12092
Above 75th percentile	161	32114	16797	13844	13.5	989	0.8242	14550
Capital Costs Per Case								
25th percentile and below	145	54308	9180	10462	2.6	165	1.1397	8546
26th-50th percentile	145	43541	11143	11221	4.4	263	1.0070	10379
51st-75th percentile	149	44308	11396	11350	4.6	267	0.9959	10617
Above 75th percentile	150	50030	13398	11935	9.3	642	0.8909	12583

Table 6.15 (cont.)

Model 5A Payment Simulation Results

Type of Facility	Winners N Hospitals	Winners N Cases	Winners Percent of Cases	Winners Avg. Profit Per Case	Losers N Hospitals	Losers N Cases	Losers Percent of Cases	Losers Avg. Loss Per Case
All Facilities	297	109248	0.546	1571	321	90791	0.454	1891
By Geographic Area								
Large Urban	136	48355	0.560	1829	133	38035	0.440	2124
Other Urban	130	53730	0.531	1331	158	47500	0.469	1642
Rural	31	7163	0.577	1626	30	5256	0.423	2450
By Region								
New England	19	8658	0.498	1427	25	8744	0.502	1599
Middle Atlantic	31	16066	0.585	1511	22	11385	0.415	1573
South Atlantic	58	27809	0.666	1661	40	13921	0.334	1314
East North Central	64	19835	0.511	1724	79	19015	0.489	1925
East South Central	22	10800	0.614	1421	14	6777	0.386	1803
West North Central	22	5443	0.527	1483	28	4894	0.473	1467
West South Central	33	10319	0.369	1431	63	17613	0.631	2486
Mountain	17	4630	0.609	1412	14	2974	0.391	1785
Pacific	31	5688	0.510	1742	36	5468	0.490	3001
Units of Acute Care Hospitals	243	70407	0.587	1834	237	49548	0.413	2104
Average daily census<10	55	7597	0.493	1817	73	7808	0.507	2634
Average daily census=>10 and <25	136	37234	0.607	1870	119	24097	0.393	2121
Average daily census=>25	52	25576	0.592	1787	45	17643	0.408	1847
Freestanding Hospital	54	38841	0.485	1094	84	41243	0.515	1634
Average daily census<25	7	1557	0.312	1078	20	3437	0.688	3053
Average daily census=>25 and <50	18	9695	0.383	1136	37	15604	0.617	1786
Average daily census=>50	29	27589	0.554	1080	27	22202	0.446	1309
Low-Income Patient Ratio								
<.10	113	45961	0.551	1477	113	37403	0.449	1597
=>,10 and <.2	110	37836	0.551	1677	116	30770	0.449	2037
=>.20 and <.3	40	11114	0.590	1825	40	7713	0.410	2246
=>.30	21	5218	0.594	2100	20	3566	0.406	2189
Missing	13	9119	0.446	990	32	11339	0.554	2127

Table 6.15 (cont.)

Model 5A Payment Simulation Results

	Winners				Losers			
Type of Facility	N Hospitals	N Cases	Percent of Cases	Avg. Profit Per Case	N Hospitals	N Cases	Percent of Cases	Avg. Loss Per Case
Teaching Status								
Non-teaching	243	85075	0.528	1605	266	75965	0.472	1861
Resident to ADC <.10	38	18854	0.652	1429	33	10062	0.348	1703
Resident to ADC =>.10 & <.20	12	4692	0.573	1509	11	3492	0.427	2838
Resident to ADC =>.20	4	627	0.330	1650	11	1272	0.670	2550
Type of Ownership								
Government	18	5630	0.433	1772	31	7360	0.567	1778
Proprietary	59	30027	0.510	1019	82	28835	0.490	1830
Voluntary	209	68673	0.573	1803	192	51165	0.427	1863
Missing	11	4918			16	3431		
Medicare Days as Percent of Total Days								
0-49	78	28574	0.585	1598	64	20290	0.415	1826
50-64	37	7643	0.368	1735	68	13148	0.632	2197
65-79	60	20271	0.490	1619	74	21064	0.510	2031
80 and above	122	52760	0.592	1514	115	36289	0.408	1735
Alaska and Hawaii	1	982	0.894	946	1	117	0.106	1161
Total Costs Per Case								
25^{th} percentile and below	137	58236	0.956	1972	10	2661	0.044	544
26^{th}-50^{th} percentile	105	38760	0.626	1143	55	23167	0.374	854
51^{st}-75^{th} percentile	40	9428	0.209	947	110	35673	0.791	1459
Above 75^{th} percentile	15	2824	0.088	1256	146	29290	0.912	3359
Capital Costs Per Case								
25^{th} percentile and below	110	44162	0.813	1908	35	10146	0.187	1440
26^{th}-50^{th} percentile	72	22031	0.506	1654	73	21510	0.494	1537
51^{st}-75^{th} percentile	71	25327	0.572	1183	78	18981	0.428	1686
Above 75^{th} percentile	33	13284	0.266	871	117	36746	0.734	2306

Table 6.16

Model 6B Payment Simulation Results
FY 1997 Cases

Type of Facility	N Hospitals	N Cases	Avg. Cost Per Case	Avg. Payment Per Case	Percent Outlier Cases	Avg. Outlier Payment	Avg. Payment to Cost Ratio	Adjusted Avg. Cost per Case
All Facilities	618	200039	11257	11258	5.5	337	1.0001	6052
By Geographic Area								
Large Urban	269	86390	11477	11616	5.2	351	1.0121	5889
Other Urban	288	101230	10970	11001	5.3	306	1.0028	6053
Rural	61	12419	12060	10856	8.9	498	0.9001	7178
By Region								
New England	44	17402	11528	11516	4.5	344	0.9989	5696
Middle Atlantic	53	27451	10168	10545	4.2	340	1.0371	5558
South Atlantic	98	41730	10541	11207	3.9	225	1.0632	5775
East North Central	143	38850	11350	11139	5.8	317	0.9815	6119
East South Central	36	17577	11001	11305	4.4	219	1.0277	6186
West North Central	50	10337	10472	10171	5.6	275	0.9713	5969
West South Central	96	27932	12178	11179	8.6	517	0.9180	6736
Mountain	31	7604	10249	10402	6.1	451	1.0149	5716
Pacific	67	11156	15379	14919	8.4	527	0.9701	7004
Units of Acute Care Hospitals	480	119955	11085	11262	5.4	322	1.0159	5928
Average daily census<10	128	15405	11590	10973	7.7	406	0.9467	6338
Average daily census=>10 and <25	255	61331	10884	11143	5.1	294	1.0237	5801
Average daily census=>25	97	43219	11190	11534	5.1	331	1.0307	5962
Freestanding Hospital	138	80084	11514	11251	5.5	361	0.9772	6237
Average daily census<25	27	4994	14657	12705	13.5	988	0.8668	7589
Average daily census=>25 and <50	55	25299	11981	11396	6.6	412	0.9512	6467
Average daily census=>50	56	49791	10962	11032	4.2	271	1.0064	5985
Low-Income Patient Ratio								
<.10	226	83364	10420	10422	4.9	283	1.0002	5881
=>.10 and <.2	226	68606	11517	11665	5.7	365	1.0128	6088
=>.20 and <.3	80	18827	12191	12389	5.3	360	1.0162	6094
=>.30	41	8784	13170	12950	6.1	360	0.9833	6394
Missing	45	20458	12114	11526	6.8	435	0.9515	6445

Table 6.16 (cont.)

Model 6B Payment Simulation Results

Type of Facility	N Hospitals	N Cases	Avg. Cost Per Case	Avg. Payment Per Case	Percent Outlier Cases	Avg. Outlier Payment	Avg. Payment to Cost Ratio	Adjusted Avg. Cost per Case
Teaching Status								
Non-teaching	509	161040	11200	11154	5.7	336	0.9959	6092
Resident to ADC <.10	71	28916	10800	11173	3.9	256	1.0345	5648
Resident to ADC =>.10 & <.20	23	8184	13335	13208	6.5	550	0.9905	6457
Resident to ADC =>.20	15	1899	14105	12938	8.6	787	0.9172	7094
Type of Ownership								
Government	49	12990	12389	12225	6.1	406	0.9868	6378
Proprietary	141	58862	11588	11209	6.2	398	0.9673	6373
Voluntary	401	119838	10942	11184	5.0	299	1.0222	5858
Missing	27	8349						
Medicare Days as Percent of Total Days								
0-49	142	48864	10619	10738	5.0	262	1.0112	5903
50-64	105	20791	13816	13124	7.4	542	0.9499	6763
65-79	134	41335	11985	11771	6.3	449	0.9822	6256
80 and above	237	89049	10671	10868	4.9	279	1.0184	5873
Alaska and Hawaii	2	1099	12159	13255	2.5	95	1.0902	5686
Total Costs Per Case								
25^{th} percentile and below	147	60897	8024	9928	1.5	77	1.2372	4473
26^{th}-50^{th} percentile	160	61927	10451	10892	3.4	170	1.0422	5737
51^{st}-75^{th} percentile	150	45101	12783	11790	7.2	421	0.9223	6930
Above 75^{th} percentile	161	32114	16797	13736	14.8	1036	0.8177	8419
Capital Costs Per Case								
25^{th} percentile and below	145	54308	9180	10497	2.7	163	1.1435	4922
26^{th}-50^{th} percentile	145	43541	11143	11166	4.8	267	1.0020	5993
51^{st}-75^{th} percentile	149	44308	11396	11373	4.9	265	0.9980	6093
Above 75^{th} percentile	150	50030	13398	11909	9.5	643	0.8889	7263

Table 6.16 (cont.)

Model 6B Payment Simulation Results

	Winners				Losers			
Type of Facility	N Hospitals	N Cases	Percent of Cases	Avg. Profit Per Case	N Hospitals	N Cases	Percent of Cases	Avg. Loss Per Case
All Facilities	283	107609	0.538	1651	335	92430	0.462	1921
By Geographic Area								
Large Urban	130	47552	0.550	1964	139	38838	0.450	2097
Other Urban	136	56917	0.562	1380	152	44313	0.438	1702
Rural	17	3140	0.253	1820	44	9279	0.747	2228
By Region								
New England	19	8731	0.502	1561	25	8671	0.498	1597
Middle Atlantic	33	17002	0.619	1668	20	10449	0.381	1723
South Atlantic	57	27222	0.652	1724	41	14508	0.348	1320
East North Central	60	19053	0.490	1622	83	19797	0.510	1974
East South Central	22	11305	0.643	1571	14	6272	0.357	1978
West North Central	19	4557	0.441	1469	31	5780	0.559	1696
West South Central	32	10201	0.365	1515	64	17731	0.635	2445
Mountain	14	4342	0.571	1442	17	3262	0.429	1564
Pacific	27	5196	0.466	2244	40	5960	0.534	2818
Units of Acute Care Hospitals	230	68571	0.572	1916	250	51384	0.428	2144
Average daily census<10	47	6496	0.422	1929	81	8909	0.578	2474
Average daily census=>10 and <25	129	35556	0.580	1967	126	25775	0.420	2099
Average daily census=>25	54	26519	0.614	1843	43	16700	0.386	2038
Freestanding Hospital	53	39038	0.487	1186	85	41046	0.513	1641
Average daily census<25	6	1359	0.272	1344	21	3635	0.728	3184
Average daily census=>25 and <50	18	9969	0.394	1201	37	15330	0.606	1746
Average daily census=>50	29	27710	0.557	1173	27	22081	0.443	1315
Low-Income Patient Ratio								
<.10	102	43678	0.524	1537	124	39686	0.476	1686
=>.10 and <.2	113	40298	0.587	1727	113	28308	0.413	2100
=>.20 and <.3	40	11142	0.592	1907	40	7685	0.408	2280
=>.30	15	3266	0.372	2649	26	5518	0.628	1918
Missing	13	9225	0.451	1199	32	11233	0.549	2054

Table 6.16 (cont.)

Model 6B Payment Simulation Results

	Winners				Losers			
Type of Facility	N Hospitals	N Cases	Percent of Cases	Avg. Profit Per Case	N Hospitals	N Cases	Percent of Cases	Avg. Loss Per Case
Teaching Status								
Non-teaching	233	84069	0.522	1663	276	76971	0.478	1913
Resident to ADC <.10	34	17908	0.619	1584	37	11008	0.381	1597
Resident to ADC =>.10 & <.20	12	5005	0.612	1641	11	3179	0.388	2911
Resident to ADC =>.20	4	627	0.330	1971	11	1272	0.670	2714
Missing								
Type of Ownership								
Government	19	6539	0.503	1693	30	6451	0.497	2046
Proprietary	58	29319	0.498	1092	83	29543	0.502	1839
Voluntary	197	67289	0.561	1889	204	52549	0.439	1866
Missing	9	4462			18	3887		
Medicare Days as Percent of Total Days								
0-49	71	26674	0.546	1697	71	22190	0.454	1778
50-64	38	7606	0.366	1853	67	13185	0.634	2160
65-79	54	19406	0.469	1794	80	21929	0.531	1991
80 and above	120	53923	0.606	1548	117	35126	0.394	1878
Alaska and Hawaii	1	982	0.894	1333	1	117	0.106	885
Total Costs Per Case								
25th percentile and below	132	57022	0.936	2077	15	3875	0.064	653
26th-50th percentile	101	38184	0.617	1242	59	23743	0.383	847
51st-75th percentile	40	10795	0.239	889	110	34306	0.761	1585
Above 75th percentile	10	1608	0.050	1372	151	30506	0.950	3295
Capital Costs Per Case								
25th percentile and below	105	42749	0.787	2033	40	11559	0.213	1330
26th-50th percentile	65	21249	0.488	1741	80	22292	0.512	1616
51st-75th percentile	71	26167	0.591	1222	78	18141	0.409	1818
Above 75th percentile	30	12369	0.247	955	120	37661	0.753	2292

Table 6.17

Model 7B Payment Simulation Results
FY 1997 Cases

Type of Facility	N Hospitals	N Cases	Avg. Cost Per Case	Avg. Payment Per Case	Percent Outlier Cases	Avg. Outlier Payment	Avg. Payment to Cost Ratio	Adjusted Avg. Cost per Case
All Facilities	618	200039	11257	11257	0.055	337	1.0000	5924
By Geographic Area								
Large Urban	269	86390	11477	11554	0.054	360	1.0067	5809
Other Urban	288	101230	10970	10912	0.055	318	0.9947	5995
Rural	61	12419	12060	11993	0.060	332	0.9944	6151
By Region								
New England	44	17402	11528	11412	0.047	356	0.9899	5644
Middle Atlantic	53	27451	10168	10514	0.043	347	1.0340	5475
South Atlantic	98	41730	10541	11259	0.038	216	1.0681	5614
East North Central	143	38850	11350	11101	0.058	320	0.9781	6014
East South Central	36	17577	11001	11349	0.043	210	1.0316	6021
West North Central	50	10337	10472	10220	0.056	272	0.9760	5788
West South Central	96	27932	12178	11154	0.087	518	0.9159	6607
Mountain	31	7604	10249	10460	0.061	450	1.0206	5563
Pacific	67	11156	15379	14990	0.083	528	0.9747	6824
Units of Acute Care Hospitals	480	119955	11085	11270	0.055	323	1.0167	5800
Average daily census<10	128	15405	11590	11154	0.074	394	0.9623	6077
Average daily census=>10 and <25	255	61331	10884	11163	0.052	294	1.0256	5670
Average daily census=>25	97	43219	11190	11465	0.053	340	1.0246	5887
Freestanding Hospital	138	80084	11514	11236	0.055	358	0.9758	6110
Average daily census<25	27	4994	14657	12719	0.130	945	0.8678	7360
Average daily census=>25 and <50	55	25299	11981	11391	0.066	412	0.9507	6330
Average daily census=>50	56	49791	10962	11008	0.043	272	1.0043	5873
Low-Income Patient Ratio								
<.10	226	83364	10420	10402	0.050	285	0.9983	5768
=>.10 and <.2	226	68606	11517	11670	0.057	363	1.0132	5953
=>.20 and <.3	80	18827	12191	12370	0.053	364	1.0146	5979
=>.30	41	8784	13170	13061	0.061	364	0.9918	6220
Missing	45	20458	12114	11553	0.068	428	0.9537	6285

Table 6.17 (cont.)

Model 7B Payment Simulation Results

Type of Facility	N Hospitals	N Cases	Avg. Cost Per Case	Avg. Payment Per Case	Percent Outlier Cases	Avg. Outlier Payment	Avg. Payment to Cost Ratio	Adjusted Avg. Cost per Case
Teaching Status								
Non-teaching	509	161040	11200	11165	0.057	334	0.9969	5955
Resident to ADC <.10	71	28916	10800	11117	0.040	260	1.0293	5561
Resident to ADC =>.10 & <.20	23	8184	13335	13184	0.067	560	0.9887	6349
Resident to ADC =>.20	15	1899	14105	12888	0.089	804	0.9137	6989
Type of Ownership								
Government	49	12990	12389	12295	0.058	396	0.9924	6189
Proprietary	141	58862	11588	11213	0.062	396	0.9676	6233
Voluntary	401	119838	10942	11165	0.051	301	1.0204	5747
Missing	27	8349						
Medicare Days as Percent of Total Days								
0-49	142	48864	10619	10754	0.050	258	1.0127	5760
50-64	105	20791	13816	13143	0.075	544	0.9513	6612
65-79	134	41335	11985	11753	0.064	448	0.9806	6133
80 and above	237	89049	10671	10862	0.049	281	1.0178	5757
Alaska and Hawaii	2	1099	12159	13377	0.024	97	1.1002	5519
Total Costs Per Case								
25th percentile and below	147	60897	8024	9902	0.015	78	1.2340	4395
26th-50th percentile	160	61927	10451	10890	0.034	172	1.0420	5623
51st-75th percentile	150	45101	12783	11787	0.073	427	0.9221	6794
Above 75th percentile	161	32114	16797	13787	0.146	1021	0.8208	8183
Capital Costs Per Case								
25th percentile and below	145	54308	9180	10460	0.027	160	1.1394	4831
26th-50th percentile	145	43541	11143	11188	0.049	271	1.0040	5865
51st-75th percentile	149	44308	11396	11371	0.049	268	0.9978	5970
Above 75th percentile	150	50030	13398	11934	0.094	638	0.8908	7085

Table 6.17 (cont.)

Model 7B Payment Simulation Results

	Winners				Losers			
Type of Facility	N Hospitals	N Cases	Percent of Cases	Avg. Profit Per Case	N Hospitals	N Cases	Percent of Cases	Avg. Loss Per Case
All Facilities	290	108650	0.543	1615	328	91389	0.457	1920
By Geographic Area								
Large Urban	132	47924	0.555	1878	137	38466	0.445	2167
Other Urban	129	54126	0.535	1357	159	47104	0.465	1684
Rural	29	6600	0.531	1815	32	5819	0.469	2202
By Region								
New England	18	8419	0.484	1507	26	8983	0.516	1637
Middle Atlantic	33	17002	0.619	1637	20	10449	0.381	1754
South Atlantic	61	29144	0.698	1618	37	12586	0.302	1369
East North Central	59	18338	0.472	1637	84	20512	0.528	1934
East South Central	22	11305	0.643	1537	14	6272	0.357	1796
West North Central	20	4691	0.454	1450	30	5646	0.546	1665
West South Central	32	9687	0.347	1560	64	18245	0.653	2396
Mountain	16	4551	0.599	1409	15	3053	0.401	1575
Pacific	29	5513	0.494	2183	38	5643	0.506	2902
Units of Acute Care Hospitals	238	69731	0.581	1869	242	50224	0.419	2153
Average daily census<10	53	7294	0.473	1874	75	8111	0.527	2515
Average daily census=>10 and <25	131	35918	0.586	1947	124	25413	0.414	2081
Average daily census=>25	54	26519	0.614	1762	43	16700	0.386	2087
Freestanding Hospital	52	38919	0.486	1159	86	41165	0.514	1637
Average daily census<25	5	1047	0.210	1653	22	3947	0.790	2890
Average daily census=>25 and <50	17	9329	0.369	1234	38	15970	0.631	1656
Average daily census=>50	30	28543	0.573	1116	26	21248	0.427	1389
Low-Income Patient Ratio								
<.10	107	45065	0.541	1446	119	38299	0.459	1740
=>.10 and <.2	114	39701	0.579	1736	112	28905	0.421	2023
=>.20 and <.3	39	10916	0.580	1896	41	7911	0.420	2191
=>.30	17	3849	0.438	2381	24	4935	0.562	2051
Missing	13	9119	0.446	1260	32	11339	0.554	2024

Table 6.17 (cont.)

Model 7B Payment Simulation Results

	Winners				Losers			
Type of Facility	N Hospitals	N Cases	Percent of Cases	Avg. Profit Per Case	N Hospitals	N Cases	Percent of Cases	Avg. Loss Per Case
Teaching Status								
Non-teaching	239	84808	0.527	1639	270	76232	0.473	1898
Resident to ADC <.10	35	18210	0.630	1490	36	10706	0.370	1679
Resident to ADC =>.10 & <.20	12	5005	0.612	1625	11	3179	0.388	2947
Resident to ADC =>.20	4	627	0.330	1896	11	1272	0.670	2752
Type of Ownership								
Government	19	6032	0.464	1889	30	6958	0.536	1814
Proprietary	57	29613	0.503	1041	84	29249	0.497	1810
Voluntary	203	68087	0.568	1844	198	51751	0.432	1909
Missing	11	4916			16	3431		
Medicare Days as Percent of Total Days								
0-49	71	27024	0.553	1628	71	21840	0.447	1713
50-64	39	7908	0.380	1840	66	12883	0.620	2216
65-79	54	18704	0.452	1857	80	22631	0.548	1960
80 and above	126	55014	0.618	1493	111	34035	0.382	1916
Alaska and Hawaii	1	982	0.894	1480	1	117	0.106	982
Total Costs Per Case								
25th percentile and below	132	57030	0.936	2044	15	3867	0.064	574
26th-50th percentile	106	39304	0.635	1196	54	22623	0.365	878
51st-75th percentile	40	10391	0.230	895	110	34710	0.770	1562
Above 75th percentile	12	1925	0.060	1324	149	30189	0.940	3286
Capital Costs Per Case								
25th percentile and below	105	42914	0.790	1971	40	11394	0.210	1322
26th-50th percentile	68	21736	0.499	1724	77	21805	0.501	1630
51st-75th percentile	75	26997	0.609	1169	74	17311	0.391	1888
Above 75th percentile	31	12559	0.251	943	119	37471	0.749	2270

7. OUTLIERS AND SIMULATIONS

In this chapter, we analyze options for the amount of outlier payment to be included in the IRF PPS. Outlier payments are additional payments, beyond the normal CMG payment, made to very expensive cases. Such payments are able to reduce hospitals' financial risk from a PPS (Keeler, Carter, and Trude, 1988). They should reduce the PPS incentive for hospitals to under serve very expensive cases. Also, by targeting payments to cases where the CMG payment is much lower than cost they may help mitigate problems with the classification system. Because outlier cases are not paid full cost, outlier payments cannot completely fix problems with the classification system, only provide some compensation. The drawbacks to outlier payments include that they may, because payments are tied to costs, encourage hospitals to provide care with value less than costs. Further, because charges are used to measure costs, it might be possible for some hospitals to game their charging structure to obtain an unwarranted portion of the outlier payments. Finally, because behavior may change after implementation of the IRFPPS, there is uncertainty about the relationship between the outlier parameters and the total amount of funds that will be spent on outlier payments. Thus, the more outlier payments that are planned, the larger the possible difference between realized total payment and the budget neutrality target.

We simulate payments to evaluate quantifiable outcomes of different targets for the amount of outlier payments. These include: financial risk, the match of payments to costs, and payments to groups of patients and groups of hospitals. We then attempt to weigh the measured effects with other unquantified impacts in order to reach a recommendation.

The simulations also allow us to summarize the performance of a PPS that would incorporate each of our major recommendations for policy: the classification system; payment for short stay transfer cases; HSRV weights; the facility payment adjustment which uses the hospital wage index, rural location, and low-income percentage; and the level of outlier payment. The classification system used for unusual cases is the same one described in Chapter 5. The HSRV weights from Table 5.6

were used. The facility adjustment is from model 5B of Chapter 6. The simulations are based on 1997 data and the method was described in Chapter 2.

In the second major subsection, we return again to the issue of classification of typical cases and evaluate whether the more detailed classification system developed in Chapter 3 would noticeably improve performance compared to the recommended CMGs. We conclude by comparing estimated RPPS payments to TEFRA payments in FY 2001.

OUTLIERS

Outlier Payment Formulas

The simulated case payment includes a fixed-loss outlier policy with the loss threshold, L, chosen so that a fixed percent of total IRFPPS payments would be made as outlier supplements. The outlier threshold for a case in hospital i in CMG k with comorbidity status x is calculated as

$$T_{ik} = R*A_i*W(k,x) + L*A_i, \qquad (7.1)$$

where, as before, R is the national conversion factor, A_i is the hospital's payment adjustment factor, W(k,x) is the relative weight for the case[43], and L is the policy parameter. This fixed loss threshold maximizes the risk protection that can be provided by any fixed amount of outlier payments.

Because the hospital cost report will not be available at the time of payment for the case, the cost of the case is estimated by multiplying the charges for the case by a cost to charge ratio (CCR). The CCR is specific to the hospital and calculated from the hospital’s most recent available cost report and a recent set of MEDPAR records. We need the MEDPAR records in order to estimate the proportion of

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[43] The relative weight for transfer cases is the weight for the CMG-comorbidity combination times the min(1,los/avg_los) where los is the case's length of stay and avg_los is the average LOS for typicals with the same CMG-comorbidity. The fixed loss threshold is multiplied by the hospital's adjustment factor as is appropriate when costs follow the log normal distribution and the adjustment factor is based on measured cost as we recommended in Chapter 6.

inpatient rehabilitation charges for each ancillary department of acute hospitals with exempt unit, and we use the same method for both types of facilities.

The estimated cost of the case, C (=charges*CCR), is compared to the threshold. If C exceeds T_{ik}, then the case receives an outlier payment:

$$OUT = 0.8*(C - T_{ik}).$$

This outlier payment is added to the CMG payment so that total payment for each case is:

$P = R*A_i*W(k,x) + OUT$,

where OUT is 0 for non-outlier cases.

We allow outlier payments to occur for all kinds of cases--including short stay transfers, deaths, and atypically short stay cases. Outlier payments will be very rare for all these unusual cases except deaths.

Simulation Parameters

We simulated policies with outlier payments equal to 0,1,2,3,4, and 5 percent of total IRF PPS payments. The first column in Table 7.1 shows the national conversion factor, R, for each of these runs. The conversion factor is much smaller than the average payment per case because almost all hospitals have adjustment factors that are greater than 1. The case weighted average adjustment factor is 1.85. As the percent of money expended through outlier payments increases, the conversion factor declines to maintain budget neutrality. Thus each non-outlier case receives less payment as more money is spent on outliers. The outlier payment is a redistribution of payment from the low cost cases to the outliers.

Table 7.1 shows the loss threshold (L used in Eq. 7.1) and the effective loss threshold seen by the average case which is just L times the average value of the adjustment factor. So, e.g., a case that cost more than $7,140 more than its payment amount at a hospital with an average adjustment factor would receive some outlier payment under the 5 percent outlier policy. For the 3 percent policy, losses at the same hospital in excess of $10,700 would receive some outlier payment.

Table 7.1

Basic Statistics for Simulation Runs

Policy	Conversion Factor	Average Payment Per Case	Loss Threshold	Adjusted Loss Threshold	Percent of Cases With Some Outlier $	Average Outlier Payment Per Case	Realized Percent Outliers
No outliers	6466	11256	None		0.00	0	0.00
1% outliers	6402	11257	11203	20726	1.26	113	1.01
2% outliers	6337	11257	7548	13964	3.10	225	2.00
3% outliers	6274	11257	5784	10700	5.22	336	2.99
4% outliers	6207	11257	4635	8575	7.59	451	4.01
5% outliers	6144	11257	3860	7140	10.09	562	4.99

Note: Based on simulation of payment to 200,039 cases at 618 hospitals. Average cost per case was $11,257.

Note: Typical adjusted loss threshold is for a hospital with an average value of the hospital adjustment factor (1.85).

The average outlier payment per case is the amount that typical payments per case must be reduced to maintain budget neutrality for the policy. One can view this as the insurance premium that is paid for the outlier protection. The outlier payment is, of course, the indemnity payment to compensate for the loss incurred by an outlier case.

Average outlier payment per outlier declines and the number of outliers increases as the percentage outlier payment increases. The percentage of outlier cases is greater than the percentage of payment to outliers. This suggests that the cost distribution is not very skewed. For example, we have to make outlier payments to 10 percent of all cases in order to spend 5 percent of funds through outlier payments. The last column of Table 7.1 just shows that we implemented the policy as planned.

Outlier Cases

In all policies, outlier payments typically go to cases that would otherwise lose a substantial amount of money. Table 7.2 shows the costs and payments of cases receiving outlier payments under each policy. For example, the cases that receive an outlier supplement under the 1 percent outlier policy cost an average of $44,406, but received CMG payments of only $17,028. Their outlier supplement added $8,978 to their total payment, but still, even after the outlier payment, their payment to cost ratio was still only 0.5856.

Table 7.2

Cost and Payment for Outlier Cases in Each Outlier Policy

Outlier Cases	Number of Outliers	Average Cost	CMG Payment (before outlier)	Average Outlier Payment Per Outlier	Average Total Payment	PTC Ratio	Outlier Payments in Excess of Costs $(000)
1% outliers	2523	44406	17028	8978	26006	0.586	298
2% outliers	6204	36059	15741	7262	23003	0.638	644
3% outliers	10444	31727	14957	6440	21397	0.674	1023
4% outliers	15182	28758	14290	5946	20236	0.704	1452
5% outliers	20175	26538	13705	5573	19278	0.726	1908

There are cases where the CCR used for the entire rehabilitation facility differs substantially from the CCRs for the actual departments where the outlier case received services. Therefore, although most outlier payments go to cases that lose money, there are some cases where the total payment, including the outlier payment, exceeds the case costs.[44]

In so far as outlier payments cause payments that exceed costs they would be better spent increasing the average payment rate. In the last column to Table 7.2, we count the amount of the outlier payments in excess of that needed to cancel all losses. It shows that the amount of such payments increases slightly faster than the percent of outlier payments. Under a 1 percent outlier payments, the total such payments in our simulation is under $300,000; at a 3 percent outlier policy it is $1.0 million and at a 5 percent outlier policy $ 1.9 million. Even with the 5 percent policy, the total amount of these excess payments is less than one-tenth of one percent of total revenues. Thus, with current behavior it does not appear to be a large problem. However, if hospitals attempted to game their charges it could be a bigger problem in the future and therefore warrants monitoring at the hospital level.

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[44] In an operational system the CCR will come from an earlier cost report than the case. We did not simulate this here, but will be able to examine this when we obtain later data.

Risk

Table 7.3 shows the risk statistic--the standard deviation of annual profit expressed as a fraction of expected annual revenue. In the absence of outlier payments, a typical rehabilitation facility manager would face a situation where annual costs had a standard deviation of 3.03 percent of expected revenue due solely to a random draw of patients.

Table 7.3

Risk As A Function of Percent Outlier Payments

	All Hospitals		**Freestanding Hospitals with ADC < 25**		**Unit with ADC < 10**	
Policy and Hospital Group	**Average Value of Risk Statistic**	**Improve-ment from Previous Policy**	**Average Value of Risk Statistic**	**Improve-ment from Previous Policy**	**Average Value of Risk Statistic**	**Improve-ment from Previous Policy**
FRG3						
No outliers	0.0303		0.0466		0.0425	
1% outliers	0.0273	9.8%	0.0424	9.0%	0.0384	9.5%
2% outliers	0.0255	6.7%	0.0384	9.5%	0.0358	6.9%
3% outliers	0.0240	5.6%	0.0350	8.7%	0.0336	6.0%
4% outliers	0.0228	5.1%	0.0325	7.3%	0.0318	5.4%
5% outliers	0.0218	4.4%	0.0307	5.6%	0.0303	4.7%

The smallest hospitals are at most financial risk from a PPS--they will find it much harder to cover the large loss that could be caused by a very small number of very expensive patients. Consequently we also show in the table the average risk faced by the smaller hospitals in our sample. There are 27 freestanding hospitals in our sample with an average daily census of less than 25 patients. They constitute about 20 percent of the freestanding hospitals in our sample and care for about 2.5 percent of the patients in our sample. Exempt units are typically much smaller than freestanding hospitals. A little more than a quarter of the units in our sample have an average daily census of 10 or less. These small units care for 12.8 percent of patients. Although the small units are on average much smaller than the small freestanding hospitals, they have lower risk because they tend to have patient populations with more homogeneous costs.

Financial risk declines as outlier payments increase, but at a declining rate of improvement. In order to help interpret the meaning of the risk statistic we use the fact that, since annual loss is the sum of losses on each patient, the law of large numbers means that annual loss has the normal distribution. Thus we plot in Figure 7.1 the probability that a hospital will experience a loss in excess of 5 percent of revenues from random causes. For a typical hospital, if there were no outlier payments, the probability would be about 5 percent--so once every 20 years a manager could expect such a large problem. If instead the policy were a 3 percent outlier, the probability of such a loss drops to below 2 percent. The rate at which risk declines with increases in outlier payment declines noticeably for typical hospitals and for small units, less so for small freestanding hospitals.

Accuracy at Case Level

By sending additional payments to the most expensive cases, outlier payments significantly improve the accuracy of payment at the case level. In order to measure this effect we regress case level payments on case level cost and show the result in Table 7.4. The scale here is the dollar scale, rather than the log scale. In the absence of any outlier payments, the CMG payments would explain 40.7 percent of case level costs. When even one percent of outlier payments are added, the R-Square rises to 53.2 percent.

The proportion of variation in costs explained by payments increases with the amount of outlier payments. At 5 percent of payments devoted to outlier payments the R-square reaches 68.9 percent. The percentage improvement from previous policy decreases as the outlier payment percentage increases.

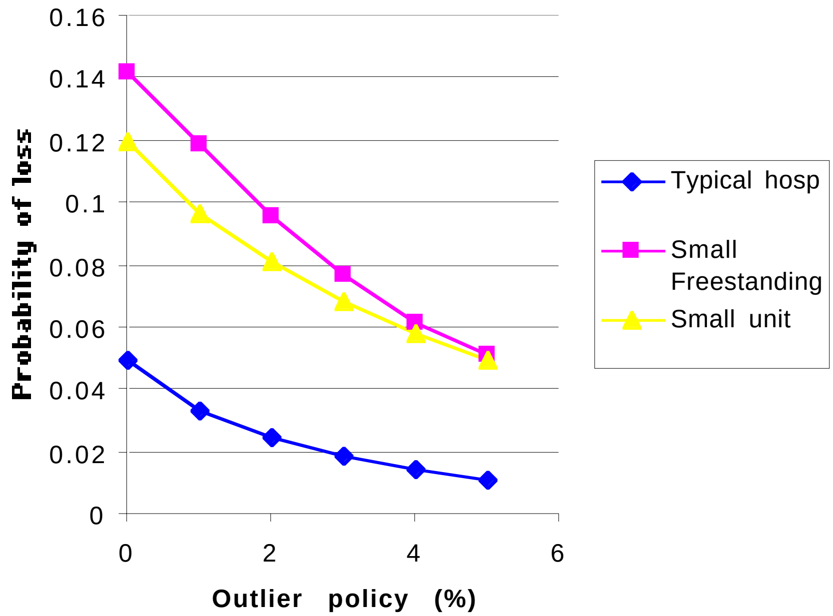

Figure 7.1-Probability of Loss of 5 Percent or More, by Amount of Outlier Payment and Type of Hospital

Table 7.4

Regression of Costs on Payment at Case Level, by Level of Outlier Payments

Policy	Coef.	t-stat	R-square	Improvement from Previous Policy	Improvement from No Outlier Policy
No outliers	1.003	370.631	0.407		
1% outliers	1.051	477.052	0.532	30.7%	30.7%
2% outliers	1.062	532.665	0.587	10.2%	44.1%
3% outliers	1.068	580.189	0.627	7.0%	54.1%
4% outliers	1.072	625.190	0.662	5.5%	62.5%
5% outliers	1.073	665.986	0.689	4.2%	69.3%

Accuracy at Hospital Level

Table 7.5 summarizes the difference between average payments and average cost at the hospital level. In the absence of outlier payments, (and as all statistics here in the absence of behavior change,) the average case would go to a hospital where average costs differ from average payments by $1,945 per case. As outlier payments increase, this number decreases, thus showing that outlier payments are more likely to go to hospitals where costs exceed payment. The root of the mean square error (RMSE), is also a typical difference, but gives more weight to hospitals that have large differences between their costs and payments. We can use this RMSE to calculate the percentage of variance in average cost across hospitals that is explained by payment, which is the Efron R-square. With no outlier payment, payment per case explains 42.6 percent of the hospital variation in cost per case. With 3 percent outlier payment this rises to 58.4 percent, and with 5 percent outliers to 65.5 percent.

Table 7.5

**Accuracy of Hospital-Level Payments.
Root Mean Square Difference Between Payment and Cost and Mean Absolute Difference Between Payment and Cost, by Policy**

Policy	Mean Absolute Deviation	Improvement from Previous Policy	Root-MSE	Efron R-square	Improvement from Previous Policy
No outliers	1945		2580	0.426	
1% outliers	1861	4.3%	2431	0.491	15.1%
2% outliers	1783	4.2%	2306	0.542	10.4%
3% outliers	1711	4.0%	2196	0.584	7.9%
4% outliers	1639	4.2%	2092	0.623	6.6%
5% outliers	1575	3.9%	2000	0.655	5.2%

Note: The statistics are case weighted.

Table 7.6 shows the payment to cost ratios for groups of hospitals for each outlier policy. For almost all groups of hospitals, the amount of outlier payment has little effect on the payment to cost ratio for the group. This is because most outlier cases are widely distributed (as one would expect if they are really random events) and occur in all types of hospitals. This may be seen more directly in Table 7.7, which shows the amount of outlier payment per case.[45]

[45] Rural hospitals and hospitals with greater than average low-income percent are getting their appropriate share of the outlier payments as may be seen by the fact that their outlier payments are very close to average. This validates our assumption of log normal costs and the need to adjust the fixed loss threshold by the hospital payment factor.

Table 7.6

Payment to Cost Ratios for Hospital Classes, by Amount of Outlier Payment

				Payment to Cost Ratio					
Class	Number of Cases	Number of Hosp.	Cost Per Case	FRG3, 0% Outlier	FRG3, 1% Outlier	FRG3, 2% Outlier	FRG3, 3% Outlier	FRG3, 4% Outlier	FRG3, 5% Outlier
All Facilities	200039	618	11257	1.000	1.000	1.000	1.000	1.000	1.000
L Urban	86390	269	11477	1.010	1.011	1.011	1.011	1.010	1.010
O Urban	101230	288	10970	0.992	0.991	0.992	0.992	0.992	0.992
Rural	12419	61	12060	0.993	0.990	0.991	0.992	0.992	0.993
New England	17402	44	11528	0.996	0.998	0.998	0.998	0.998	0.997
Middle Atlantic	27451	53	10168	1.006	1.012	1.013	1.013	1.012	1.012
South Atlantic	41730	98	10541	1.074	1.069	1.066	1.063	1.059	1.057
East North Central	38850	143	11350	0.997	0.995	0.994	0.993	0.993	0.992
East South Central	17577	36	11001	1.029	1.024	1.022	1.020	1.019	1.018
West North Central	10337	50	10472	1.013	1.010	1.009	1.008	1.006	1.005
West South Central	27932	96	12178	0.892	0.897	0.904	0.910	0.916	0.921
Mountain	7604	31	10249	0.993	1.002	1.007	1.009	1.011	1.012
Pacific	11156	67	15379	0.988	0.985	0.985	0.985	0.986	0.987
Unit of Acute Hospital	119955	480	11085	1.022	1.020	1.020	1.019	1.018	1.017
Unit Size < 10	15405	128	11590	0.958	0.957	0.959	0.961	0.963	0.965
10<= Unit Size <25	61331	255	10884	1.034	1.031	1.029	1.028	1.026	1.025
25<= Unit Size	43219	97	11190	1.029	1.030	1.029	1.029	1.028	1.027
Freestanding Hospital	80084	138	11514	0.968	0.970	0.971	0.973	0.974	0.975
Free Size <25	4994	27	14657	0.850	0.864	0.876	0.887	0.896	0.903
25<= Free Size <50	25299	55	11981	0.939	0.942	0.945	0.948	0.951	0.954
50<= Free Size	49791	56	10962	1.000	1.000	0.999	0.998	0.997	0.996
LIP <.1	83364	226	10420	0.996	0.996	0.996	0.995	0.995	0.994
.1<= LIP <.2	68606	226	11517	1.015	1.015	1.015	1.015	1.015	1.015
.2<= LIP <.3	18827	80	12191	1.028	1.028	1.027	1.026	1.024	1.023
.3<= LIP	8784	41	13170	1.009	1.005	1.003	1.002	1.001	1.000
Missing	20458	45	12114	0.933	0.936	0.940	0.944	0.948	0.951
0=tch	161040	509	11200	0.996	0.996	0.997	0.997	0.997	0.998
.0< TCH <.1	28916	71	10800	1.038	1.037	1.033	1.030	1.027	1.025
.1<= TCH <.2	8184	23	13335	0.972	0.978	0.980	0.982	0.984	0.985
.2<= TCH	1899	15	14105	0.904	0.918	0.925	0.928	0.931	0.933
Government	12990	49	12389	0.990	0.992	0.992	0.991	0.991	0.991
Proprietary	58862	141	11588	0.956	0.960	0.962	0.964	0.966	0.968
Voluntary	119838	401	10942	1.026	1.024	1.023	1.022	1.020	1.019
Cert <1985	51226	159	11332	1.029	1.027	1.025	1.023	1.022	1.020
1985<= Cert <1991	60944	173	11022	0.999	0.999	0.998	0.998	0.998	0.998
1991<= Cert	84601	273	11402	0.980	0.982	0.984	0.985	0.986	0.987
Missing	3268	13	10678	1.082	1.076	1.072	1.070	1.069	1.067
% Medicare Days 80 and Above	48864	142	10619	1.015	1.012	1.010	1.010	1.009	1.009
% Medicare Days <5	20791	105	13816	0.949	0.954	0.956	0.958	0.959	0.961
% Medicare Days 50 to 64	41335	134	11985	0.979	0.983	0.985	0.986	0.987	0.987
% Medicare Days 65 to 79	89049	237	10671	1.018	1.016	1.016	1.015	1.014	1.014
Alaska/Hawaii	1099	2	12159	1.112	1.102	1.094	1.086	1.079	1.074

Table 7.6 (cont.)

Cost Quartile-Q1	60897	147	8024	1.251	1.242	1.233	1.224	1.215	1.207
Cost Quartile-Q2	61927	160	10451	1.050	1.044	1.040	1.036	1.033	1.030
Cost Quartile-Q3	45101	150	12783	0.921	0.924	0.926	0.928	0.930	0.932
Cost Quartile-Q4	32114	161	16797	0.797	0.809	0.821	0.831	0.840	0.849
capcs_Q1	54308	145	9180	1.154	1.149	1.143	1.138	1.133	1.128
capcs_Q2	43541	145	11143	1.014	1.011	1.009	1.008	1.006	1.005
capcs_Q3	44308	149	11396	1.005	1.001	0.999	0.998	0.997	0.996
capcs_Q4	50030	150	13398	0.868	0.876	0.883	0.889	0.895	0.901
cmi_q1	57296	155	9486	1.025	1.024	1.023	1.021	1.020	1.019
cmi_q2	61625	154	10501	1.032	1.030	1.027	1.026	1.024	1.023
cmi_q3	49414	155	12145	0.972	0.974	0.976	0.977	0.979	0.980
cmi_q4	31704	154	14542	0.960	0.964	0.966	0.969	0.971	0.973

The only groups of hospitals where one finds noticeably more than a one percentage point change in the payment to cost ratio as a function of outlier policy are found at the bottom of the tables. Going to a 5 percent outlier policy from a no outlier policy reduces the PTC ratio of the 25 percent least costly hospitals from 1.251 to 1.207 and increases the PTC ratio of the 25 percent most costly hospitals from 0.797 to 0.849. Because of the history of TEFRA, we do not know the extent to which the differing costs among these groups reflects inefficiency and different practice patterns versus the extent to which it reflects problems in our case classification system.

The last set of hospital groups in Tables 7.6 and 7.7 are defined based on quartile of the CMI. Although the pattern is not completely linear, hospitals with a CMI that is less than average are slightly overpaid in these runs and those with a higher CMI are underpaid. This is consistent with the case mix compression observed in Chapter 5. Outlier payments provide only a slight amelioration of the compression. For the quartile of hospitals with the highest CMI, the PTC ratio is 0.960 with no outlier payment and 0.973 with a 5 percent outlier policy. Thus outlier payments can only slightly ameliorate the effects of compression and classification error.

Excluding hospital groups specifically defined based on their costliness, the largest deviation from 1 in the PTC ratio is for the small number of freestanding hospitals with an average daily census of less than 25. These hospitals have fewer than 5,000 cases in our sample, but have a PTC ratio of only 0.876. All other groups have PTC ratios within 10 percent of 1 and almost all within 5 percent.

Table 7.7

Outlier Payment Per Case for Hospital Classes, by Amount of Outlier Payment

				Outlier Payment Per Case					
Class	**Number of Cases**	**Number of Hosp.**	**Cost Per Case**	**FRG3, 0% Outlier**	**FRG3, 1% Outlier**	**FRG3, 2% Outlier**	**FRG3, 3% Outlier**	**FRG3, 4% Outlier**	**FRG3, 5% Outlier**
All Facilities	200039	618	11257	0	113	225	336	451	562
L Urban	86390	269	11477	0	127	239	349	464	573
O Urban	101230	288	10970	0	104	215	324	438	548
Rural	12419	61	12060	0	92	218	345	475	598
New England	17402	44	11528	0	144	255	368	480	586
Middle Atlantic	27451	53	10168	0	166	272	370	469	565
South Atlantic	41730	98	10541	0	66	141	218	301	383
East North Central	38850	143	11350	0	92	192	294	403	508
East South Central	17577	36	11001	0	60	146	240	340	441
West North Central	10337	50	10472	0	72	164	256	350	442
West South Central	27932	96	12178	0	168	362	543	726	894
Mountain	7604	31	10249	0	195	340	466	587	698
Pacific	11156	67	15379	0	113	257	414	584	752
Unit of Acute Hospital	119955	480	11085	0	96	201	305	411	514
Unit Size <10	15405	128	11590	0	94	224	359	499	631
10<= Unit Size <25	61331	255	10884	0	80	173	267	364	460
25<= Unit Size	43219	97	11190	0	120	234	340	446	548
Freestanding Hospital	80084	138	11514	0	139	261	383	511	635
Free Size <25	4994	27	14657	0	322	625	900	1165	1397
25<= Free Size <50	25299	55	11981	0	154	303	449	601	747
50<= Free Size	49791	56	10962	0	112	203	298	400	501
LIP <.1	83364	226	10420	0	101	198	295	396	494
.1<= LIP <.2	68606	226	11517	0	118	234	349	467	582
.2<= LIP <.3	18827	80	12191	0	125	233	339	451	560
.3<= LIP	8784	41	13170	0	81	188	302	424	545
Missing	20458	45	12114	0	150	315	474	634	784
0=tch	161040	509	11200	0	109	224	338	456	570
.0< TCH <.1	28916	71	10800	0	97	175	252	335	416
.1<= TCH <.2	8184	23	13335	0	205	359	515	671	818
.2<= TCH	1899	15	14105	0	317	540	714	881	1039
Government	12990	49	12389	0	145	263	379	500	619
Proprietary	58862	141	11588	0	149	286	420	560	692
Voluntary	119838	401	10942	0	94	192	290	392	491
Cert <1985	51226	159	11332	0	103	194	288	386	483
1985<= Cert <1991	60944	173	11022	0	105	209	315	427	535
1991<= Cert	84601	273	11402	0	127	259	385	514	635
Missing	3268	13	10678	0	55	128	221	320	415
% Medicare Days 80 and Above	48864	142	10619	0	73	168	268	374	476
% Medicare Days <5	20791	105	13816	0	197	355	509	667	819
% Medicare Days 50 to 64	41335	134	11985	0	166	302	430	559	681
% Medicare Days 65 to 79	89049	237	10671	0	91	190	290	393	494

Table 7.7 (cont.)

Alaska/Hawaii	1099	2	12159	0	7	42	85	139	205
Cost Quartile-Q1	60897	147	8024	0	26	53	84	117	151
Cost Quartile-Q2	61927	160	10451	0	53	117	186	263	341
Cost Quartile-Q3	45101	150	12783	0	148	290	432	580	723
Cost Quartile-Q4	32114	161	16797	0	347	669	970	1268	1542
capcs_Q1	54308	145	9180	0	59	111	166	224	282
capcs_Q2	43541	145	11143	0	83	173	266	363	460
capcs_Q3	44308	149	11396	0	75	169	265	368	470
capcs_Q4	50030	150	13398	0	230	438	635	835	1021
cmi_q1	57296	155	9486	0	88	169	251	336	420
cmi_q2	61625	154	10501	0	80	164	253	347	438
cmi_q3	49414	155	12145	0	136	276	411	550	682
cmi_q4	31704	154	14542	0	188	366	537	709	873

Outlier Payments and Weights

RICs vary substantially in the amount of outlier payments that they receive under each outlier policy, as shown in Table 7.8. This recalls us to the issue of 'fair weights'--whether the relative CMG weights should be decreased for CMGs that get a higher than average portion of outlier payments. However, the RICs that get high outlier payments (in order, RICs 21,18, 4, 19, and 51) would all, in the absence of outlier payments, have PTC ratios that are less than 1. Similarly, patients with comorbidities tend to get higher than average outlier payments and, in the absence of outlier payments, would have lower PTC ratios than those without. Thus the first few percent of outlier payments tend to improve the fairness of payments across RICs and between those with and without comorbidities.

The general impression that outliers help equalize payments to cost across RICs is quantified in Table 7.9 which shows the mean absolute deviation between the PTC of each RIC and 1 as a function of outlier amount. The first 2 percent of outlier policy increase equality. Although the deviation rises again, at all policies it remains lower than the no outlier policy. If one used fair weights, the variation in PTC ratio would presumably look like the no outlier policy.

Table 7.8

Outlier Payments and Payment to Cost Ratios by RIC and Presence of Comorbidities Under Alternative Outlier Policies

	Average Outlier Payment Per Case					Payment to Cost Ratios					
Patient Group	**1%**	**2%**	**3%**	**4%**	**5%**	**0%**	**1%**	**2%**	**3%**	**4%**	**5%**
RIC											
1	115	264	416	573	723	1.001	0.999	0.999	0.999	1.000	1.000
2	283	500	700	895	1068	0.989	0.998	1.003	1.007	1.010	1.012
3	240	441	617	795	959	1.000	1.008	1.012	1.015	1.018	1.020
4	811	1296	1645	1950	2205	0.948	0.984	1.002	1.012	1.020	1.025
5	206	401	575	741	888	1.004	1.011	1.017	1.021	1.024	1.026
6	165	307	440	574	705	0.991	0.995	0.997	0.999	1.000	1.001
7	36	101	178	265	354	0.999	0.992	0.988	0.986	0.984	0.983
8	16	39	69	106	148	1.025	1.017	1.010	1.004	0.998	0.993
9	73	150	234	325	418	1.000	0.998	0.996	0.995	0.994	0.993
10	218	405	588	765	926	0.979	0.986	0.991	0.996	0.999	1.002
11	155	364	547	723	876	1.005	1.007	1.014	1.019	1.023	1.025
12	81	163	248	346	449	0.933	0.933	0.932	0.931	0.932	0.934
13	96	204	311	419	522	0.947	0.946	0.947	0.948	0.949	0.950
14	148	245	345	447	545	1.002	1.007	1.007	1.007	1.007	1.007
15	486	742	955	1159	1343	0.965	0.995	1.006	1.014	1.020	1.026
16	34	125	210	299	383	1.007	1.001	1.001	1.000	1.000	1.000
17	257	472	653	822	977	0.979	0.989	0.997	1.002	1.005	1.008
18	953	1429	1753	2049	2312	0.938	0.984	1.001	1.011	1.018	1.024
19	618	1003	1342	1658	1923	0.990	1.016	1.029	1.039	1.047	1.053
20	131	262	389	520	645	1.005	1.007	1.009	1.010	1.012	1.014
21	984	1346	1604	1854	2082	0.948	1.002	1.016	1.024	1.030	1.036
50	0	0	0	1	2	1.101	1.090	1.079	1.069	1.058	1.048
51	507	742	915	1069	1206	0.952	0.989	1.001	1.007	1.012	1.015
Comorbidity?											
No	91	189	289	336	500	1.002	1.000	0.999	0.999	0.998	0.998
Yes	335	589	793	992	1172	0.982	0.997	1.005	1.011	1.016	1.019
Total	113	225	336	451	562	1.000	1.000	1.000	1.000	1.000	1.000

If instead of RIC, we presented data for each FRG, we would find that FRGs with higher weights tend to have noticeably more outlier payments and consequently higher PTC. It is this phenomenon which allows the current set of weights to provide some increase in total payment to hospitals with high CMIs and therefore a decrease in CMI compression. This too would be lost with a change to fair weights.

Table 7.9

Mean Absolute Deviation of PTC Ratio by RIC from 1, by Outlier Policy

Policy	Mean Deviation
No outliers	0.026
1% outliers	0.016
2% outliers	0.016
3% outliers	0.018
4% outliers	0.019
5% outliers	0.021

Recommendation

The BBA gives HCFA the latitude to pay up to 5 percent in outlier payments. How much should it pay? The amount of outlier payments must be arrived at from a tradeoff between reducing risk and improving fairness in the system against unwanted gaming with charges and/or unnecessary services. We find that outlier payments in the RPPS affect a substantially higher proportion of patients than they do in the acute PPS for the same percentage of outlier payments. This increases the opportunities to profit from gaming such as that which may have occurred in the acute PPS. Further, we found that the rate at which the benefits of outlier policy increased declined with an increasing amount of outlier payments. Both facts point to limiting the amount of outlier payment below the statutory maximum. Also, the more outlier payments that are planned, the larger the possible difference between realized total payment and the budget neutrality target. Although there is no hard and fast rule, we recommend a 3 percent outlier payment policy. The field's input on this tradeoff could be very useful. Our TEP agreed with the 3 percent recommendation by a large margin (12 to 4).

Our work on outliers points out that, at this stage in development of the IRF PPS, it would be counter productive to use 'Fair Weights' (what MEDPAC calls 'DRG specific outlier funding'). If the classification system and weights were to be improved, this recommendation should be reevaluated.

HCFA may wish to eliminate the possibility of outlier payments to unusual cases: short stay transfers, deaths, and even the tiny amount of outlier payments that might go to atypical low cost cases. As always, we recommend allowing outlier payments in our belief that payment accuracy leads to the greatest exercise of clinical judgment.

A MORE DETAILED CLASSIFICATION SYSTEM

In this section, we return to the issue discussed in Chapter 3--would a more detailed classification system provide more accurate payments? We will compare payments from the CMG system that is based on the recommended FRG system with payments from a similar CMG system that is based on the more detailed FRG system described in Appendix A. We compare the two systems based on accuracy at the patient level and hospital level and on their PTC ratios for groups of hospitals and patients. Because accuracy is affected by level of outlier payments, we use policies of 0, 3, and 5 percent of payments from outliers. The weights for the more detailed CMGs were computed using exactly the same algorithm as was used for the weights for the CMGs based on the recommended FRGs.

For the record, Table 7.10 provides the basic statistics for the new runs. The national conversion factors are almost identical to those with the recommended CMG system. The outlier loss thresholds are less than 1 percent lower.

Table 7.10

Payment Parameters, and Basic Statistics for Runs with More Detailed CMG Systems

Outlier Policy	Con-version Factor	Loss Threshold	Average Payment Per Case	Average Outlier Payment Per Case	Percent of Cases with Outlier Payments	Average Outlier Payment Per Outlier	Realized Percent Outliers
None	6467		11257	0	0.00%	0	0.00%
3%	6274	5755	11256	336	5.21%	6447	2.99%
5%	6144	3838	11256	562	10.08%	5570	4.99%

Note: Based on simulation of payment by 200,039 cases at 618 hospitals. Average cost per case was $11,257.

Patient Level Analysis

We begin with an aspect of performance that was only briefly covered above: payment to groups of patients. We show the payment to cost ratios for groups of patients in Table 7.11. There is almost no difference between the 2 CMG systems in any of the PTC ratios. Outlier payments also have only a minor effect. Although the 3 percent outlier policy does move many ratios closer to 1 from the 0 percent outlier system, it has a very small opposite affect for sex and marital status.

Although male patients' average cost is almost 10 percent more than that of female patients, and gender is not used as a potential classification variable, our classification system explains these differences and the PTC ratios of the 2 groups are almost 1. Similarly, although age only rarely affects classification, the PTC ratios are typically very close to 1, especially with the 3 percent outlier policy. The only exception is the relatively small group of those 95 and older who are paid a little more relative to their costs. Patients who are not married are paid somewhat less than their costs, while those who are married are paid somewhat more than their costs.

Table 7.11 also shows PTC ratios for transfer cases in order to examine the effect of the policy decisions. Despite a per diem payment equal to that of typical cases in the CMG and the lack of an additional per case payment, in the 0 outlier policy, short stay transfers are paid almost identically to costs. We believe this is because the weight depends on both typical and long stay transfer cases, but we divided by the average LOS of only typical cases to determine the per diem weight. Adding outlier payments decreases the PTC for short stay atypicals because these cases hardly ever receive outlier payments.

Because long stay transfers (like long stay typicals) are paid less than their costs, the average transfer payment is substantially lower than its costs (87.8 percent of costs for the recommended FRGs and a 3 percent outlier policy).

In the absence of outlier payments, atypical short stay cases are slightly overpaid relative to their costs, and deaths are slightly underpaid. Outlier payments help ameliorate the inequality. This may require further investigation, although the answer probably lies in the relatively small sample size.

Table 7.11

Average Cost Per Case and Payment to Cost Ratios for Patient Groups, by CMG System and Outlier Policy

			More Detailed FRGs			Recommended FRGs		
Patient Characteristic	**Number of Cases**	**Cost**	**0% Outlier**	**3% Outlier**	**5% Outlier**	**0% Outlier**	**3% Outlier**	**5% Outlier**
Total	200039	11257	1.000	1.000	1.000	1.000	1.000	1.000
Male	75895	11910	0.998	1.005	1.007	0.997	1.004	1.007
Female	124144	10858	1.002	0.997	0.995	1.002	0.997	0.995
Age								
Below 65	16396	12401	0.971	0.994	1.000	0.967	0.990	0.997
65 - 69	27327	11448	0.988	0.996	0.998	0.984	0.993	0.996
70 - 74	39647	11113	1.000	1.002	1.003	1.001	1.004	1.005
75 - 79	46785	11103	0.999	0.998	0.998	1.005	1.003	1.002
80 - 84	38606	11138	1.010	1.002	1.000	1.009	1.001	0.999
85 - 89	22331	11139	1.009	0.998	0.995	1.003	0.992	0.989
90 - 94	7466	10868	1.032	1.017	1.010	1.036	1.020	1.013
95 and Above	1481	10652	1.067	1.048	1.040	1.077	1.058	1.049
Currently Unmarried	112869	11255	0.983	0.981	0.981	0.982	0.981	0.981
Married	87170	11259	1.023	1.025	1.025	1.023	1.025	1.025
No Comorbidity	181450	11012	1.002	0.999	0.998	1.002	0.999	0.998
With Comorbidity	18589	13650	0.980	1.009	1.018	0.982	1.011	1.019
No Transfers	157844	10837	1.044	1.038	1.036	1.044	1.039	1.036
All Transfers	42195	12828	0.862	0.879	0.886	0.860	0.877	0.885
Long Stay Transfers	14259	20142	0.741	0.793	0.819	0.736	0.790	0.815
Short Stay Transfers	27936	9095	1.001	0.977	0.964	1.001	0.977	0.964
Atypical Short Stay	3400	2056	1.100	1.067	1.046	1.101	1.069	1.048
Deaths	950	9766	0.952	1.007	1.015	0.952	1.007	1.015

We also calculated PTC ratios for each RIC from the more detailed classification systems and found them almost identical to those presented earlier in Table 7.8 so we do not present the details. Table 7.12, however, summarizes the amount of inequality across RICs using the more detailed FRGs and compares them to similar data from Table 7.9 for the recommended CMGs. The only difference at this significance level is for the no outlier policy.

Table 7.12

Mean Absolute Deviation of PTC Ratio by RIC from 1, by CMG System and Outlier Policy

	Mean Deviation	
Policy	**Detailed FRGs**	**Rec. FRGs**
No outliers	0.025	0.026
3% outliers	0.018	0.018
5% outliers	0.021	0.021

In order to examine patient level accuracy, the first section of Table 7.13 shows the statistics of a case level regression of cost on payment using the more detailed CMGs. The next three columns of Table 7.13 repeats the relevant lines of Table 7.4 in order to make comparison easy. Despite having almost 50 percent more groups, the more detailed CMGs improve the percentage of variance in patient level cost that is explained by payment by less than one percent. With a 3 percent outlier policy the improvement drops to less than one-half of 1 percent.

Table 7.13

Regression of Costs on Payment at Case Level, by CMG System and Amount of Outlier Payment

	More Detailed FRGs			Recommended FRGs			R-square
Policy	**Coef.**	**t-stat**	**R-square**	**Coef.**	**t-stat**	**R-square**	**Improve-ment (%)**
No outliers	1.001	373.631	0.411	1.003	370.631	0.407	0.96%
3% outliers	1.066	583.912	0.630	1.068	580.189	0.627	0.46%
5% outliers	1.071	669.906	0.692	1.073	665.986	0.689	0.36%

Hospital Level Analysis

We just saw that the more detailed FRGs seem to have little effect on accuracy at the patient level or on payment for groups of patients. Here we show that they also have little effect at the hospital level.

Table 7.14 shows the value of the risk statistic for the more detailed FRGs and repeats the information for the recommended FRGs from Table 7.3. The more detailed FRGs have very little effect on risk for all hospitals or for the very small hospitals. For the small freestanding hospitals, risk is even a tiny bit worse with the more detailed FRGs.

Table 7.14

Risk Statistic for All Hospitals and Small Hospitals as a Function of the CMG Classification System and Percent Outlier Payments

Outlier Policy and Hospital Group	Detailed FRGs	Recommended FRGs	Improvement (%)
All Hospitals			
No Outliers	0.0302	0.0303	0.39%
3% Outliers	0.0239	0.0240	0.51%
5% Outliers	0.0217	0.0218	0.51%
Freestanding ADC < 25			
No Outliers	0.0469	0.0466	-0.65%
3% Outliers	0.0351	0.0350	-0.07%
5% Outliers	0.0307	0.0307	-0.20%
Unit ADC < 10			
No Outliers	0.0422	0.0425	0.54%
3% Outliers	0.0334	0.0336	0.59%
5% Outliers	0.0301	0.0303	0.66%

Table 7.15 compares the hospital level accuracy of the CMGs based on the detailed FRGs with those from the recommended FRGs. The only differences are single digit differences in the fourth significant digit. And the detailed FRGs are as likely to increase error as to decrease it.

Table 7.15

Accuracy of Hospital Level Payments by CMG System and Outlier Policy

	Mean Absolute Deviation			Root-MSE		
Policy	Detailed FRGs	Recommended FRGs	Improvement (%)	Detailed FRGs	Recommended FRGs	Improvement (%)
No Outliers	1946	1945	-0.1%	2581	2580	0.0%
3% Outliers	1712	1711	0.0%	2196	2196	0.0%
5% Outliers	1575	1575	0.0%	1999	2000	0.0%

Table 7.16 gives the PTC for groups of hospitals from the more detailed CMGs. They are almost identical to the PTC ratios with the same outlier policy from Table 7.6. It is interesting that the more

detailed CMGs have so little effect on the CMI compression in the weights. Again there is little reason to prefer the more detailed CMGs. (Because the CMIs change, several hospitals are in different quartiles in Table 7.16 than in Table 7.6.)

Table 7.16

Payment to Cost Ratios for Hospital Classes from the More Detailed CMGs, by Amount of Outlier Payments

				Payment to Cost Ratio		
Class	Number of Cases	Number of Hosp.	Cost Per Case	FRG3, 0% Outlier	FRG3, 3% Outlier	FRG3, 5% Outlier
All Facilities	200039	618	11257	1.0000	0.9999	0.9999
L Urban	86390	269	11477	1.0097	1.0100	1.0093
O Urban	101230	288	10970	0.9922	0.9920	0.9925
Rural	12419	61	12060	0.9932	0.9920	0.9930
New England	17402	44	11528	0.9932	0.9955	0.9945
Middle Atlantic	27451	53	10168	1.0055	1.0117	1.0107
South Atlantic	41730	98	10541	1.0750	1.0634	1.0575
East North Central	38850	143	11350	0.9976	0.9937	0.9925
East South Central	17577	36	11001	1.0291	1.0201	1.0177
West North Central	10337	50	10472	1.0115	1.0057	1.0032
West South Central	27932	96	12178	0.8915	0.9094	0.9205
Mountain	7604	31	10249	0.9966	1.0122	1.0146
Pacific	11156	67	15379	0.9892	0.9867	0.9888
Unit Size < 10	15405	128	11590	0.9575	0.9598	0.9641
10 <= Unit Size < 25	61331	255	10884	1.0334	1.0270	1.0241
25 <= Unit Size	43219	97	11190	1.0290	1.0286	1.0266
Free Size < 25	4994	27	14657	0.8516	0.8877	0.9044
25 <= Free Size < 50	25299	55	11981	0.9386	0.9480	0.9541
50 <= Free Size	49791	56	10962	1.0012	0.9984	0.9968
Unit of Acute Hospital	119955	480	11085	1.0216	1.0186	1.0169
Freestanding Hospital	80084	138	11514	0.9687	0.9731	0.9754
LIP <.1	83364	226	10420	0.9961	0.9946	0.9936
.1 <= LIP < .2	68606	226	11517	1.0153	1.0153	1.0151
.2 <= LIP < .3	18827	80	12191	1.0277	1.0248	1.0224
.3 <= LIP	8784	41	13170	1.0123	1.0049	1.0030
Missing	20458	45	12114	0.9332	0.9444	0.9513
0=tch	161040	509	11200	0.9965	0.9968	0.9975
.0 < TCH < .1	28916	71	10800	1.0374	1.0298	1.0242
.1 <= TCH < .2	8184	23	13335	0.9742	0.9837	0.9867
.2 <= TCH	1899	15	14105	0.9053	0.9287	0.9335
Government	12990	49	12389	0.9903	0.9913	0.9906
Proprietary	58862	141	11588	0.9569	0.9646	0.9688
Voluntary	119838	401	10942	1.0253	1.0212	1.0190

Table 7.16 (cont.)

Cert < 1985	51226	159	11332	1.0301	1.0248	1.0213
1985 <= Cert < 1991	60944	173	11022	0.9989	0.9976	0.9974
1991 <= Cert	84601	273	11402	0.9796	0.9841	0.9864
Missing	3268	13	10678	1.0812	1.0695	1.0658
% Medicare Days 80 and Above	48864	142	10619	1.0143	1.0093	1.0085
% Medicare Days < 50	20791	105	13816	0.9498	0.9583	0.9616
% Medicare Days (50 to 64)	41335	134	11985	0.9783	0.9850	0.9864
% Medicare Days (65 to 79)	89049	237	10671	1.0186	1.0152	1.0139
Alaska/Hawaii	1099	2	12159	1.1236	1.0969	1.0836
Others	198940	616	11252	0.9992	0.9994	0.9994
Cost Quartile-Q1	60897	147	8024	1.2489	1.2220	1.2054
Cost Quartile-Q2	61927	160	10451	1.0509	1.0373	1.0310
Cost Quartile-Q3	45101	150	12783	0.9221	0.9283	0.9325
Cost Quartile-Q4	32114	161	16797	0.7966	0.8305	0.8487
capcs_Q1	54308	145	9180	1.1535	1.1370	1.1265
capcs_Q2	43541	145	11143	1.0143	1.0079	1.0048
capcs_Q3	44308	149	11396	1.0045	0.9977	0.9955
capcs_Q4	50030	150	13398	0.8687	0.8901	0.9016
cmi_q1	58464	160	9439	1.0282	1.0235	1.0203
cmi_q2	61572	150	10668	1.0179	1.0142	1.0125
cmi_q3	48600	154	12079	0.9790	0.9816	0.9836
cmi_q4	31403	154	14526	0.9671	0.9746	0.9782

IMPACT ANALYSES

Table 7.17 shows the results of our simulation of payments in FY 2001. The national conversion factor is 6,118, which produces PPS payments equal to 94 percent of the FY 2001 TEFRA payments for the sample of cases for which we have case mix and TEFRA data. In FY 2001 the actual payment will be one-third of the PPS payment and two-thirds of the TEFRA payment. Thus the total payment will be the mandated 98 percent of the TEFRA payment. The fixed loss threshold is 7,145.

As explained in Chapter 2, the number of hospitals and cases in this simulation is lower than the number of hospitals and cases in our FY 1997 simulations because HCFA projected TEFRA costs and payments only for existing hospitals with cost reports for PPS 12, 13, and 14.

Despite the different sample size and the different estimate of average case cost, most of the conclusions about the groups of hospitals that do well (i.e., PTC ratios greater than average) and poorly from the FY 1997 simulations show up here to. For example, free standing hospitals and those in the West South Central Census region do relatively poorly under the RPPS. However, there are groups whose performance differs in this table. In particular, rural hospitals which have just an average PTC ratio in the 1997 simulations, do better than average here.

Table 7.17

Impact of FY2001 IRF PPS Payment on Classes of Hospitals

Class	Number of Cases	Number of Hosp.	PPS Payment Per Case	TEFRA Payment Per Case	Phased Payment Per Case	Cost Per Case	Payment to Cost Ratio	Payment to TEFRA Payment Ratio
All Facilities	167390	505	11091	11799	11563	11833	0.977	0.980
L Urban	69344	218	11567	12203	11991	12211	0.982	0.983
O Urban	88232	238	10670	11495	11220	11535	0.973	0.976
Rural	9814	49	11519	11688	11632	11837	0.983	0.995
New England	15320	37	11167	11871	11637	12192	0.954	0.980
Middle Atlantic	24937	46	10317	11086	10829	11042	0.981	0.977
South Atlantic	34845	79	10937	11131	11066	11116	0.995	0.994
East North Central	33018	120	11131	11763	11552	11770	0.981	0.982
East South Central	12344	26	10994	11108	11070	10996	1.007	0.997
West North Central	9175	44	10536	11136	10936	11247	0.972	0.982
West South Central	22995	73	10803	12528	11953	12567	0.951	0.954
Mountain	5659	25	10603	12033	11556	12095	0.956	0.960
Pacific	9097	55	15264	15950	15721	16080	0.978	0.986
Unit of Acute Hospital	101518	398	11134	11453	11346	11509	0.986	0.991
Unit Size < 10	12962	102	10824	11361	11182	11533	0.970	0.984
10 <= Unit Size < 25	51783	211	10952	11225	11134	11242	0.990	0.992
25 <= Unit Size	36773	85	11500	11805	11703	11876	0.985	0.991
Freestanding Hospital	65872	107	11026	12334	11898	12333	0.965	0.965
Free Size < 25	3527	18	13444	15391	14742	15465	0.953	0.958
25 <= Free Size < 50	19248	40	11038	12251	11846	12261	0.966	0.967
50 <= Free Size	43097	49	10823	12121	11688	12108	0.965	0.964
LIP < .1	76374	197	10285	11058	10801	11070	0.976	0.977
.1 <= LIP < .2	56138	190	11603	12124	11950	12162	0.983	0.986
.2 <= LIP < .3	13308	58	12356	13213	12927	13378	0.966	0.978
.3 <= LIP	7191	32	13223	13457	13379	13433	0.996	0.994

Table 7.17 (cont.)

Missing	14379	28	11141	12331	11934	12374	0.964	0.968
0=tch	132437	407	10971	11671	11438	11704	0.977	0.980
.0 < TCH < .1	26377	67	11023	11584	11397	11579	0.984	0.984
.1 <= TCH < .2	7309	20	13165	14401	13989	14583	0.959	0.971
.2 <= TCH	1267	11	13168	14656	14160	14704	0.963	0.966
Government	10419	40	12303	13740	13261	13878	0.956	0.965
Proprietary	51353	117	11079	12251	11860	12261	0.967	0.968
Voluntary	105618	348	10978	11389	11252	11423	0.985	0.988
Cert. < 1985	46939	148	11617	12145	11969	12292	0.974	0.986
1985 <= Cert. < 1991	57222	162	10880	11745	11457	11761	0.974	0.975
1991 <= Cert.	62149	191	10892	11605	11367	11572	0.982	0.980
Missing	1080	4	10961	10806	10858	10698	1.015	1.005
% Medicare Days 80 and above	41727	115	10366	10670	10568	10602	0.997	0.991
% Medicare Days <50	17528	85	13386	15008	14467	15268	0.948	0.964
% Medicare Days (50 to 64)	31504	105	11790	12763	12438	12881	0.966	0.975
% Medicare Days (65 to 79)	76631	200	10675	11285	11081	11287	0.982	0.982
Alaska/Hawaii	1099	2	13366	13877	13706	13666	1.003	0.988
Q1	52341	129	9671	8647	8988	8580	1.048	1.039
Q2	54614	136	10719	11444	11202	11386	0.984	0.979
Q3	36495	125	11673	13252	12725	13415	0.949	0.960
Q4	23940	115	14161	17290	16247	17555	0.925	0.940
capcs_Q1	47534	126	10396	9950	10098	9888	1.021	1.015
capcs_Q2	38473	124	11082	11932	11649	11894	0.979	0.976
capcs_Q3	38689	133	11174	11769	11571	11869	0.975	0.983
capcs_Q4	42694	122	11799	13767	13111	13910	0.943	0.952

The calculation of the national conversion rate here will meet the budget neutrality target if and only if the relationship between IRF PPS payments and TEFRA payments in our sample is the same as in the population. We will address this and other issues in our future research discussed in the next chapter.

8. FUTURE RESEARCH

In the remainder of this project, we will address several issues that might affect the initial implementation of the IRF PPS and also work on longer range issues of monitoring and refining the system. Our work plan (Carter, Relles, Wynn, 2000) gives our general research approach to the implementation, monitoring, and refinement tasks. Here, we provide details in a few areas which have become clearer since that work plan was written.

UPDATING WITH LATER DATA

We intend to obtain MEDPAR and FIM discharge data covering calendar years 1998 and 1999, an updated PPS14 HCRIS file, and a PPS15 HCRIS file. This additional data will allow us to analyze trends in case mix, discharge setting, and cost which is essential for adequate development of a monitoring system.

We will rerun the classification analyses, weights, and facility adjustment analyses with the newest data to ensure that the system adequately represents the current inpatient rehabilitation system. This will give us an opportunity to incorporate suggestions from the Technical Expert Panel (TEP) and others about areas where our recommendations could be improved.

POTENTIAL MODIFICATIONS TO THE CLASSIFICATION SYSTEM FOR TYPICAL CASES

We intend to improve the functional rehabilitation groups that are the basis for the CMGs for typical cases by exploring several avenues.

(1) We will develop a ‘gold standard’ model which utilizes the current CART input (RIC, FIM motor score, FIM cognitive score, age, and comorbidity) as well as possible additional information such as individual FIM items or subscales of the motor and cognitive scales. This model will not be developed via CART but will rather provide the statistically best prediction of case costs from the available data. Its performance will be compared to every proposed set of FRGCs in

order to develop a set of groups which predicts ‘almost as well’ as any model that can be built with our data.

(2) We will obtain clinical advice about the appropriateness of alternative FRGCs from (one or more) subcommittees of our Technical Expert Panel. We will have TEP members evaluate our comorbidity list and suggest modifications. We will have them examine the qualitative nature of the trees and determine if they reflect real clinical phenomena. For example, is it reasonable that cognitive function matters only for those with higher motor function? Should we restrict the age cuts to pre-selected groups (e.g. <65, <75, <85)? Should we standardize the motor score cuts?

(3) We will run CART on the 1998 and 1999 data and examine the stability of the individual trees in each RIC. Based on this and on the clinical advice just discussed, we will develop one or more set of FRGCs which we believe are reasonable candidates for the final payment system.

(4) We will develop an algorithm for updating the FRGCs over time. Many members of our TEP believed that they needed stability in the classification system. We found that old FRGCs predict quite well on new data (Carter et al., 2000; Carter, Relles, et al., 1997). Nevertheless, it is important that the FRGCs be updated when new practices are introduced for subsets of patients or when the rehabilitation population changes because of changes in practice patterns. Our analyses will develop criteria for detecting when changes are required and methods for marginal changes in the groups without the wholesale change introduced via CART.

(5) We will evaluate alternatives via (1) comparing the loss in explanatory power compared to the gold standard model, (2) comparing the stability of the predictions over time, and (3) payment simulations.

WEIGHTS AND COMPRESSION

We found in Chapter 5 that the CMG relative weights for typical cases exhibit CMI compression--i.e., hospitals with high CMIs have higher standardized costs relative to their CMI than hospitals with low CMIs. The direction of the effect remains when we simulate payments to all cases, use the best payment adjustment factors, and allow outlier payments. For example, using the 3 percent outlier policy and the recommended CMGs, the PTC for the 25 percent of hospitals with the highest CMIs is 0.969 while the average PTC ratio for the hospitals with lower than median CMIs is greater than 1.

Theoretical Causes of Compression

It seems unlikely that hospitals with a high CMI are on average more efficient than those with a lower CMI. Further, we found that increasing the number of classification categories has only a tiny effect on CMI compression so we don't think that the hospitals with a high CMI are consistently getting patients that are more costly within each CMG and identifiable from their FIM scores, comorbidities, and/or age.

A more likely explanation for the CMI compression is that the resources needed by CMGs with high relative weights are underestimated by our relative weights and those with low relative weights are overestimated. Three reasons for such weight compression are usually given:[46] (1) Each hospital is assigned just one per diem for routine cost yet per diem nursing costs may vary by FRGC. (2) A single cost-to-charge ratio is used within each ancillary department. Some observers believe that acute care prices are set so that low cost services subsidize higher cost services, even within a particular ancillary department. To the extent that this is true in rehabilitation facilities, then the cost-based weights of CMGs that use those low cost services (which might be low cost CMGs) will be overestimated and the cost-based weights of CMGs that use the higher cost services will be underestimated. (3) Errors in classification of cases into CMGs will tend to make the weights more similar than they should be. Pettengill

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[46] See Lave (1986) or Carter and Rogowski (1992).

and Vertrees (1982) used simulation to show the effect of varying amounts of classification error on weight compression.

A First Cut at the Evidence

Table 8.1 provides basic cost and utilization information for the hospitals in our 1997 analysis sample by their CMI quartile. As one can see from the average values in each quartile there is a large spread across hospitals in CMIs and costs. After the costs per case at each hospital are adjusted for its CMI and payment factor the difference is greatly reduced, but still hospitals with CMIs lower than the median have approximately $600 lower adjusted costs than those with CMIs in the higher half of the distribution. It is this discrepancy that we need to understand better, and eliminate if possible.

Table 8.1

Mean Cost and Utilization Statistics for Hospitals Grouped by CMI Quartile

	Quartile 1	**Quartile 2**	**Quartile 3**	**Quartile 4**
CMI	0.8589	0.9783	1.0589	1.2125
Cost	9486	10501	12145	14542
Standardized for CMI and Adj. Factor	11225	11099	11793	11648
Routine Cost Per Day	420	407	441	477
Standardized for Wages	423	419	459	473
LOS Non-transfer Cases	13.54	15.13	16.29	18.01
Ratio LOS to Expected ALOS	1.002	0.999	1.005	0.992
% Transfers to Hospitals	6.14%	7.74%	8.30%	8.53%
Ratio to Expected	1.0242	1.0414	1.0125	0.8918
% Short Stay Hospital Transfers	4.78%	6.14%	6.47%	6.81%
% SNF/NH Transfers	11.10%	13.07%	14.23%	17.82%
Ratio to Expected	1.1065	0.9969	0.9439	0.9707
% Short Stay SNF/NH Transfers	6.66%	7.43%	8.30%	11.26%
% Comorbidities	6.88%	8.37%	9.59%	11.54%

Note: Based on 1997 analysis sample. Expected values are based on the CMG distribution of cases.

The discrepancy across CMI quartiles in the routine cost for each day is consistent with the hypothesis that using a single per diem for all patients is a major cause of compression.[47]. If nursing costs are positively correlated with CMG weight, then the weights for high weight CMGs are lower than they should be. The magnitude of the difference in per diem costs is substantial enough to be a numerically important cause of compression.

Table 8.1 also shows the average LOS of non-transfer cases in each CMI quartile. Of course LOS rises with the CMI as the hospitals get patients with a need for more rehabilitation. To see whether practice patterns might be affecting the compression, we compare the average LOS in each group to the average LOS of all non-transfer patients in the same set of CMGs. These ratios are almost exactly 1 in all quartiles. Thus we believe that the compression is not seriously influenced by differential practice patterns in each quartile with respect to LOS. This is consistent with our presumption that efficiency does not differ substantially across quartiles.

Transfer rates also increase with CMI quartile. The differences in transfer rates to SNF are largely explained by the differences in case mix as the ratio to expected transfer rate is close to 1 for all groups but the first quartile. The lower than average rate of transfers to hospitals in the highest CMI quartile is interesting and may reflect a greater typical effort spent in keeping the patients in their rehabilitation beds. Although the extra care for less than 1 percent of patients (0.0092=(1-0.892)*0.0853) is unlikely to be a numerically important cause of the compression, it merits investigation in the refinement portion of our project.

The last row of Table 8.1 shows that, as we would expect, cases with comorbidity occur much more frequently in the hospitals with the higher CMIs. We expect that comorbidities are under coded on our data set. If so, these errors in classification of cases into CMGs will tend to make the weights more similar than they should be, and tend to compress the weights. Although this still involves only a fraction of cases, the fraction is possibly large enough to contribute to (but not explain) the existing compression.

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[47] The discrepancy in per diems is also consistent with the hypothesis of a problem with the wage index.

Research Plans

In the short run, we intend to address the possibility of compression in the CMG weights due to comorbidity coding and variation in nursing costs.

We will use the MEDPAR record for each patient's preceding acute stay to examine coding. The acute stay record was identified for approximately 80 percent of 1996 and 1997 patients. We expect that, because comorbidities affect payment in the acute PPS, they are more accurately coded on these records. We will begin by examining how frequently chronic diseases that one would expect to persist are coded on each record. We would expect that these would be more frequently coded on the acute record than on the rehabilitation record.

We will also analyze whether relevant comorbidities that appear in the acute stay record and do not appear on the rehabilitation record increase the cost of the rehabilitation stay after controlling for CMG. If so, we would expect that these comorbidities would be coded under the IRF PPS and we could use them to classify cases with comorbidities and thereby improve the weights.

We also plan to study how nursing costs vary with the patient characteristics related to CMG assignment. In the summer of 2000, the Aspen Systems Corporation will gather staff time data along with MDS-PAC (and some FIM) data. We intend to analyze this data to examine how, if at all, nursing time varies systematically with RIC, the FIM motor score, FIM cognitive score, comorbidity, and age.

If we can build a model which predicts nursing time as a function of the patient characteristics that affect CMG assignment, we can improve our weight calculation. We would use the model to determine how nursing time varies as a function of CMG and then go from this model to an estimate of how relative routine cost per diems vary as a function of CMG. The details will depend on the model for nursing time. Once we have relative routine care per diem costs per CMG, we can allocate the observed routine costs at each hospital across the patients at that hospital. We would then use the better estimates of routine costs per patient to improve the weights.

UPDATING FACILITY LEVEL ADJUSTMENTS

We will update our recommended facility adjustments using the 1998 and 1999 data. In addition, based on our TEP meeting, we will consider the possibility of two new factors for facility adjustments and perform certain additional analyses related to our existing recommendations.

Freestanding Hospitals

The possibility of an adjustment for freestanding hospitals was raised at the TEP because of the lower than average PTC ratio of such facilities. Opinion on the appropriateness of such an adjustment was very divided, with about half the TEP members believing it was inappropriate. One of the major concerns about paying extra for freestanding hospitals is that that status as a freestanding hospital is subject to manipulation.

We will analyze the data so as to explicate the reason for additional costs at freestanding hospitals and the possible value of such an adjustment. In particular, we will compare the role of capital costs, size of facility, and administrative costs in determining the costs of freestanding hospitals. We will also examine the role of freestanding rehabilitation hospitals in providing access to inpatient care in geographic regions where it might otherwise be difficult to obtain.

Functional Improvement

The second facility adjustment suggested by the TEP was for hospitals that produced higher than expected functional improvement (or perhaps reasonable functional improvement for a higher than expected proportion of their patients). The argument is that, if reducing cost is the only way that managers are rewarded, it is the primary thing that they will do. If higher functional gain brings higher payment, it will become important too. Other TEP members, perhaps the majority, would prefer that functional improvement be treated initially as a monitoring issue. These panelists fear that it might lead to access problems for patients who are expected to gain less function than average. One might initially use functional improvement for monitoring with the intent of moving toward using it for payment.

We will attempt to lay out how one might treat functional improvement as a facility adjustment as well as a monitoring tool. For example, we will analyze FIM gain--improvement in FIM score from admission to discharge. In particular, we will analyze how patient level costs are related to FIM gain, after controlling for impairment, FIM items, and patient and hospital characteristics. Appropriate scales and psychometric transformations will be used in the analyses. We will also examine whether practice patterns that result in greater functional improvement are one of the reasons for CMI compression.

Additional Analyses of Recommended Facility Adjustments

We will examine in greater detail several hypotheses about why rural hospitals cost more than urban hospitals after controlling for case mix and wages. First, it may be that therapy costs are higher in rural areas than reflected in the wage index. We will try to get data on both therapy costs and occupational mix at rehabilitation hospitals to attempt to explore this more fully. Second, many of the units are in very small hospitals and so overhead and capital costs are spread over few patients. This is distinct from the point that many rural IRF are small units or small hospitals themselves. As in the case of freestanding hospitals, we will examine the desirability of a rural facility adjustment by analyzing access to inpatient rehabilitation for rural patients. This might show the extent to which the extra costs associated with rural facilities have a social payoff.

The DSH and low-income percent that we calculate may be affected by Medicaid rules if there are states where Medicaid does not pay for rehabilitation. We need to think about the implications of this for the fairness of the low-income adjustment.

REPRESENTATIVENESS OF SAMPLE

We saw in Chapter 2 that our sample over represents freestanding hospitals and larger facilities. In developing our plans for implementation and monitoring the system we need to understand more fully the implications of this lack of representativeness. The national conversion factor that will meet the budget neutrality target depends on the extent to which our sample has a relationship between IRF PPS payments and TEFRA payments that reflects the universe. In order to detect changes in case mix and cost in response to changes in the payment system, the monitoring system that we plan must predict case mix and cost under current conditions.

We intend to model the relationship between hospital characteristics and case mix and cost. Further, we intend to explore the extent to which MEDPAR data on rehabilitation cases and on the preceding acute stay can be used to predict case weight. If so, it might provide a substantially improved ability to estimate case mix at the non-sample hospitals. Since we already have the adjustment factor and TEFRA payments at most other hospitals, this will enable us to understand how, if at all, the relationship between TEFRA payment and IRF PPS payment is likely to differ between our sample and the hospitals for which case mix is unavailable.

ASSESSMENT INSTRUMENT

The data that we have been using comes from the FIM instrument--either the version used by UDSmr or that used by Caredata.com (with comorbidities from the MEDPAR). The MDS-PAC will be used to collect impairment group, functional status, comorbidity, age and discharge destination for the IRF PPS. We need to understand how, if at all, the change in the instrument will affect the classification of cases. This has implications for the reliability of classification which in turn affects HCFA's ability to meet the mandated budget neutrality target and may affect system incentives and fairness to hospitals. In addition, we would like to better understand the benefits and costs of using the MDS-PAC.

Some Differences Between the Instruments

The time at which the two instruments are filled out suggests the possibility of bias in the functional measure from the MDS-PAC as a predictor of the FIM scores. The UDSmr instruction guide says that all admission items must be completed within 72 hours. Presumably this allows filling in the form earlier if that meets the needs of the care planning activity. We believe that the MDS-PAC regulation will say the items reflect performance during the first three days, and should be completed on the fourth day. Bias might arise if performance systematically improves in the first few days of the hospitalization, or if the larger period of time results in more observations of extreme dependence. The more specific time phasing of the MDS-PAC may result in more consistent coding across patients.

The FIM motor items are largely found on the MDS-PAC instrument, but with a reversed scale. On the FIM, item responses run from 1 to 7 and 1 denotes most dependent. On the MDS-PAC, item responses typically run from 0 to 6, but 0 is most *independent*. There are also slightly different verbal descriptions for intermediate points on the scale and more detail about some issues such as continence on the MDS-PAC.

The similarity of the two instruments on motor items suggest that it should be possible to construct a very reliable predictor of FIM motor score from the MDS-PAC and use this for FRG assignment.

The cognitive score FIM items are not replicated, but nevertheless highly related information appears. An attempt has been made to build a crosswalk from the MDS-PAC items to the FIM cognitive score.

We understand that the MDS-PAC will request the impairment that is the primary cause of the hospitalization and use the impairment codes now found on the UDSmr version of the FIM instrument. Thus RIC assignment should no longer be an issue.

The additional information on the MDS-PAC on cognitive function, communication, mood and behavior, and other medical issues might eventually allow improved CMGs. If this instrument were to be used in nursing homes or other post acute sites, it would allow a greater understanding of differences and similarities of case mix and outcomes across types of institutions. The additional cost of collecting and transmitting this information, over and above the cost of obtaining the more parsimonious FIM data, is not known.

Data Collection

We will gather and analyze data in order to compare the two instruments. We will select only hospitals who now use the FIM from either UDSmr or Caredata.com. We hope to involve both organizations in our study. We will select hospitals to get coverage of several geographic areas, but expect that some clustering by MSA will improve the efficiency of the study.

We will see that the participating hospitals receive training on filling out the MDS-PAC. After the training, there will be an interval when the hospitals will fill out the forms on their patients before data collection begins. This will allow the hospitals to develop familiarity with the instrument and to develop their own procedures. We are considering having a test on the instrument which can be used to 'certify' that the hospital staff understand the instrument and uncover problems before the beginning of data collection.

We will have the same patients coded with both instruments by the hospital staff. We expect to ask all participating hospitals to code all Medicare admissions in a six- to eight-week time period on the MDS-PAC in addition to their normal coding of the admission FIM instrument. The FIM will be coded using the same procedures that the hospital currently uses. The MDS-PAC will be coded according to the planned method for coding.

We will retrieve the Medicare claims record for the same set of patients from the NearLine Claims History File. This record will be used to retrieve LOS and comorbidity information.

For a subset of patients we will replicate the coding of each instrument by highly trained, uniform coders. These coders will also record the time they spend filling out each instrument.

Study Goals

One of the primary goals of this study will be to measure the accuracy of CMG assignment using the MDS-PAC. We will assign FRG using both instruments and a FIM to MDS-PAC crosswalk, and then compare the accuracy of assignment from the MDS-PAC. We will begin with the existing cross walk, but change it if we find that a different cross walk improves the accuracy with which the MDS-PAC predicts FRG. We will also compare the rate of assignment of relevant comorbidities by the MDS-PAC with that found on the MEDPAR records. If substantial differences are found in the assignment of CMG that are not remediable by fixing the crosswalk, we will estimate the effect of the differences on the national case mix index (and on the CMIs for the larger hospitals in the sample if possible).

A comparison of coding between the hospitals' staff and the 'uniform' coders will show the extent to which coding of each instrument is consistent across different hospitals. The uniform coders will also record the amount of time that it takes to fill out each instrument. We will use these data to estimate the cost of data collected from each instrument.

The study will also investigate whether the MDS-PAC can produce CMGs that are superior in explaining LOS to those produced by the FIM. The intent of this portion of the study is NOT to produce operational CMGs; rather it is to obtain an indication of the potential value of refinements to the CMG system that can be developed when the MDS-PAC data are available for the universe of rehabilitation facilities. This activity will likely be limited to the larger RICs. We will begin by using the FIM data to develop new CMGs based only on this sample of cases. Then we will re-derive the FRGs using the cross walk to the FIM motor and cognitive scales from the MDS-PAC. We will determine if we get essentially the same splits or whether they differ systematically from what we get on same data with FIM scores. Then we will re-derive functional groups, adding new variables and/or scales from the MDS-PAC, and determine if they significantly improve the ability of the FRGs to predict LOS. For example, we will use different cognitive scales.

APPENDIX A. ADDITIONAL INFORMATION CONCERNING CLASSIFICATION

Alternative RIC Groupings

The table below shows the alternative RICs we defined and evaluated. RICs are grouped to reflect the complete repartitioning of one or more sets of old RICs.

Table A.1

Grouping of Impairment Group Codes into Alternative Rehabilitation Impairment Categories

Change Proposal	New Ric	Impairment Code
1.	21	16
	22	12, 12.1, 12.9
	23	11, 13, 15, 17 through 17.9
2.	24	11
	25	12, 12.1, 12.9, 13, 15, 16, 17 through 117.9
3.	26	3.1
	27	3.2, 3.3, 3.5, 3.8, 3.9, 3.99
4.	28	3.4, 4.1, 4.11, 4.11 through 4.13
5.	29	2.2, 2.21, 2.22, 14.2
	30	14.1, 14.13
	31	4.2, 4.21 through 4.23, 14.3
6.	32	2.1, 2.11, 2.9, 3.1, 3.2, 3.5
	33	3.3, 3.8, 3.9, 3.99
7.	34	8.1, 8.11, 8.12
	35	8.2, 8.3, 8.4, 8.9
8.	36	10, 10.1, 10.9, 17.51, 17.52
	37	11, 12, 12.1, 12.9, 13, 15, 16, 17 through 17.4, 17.6 through 17.9
9.	38	2.2, 2.21, 2.22, 14.2
	39	4.2, 4.21 through 4.23, 14.1, 14.13, 14.3
10.	40	2.2, 2.21, 2.22, 14.1, 14.13, 14.2
	41	4.2, 4.21 through 4.23, 14.3
11.	42	8.1, 8.11, 8.12, 8.2, 8.3
	43	8.4, 8.9
12.	44	8.4, 14.9
	45	8.1, 8.11, 8.12, 8.2, 8.3

CART Model

Table A.2 shows the 143-node models produced by CART, using the one standard error rule. This model was evaluated in the simulation study (see Chapter 7).

Table A.2

More Detailed FRG Model: 143-Node Models Resulting from CART

RIC	FRG	Condition	Average Cost	N
01	20	M<45.5 & M<35.5 & A<83.5 & M<30.5 & A<72.5	23708	2350
01	19	M<45.5 & M<35.5 & A<83.5 & M<30.5 & A>72.5	21813	3134
01	18	M<45.5 & M<35.5 & A<83.5 & M>30.5	19425	2831
01	15	M<45.5 & M<35.5 & A>83.5 & A<90.5 & C<14.5	16737	498
01	17	M<45.5 & M<35.5 & A>83.5 & A<90.5 & C>14.5	18840	868
01	13	M<45.5 & M<35.5 & A>83.5 & A>90.5	15612	237
01	16	M<45.5 & M>35.5 & M<41.5 & A<76.5	17461	2682
01	14	M<45.5 & M>35.5 & M<41.5 & A>76.5	16209	2280
01	12	M<45.5 & M>35.5 & M>41.5 & A<86.5	15203	3578
01	10	M<45.5 & M>35.5 & M>41.5 & A>86.5	12240	336
01	11	M>45.5 & M<56.5 & M<50.5 & C<26.5	13385	2666
01	09	M>45.5 & M<56.5 & M<50.5 & C>26.5	12229	2223
01	08	M>45.5 & M<56.5 & M>50.5 & C<27.5	11728	3088
01	07	M>45.5 & M<56.5 & M>50.5 & C>27.5 & M<53.5	10628	1334
01	05	M>45.5 & M<56.5 & M>50.5 & C>27.5 & M>53.5	9615	1256
01	06	M>45.5 & M>56.5 & M<61.5 & C<26.5	10481	1277
01	04	M>45.5 & M>56.5 & M<61.5 & C>26.5	8483	1763
01	03	M>45.5 & M>56.5 & M>61.5 & C<28.5	8232	1436
01	02	M>45.5 & M>56.5 & M>61.5 & C>28.5 & M<66.5	7308	862
01	01	M>45.5 & M>56.5 & M>61.5 & C>28.5 & M>66.5	6186	732
02	06	M<40.5 & M<24.5	23288	187
02	05	M<40.5 & M>24.5	16994	412
02	04	M>40.5 & M<57.5 & C<21.5	13940	368
02	03	M>40.5 & M<57.5 & C>21.5	11553	362
02	02	M>40.5 & M>57.5 & C<29.5	10202	234
02	01	M>40.5 & M>57.5 & C>29.5	6717	90
03	06	M<44.5 & M<34.5	20089	705
03	05	M<44.5 & M>34.5	14921	585
03	04	M>44.5 & M<57.5 & C<24.5	12068	531
03	03	M>44.5 & M<57.5 & C>24.5	10519	461
03	02	M>44.5 & M>57.5 & C<21.5	10350	149
03	01	M>44.5 & M>57.5 & C>21.5	7940	454
04	04	M<33.5 & M<16.5	33571	86
04	03	M<33.5 & M>16.5	20652	234
04	02	M>33.5 & M<54.5	12883	328
04	01	M>33.5 & M>54.5	9123	164
05	06	M<45.5 & M<33.5	20232	717
05	05	M<45.5 & M>33.5 & M<38.5	15226	400
05	04	M<45.5 & M>33.5 & M>38.5	12268	702
05	03	M>45.5 & M<54.5	9502	1279
05	02	M>45.5 & M>54.5 & M<67.5	7386	1089
05	01	M>45.5 & M>54.5 & M>67.5	5474	174
06	04	M<45.5 & M<37.5	15786	1462
06	03	M<45.5 & M>37.5	12389	1114
06	02	M>45.5 & M<55.5	10540	1757
06	01	M>45.5 & M>55.5	8491	1436

Table A.2 (cont.)

07	10	M<45.5 & M<39.5	13430	4219
07	09	M<45.5 & M>39.5 & M<42.5	11874	1669
07	08	M<45.5 & M>39.5 & M>42.5	11109	2058
07	07	M>45.5 & M<54.5 & C<33.5 & M<49.5	10533	1850
07	06	M>45.5 & M<54.5 & C<33.5 & M>49.5	9561	1934
07	05	M>45.5 & M<54.5 & C>33.5 & M<50.5	9491	1506
07	03	M>45.5 & M<54.5 & C>33.5 & M>50.5	8553	1326
07	02	M>45.5 & M>54.5 & M<60.5 & A<81.5	7756	1601
07	04	M>45.5 & M>54.5 & M<60.5 & A>81.5	8692	873
07	01	M>45.5 & M>54.5 & M>60.5	7029	959
08	20	M<49.5 & M<42.5 & C<33.5 & M<35.5	12391	1058
08	19	M<49.5 & M<42.5 & C<33.5 & M>35.5	10430	1833
08	15	M<49.5 & M<42.5 & C>33.5 & A<77.5	9249	1157
08	18	M<49.5 & M<42.5 & C>33.5 & A>77.5	10273	629
08	16	M<49.5 & M>42.5 & C<33.5 & A<84.5 & C<26.5	9376	740
08	14	M<49.5 & M>42.5 & C<33.5 & A<84.5 & C>26.5 & M<46.5	8900	1224
08	12	M<49.5 & M>42.5 & C<33.5 & A<84.5 & C>26.5 & M>46.5	8086	1336
08	17	M<49.5 & M>42.5 & C<33.5 & A>84.5	9757	540
08	10	M<49.5 & M>42.5 & C>33.5 & A<79.5	7709	3168
08	13	M<49.5 & M>42.5 & C>33.5 & A>79.5	8345	1037
08	11	M>49.5 & M<58.5 & C<33.5 & C<29.5	7900	1888
08	09	M>49.5 & M<58.5 & C<33.5 & C>29.5 & M<54.5	7397	2167
08	06	M>49.5 & M<58.5 & C<33.5 & C>29.5 & M>54.5	6833	1447
08	08	M>49.5 & M<58.5 & C>33.5 & M<51.5	7117	2082
08	04	M>49.5 & M<58.5 & C>33.5 & M>51.5 & A<80.5	6381	6926
08	07	M>49.5 & M<58.5 & C>33.5 & M>51.5 & A>80.5	6966	1339
08	05	M>49.5 & M>58.5 & M<68.5 & C<31.5	6510	976
08	03	M>49.5 & M>58.5 & M<68.5 & C>31.5 & M<62.5	5942	4123
08	02	M>49.5 & M>58.5 & M<68.5 & C>31.5 & M>62.5	5588	2823
08	01	M>49.5 & M>58.5 & M>68.5	4927	969
09	06	M<46.5 & M<37.5	13427	853
09	05	M<46.5 & M>37.5	10942	1643
09	04	M>46.5 & M<58.5 & C<31.5	9478	1090
09	03	M>46.5 & M<58.5 & C>31.5 & M<52.5	8996	953
09	02	M>46.5 & M<58.5 & C>31.5 & M>52.5	7956	973
09	01	M>46.5 & M>58.5	6794	1082
10	04	M<52.5 & M<42.5	15669	1478
10	03	M<52.5 & M>42.5	12962	1719
10	02	M>52.5 & M<57.5	11427	879
10	01	M>52.5 & M>57.5	9784	1378
11	04	M<46.5	16140	185
11	03	M>46.5 & M<60.5 & A<67.5	13487	60
11	02	M>46.5 & M<60.5 & A>67.5	9498	174
11	01	M>46.5 & M>60.5	7324	60
12	07	M<48.5 & M<36.5	13777	255
12	06	M<48.5 & M>36.5 & C<31.5	11504	431
12	05	M<48.5 & M>36.5 & C>31.5	9890	323
12	04	M>48.5 & C<33.5 & M<56.5	9537	517

Table A.2 (cont.)

12	02	M>48.5 & C<33.5 & M>56.5	8200	340
12	03	M>48.5 & C>33.5 & M<54.5	8467	353
12	01	M>48.5 & C>33.5 & M>54.5	7213	645
13	03	M<48.5	12387	656
13	02	M>48.5 & M<60.5	8874	628
13	01	M>48.5 & M>60.5	7227	243
14	05	M<53.5 & M<40.5	14368	800
14	04	M<53.5 & M>40.5 & M<48.5	11049	1103
14	03	M<53.5 & M>40.5 & M>48.5	9866	1012
14	02	M>53.5 & M<58.5	8742	1009
14	01	M>53.5 & M>58.5	7505	1756
15	05	M<50.5 & M<27.5	23292	144
15	04	M<50.5 & M>27.5 & M<42.5	15599	503
15	03	M<50.5 & M>27.5 & M>42.5	12969	670
15	02	M>50.5 & A<77.5	11107	1537
15	01	M>50.5 & A>77.5	9366	717
16	05	M<49.5 & C<33.5	11324	484
16	04	M<49.5 & C>33.5	9642	230
16	03	M>49.5 & C<32.5	9079	464
16	02	M>49.5 & C>32.5 & M<57.5	7740	300
16	01	M>49.5 & C>32.5 & M>57.5	6447	412
17	02	M<42.5	15749	267
17	01	M>42.5	9996	394
18	02	M<34.5	25747	97
18	01	M>34.5	12069	127
19	03	M<43.5	24214	132
19	02	M>43.5 & M<54.5	12684	69
19	01	M>43.5 & M>54.5	8086	77
20	20	M<47.5 & M<38.5 & A<83.5 & M<31.5	16519	1026
20	19	M<47.5 & M<38.5 & A<83.5 & M>31.5 & A<74.5	15312	564
20	17	M<47.5 & M<38.5 & A<83.5 & M>31.5 & A>74.5	13668	533
20	16	M<47.5 & M<38.5 & A>83.5	12557	675
20	18	M<47.5 & M>38.5 & A<65.5	14563	375
20	14	M<47.5 & M>38.5 & A>65.5 & M<42.5	12136	1107
20	15	M<47.5 & M>38.5 & A>65.5 & M>42.5 & A<70.5	12336	263
20	12	M<47.5 & M>38.5 & A>65.5 & M>42.5 & A>70.5	10959	1525
20	13	M>47.5 & M<59.5 & M<54.5 & A<65.5	12023	339
20	11	M>47.5 & M<59.5 & M<54.5 & A>65.5 & C<33.5	10209	2115
20	08	M>47.5 & M<59.5 & M<54.5 & A>65.5 & C>33.5	9207	831
20	10	M>47.5 & M<59.5 & M>54.5 & A<72.5	9722	585
20	06	M>47.5 & M<59.5 & M>54.5 & A>72.5 & C<30.5	9024	534
20	04	M>47.5 & M<59.5 & M>54.5 & A>72.5 & C>30.5	8278	813
20	07	M>47.5 & M>59.5 & M<69.5 & A<73.5 & C<33.5	9113	303
20	03	M>47.5 & M>59.5 & M<69.5 & A<73.5 & C>33.5	7849	326
20	05	M>47.5 & M>59.5 & M<69.5 & A>73.5 & C<27.5	8570	206
20	02	M>47.5 & M>59.5 & M<69.5 & A>73.5 & C>27.5	7133	939
20	09	M>47.5 & M>59.5 & M>69.5 & A<58.5	9432	55
20	01	M>47.5 & M>59.5 & M>69.5 & A>58.5	6093	358
21	01	1.0	14849	103

APPENDIX B. COMORBIDITY ANALYSES

We began our analyses of comorbidities by asking our clinical consultants to review the set of comorbidity variables in Appendix B in Carter, Relles, et al. (1997) in order to determine which hypotheses should be changed or updated. Table B.1 lists the results of this review and is the set of comorbidity variables which we considered in our empirical analysis. In some runs, RIC specific exclusions were implemented.

These analyses were all performed on half of the preliminary sample, so that the other half could be reserved to validate our conclusions about which comorbidities affected cost after controlling for FRG. We began our analyses using the FRGs from our 1997 study and then verified all the positive results on the validation half sample and also using our recommended set of FRGs (defined in Chapter 3) on the full sample. Because we believe effects vary by RIC, the test for each comorbidity variable consisted of a regression of the cost of the case on FRG dummies and that variable. Separate regressions were run set for each RIC and year and, in addition, regressions combining all RICs in each year.

Unless otherwise stated, the significance level used here is 0.01.

Major Comorbidities

The major comorbidity variable predicted increased costs, although the amount of the increase varied by RIC. In the fitting data set, regressions in each RIC and year, controlling for FRG, comorbidity predicts significant increased cost ($p < 0.01$) in 25 of the 40 regressions. The coefficient was positive in all but two regressions in the pulmonary RIC. Although the case weighted average effect of comorbidity on costs is only 8 or 9 percent, it was much larger in many RICs. In the evaluation data set, the coefficient was positive in 39 of the 40 regressions and significant in 24 of the 40 regressions.

Implementing the recommendations for exclusions from Dr. Stineman actually make this set of DX an even better predictor of costs. The

RIC-specific exclusions are necessary for face validity. We do not want to confuse the principle cause of the hospitalizations with comorbidity. It is a bonus that using these exclusions actually helps the predictions. In both the fitting and the evaluation sample, the major comorbidity variable has a much larger coefficient in the stroke RIC after the RIC exclusions than before, though the exclusion has little effect on most other RICs. The variable after exclusions should be better because there is likely some random element in coding the excluded comorbidities; however this might have been offset if cases that cost more might have received more attention and therefore more DXs.

Variables Found in the Fitting Data Set to Have Significant Effects on Costs

Deep vein thrombosis including pulmonary embolism appears to predict increased cost. Thirty-five of 40 regressions were positive. Ten are positive and significant for both with and without RIC exclusions. This is confirmed in the evaluation regressions: 33 of 40 are positive; 12 are significant, and many others marginally so.

Renal failure also predicts cost. ESRD1 (which is dialysis status) is positive in all but four of the 36 regressions where it is tested and significant in eight of them; ESRD2, which includes ESRD1, is positive in all but five of 40 regressions and significant in 17. The ESRD variables have no RIC exclusions. The findings were confirmed in the evaluation data set; ESRD1 was positive in 31 of 34 regressions on evaluation data set; positive and significant in six; ESRD2 positive in all, significant in 17.

There was no significant difference between the effect of infect1 and infect2 in the fitting data set, probably because infect2 is quite rare in our data set. So we report on infect3, which combines the diagnoses in infect1 and infect2. Variable infect3 has a significant effect on costs. The coefficient is positive in 38 of 40 fitting regressions and significant in 21 of the regressions. It is positive in all regressions after RIC-specific exclusions. In the evaluation data set, infect is positive in all but two and significant in 23.

Tracheotomy status is relatively rare: fewer than 200 cases per year. But it was positive in all but four regressions and significant in six. In the evaluation set it was testable in all but four, positive in all but three; positive and significant in eight.

Malnutrition, or at least some kinds, also affects cost. It was originally defined as shown in Table B.1 In the fitting data set, it was positive in 32 of 40 cases; positive and significant in three but positive and $p < 0.05$ in 10 regressions; negative and significant in one. However after application of the exclusions in Table B.2, it was reduced to a single code of 579.3 which does not appear at all in many RICs. When it does appear, however, this code has a substantial affect on costs. As shown in Table 3.14 in the main text, this variable increase average cost by 19 percent when it is present.

The neurological disabilities have a significant effect on costs; the variable is positive in 38 of 40 regressions and significant in 15. (Using RIC exclusions slightly improves prediction in RIC 3, which was positive and significant in both years). In the fitting sample, it was positive in 34 of 40 regressions; significant in 12. This is confirmed in the evaluation data set. Some of the effect found in our preliminary split sample analysis was due to some diagnoses that were subsequently eliminated as vague. However, the variable remained positive and significant in 9 regressions even after all exclusions were enforced.

Of all the variables that might be added, the neurological disabilities had the smallest magnitude effect on costs. It also adds the most cases to be paid the comorbidity payment and was significant because of its widespread distribution. In a regression which included all RICs, and dummies for all values of FRG2, the coefficient on the neurological disability was only 0.032 in 1996 and 0.027 in 1997. As shown in Table 3.14 in Chapter 3, all the other variables included in our comorbidity group had substantially larger effects. We believe that it would be better to not pay for this small effect than to combine this list with the other diagnoses and thus overpay cases with neurological comorbidities and underpay cases with other, more expensive, comorbidities.

A separate payment rate for the neurological comorbidities could be established. We believe that the small increase in accuracy would not justify instituting multiple levels of comorbidity payment at this time. When operating system data are available, this question should be examined again.

Variables Which Do Not Substantially Increase Costs

The remaining variables in the table did not have consistent effects on cost in our preliminary analyses. Indeed, most were as likely to have a positive effect on costs as a negative one. This was true of even very serious problems. We detail only a few results:

(1) Brain cancer is very rare (a little over 100 cases per year in our fitting data set). However, in the 17 regressions where it could be tested, it was negative in 11. When the full data were pooled across RICs it was negative in both years and significant in 97.

(2) Cancer was as likely to be negative as positive. In the fitting data set, it was positive in only 14 of the 40 regressions and never positive and significant. It was negative and significant in RIC 1.

(3) As in our earlier study, the psychiatric variables do not reliably predict cost. However, we would recommend re-evaluating depression in coming years, as it might affect costs if it were more reliably coded.

Variable number of

	positive regression	positive & significant	negative & significant
Delirium	27	2	1
Dementia	16	1	4
Depress	32	3	0

(4) Diabetes - insulin dependent diabetes is positive in 29 of 40 regressions and significant in four cases. Although the overall effect (across all RICs) is positive and significant in both years, the overall magnitude of the effect is too small to warrant payment (0.04). As

discussed with the neurological disabilities above, we do not recommend instituting multiple payment levels at this time.

(5) Non-insulin dependent diabetes is positive in only 23 of 40 regressions and not significant when pooled across RICs.

Table B.1

Comorbidity Variables that Were Investigated

Variable	Comments	ICD-9-CM Codes
ESRD1	Patients on dialysis	V451 RENAL DIALYSIS STATUS
ESRD2	Include patients that	V451 RENAL DIALYSIS STATUS
	may also be on	585 CHRONIC RENAL FAILURE
	dialysis	403.01 MALIGNANT HYPERTENSIVE RENAL DISEASE, WITH RENAL FAILURE
		403.11 BENIGN HYPERTENSIVE RENAL DISEASE, WITH RENAL FAILURE
		403.91 HYPERTENSIVE RENAL DISEASE UNSP., WITH RENAL FAILURE
INFECT	Selected infections	038.0-038.9, 054.5, 998.5, 098.89, 027.0 to 027.9 SEPTICEMIA
		569.61, 380.10, 611.0, 607.2, 998.5, 373.13, 681.00 to 682.9, 608.4, 376.01, 597.0, 567.2, 608.0, 608.4, 528.3, 527.3 CELLULITIS
		707.0, 707.1, 440.23, 440.24 DECUBITUS ULCER
		480.0 to 487.0, 514, 507.0 to 507.8, 518.3, 466.1, 515, 506.0, 112.4, 136.3, 513.0 PNEUMONIA
		996.61 INFECTION SHUNT
		996.64 *INFECTION INDWELLING URINARY CATHETER
		998.5 POST OP WOUND INFECTION
INFECT2	HIV,TB, disseminated candidiasis, histoplasmosis	0795,011xx to 018xx,1125,115xx
INFECT3	Selected infections	Infect or infect2
TRACH	Tracheotomy	V44.0, V55.0 TRACHEOTOMY STATUS
VENT	Ventilator status	V46.1 Respirator
LUNG1	Selected lung related diseases	490 Bronchitis, not specified as acute or chronic
		491x Chronic bronchitis
		492x Emphysema
		494xx Bronchiectasis
		496 Chronic airway obstruction, NEC
		501 Abestosis
		518xx Other diseases of lung
		519x Other diseases of respiratory system
ASTHMA	Asthma	493xx Asthma
LUNGHRT	Chronic pulmonary heart disease	416x Chronic pulmonary heart disease
LUNG2	All lung related diseases	any condition listed in LUNG1, ASTHMA, or LUNGHRT
DEPRESS	Depressions	311, 300.4, 290.21, 298.0, 296.20 to 296.89,

Table B.1 (cont.)

Variable	Comments	ICD-9-CM Codes
DELERIM	Delirium	780.02, 780.09, 780.3, 291.0 to 291.8, 292.0 to 292.9, 293.89, 296.1, 296.0, 300.11
DEMENTIA	Dementias	290.0 to 290.43, 294.1, 295.00 to 295.15, 295.30 to 295.35, 094.1
PSYCH1	Selected psychiatric disorders	codes 290 to 319, except those listed in DEPRESS, DELERIM, and DEMENTIA
PSYCH2	All psychiatric disorders	codes 290 to 319
DIAB1	Insulin dependent diabetes (not out of control)	250.01, 250.11, 250.21, 250.31, 250.31, 250.41, 250.51, 250.61, 250.71, 250.81, 250.91
DIAB2	Diabetes (not out of control)	250.00, 250.10, 250.20, 250.30, 250.40, 250.50, 250.60, 250.70, 250.80, 250.90
BRCANC	Brain cancer	191X brain cancer
GIHEM	GI Hemorrhage	578x gastrointestinal hemorrhage
V730		730x osteomylitis, periostitis and other infections of bone
AMP	Leg amputation above foot	V49.75, V49.76, V49.77 Amputation status
MALNUT	Malnutrition	260.0 to 263.9; 579.3
DVT	Deep venous thrombosis	415.19; 451.0 to 453.9
HEART1	CHF or CAD	428.x, 402.01, 402.11, 402.91, 404.01, 404.03, 404.11, 404.13, 404.91, 404.93,425.x, 411.1,411.8x,412,413.x,414.xx
HEART2	Chronic heart conditions: CHF, arrhythmias,CAD	428.x, 402.01, 402.11, 402.91, 404.01, 404.03, 404.11, 404.13, 404.91, 404.93,425.x, 427.31, 427.3,427.0 to 427.2; 427.4 to 427.9, 411.1,411.8x,412,413.x,414.xx
HEART3	CHF or CAD and valve disease	HEART1=1 AND (393.xx to 398.xx)
CANCER	All cancers except brain cancer	140xx thru 190xx, 192xx thru 208xx
LIVER	Chronic liver disease	571.xx, 572.xx
PANCREAT	Acute and chronic pancreatic disease	577X
LIVPAN	Liver or pancreatitis	PANCREAT or LIVER
COAG	Coagulation problems	286.5,286.7,286.9,E858.2,E934.2,E934.4, E934.9
GIHEM1	GI Hemorrhage	2851,5310x,5312x,5314x,5316x,5320x,5322x, 5324x,5326x,5330x,5332x,5334x,5336x,5340x, 5342x,5344x,5346x,535x1,
GIHEM2	GI Hemorrhage or Coagulation problem	COAG or GIHEM1
NEURO	Neurological disorders, including swallowing disorders, hemiparesis, etc	784.3x to 784.5x, 438.1x,787.2x,348.xx, 349.xx,7810,7811,7814,7815,7816,7816,7817, 7818,7819 342xx, 4382x to 4385x

Table B.2

Listing of Codes Removed as Unimportant, Vague, or Preventable

OBS	ICD9	NAME
1	263	PROT-CAL MALNUTR NEC/NOS*
2	2630	MALNUTRITION MOD DEGREE
3	2631	MALNUTRITION MILD DEGREE
4	2632	ARREST DEVEL D/T MALNUTR
5	2638	PROTEIN-CAL MALNUTR NEC
6	2639	PROTEIN-CAL MALNUTR NOS
7	3489	BRAIN CONDITION NOS
8	349	CNS DISORDER NEC/NOS*
9	3490	LUMBAR PUNCTURE REACTION
10	3498	OTHER CNS DISORDERS*
11	34981	CEREBROSPINAL RHINORRHEA
12	34982	TOXIC ENCEPHALOPATHY
13	3499	CNS DISORDER NOS
14	37313	ABSCESS OF EYELID
15	38010	INFEC OTITIS EXTERNA NOS
16	40311	BEN HYP RENAL W REN FAIL
17	40391	HYP RENAL NOS W REN FAIL
18	43810	LATE EF-SPCH/LNG DEF NOS
19	43812	LATE EFF CV DIS-DYSPHSIA
20	43819	LATE EF-SPCH/LANG DF NEC
21	451	THROMBOPHLEBITIS*
22	4510	SUPERFIC PHLEBITIS-LEG
23	4511	DEEP PHLEBITIS-LEG*
24	45111	FEMORAL VEIN PHLEBITIS
25	45119	DEEP PHLEBITIS-LEG NEC
27	4518	THROMBOPHLEBITIS NEC*
28	45181	ILIAC THROMBOPHLEBITIS
29	45182	PHLBTS SPRFC VN UP EXTRM
30	45183	PHLBTS DEEP VN UP EXTRM
31	45184	PHLBTS VN NOS UP EXTRM
32	4519	THROMBOPHLEBITIS NOS
33	4538	VENOUS THROMBOSIS NEC
34	4539	VENOUS THROMBOSIS NOS
35	4871	FLU W RESP MANIFEST NEC
36	4878	FLU W MANIFESTATION NEC
37	5273	SALIVARY GLAND ABSCESS
38	585	CHRONIC RENAL FAILURE
39	5970	URETHRAL ABSCESS
40	6072	INFLAM DIS, PENIS NEC
41	6080	SEMINAL VESICULITIS
42	6084	MALE GEN INFLAM DIS NEC
43	6110	INFLAM DISEASE OF BREAST
44	6810	CELLULITIS OF FINGER*

Table B.2 (cont.)

45	68100	CELLULITIS, FINGER NOS
46	68101	FELON
47	68102	ONYCHIA OF FINGER
48	6811	CELLULITIS OF TOE*
49	68110	CELLULITIS, TOE NOS
50	68111	ONYCHIA OF TOE
51	6819	CELLULITIS OF DIGIT NOS
52	6829	CELLULITIS NOS
53	707	CHRONIC ULCER OF SKIN*
54	7070	DECUBITUS ULCER
55	7071	CHRONIC ULCER OF LEG
56	7078	CHRONIC SKIN ULCER NEC
57	7079	CHRONIC SKIN ULCER NOS
58	7810	ABN INVOLUN MOVEMENT NEC
59	7811	SMELL & TASTE DISTURB
60	7814	TRANSIENT LIMB PARALYSIS
61	7815	CLUBBING OF FINGERS
62	7819	NERV/MUSCULSKEL SYM NEC
63	7844	VOICE DISTURBANCE*
64	78440	VOICE DISTURBANCE NOS
65	78441	APHONIA
66	78449	VOICE DISTURBANCE NEC
67	7845	SPEECH DISTURBANCE NEC
68	7872	DYSPHAGIA
69	99851	INFECTED POSTOP SEROMA
70	99859	OTHER POSTOP INFECTION
71	V400	PROBLEMS WITH LEARNING
72	V550	ATTEN TO TRACHEOSTOMY

Table B.3

List of Relevant Comorbidities with RIC Exclusions

ICD9	NAME	RIC where this comorbidity is not relevant
011	PULMONARY TUBERCULOSIS*	
0110	TB OF LUNG, INFILTRATIVE*	
01100	TB LUNG INFILTR-UNSPEC	None
01101	TB LUNG INFILTR-NO EXAM	None
01102	TB LUNG INFILTR-EXM UNKN	None
01103	TB LUNG INFILTR-MICRO DX	None
01104	TB LUNG INFILTR-CULT DX	None
01105	TB LUNG INFILTR-HISTO DX	None
01106	TB LUNG INFILTR-OTH TEST	None
0111	TB OF LUNG, NODULAR*	
01110	TB LUNG NODULAR-UNSPEC	None
01111	TB LUNG NODULAR-NO EXAM	None
01112	TB LUNG NODUL-EXAM UNKN	None
01113	TB LUNG NODULAR-MICRO DX	None
01114	TB LUNG NODULAR-CULT DX	None
01115	TB LUNG NODULAR-HISTO DX	None
01116	TB LUNG NODULAR-OTH TEST	None
0112	TB OF LUNG W CAVITATION*	
01120	TB LUNG W CAVITY-UNSPEC	None
01121	TB LUNG W CAVITY-NO EXAM	None
01122	TB LUNG CAVITY-EXAM UNKN	None
01123	TB LUNG W CAVIT-MICRO DX	None
01124	TB LUNG W CAVITY-CULT DX	None
01125	TB LUNG W CAVIT-HISTO DX	None
01126	TB LUNG W CAVIT-OTH TEST	None
0113	TUBERCULOSIS OF BRONCHUS*	
01130	TB OF BRONCHUS-UNSPEC	None
01131	TB OF BRONCHUS-NO EXAM	None
01132	TB OF BRONCHUS-EXAM UNKN	None
01133	TB OF BRONCHUS-MICRO DX	None
01134	TB OF BRONCHUS-CULT DX	None
01135	TB OF BRONCHUS-HISTO DX	None
01136	TB OF BRONCHUS-OTH TEST	None
0114	TB FIBROSIS OF LUNG*	None
01140	TB LUNG FIBROSIS-UNSPEC	None
01141	TB LUNG FIBROSIS-NO EXAM	None
01142	TB LUNG FIBROS-EXAM UNKN	None

01143	TB LUNG FIBROS-MICRO DX	None
01144	TB LUNG FIBROSIS-CULT DX	None
01145	TB LUNG FIBROS-HISTO DX	None
01146	TB LUNG FIBROS-OTH TEST	None
0115	TB BRONCHIECTASIS*	
01150	TB BRONCHIECTASIS-UNSPEC	None
01151	TB BRONCHIECT-NO EXAM	None
01152	TB BRONCHIECT-EXAM UNKN	None
01153	TB BRONCHIECT-MICRO DX	None
01154	TB BRONCHIECT-CULT DX	None
01155	TB BRONCHIECT-HISTO DX	None
01156	TB BRONCHIECT-OTH TEST	None
0116	TUBERCULOUS PNEUMONIA*	
01160	TB PNEUMONIA-UNSPEC	15
01161	TB PNEUMONIA-NO EXAM	15
01162	TB PNEUMONIA-EXAM UNKN	15
01163	TB PNEUMONIA-MICRO DX	15
01164	TB PNEUMONIA-CULT DX	15
01165	TB PNEUMONIA-HISTO DX	15
01166	TB PNEUMONIA-OTH TEST	15
0117	TUBERCULOUS PNEUMOTHORAX*	
01170	TB PNEUMOTHORAX-UNSPEC	15
01171	TB PNEUMOTHORAX-NO EXAM	15
01172	TB PNEUMOTHORX-EXAM UNKN	15
01173	TB PNEUMOTHORAX-MICRO DX	15
01174	TB PNEUMOTHORAX-CULT DX	15
01175	TB PNEUMOTHORAX-HISTO DX	15
01176	TB PNEUMOTHORAX-OTH TEST	15
0118	PULMONARY TB NEC*	
01180	PULMONARY TB NEC-UNSPEC	None
01181	PULMONARY TB NEC-NO EXAM	None
01182	PULMON TB NEC-EXAM UNKN	None
01183	PULMON TB NEC-MICRO DX	None
01184	PULMON TB NEC-CULT DX	None
01185	PULMON TB NEC-HISTO DX	None
01186	PULMON TB NEC-OTH TEST	None
0119	PULMONARY TB NOS*	
01190	PULMONARY TB NOS-UNSPEC	None
01191	PULMONARY TB NOS-NO EXAM	None
01192	PULMON TB NOS-EXAM UNKN	None
01193	PULMON TB NOS-MICRO DX	None
01194	PULMON TB NOS-CULT DX	None
01195	PULMON TB NOS-HISTO DX	None
01196	PULMON TB NOS-OTH TEST	None

012	OTHER RESPIRATORY TB*	
0120	TUBERCULOUS PLEURISY*	
01200	TB PLEURISY-UNSPEC	None
01201	TB PLEURISY-NO EXAM	None
01202	TB PLEURISY-EXAM UNKN	None
01203	TB PLEURISY-MICRO DX	None
01204	TB PLEURISY-CULT DX	None
01205	TB PLEURISY-HISTOLOG DX	None
01206	TB PLEURISY-OTH TEST	None
0121	TB THORACIC LYMPH NODES*	
01210	TB THORACIC NODES-UNSPEC	None
01211	TB THORAX NODE-NO EXAM	None
01212	TB THORAX NODE-EXAM UNKN	None
01213	TB THORAX NODE-MICRO DX	None
01214	TB THORAX NODE-CULT DX	None
01215	TB THORAX NODE-HISTO DX	None
01216	TB THORAX NODE-OTH TEST	None
0122	ISOLATED TRACH/BRONCH TB*	
01220	ISOL TRACHEAL TB-UNSPEC	None
01221	ISOL TRACHEAL TB-NO EXAM	None
01222	ISOL TRACH TB-EXAM UNKN	None
01223	ISOLAT TRACH TB-MICRO DX	None
01224	ISOL TRACHEAL TB-CULT DX	None
01225	ISOLAT TRACH TB-HISTO DX	None
01226	ISOLAT TRACH TB-OTH TEST	None
0123	TUBERCULOUS LARYNGITIS*	
01230	TB LARYNGITIS-UNSPEC	None
01231	TB LARYNGITIS-NO EXAM	None
01232	TB LARYNGITIS-EXAM UNKN	None
01233	TB LARYNGITIS-MICRO DX	None
01234	TB LARYNGITIS-CULT DX	None
01235	TB LARYNGITIS-HISTO DX	None
01236	TB LARYNGITIS-OTH TEST	None
0128	RESPIRATORY TB NEC*	
01280	RESP TB NEC-UNSPEC	None
01281	RESP TB NEC-NO EXAM	None
01282	RESP TB NEC-EXAM UNKN	None
01283	RESP TB NEC-MICRO DX	None
01284	RESP TB NEC-CULT DX	None
01285	RESP TB NEC-HISTO DX	None
01286	RESP TB NEC-OTH TEST	None
013	CNS TUBERCULOSIS*	
0130	TUBERCULOUS MENINGITIS*	
01300	TB MENINGITIS-UNSPEC	3

01301	TB MENINGITIS-NO EXAM	3
01302	TB MENINGITIS-EXAM UNKN	3
01303	TB MENINGITIS-MICRO DX	3
01304	TB MENINGITIS-CULT DX	3
01305	TB MENINGITIS-HISTO DX	None
01306	TB MENINGITIS-OTH TEST	3
0131	TUBERCULOMA OF MENINGES*	
01310	TUBRCLMA MENINGES-UNSPEC	3
01311	TUBRCLMA MENING-NO EXAM	3
01312	TUBRCLMA MENIN-EXAM UNKN	3
01313	TUBRCLMA MENING-MICRO DX	3
01314	TUBRCLMA MENING-CULT DX	3
01315	TUBRCLMA MENING-HISTO DX	3
01316	TUBRCLMA MENING-OTH TEST	3
0132	TUBERCULOMA OF BRAIN*	
01320	TUBERCULOMA BRAIN-UNSPEC	3
01321	TUBRCLOMA BRAIN-NO EXAM	3
01322	TUBRCLMA BRAIN-EXAM UNKN	3
01323	TUBRCLOMA BRAIN-MICRO DX	3
01324	TUBRCLOMA BRAIN-CULT DX	3
01325	TUBRCLOMA BRAIN-HISTO DX	3
01326	TUBRCLOMA BRAIN-OTH TEST	3
0133	TB ABSCESS OF BRAIN*	
01330	TB BRAIN ABSCESS-UNSPEC	3
01331	TB BRAIN ABSCESS-NO EXAM	3
01332	TB BRAIN ABSC-EXAM UNKN	3
01333	TB BRAIN ABSC-MICRO DX	3
01334	TB BRAIN ABSCESS-CULT DX	3
01335	TB BRAIN ABSC-HISTO DX	3
01336	TB BRAIN ABSC-OTH TEST	3
0134	TUBERCULOMA SPINAL CORD*	None
01340	TUBRCLMA SP CORD-UNSPEC	None
01341	TUBRCLMA SP CORD-NO EXAM	None
01342	TUBRCLMA SP CD-EXAM UNKN	None
01343	TUBRCLMA SP CRD-MICRO DX	None
01344	TUBRCLMA SP CORD-CULT DX	None
01345	TUBRCLMA SP CRD-HISTO DX	None
01346	TUBRCLMA SP CRD-OTH TEST	None
0135	TB ABSCESS SPINAL CORD*	
01350	TB SP CRD ABSCESS-UNSPEC	5
01351	TB SP CRD ABSC-NO EXAM	5
01352	TB SP CRD ABSC-EXAM UNKN	5
01353	TB SP CRD ABSC-MICRO DX	5
01354	TB SP CRD ABSC-CULT DX	5

01355	TB SP CRD ABSC-HISTO DX	5
01356	TB SP CRD ABSC-OTH TEST	5
0136	TB ENCEPHALITIS/MYELITIS*	
01360	TB ENCEPHALITIS-UNSPEC	None
01361	TB ENCEPHALITIS-NO EXAM	None
01362	TB ENCEPHALIT-EXAM UNKN	None
01363	TB ENCEPHALITIS-MICRO DX	None
01364	TB ENCEPHALITIS-CULT DX	None
01365	TB ENCEPHALITIS-HISTO DX	None
01366	TB ENCEPHALITIS-OTH TEST	None
0138	CNS TUBERCULOSIS NEC*	
01380	CNS TB NEC-UNSPEC	None
01381	CNS TB NEC-NO EXAM	None
01382	CNS TB NEC-EXAM UNKN	None
01383	CNS TB NEC-MICRO DX	None
01384	CNS TB NEC-CULT DX	None
01385	CNS TB NEC-HISTO DX	None
01386	CNS TB NEC-OTH TEST	None
0139	CNS TUBERCULOSIS NOS*	
01390	CNS TB NOS-UNSPEC	None
01391	CNS TB NOS-NO EXAM	None
01392	CNS TB NOS-EXAM UNKN	None
01393	CNS TB NOS-MICRO DX	None
01394	CNS TB NOS-CULT DX	None
01395	CNS TB NOS-HISTO DX	None
01396	CNS TB NOS-OTH TEST	None
014	INTESTINAL TB*	
0140	TUBERCULOUS PERITONITIS*	
01400	TB PERITONITIS-UNSPEC	None
01401	TB PERITONITIS-NO EXAM	None
01402	TB PERITONITIS-EXAM UNKN	None
01403	TB PERITONITIS-MICRO DX	None
01404	TB PERITONITIS-CULT DX	None
01405	TB PERITONITIS-HISTO DX	None
01406	TB PERITONITIS-OTH TEST	None
0148	INTESTINAL TB NEC*	
01480	INTESTINAL TB NEC-UNSPEC	None
01481	INTESTIN TB NEC-NO EXAM	None
01482	INTEST TB NEC-EXAM UNKN	None
01483	INTESTIN TB NEC-MICRO DX	None
01484	INTESTIN TB NEC-CULT DX	None
01485	INTESTIN TB NEC-HISTO DX	None
01486	INTESTIN TB NEC-OTH TEST	None
015	TB OF BONE AND JOINT*	

0150	TB OF VERTEBRAL COLUMN*	
01500	TB OF VERTEBRA-UNSPEC	None
01501	TB OF VERTEBRA-NO EXAM	None
01502	TB OF VERTEBRA-EXAM UNKN	None
01503	TB OF VERTEBRA-MICRO DX	None
01504	TB OF VERTEBRA-CULT DX	None
01505	TB OF VERTEBRA-HISTO DX	None
01506	TB OF VERTEBRA-OTH TEST	None
0151	TB OF HIP*	
01510	TB OF HIP-UNSPEC	None
01511	TB OF HIP-NO EXAM	None
01512	TB OF HIP-EXAM UNKN	None
01513	TB OF HIP-MICRO DX	None
01514	TB OF HIP-CULT DX	None
01515	TB OF HIP-HISTO DX	None
01516	TB OF HIP-OTH TEST	None
0152	TB OF KNEE*	None
01520	TB OF KNEE-UNSPEC	None
01521	TB OF KNEE-NO EXAM	None
01522	TB OF KNEE-EXAM UNKN	None
01523	TB OF KNEE-MICRO DX	None
01524	TB OF KNEE-CULT DX	None
01525	TB OF KNEE-HISTO DX	None
01526	TB OF KNEE-OTH TEST	None
0155	TB OF LIMB BONES*	
01550	TB OF LIMB BONES-UNSPEC	None
01551	TB LIMB BONES-NO EXAM	None
01552	TB LIMB BONES-EXAM UNKN	None
01553	TB LIMB BONES-MICRO DX	None
01554	TB LIMB BONES-CULT DX	None
01555	TB LIMB BONES-HISTO DX	None
01556	TB LIMB BONES-OTH TEST	None
0156	TB OF MASTOID*	
01560	TB OF MASTOID-UNSPEC	None
01561	TB OF MASTOID-NO EXAM	None
01562	TB OF MASTOID-EXAM UNKN	None
01563	TB OF MASTOID-MICRO DX	None
01564	TB OF MASTOID-CULT DX	None
01565	TB OF MASTOID-HISTO DX	None
01566	TB OF MASTOID-OTH TEST	None
0157	TB OF BONE NEC*	
01570	TB OF BONE NEC-UNSPEC	None
01571	TB OF BONE NEC-NO EXAM	None
01572	TB OF BONE NEC-EXAM UNKN	None

01573	TB OF BONE NEC-MICRO DX	None
01574	TB OF BONE NEC-CULT DX	None
01575	TB OF BONE NEC-HISTO DX	None
01576	TB OF BONE NEC-OTH TEST	None
0158	TB OF JOINT NEC*	
01580	TB OF JOINT NEC-UNSPEC	None
01581	TB OF JOINT NEC-NO EXAM	None
01582	TB JOINT NEC-EXAM UNKN	None
01583	TB OF JOINT NEC-MICRO DX	None
01584	TB OF JOINT NEC-CULT DX	None
01585	TB OF JOINT NEC-HISTO DX	None
01586	TB OF JOINT NEC-OTH TEST	None
0159	TB OF BONE & JOINT NOS*	None
01590	TB BONE/JOINT NOS-UNSPEC	None
01591	TB BONE/JT NOS-NO EXAM	None
01592	TB BONE/JT NOS-EXAM UNKN	None
01593	TB BONE/JT NOS-MICRO DX	None
01594	TB BONE/JT NOS-CULT DX	None
01595	TB BONE/JT NOS-HISTO DX	None
01596	TB BONE/JT NOS-OTH TEST	None
016	GENITOURINARY TB*	
0160	TB OF KIDNEY*	
01600	TB OF KIDNEY-UNSPEC	None
01601	TB OF KIDNEY-NO EXAM	None
01602	TB OF KIDNEY-EXAM UNKN	None
01603	TB OF KIDNEY-MICRO DX	None
01604	TB OF KIDNEY-CULT DX	None
01605	TB OF KIDNEY-HISTO DX	None
01606	TB OF KIDNEY-OTH TEST	None
0161	TB OF BLADDER*	
01610	TB OF BLADDER-UNSPEC	None
01611	TB OF BLADDER-NO EXAM	None
01612	TB OF BLADDER-EXAM UNKN	None
01613	TB OF BLADDER-MICRO DX	None
01614	TB OF BLADDER-CULT DX	None
01615	TB OF BLADDER-HISTO DX	None
01616	TB OF BLADDER-OTH TEST	None
0162	TB OF URETER*	
01620	TB OF URETER-UNSPEC	None
01621	TB OF URETER-NO EXAM	None
01622	TB OF URETER-EXAM UNKN	None
01623	TB OF URETER-MICRO DX	None
01624	TB OF URETER-CULT DX	None
01625	TB OF URETER-HISTO DX	None

01626	TB OF URETER-OTH TEST	None
0163	TB OF URINARY ORGAN NEC*	
01630	TB URINARY NEC-UNSPEC	None
01631	TB URINARY NEC-NO EXAM	None
01632	TB URINARY NEC-EXAM UNKN	None
01633	TB URINARY NEC-MICRO DX	None
01634	TB URINARY NEC-CULT DX	None
01635	TB URINARY NEC-HISTO DX	None
01636	TB URINARY NEC-OTH TEST	None
0164	TB OF EPIDIDYMIS*	
01640	TB EPIDIDYMIS-UNSPEC	None
01641	TB EPIDIDYMIS-NO EXAM	None
01642	TB EPIDIDYMIS-EXAM UNKN	None
01643	TB EPIDIDYMIS-MICRO DX	None
01644	TB EPIDIDYMIS-CULT DX	None
01645	TB EPIDIDYMIS-HISTO DX	None
01646	TB EPIDIDYMIS-OTH TEST	None
0165	TB MALE GENITAL ORG NEC*	None
01650	TB MALE GENIT NEC-UNSPEC	None
01651	TB MALE GEN NEC-NO EXAM	None
01652	TB MALE GEN NEC-EX UNKN	None
01653	TB MALE GEN NEC-MICRO DX	None
01654	TB MALE GEN NEC-CULT DX	None
01655	TB MALE GEN NEC-HISTO DX	None
01656	TB MALE GEN NEC-OTH TEST	None
0166	TB OF OVARY AND TUBE*	None
01660	TB OVARY & TUBE-UNSPEC	None
01661	TB OVARY & TUBE-NO EXAM	None
01662	TB OVARY/TUBE-EXAM UNKN	None
01663	TB OVARY & TUBE-MICRO DX	None
01664	TB OVARY & TUBE-CULT DX	None
01665	TB OVARY & TUBE-HISTO DX	None
01666	TB OVARY & TUBE-OTH TEST	None
0167	TB FEMALE GENIT ORG NEC*	None
01670	TB FEMALE GEN NEC-UNSPEC	None
01671	TB FEM GEN NEC-NO EXAM	None
01672	TB FEM GEN NEC-EXAM UNKN	None
01673	TB FEM GEN NEC-MICRO DX	None
01674	TB FEM GEN NEC-CULT DX	None
01675	TB FEM GEN NEC-HISTO DX	None
01676	TB FEM GEN NEC-OTH TEST	None
0169	GENITOURINARY TB NOS*	None
01690	GU TB NOS-UNSPEC	None
01691	GU TB NOS-NO EXAM	None

01692	GU TB NOS-EXAM UNKN	None
01693	GU TB NOS-MICRO DX	None
01694	GU TB NOS-CULT DX	None
01695	GU TB NOS-HISTO DX	None
01696	GU TB NOS-OTH TEST	None
017	TUBERCULOSIS NEC*	None
0170	TB SKIN & SUBCUTANEOUS*	None
01700	TB SKIN/SUBCUTAN-UNSPEC	None
01701	TB SKIN/SUBCUT-NO EXAM	None
01702	TB SKIN/SUBCUT-EXAM UNKN	None
01703	TB SKIN/SUBCUT-MICRO DX	None
01704	TB SKIN/SUBCUT-CULT DX	None
01705	TB SKIN/SUBCUT-HISTO DX	None
01706	TB SKIN/SUBCUT-OTH TEST	None
0171	ERYTHEMA NODOSUM IN TB*	None
01710	ERYTHEMA NODOS TB-UNSPEC	None
01711	ERYTHEM NODOS TB-NO EXAM	None
01712	ERYTHEM NOD TB-EXAM UNKN	None
01713	ERYTHEM NOD TB-MICRO DX	None
01714	ERYTHEM NODOS TB-CULT DX	None
01715	ERYTHEM NOD TB-HISTO DX	None
01716	ERYTHEM NOD TB-OTH TEST	None
0172	TB OF PERIPH LYMPH NODE*	None
01720	TB PERIPH LYMPH-UNSPEC	None
01721	TB PERIPH LYMPH-NO EXAM	None
01722	TB PERIPH LYMPH-EXAM UNK	None
01723	TB PERIPH LYMPH-MICRO DX	None
01724	TB PERIPH LYMPH-CULT DX	None
01725	TB PERIPH LYMPH-HISTO DX	None
01726	TB PERIPH LYMPH-OTH TEST	None
0173	TB OF EYE*	None
01730	TB OF EYE-UNSPEC	None
01731	TB OF EYE-NO EXAM	None
01732	TB OF EYE-EXAM UNKN	None
01733	TB OF EYE-MICRO DX	None
01734	TB OF EYE-CULT DX	None
01735	TB OF EYE-HISTO DX	None
01736	TB OF EYE-OTH TEST	None
0174	TB OF EAR*	None
01740	TB OF EAR-UNSPEC	None
01741	TB OF EAR-NO EXAM	None
01742	TB OF EAR-EXAM UNKN	None
01743	TB OF EAR-MICRO DX	None
01744	TB OF EAR-CULT DX	None

01745	TB OF EAR-HISTO DX	None
01746	TB OF EAR-OTH TEST	None
0175	TB OF THYROID GLAND*	None
01750	TB OF THYROID-UNSPEC	None
01751	TB OF THYROID-NO EXAM	None
01752	TB OF THYROID-EXAM UNKN	None
01753	TB OF THYROID-MICRO DX	None
01754	TB OF THYROID-CULT DX	None
01755	TB OF THYROID-HISTO DX	None
01756	TB OF THYROID-OTH TEST	None
0176	TB OF ADRENAL GLAND*	None
01760	TB OF ADRENAL-UNSPEC	None
01761	TB OF ADRENAL-NO EXAM	None
01762	TB OF ADRENAL-EXAM UNKN	None
01763	TB OF ADRENAL-MICRO DX	None
01764	TB OF ADRENAL-CULT DX	None
01765	TB OF ADRENAL-HISTO DX	None
01766	TB OF ADRENAL-OTH TEST	None
0177	TB OF SPLEEN*	None
01770	TB OF SPLEEN-UNSPEC	None
01771	TB OF SPLEEN-NO EXAM	None
01772	TB OF SPLEEN-EXAM UNKN	None
01773	TB OF SPLEEN-MICRO DX	None
01774	TB OF SPLEEN-CULT DX	None
01775	TB OF SPLEEN-HISTO DX	None
01776	TB OF SPLEEN-OTH TEST	None
0178	TB OF ESOPHAGUS*	None
01780	TB ESOPHAGUS-UNSPEC	None
01781	TB ESOPHAGUS-NO EXAM	None
01782	TB ESOPHAGUS-EXAM UNKN	None
01783	TB ESOPHAGUS-MICRO DX	None
01784	TB ESOPHAGUS-CULT DX	None
01785	TB ESOPHAGUS-HISTO DX	None
01786	TB ESOPHAGUS-OTH TEST	None
0179	TB OF ORGAN NEC*	None
01790	TB OF ORGAN NEC-UNSPEC	None
01791	TB OF ORGAN NEC-NO EXAM	None
01792	TB ORGAN NEC-EXAM UNKN	None
01793	TB OF ORGAN NEC-MICRO DX	None
01794	TB OF ORGAN NEC-CULT DX	None
01795	TB OF ORGAN NEC-HISTO DX	None
01796	TB OF ORGAN NEC-OTH TEST	None
018	MILIARY TUBERCULOSIS*	None
0180	ACUTE MILIARY TB*	None

01800	ACUTE MILIARY TB-UNSPEC	None
01801	ACUTE MILIARY TB-NO EXAM	None
01802	AC MILIARY TB-EXAM UNKN	None
01803	AC MILIARY TB-MICRO DX	None
01804	ACUTE MILIARY TB-CULT DX	None
01805	AC MILIARY TB-HISTO DX	None
01806	AC MILIARY TB-OTH TEST	None
0188	MILIARY TB NEC*	None
01880	MILIARY TB NEC-UNSPEC	None
01881	MILIARY TB NEC-NO EXAM	None
01882	MILIARY TB NEC-EXAM UNKN	None
01883	MILIARY TB NEC-MICRO DX	None
01884	MILIARY TB NEC-CULT DX	None
01885	MILIARY TB NEC-HISTO DX	None
01886	MILIARY TB NEC-OTH TEST	None
0189	MILIARY TUBERCULOSIS NOS*	None
01890	MILIARY TB NOS-UNSPEC	None
01891	MILIARY TB NOS-NO EXAM	None
01892	MILIARY TB NOS-EXAM UNKN	None
01893	MILIARY TB NOS-MICRO DX	None
01894	MILIARY TB NOS-CULT DX	None
01895	MILIARY TB NOS-HISTO DX	None
01896	MILIARY TB NOS-OTH TEST	None
0270	LISTERIOSIS	None
0271	ERYSIPELOTHRIX INFECTION	None
0272	PASTEURELLOSIS	None
0278	ZOONOTIC BACT DIS NEC	None
0279	ZOONOTIC BACT DIS NOS	None
0360	MENINGOCOCCAL MENINGITIS	5
0362	MENINGOCOCCEMIA	5
0363	MENINGOCOCC ADRENAL SYND	5
03640	MENINGOCOCC CARDITIS NOS	5
03642	MENINGOCOCC ENDOCARDITIS	5
03643	MENINGOCOCC MYOCARDITIS	5
037	TETANUS	None
0380	STREPTOCOCCAL SEPTICEMIA	None
0381	STAPHYLOCOCC SEPTICEMIA*	None
03810	STAPHYLCOCC SEPTICEM NOS	None
03811	STAPH AUREUS SEPTICEMIA	None
03819	STAPHYLCOCC SEPTICEM NEC	None
0382	PNEUMOCOCCAL SEPTICEMIA	15
0383	ANAEROBIC SEPTICEMIA	None
0384	GRAM-NEG SEPTICEMIA NEC*	None
03840	GRAM-NEG SEPTICEMIA NOS	None

03841	H. INFLUENAE SEPTICEMIA	None
03842	E COLI SEPTICEMIA	None
03843	PSEUDOMONAS SEPTICEMIA	None
03844	SERRATIA SEPTICEMIA	None
03849	GRAM-NEG SEPTICEMIA NEC	None
0388	SEPTICEMIA NEC	None
0389	SEPTICEMIA NOS	None
042	HUMAN IMMUNO VIRUS DIS	None
0520	POSTVARICELLA ENCEPHALIT	None
0521	VARICELLA PNEUMONITIS	None
0530	HERPES ZOSTER MENINGITIS	3
0543	HERPETIC ENCEPHALITIS	3
0545	HERPETIC SEPTICEMIA	3
05472	H SIMPLEX MENINGITIS	3
05479	H SIMPLEX COMPLICAT NEC	None
0550	POSTMEASLES ENCEPHALITIS	3
0551	POSTMEASLES PNEUMONIA	15
07020	HPT B ACTE COMA WO DLTA	None
07021	HPT B ACTE COMA W DLTA	None
07022	HPT B CHRN COMA WO DLTA	3
07023	HPT B CHRN COMA W DLTA	3
07041	HPT C ACUTE W HEPAT COMA	None
07042	HPT DLT WO B W HPT COMA	None
07043	HPT E W HEPAT COMA	None
07044	CHRNC HPT C W HEPAT COMA	3
07049	OTH VRL HEPAT W HPT COMA	None
0706	VIRAL HEPAT NOS W COMA	3
0721	MUMPS MENINGITIS	3
0722	MUMPS ENCEPHALITIS	3
0723	MUMPS PANCREATITIS	None
0795	RETROVIRUS*	
09042	CONGEN SYPH MENINGITIS	3
09320	SYPHIL ENDOCARDITIS NOS	14
09382	SYPHILITIC MYOCARDITIS	14
0942	SYPHILITIC MENINGITIS	3
09487	SYPH RUPT CEREB ANEURYSM	1
09889	GONOCOCCAL INF SITE NEC	None
1124	CANDIDIASIS OF LUNG	15
1125	DISSEMINATED CANDIDIASIS	None
11281	CANDIDAL ENDOCARDITIS	14
11283	CANDIDAL MENINGITIS	3
1142	COCCIDIOIDAL MENINGITIS	3
115	HISTOPLASMOSIS*	
1150	HISTOPLASMA CAPSULATUM*	None

11500	HISTOPLASMA CAPSULAT NOS	None
11501	HISTOPLASM CAPSUL MENING	3
11502	HISTOPLASM CAPSUL RETINA	None
11503	HISTOPLASM CAPS PERICARD	None
11504	HISTOPLASM CAPS ENDOCARD	14
11505	HISTOPLASM CAPS PNEUMON	15
11509	HISTOPLASMA CAPSULAT NEC	None
1151	HISTOPLASMA DUBOISII*	
11510	HISTOPLASMA DUBOISII NOS	None
11511	HISTOPLASM DUBOIS MENING	3
11512	HISTOPLASM DUBOIS RETINA	None
11513	HISTOPLASM DUB PERICARD	None
11514	HISTOPLASM DUB ENDOCARD	14
11515	HISTOPLASM DUB PNEUMONIA	15
11519	HISTOPLASMA DUBOISII NEC	None
1159	HISTOPLASMOSIS, UNSPEC*	
11590	HISTOPLASMOSIS NOS	None
11591	HISTOPLASMOSIS MENINGIT	3
11592	HISTOPLASMOSIS RETINITIS	None
11593	HISTOPLASMOSIS PERICARD	None
11594	HISTOPLASMOSIS ENDOCARD	14
11595	HISTOPLASMOSIS PNEUMONIA	15
11599	HISTOPLASMOSIS NEC	None
1300	TOXOPLASM MENINGOENCEPH	3
1303	TOXOPLASMA MYOCARDITIS	14
1304	TOXOPLASMA PNEUMONITIS	15
1363	PNEUMOCYSTOSIS	15
20400	ACT LYM LEUK W/O RMSION	None
20500	ACT MYL LEUK W/O RMSION	None
20600	ACT MONO LEUK W/O RMSION	None
20700	ACT ERTH/ERYLK W/O RMSON	None
20800	ACT LEUK UNS CL W/O RMSN	None
260	KWASHIORKOR	None
261	NUTRITIONAL MARASMUS	None
262	OTH SEVERE MALNUTRITION	None
27700	CYSTIC FIBROS W/O ILEUS	15
27701	CYSTIC FIBROSIS W ILEUS	15
2860	CONG FACTOR VIII DIORD	None
2861	CONG FACTOR IX DISORDER	None
2866	DEFIBRINATION SYNDROME	None
3200	HEMOPHILUS MENINGITIS	3
3201	PNEUMOCOCCAL MENINGITIS	3
3202	STREPTOCOCCAL MENINGITIS	3
3203	STAPHYLOCOCC MENINGITIS	3

3207	MENING IN OTH BACT DIS	3
32081	ANAEROBIC MENINGITIS	3
32082	MNINGTS GRAM-NEG BCT NEC	3
32089	MENINGITIS OTH SPCF BACT	3
3209	BACTERIAL MENINGITIS NOS	3
3210	CRYPTOCOCCAL MENINGITIS	3
3211	MENING IN OTH FUNGAL DIS	3
3214	MENINGIT D/T SARCOIDOSIS	3
3218	MENING IN OTH NONBAC DIS	3
3240	INTRACRANIAL ABSCESS	3
3241	INTRASPINAL ABSCESS	3
3249	CNS ABSCESS NOS	3
34511	GEN CNV EPIL W INTR EPIL	3
3453	GRAND MAL STATUS	3
3481	ANOXIC BRAIN DAMAGE	3
37601	ORBITAL CELLULITIS	None
37602	ORBITAL PERIOSTITIS	None
37603	ORBITAL OSTEOMYELITIS	None
3980	RHEUMATIC MYOCARDITIS	14
40301	MAL HYP REN W RENAL FAIL	None
40401	MAL HYPER HRT/REN W CHF	None
40403	MAL HYP HRT/REN W CHF&RF	14
41001	AMI ANTEROLATERAL, INIT	14
41011	AMI ANTERIOR WALL, INIT	14
41021	AMI INFEROLATERAL, INIT	14
41031	AMI INFEROPOST, INITIAL	14
41041	AMI INFERIOR WALL, INIT	14
41051	AMI LATERAL NEC, INITIAL	14
41061	TRUE POST INFARCT, INIT	14
41071	SUBENDO INFARCT, INITIAL	14
41081	AMI NEC, INITIAL	14
41091	AMI NOS, INITIAL	14
4151	PULMON EMBOLISM/INFARCT*	15
41511	IATROGEN PULM EMB/INFARC	15
41519	PULM EMBOL/INFARCT NEC	15
4210	AC/SUBAC BACT ENDOCARD	14
4211	AC ENDOCARDIT IN OTH DIS	14
4219	AC/SUBAC ENDOCARDIT NOS	14
4220	AC MYOCARDIT IN OTH DIS	14
42290	ACUTE MYOCARDITIS NOS	14
42291	IDIOPATHIC MYOCARDITIS	14
42292	SEPTIC MYOCARDITIS	14
42293	TOXIC MYOCARDITIS	14
42299	ACUTE MYOCARDITIS NEC	14

42741	VENTRICULAR FIBRILLATION	14
4275	CARDIAC ARREST	14
430	SUBARACHNOID HEMORRHAGE	1
431	INTRACEREBRAL HEMORRHAGE	1
4320	NONTRAUM EXTRADURAL HEM	1
4321	SUBDURAL HEMORRHAGE	1
43301	OCL BSLR ART W INFRCT	1
43311	OCL CRTD ART W INFRCT	1
43321	OCL VRTB ART W INFRCT	1
43331	OCL MLT BI ART W INFRCT	1
43381	OCL SPCF ART W INFRCT	1
43391	OCL ART NOS W INFRCT	1
43401	CRBL THRMBS W INFRCT	1
43411	CRBL EMBLSM W INFRCT	1
43491	CRBL ART OCL NOS W INFRC	1
436	CVA	1
44023	ATH EXT NTV ART ULCRTION	None
44024	ATH EXT NTV ART GNGRENE	None
4410	DISSECTING ANEURYSM*	None
44100	DSCT OF AORTA UNSP SITE	None
44101	DSCT OF THORACIC AORTA	None
44102	DSCT OF ABDOMINAL AORTA	None
44103	DSCT OF THORACOABD AORTA	None
4411	RUPTUR THORACIC ANEURYSM	None
4413	RUPT ABD AORTIC ANEURYSM	None
4415	RUPT AORTIC ANEURYSM NOS	None
4416	THORACOABD ANEURYSM RUPT	None
4463	LETHAL MIDLINE GRANULOMA	None
45189	THROMBOPHLEBITIS NEC	None
452	PORTAL VEIN THROMBOSIS	None
453	OTH VENOUS THROMBOSIS*	None
4530	BUDD-CHIARI SYNDROME	None
4531	THROMBOPHLEBITIS MIGRANS	None
4532	VENA CAVA THROMBOSIS	None
4533	RENAL VEIN THROMBOSIS	None
46411	AC TRACHEITIS W OBSTRUCT	15
46421	AC LARYNGOTRACH W OBSTR	None
46431	AC EPIGLOTTITIS W OBSTR	15
4661	ACUTE BRONCHIOLITIS*	None
4800	ADENOVIRAL PNEUMONIA	None
4801	RESP SYNCYT VIRAL PNEUM	None
4802	PARINFLUENZA VIRAL PNEUM	None
4808	VIRAL PNEUMONIA NEC	None
4809	VIRAL PNEUMONIA NOS	None

481	PNEUMOCOCCAL PNEUMONIA	None
482	OTH BACTERIAL PNEUMONIA*	None
4820	K. PNEUMONIAE PNEUMONIA	None
4821	PSEUDOMONAL PNEUMONIA	None
4822	H.INFLUENZAE PNEUMONIA	15
4823	STREPTOCOCCAL PNEUMONIA*	None
48230	STREPTOCOCCAL PNEUMN NOS	15
48231	PNEUMONIA STRPTOCOCCUS A	15
48232	PNEUMONIA STRPTOCOCCUS B	15
48239	PNEUMONIA OTH STREP	15
4824	STAPHYLOCOCCAL PNEUMONIA*	None
48240	STAPHYLOCOCCAL PNEU NOS	None
48241	STAPH AUREUS PNEUMONIA	None
48249	STAPH PNEUMONIA NEC	None
4828	BACTERIAL PNEUMONIA NEC*	None
48281	PNEUMONIA ANAEROBES	None
48282	PNEUMONIA E COLI	None
48283	PNEUMO OTH GRM-NEG BACT	None
48284	LEGIONNAIRES' DISEASE	None
48289	PNEUMONIA OTH SPCF BACT	None
4829	BACTERIAL PNEUMONIA NOS	None
483	PNEUMONIA: ORGANISM NEC*	None
4830	PNEU MYCPLSM PNEUMONIAE	15
4831	PNEUMONIA D/T CHLAMYDIA	None
4838	PNEUMON OTH SPEC ORGNSM	15
484	PNEUM IN OTH INFEC DIS*	None
4841	PNEUM W CYTOMEG INCL DIS	15
4843	PNEUMONIA IN WHOOP COUGH	15
4845	PNEUMONIA IN ANTHRAX	15
4846	PNEUM IN ASPERGILLOSIS	15
4847	PNEUM IN OTH SYS MYCOSES	15
4848	PNEUM IN INFECT DIS NEC	15
485	BRONCHOPNEUMONIA ORG NOS	15
486	PNEUMONIA, ORGANISM NOS	15
487	INFLUENZA*	
4870	INFLUENZA WITH PNEUMONIA	None
5060	FUM/VAPOR BRONC/PNEUMON	None
5061	FUM/VAPOR AC PULM EDEMA	15
5070	FOOD/VOMIT PNEUMONITIS	15
5071	OIL/ESSENCE PNEUMONITIS	15
5078	SOLID/LIQ PNEUMONIT NEC	15
5100	EMPYEMA WITH FISTULA	15
5109	EMPYEMA W/O FISTULA	15
5111	BACT PLEUR/EFFUS NOT TB	15

5130	ABSCESS OF LUNG	15
5131	ABSCESS OF MEDIASTINUM	15
514	PULM CONGEST/HYPOSTASIS	None
515	POSTINFLAM PULM FIBROSIS	None
5183	PULMONARY EOSINOPHILIA	None
5185	POST TRAUM PULM INSUFFIC	15
51881	ACUTE RESPIRATRY FAILURE	15
5192	MEDIASTINITIS	15
5283	CELLULITIS/ABSCESS MOUTH	None
5304	PERFORATION OF ESOPHAGUS	15
53082	ESOPHAGEAL HEMORRHAGE	None
53100	AC STOMACH ULCER W HEM	None
53101	AC STOMAC ULC W HEM-OBST	None
53110	AC STOMACH ULCER W PERF	None
53111	AC STOM ULC W PERF-OBST	None
53120	AC STOMAC ULC W HEM/PERF	None
53121	AC STOM ULC HEM/PERF-OBS	None
53140	CHR STOMACH ULC W HEM	None
53141	CHR STOM ULC W HEM-OBSTR	None
53150	CHR STOMACH ULCER W PERF	None
53151	CHR STOM ULC W PERF-OBST	None
53160	CHR STOMACH ULC HEM/PERF	None
53161	CHR STOM ULC HEM/PERF-OB	None
53200	AC DUODENAL ULCER W HEM	None
53201	AC DUODEN ULC W HEM-OBST	None
53210	AC DUODENAL ULCER W PERF	None
53211	AC DUODEN ULC PERF-OBSTR	None
53220	AC DUODEN ULC W HEM/PERF	None
53221	AC DUOD ULC HEM/PERF-OBS	None
53240	CHR DUODEN ULCER W HEM	None
53241	CHR DUODEN ULC HEM-OBSTR	None
53250	CHR DUODEN ULCER W PERF	None
53251	CHR DUODEN ULC PERF-OBST	None
53260	CHR DUODEN ULC HEM/PERF	None
53261	CHR DUOD ULC HEM/PERF-OB	None
53300	AC PEPTIC ULCER W HEMORR	None
53301	AC PEPTIC ULC W HEM-OBST	None
53310	AC PEPTIC ULCER W PERFOR	None
53311	AC PEPTIC ULC W PERF-OBS	None
53320	AC PEPTIC ULC W HEM/PERF	None
53321	AC PEPT ULC HEM/PERF-OBS	None
53340	CHR PEPTIC ULCER W HEM	None
53341	CHR PEPTIC ULC W HEM-OBS	None
53350	CHR PEPTIC ULCER W PERF	None

53351	CHR PEPTIC ULC PERF-OBST	None
53360	CHR PEPT ULC W HEM/PERF	None
53361	CHR PEPT ULC HEM/PERF-OB	None
53400	AC MARGINAL ULCER W HEM	None
53401	AC MARGIN ULC W HEM-OBST	None
53410	AC MARGINAL ULCER W PERF	None
53411	AC MARGIN ULC W PERF-OBS	None
53420	AC MARGIN ULC W HEM/PERF	None
53421	AC MARG ULC HEM/PERF-OBS	None
53440	CHR MARGINAL ULCER W HEM	None
53441	CHR MARGIN ULC W HEM-OBS	None
53450	CHR MARGINAL ULC W PERF	None
53451	CHR MARGIN ULC PERF-OBST	None
53460	CHR MARGIN ULC HEM/PERF	None
53461	CHR MARG ULC HEM/PERF-OB	None
53501	ACUTE GASTRITIS W HMRHG	None
53511	ATRPH GASTRITIS W HMRHG	None
53521	GSTR MCSL HYPRT W HMRG	None
53531	ALCHL GSTRITIS W HMRHG	None
53541	OTH SPF GASTRT W HMRHG	None
53551	GSTR/DDNTS NOS W HMRHG	None
53561	DUODENITIS W HMRHG	None
5374	GASTRIC/DUODENAL FISTULA	None
53783	ANGIO STM/DUDN W HMRHG	None
5400	AC APPEND W PERITONITIS	None
5570	AC VASC INSUFF INTESTINE	None
56202	DVRTCLO SML INT W HMRHG	None
56203	DVRTCLI SML INT W HMRHG	None
56212	DVRTCLO COLON W HMRHG	None
56213	DVRTCLI COLON W HMRHG	None
5670	PERITONITIS IN INFEC DIS	None
5671	PNEUMOCOCCAL PERITONITIS	None
5672	SUPPURAT PERITONITIS NEC	None
5678	PERITONITIS NEC	None
5679	PERITONITIS NOS	None
56960	COLSTOMY/ENTER COMP NOS	None
56961	COLOSTY/ENTEROST INFECTN	None
56969	COLSTMY/ENTEROS COMP NEC	None
56983	PERFORATION OF INTESTINE	None
56985	ANGIO INTES W HMRHG	None
570	ACUTE NECROSIS OF LIVER	None
5720	ABSCESS OF LIVER	None
5724	HEPATORENAL SYNDROME	None
5734	HEPATIC INFARCTION	None

5754	PERFORATION GALLBLADDER	None
5763	PERFORATION OF BILE DUCT	None
5772	PANCREAT CYST/PSEUDOCYST	None
5793	INTEST POSTOP NONABSORB	None
5800	AC PROLIFERAT NEPHRITIS	None
5804	AC RAPIDLY PROGR NEPHRIT	None
58081	AC NEPHRITIS IN OTH DIS	None
58089	ACUTE NEPHRITIS NEC	None
5809	ACUTE NEPHRITIS NOS	None
5834	RAPIDLY PROG NEPHRIT NOS	None
5845	LOWER NEPHRON NEPHROSIS	None
5846	AC RENAL FAIL, CORT NECR	None
5847	AC REN FAIL, MEDULL NECR	None
5848	AC RENAL FAILURE NEC	None
5849	ACUTE RENAL FAILURE NOS	None
5902	RENAL/PERIRENAL ABSCESS	None
5966	BLADDER RUPT, NONTRAUM	None
65930	SEPTICEMIA IN LABOR-UNSP	None
65931	SEPTICEM IN LABOR-DELIV	None
66500	PRELABOR RUPT UTER-UNSP	None
66501	PRELABOR RUPT UTERUS-DEL	None
66503	PRELAB RUPT UTER-ANTEPAR	None
66510	RUPTURE UTERUS NOS-UNSP	None
66511	RUPTURE UTERUS NOS-DELIV	None
66910	OBSTETRIC SHOCK-UNSPEC	None
66911	OBSTETRIC SHOCK-DELIVER	None
66912	OBSTET SHOCK-DELIV W P/P	None
66913	OBSTETRIC SHOCK-ANTEPAR	None
66914	OBSTETRIC SHOCK-POSTPART	None
66930	AC REN FAIL W DELIV-UNSP	None
66932	AC REN FAIL-DELIV W P/P	None
66934	AC RENAL FAILURE-POSTPAR	None
67300	OB AIR EMBOLISM-UNSPEC	None
67301	OB AIR EMBOLISM-DELIVER	None
67302	OB AIR EMBOL-DELIV W P/P	None
67303	OB AIR EMBOLISM-ANTEPART	None
67304	OB AIR EMBOLISM-POSTPART	None
67310	AMNIOTIC EMBOLISM-UNSPEC	None
67311	AMNIOTIC EMBOLISM-DELIV	None
67312	AMNIOT EMBOL-DELIV W P/P	None
67313	AMNIOTIC EMBOL-ANTEPART	None
67314	AMNIOTIC EMBOL-POSTPART	None
67320	OB PULM EMBOL NOS-UNSPEC	15
67322	PULM EMBOL NOS-DEL W P/P	15

67323	PULM EMBOL NOS-ANTEPART	15
67324	PULM EMBOL NOS-POSTPART	15
67330	OB PYEMIC EMBOL-UNSPEC	None
67331	OB PYEMIC EMBOL-DELIVER	None
67332	OB PYEM EMBOL-DEL W P/P	None
67333	OB PYEMIC EMBOL-ANTEPART	None
67334	OB PYEMIC EMBOL-POSTPART	None
67380	OB PULMON EMBOL NEC-UNSP	None
67381	PULMON EMBOL NEC-DELIVER	15
67382	PULM EMBOL NEC-DEL W P/P	15
67383	PULMON EMBOL NEC-ANTEPAR	15
67384	PULMON EMBOL NEC-POSTPAR	15
67400	PUERP CEREBVASC DIS-UNSP	3
682	OTHER CELLULITIS/ABSCESS*	
6820	CELLULITIS OF FACE	None
6821	CELLULITIS OF NECK	None
6822	CELLULITIS OF TRUNK	None
6823	CELLULITIS OF ARM	None
6824	CELLULITIS OF HAND	None
6825	CELLULITIS OF BUTTOCK	None
6826	CELLULITIS OF LEG	None
6827	CELLULITIS OF FOOT	None
6828	CELLULITIS, SITE NEC	None
76501	EXTREME IMMATUR <500G	None
76502	EXTREME IMMATUR 500-749G	None
76503	EXTREME IMMATUR 750-999G	None
7817	TETANY	None
78551	CARDIOGENIC SHOCK	14
78559	SHOCK W/O TRAUMA NEC	None
7991	RESPIRATORY ARREST	15
9580	AIR EMBOLISM	None
9581	FAT EMBOLISM	None
9585	TRAUMATIC ANURIA	None
99602	MALFUNC PROSTH HRT VALVE	14
99661	REACT-CARDIAC DEV/GRAFT	14
99662	REACT-OTH VASC DEV/GRAFT	None
99663	REACT-NERV SYS DEV/GRAFT	None
99664	REACT-INDWELL URIN CATH	None
99666	REACT-INTER JOINT PROST	8
99667	REACT-OTH INT ORTHO DEV	9
99669	REACT-INT PROS DEVIC NEC	None
99762	INFECTION AMPUTAT STUMP	10, 11
9980	POSTOPERATIVE SHOCK	None
9983	POSTOP WOUND DISRUPTION	None

9985	POSTOPERATIVE INFECTION*	None
9986	PERSIST POSTOP FISTULA	None
9991	AIR EMBOL COMP MED CARE	None
V440	TRACHEOSTOMY STATUS	None
V451	RENAL DIALYSIS STATUS	None
V461	DEPENDENCE ON RESPIRATOR	15

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