
Development and Evaluation of Clinical Risk Groups (CRGs)

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Clinical Risk Groups are a clinical model in which each individual is assigned to a single mutually exclusive risk group which relates the historical clinical and demographic characteristics of the individual to the amount and type of healthcare resources that individual will consume in the future. Since the CRGs are clinically based, they create a language that links the clinical and financial aspects of care. CRGs are designed to serve as the foundation of management systems which support care pathways, product line management and case management. This article describes the development and structure of the CRGs and evaluates the performance of CRGs for risk adjusting capitated payments. The CRGs were developed through a highly iterative process that combined extensive clinical input with evaluation and verification from historical data.

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Introduction

Expenditures for healthcare services constitute an increasingly large percentage of the U.S. gross domestic product (GDP). In 1980 healthcare expenditures were 8.9 percent of the GDP, grew to 12.1 percent in 1990 and are projected to be 16.1 percent by the year 2000.¹ In contrast, most other developed countries utilize much less of their GDP on healthcare. Equivalent statistics from 1993 for Germany, Japan and the United Kingdom were 8.6 percent, 7.3 percent and 7.1 percent, respectively.² High healthcare expenditures create a financial burden for Federal and state governments, businesses and individuals. It also creates a competitive disadvantage relative to the price of U.S. products and services in the international market place.

Attempts to control healthcare expenditures in the U.S. have utilized three primary strategies.

- Shift financial risk from payers to providers
- Provide financial incentives for providers to deliver care efficiently
- Create competition among providers based on price and scope and quality of services

During the past three decades, there has been an evolution of the basic unit of payment upon which healthcare services are paid. The unit of payment has evolved through items, cost, per diems, per case,

episodes and capitation. Various payers have utilized some or all of these units of payment. Each of the successive evolutions of the unit of payment has aggregated more services into the unit of payment. Per diem payment aggregates all hospital services provided in a day. Per case payment aggregates all hospital services provided for a hospital admission. Episode payment aggregates all healthcare services for a particular illness over a period of time. Capitated payment aggregates all healthcare services for an individual over a period of time. As illustrated in Figure 1, this evolution of the unit of payment into larger and larger units of payment shifts the financial risk from payer to provider. The inherent assumption underlying the transfer of financial risk from payer to provider is that since providers control the provision of services, they can also control the overall cost of services.

The shift of financial risk from payer to provider also creates the incentive for providers to control costs since providers will benefit financially if their costs are low and suffer financially if their costs are high. Thus, the evolution of healthcare cost containment strategies has focused on the shift of risk from payer to provider which

creates incentives for providers to deliver care efficiently. More recently, with the advent of managed care, the process of establishing the price for each unit of service has evolved from a negotiation between provider and payer to a competition among providers in which payers limit the number of providers with whom they do business, based in part on the price offered by the provider. In one form or another, the basis of many managed care arrangements is the payment of a capitated rate that has been competitively established. The long-term success of such arrangements depends on the establishment of capitated rates that are fair and realistic, and the ability of the providers to respond to the incentive to control cost in a way that is effective for all population groups.

The adoption of managed care has expanded rapidly. Managed care enrollment for Medicare in 1998 was 18.3 percent of beneficiaries,³ and for Medicaid in 1997 was over 40 percent of beneficiaries.⁴ However, major problems have arisen in the managed care approach. A study by the Medicare Payment Advisory

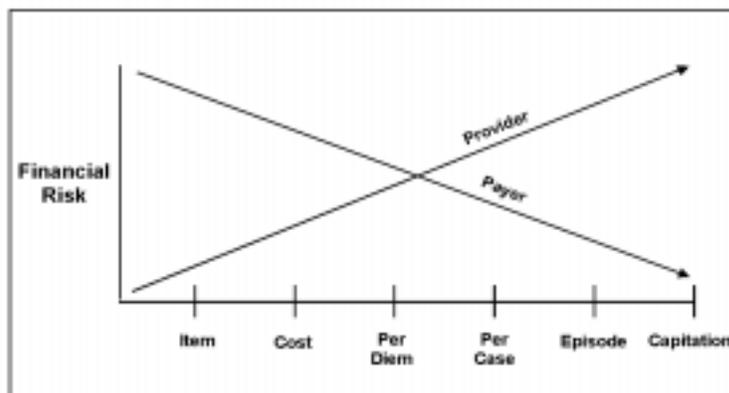


Figure 1. Evolution of Unit of Payment

Commission (MedPAC) showed a significant bias in enrollment and disenrollment patterns in managed care organizations (MCOs) contracting with Medicare.⁵ The Medicare program offers recipients the option to voluntarily enroll in a MCO or remain in the fee-for-service delivery system. New enrollees in Medicare MCOs appear to be relatively healthy, with expenditures that are about 35 percent below the Medicare fee-for-service average in the six months before enrollment. By contrast, Medicare beneficiaries disenrolling from MCOs had expenditures 60 percent higher than the Medicare fee-for-service average in the six months following disenrollment. Thus, healthy beneficiaries tend to enroll in Medicare MCOs and sick beneficiaries tend to disenroll from Medicare MCOs.⁶ In an effort to keep costs low, some MCOs have targeted their marketing efforts toward healthy individuals.⁷ Unfortunately, it is easier to attract healthy beneficiaries and avoid enrolling sick beneficiaries than it is to learn to deliver cost effective care. The advertising policy, facility location and types of services offered (e.g., sports medicine) can easily be used to create a bias selection of healthy enrollees. As a result of biased enrollment and disenrollment Medicare is overpaying capitated MCOs by 5-20 percent.⁸

While some managed care plans have profited by enrolling Medicare beneficiaries, others have terminated or reduced participation in Medicare citing the high cost of caring for Medicare beneficiaries.⁹ Many MCOs have not been able to afford the high risks associated with very sick Medicare beneficiaries. There have been similar experiences with MCOs enrolling Medicaid beneficiaries.¹⁰ Most managed care plans started in the private sector

with the enrollment of working populations in which the vast majority of enrollees are relatively healthy. The financial risks and clinical management challenges associated with the transition to Medicare and Medicaid populations in which a significant proportion of the population is relatively sick is proving to be difficult for many MCOs.

The fundamental issue underlying the problems that managed care is experiencing relates to risk adjustment. MedPAC has defined risk adjustment as follows.¹¹

“The process used to adjust plan payments to compensate for differences in the health plan’s health status of enrollees across plans.”

Payers, in general, have done an inadequate job of risk adjusting payments to MCOs. Since the success of payment on capitated basis relies on MCOs being able to manage the financial risk and respond to the incentive to be efficient, the failure to adequately adjust payments for the risk associated with the enrolled population represents a fundamental flaw in the managed care approach. Kuttner has described the dangers of inadequate risk adjustment as follows:¹²

“Thus failure to adjust compensation for patient’s health status reinforces two of the more worrisome trends in the present healthcare system. First, it rewards plans for a business strategy of ‘risk selection’ in which they deliberately market their services to relatively healthy populations and avoid relatively sick ones. This strategy, in turn, punishes plans and physicians that do a good job of treating the sick, thus reinforcing the incentive to stint on care that is already present in a system that increasingly relies on

payment by means of capitation rather than on fee-for-service reimbursement. Second, as risks are shifted to the individual physician, doctors with sicker patients must work longer hours or receive a reduced income or make unethical or clinically dangerous decisions to withhold necessary care.”

The incentive to enroll the healthy individuals is dramatic. Figure 2 shows the distribution of Medicare beneficiaries and program payments. 73.5 percent of Medicare beneficiaries consume 7.6 percent of program expenditures, while 9.8 percent of beneficiaries consume 68.4 percent of program expenditures.¹³ Thus, there is an enormous concentration of expenditures in relatively few individuals. With such a concentration, a strategy for financial success under a capitated payment system with inadequate risk adjustment is clear: enroll the 73.6 percent of beneficiaries that consume 7.6 percent of the expenditures and avoid enrolling the 9.8 percent of beneficiaries that consume 68.4 percent of the expenditures. A financially successful strategy toward disenrollment is also clear. Enrollee expenditures from the previous year are a relatively good predictor of the

next year’s expenditures.¹⁴ Thus, managed care organizations can easily identify the enrollees who are likely to be high cost in the future. The failure to have adequate risk adjustment creates a perverse set of incentives. For example, an MCO recognized as providing high quality care to individuals with HIV could be financially penalized if it enrolled too many HIV infected individuals. The failure to include adequate risk adjustment in capitated payment arrangements is jeopardizing the potential success of managed care. In particular, inadequate payment for the sickest individuals may lead to access problems. Thus, there is a critical need for a comprehensive and accurate method for risk adjusting capitation payments.

The objective of this research was to develop a classification system for accurately describing the health status of individuals enrolled in MCOs. The challenges associated with the development of a classification system for risk adjustment are substantial. The enormous concentration of expenditures in relatively few individuals make the identification and classification of these individuals crucial to the effectiveness of risk adjustment. Since individuals with severe disease in multiple organ sys-

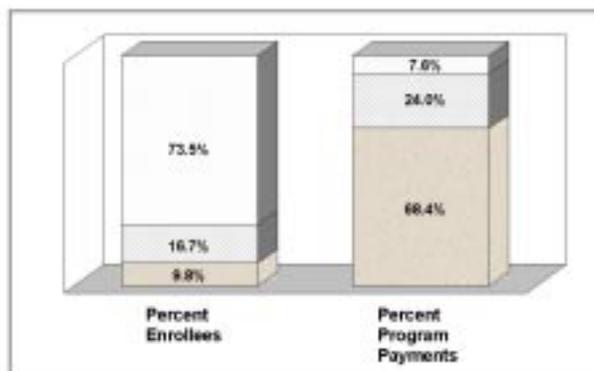


Figure 2. 1992 Distribution of Medicare Enrollees and Program Payments

tems are likely to be a substantial proportion of the high expenditure individuals, the classification system needs to include a detailed clinical specification of individuals with multiple comorbid diseases including a determination of their relative severity of illness.

The initial motivation for developing the classification system was for risk adjustment of capitated payments. However, the development focused on developing a management tool for MCOs, since the success of a capitated payment system is dependent on MCOs being able to respond to the incentives in the system and deliver care efficiently and effectively. The classification system that resulted is not only a management tool but can also be used as a basis for risk adjusting capitated payments. Risk adjustment, incentives for efficiency and management's response are all interrelated in a capitated payment system. An effective solution to the problem of risk adjustment must address these interrelated issues simultaneously. Further, risk adjustment is only one part of a capitated payment system. The classification system for risk adjustment can not be developed in isolation from the other components of the full payment system (e.g., stop loss, annual updates, etc.). The development of the classification system for risk adjustment must, therefore, explicitly address the full design of a capitated payment system and address how risk adjustment is integrated into each component of the payment system. Finally, the classification system must be viewed as part of an overall system for monitoring and evaluating MCO performance. The classification system is not only key to the capitated payment methodology but is also key to the methodology for tracking the populations served by each MCO and monitoring MCO performance as measured through patient satis-

faction surveys, disenrollment rates and other outcome measures. It is essential for the classification system to be able to differentiate MCO performance for healthy populations who require relatively few services from MCO performance for sicker populations who require more extensive services.

The classification system for risk adjustment developed during this research is named Clinical Risk Groups (CRGs). As the name implies, CRGs are risk groups that can be used as the basis of risk adjustment in a capitated payment system and are also clinically precise so that they can be used as a management tool for MCOs.

The design and development of CRGs was greatly influenced by the success of the Medicare inpatient Prospective Payment System (PPS). The Medicare PPS was the first large scale implementation of a payment system that incorporated the clinical characteristics of a patient into the determination of the payment amount for the patient. The Medicare PPS is a per case payment system that uses the Diagnosis Related Groups (DRGs) as the basic unit of payment. Based on the patient's diagnoses, procedures, age and sex the DRGs assign each patient to a single, mutually exclusive and clinically coherent group of patients that are expected to consume similar amounts and types of hospital resources. In the Medicare PPS, a prospective payment amount is established for each DRG. The Medicare PPS has been an extremely effective payment system. The Brookings Institute has estimated that as a result of the PPS, Medicare has reduced Medicare expenditures for inpatient care have been reduced by \$17 billion per year.¹⁵ Further, these savings have been achieved with no apparent impact on quality of care.¹⁶ In addition to

the Medicare program, there are a number of state Medicaid programs, private sector payers and foreign countries that have implemented DRG-based payment systems.¹⁷

Like DRGs, CRGs provide a means of incorporating the clinical characteristics of individuals into the determination of the payment amount. While the role of DRGs and CRGs in a payment system are similar, there are some fundamental differences between the two classification systems. One is the difference between casemix adjustment and risk adjustment. DRGs are assigned after the services are rendered while CRGs must be assigned before the services are rendered. Thus, DRGs explain past resource use while CRGs must predict future resource use. A second fundamental difference is that DRGs classify a single encounter at a point in time, (i.e., a hospitalization), while CRGs classify the individual and all medical care services for an extended period of time. Despite these differences, many of the fundamental lessons learned from the successful implementation of the Medicare PPS still apply to the problems associated with the establishment of capitated payment rates.

Lessons Learned from the Medicare PPS

There are several key attributes of the Medicare PPS that were critical to its success. These attributes were also key to the success of efforts by Medicaid programs and other payers to implement an inpatient PPS system.

Payment was based on a Categorical Clinical Model

Since the DRGs were developed as groups of clinically similar patients, a lan-

guage was created that linked the clinical and financial aspects of care. The importance of the communication value of DRGs can not be emphasized enough. The language of DRGs provided administrators and physicians a meaningful basis for evaluating both the processes of care and the associated financial impacts. Indeed, DRGs were originally developed to be a management tool. The availability of a DRG definitions manual, in which the clinical characteristics of each DRG were clearly specified, was essential for creating a basis of communications (nearly 100,000 copies of the DRG definitions manual have been distributed). DRGs revolutionized hospital management. Development of care pathways by DRG and profit and loss reports by DRG product lines became commonplace. With the adoption of these new management methods, length of stay and the use of ancillary services dropped dramatically.¹⁸ The simple categorical nature of DRGs created a powerful communications tool. The Medicare PPS did not by itself reduce Medicare inpatient expenditures. What it did was to create the foundation for a new approach to hospital management which resulted in increased efficiency which in turn permitted Medicare payment levels to be reduced without creating a financial crisis for hospitals.

DRGs not only provided a communications tool for hospital management, but they also provided an effective means for hospitals and Medicare to communicate. Instead of accountants and lawyers arguing the fine points of cost accounting, the focus of payment deliberations became the determination of a fair payment rate for patients with specific clinical problems. The vast majority of modifications to the DRGs since the inception of the Medicare PPS have resulted from recommendations

from hospitals. The recommendations have almost always been the result of clinicians identifying specific types of patients with unique needs that were not adequately addressed in the DRGs. A recent example of such a clinical dialogue is the DRGs related to burns.¹⁹ The fiscal year 1999 update to the DRGs included a major restructuring of the burn DRGs. This restructuring was the direct result of detailed and specific recommendations provided to Medicare by burn specialists.

Separate Methodology for Computation of Payment Weights

The Medicare PPS establishes a relative payment weight for each DRG which is the basis for setting the actual payment amount. The process of establishing the relative DRG payment weight is straightforward and basically involves estimating the average cost of patients in each DRG. The categorical nature of DRGs permits a separation of the computation of the relative payment weights and the definition of the DRG categories. Such a separation is an inherent by-product of the categorical nature of DRGs and can not be readily implemented in noncategorical systems. For example, payment rates could be computed based on linear or logistic regression techniques. In a regression model, the presence of certain clinical factors are used as variables in the regression. The coefficients in the regression equation would be equivalent to the relative payment weights in the DRG system. However, in a regression model, the clinical model and payment coefficients are inextricably intertwined. There is no independent definition of the clinical model and the payment coefficients.

The separation of the methodologies for developing the clinical model and the payment weights was a critical factor in the success and widespread adoption of the

DRG system. An example of the importance of the separation of the clinical and payment weight methodologies is illustrated by the first set of DRG payment weights used in the Medicare PPS.²⁰ In this initial set of DRG payment weights there were five pairs of DRGs in which patients with a complication or comorbidity, which would clinically be expected to result in a higher payment weight, actually had a *lower* payment weight than patients without a complication or comorbidity. This anomaly reflected limitations in the database used to compute the initial set of DRG payment weights. The important point is that the clinical definition of the DRGs was *not* altered based on the anomaly. In a regression model the anomaly in the data would implicitly be reflected in the coefficients in the regression equation. In the third year of the Medicare PPS the DRG payment weights were recomputed with more accurate data and the anomalies in the DRG payment weights were eliminated without any change to the clinical definition of the DRGs. Thus, the separation of the clinical and payment weight methodologies allowed a stable clinical methodology to be maintained while the payment weights evolved in response to more accurate and complete data.

The independence of the clinical model and payment weights plus the straightforward method for computing the DRG payment weights (i.e., a simple average) facilitated the widespread use of the DRGs by other payers and foreign countries. The clinical definition of the DRGs has been relatively stable but the relative payment weights have varied substantially. The clinical definition of the DRGs reflect the type of patient while the DRG payment weights reflect the treatment processes and methods. Since new diseases (e.g. HIV) are rare, the clinical definition of the DRGs are

expected to be relatively stable. However, since treatment processes and methods are constantly changing, the DRG payment weights often undergo substantial change. Most non-Medicare payers (e.g., Medicaid) that have used DRGs, compute their own DRG payment weights while leaving the standard DRG definitions unchanged.²¹ In a regression model this would be difficult since it would require the payer to have available both the expertise and the statistical packages necessary to recompute the regression coefficients. Further, it is rare that the regression coefficients computed by a statistical package are used unaltered in the final model. Issues such as the interpretation of negative coefficients must be evaluated before the regression model is finalized. Such capabilities are not readily available for most payers. The dynamic nature of treatment processes and methods and the complexities of using regression techniques, in practice, requires the payer to be dependent on the developer of a regression-based risk adjustment system for ongoing updates to the system. In contrast, the simple computation of average values needed to compute DRG payment weights can be easily accomplished by most payers and allows payers to update the payment system independent of the developers of the DRGs.

Separate Payment Adjustments for Nonclinical Factors

The DRG relative payment weights reflect the relative costliness of patients due to their clinical condition. However, there are other factors beyond the patient's clinical condition, which can legitimately affect hospital cost. In the Medicare PPS there are payment adjustments for factors such as the teaching status of the hospital or proportion of a Medicaid and Medicare patients (referred to as disproportionate

share). Such payment adjustments are the components of the Medicare PPS that are most subject to political negotiation and, therefore, most subject to change and most likely to be different across payers.

The design of the Medicare PPS kept these adjustment factors independent of the clinical definition of the DRGs and the computation of the DRG relative payment weights. This separation of components allowed other payers to adopt the DRG payment model without using the payment adjustment factors chosen by Medicare. Further, by keeping the nonclinical adjustment factors separate from the DRG definitions, the value of the DRGs as the basis of communications with physicians was maintained. The independence of the nonclinical payment adjustment factors from the clinical definition of the DRGs and the DRG payment weights would not, in general, be possible in a regression model. In a regression model, both the clinical variables and the nonclinical clinical variables are used to determine the regression equation and it would be difficult to isolate the impact of the nonclinical variables. Indeed, the coefficients of the clinical variables in the regression could change substantially if the nonclinical variables changed or were excluded.

Outlier Payments Specific to the Patient's Condition

No patient classification system can accurately classify 100 percent of the patients. Some patients have clinical conditions that are so unique that they defy classification. The Medicare DRG PPS recognizes this by defining outliers on a DRG specific basis. If a patient's resource use exceeds a DRG specific level the hospital is given additional payment. The evaluation by providers of the accuracy and fairness of any payment system is very much affected by how the system handles

the extremely expensive cases. While the truly expensive cases are relatively few in number, they do have a substantial financial impact. The method for handling outliers is critical to both the provider perception of the payment system and the effectiveness of internal management systems. Indeed, the basis of and method for determining outliers is integral to any payment system, and in some ways as important as the patient classification system itself. Outliers are in essence an insurance mechanism that protects providers from excessive losses. But just as important, the handling of outliers is an integral part of management systems that providers put in place to respond to the payment system. In the Medicare PPS a single fixed outlier amount could have been established (e.g., \$75,000). However, a single outlier amount, while administratively simple, would be too high for hernia patients and too low for heart transplant patients. Instead, Medicare sets unique outlier levels separately for each DRG. A definition of outliers that was meaningful in the context of the clinical definition of the DRG and relative DRG payment weight was an essential component of an internally consistent payment system that formed the foundation based on which hospitals could develop an effective management response. Thus, in addition to product plans and clinical pathways for individual DRGs, hospitals also instituted case management interventions for outlier patients.

The DRG payment system is summarized in Figure 3. While the basic idea of

the Medicare PPS was simple (i.e., set prospective payment rates per admission in order to provide hospitals with the incentive to control costs), the design decisions relating to payment weights, payment adjustments and outliers were crucial to its effectiveness. Further, the categorical nature of DRGs resulted in a communications revolution that was at the core of the success of PPS.

Characteristics of a CRG-Based Payment System

The lessons learned in the implementation of the Medicare PPS and the PPS systems implemented by other payers are relevant to the problem of establishing risk adjusted capitated payment rates. The design and development of the CRGs and their use in a payment system reflects many of the key decisions made in the implementation of the Medicare PPS. A CRG-based payment system was designed to have the following characteristics.

The CRGs are a Categorical Clinical Model

The CRGs are a categorical clinical model in which each individual is assigned to a single mutually exclusive risk group which relates the historical clinical and demographic characteristics of the individual to the amount and type of healthcare resources that individual will consume in the future. Since the CRGs are clinically based, they create a language that links the clinical and financial aspects of care.

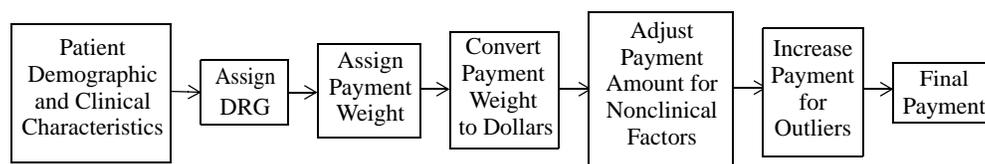


Figure 3. DRG Payment System

Thus, CRGs are designed to serve as the foundation of management systems which support care pathways, product line management and case management. The CRG Definitions Manual contains a complete specification of the CRG logic, permitting physicians to independently assess the clinical validity of CRGs.

The CRGs are Severity Adjusted

While the DRGs used by Medicare do not explicitly adjust for severity of illness, more advanced versions of the DRGs have been developed that contain severity of illness subclasses within each DRG.²² These more advanced versions of DRGs not only improve the clinical accuracy of the DRGs and their applicability to patients in all age categories, but also allow the applications of DRGs to be expanded to include outcomes analysis. Indeed, more than 20 states use severity of illness adjusted DRGs to disseminate provider performance reports to the public.²³ The addition of severity of illness subclasses to the DRGs further improved the value of DRGs as a communication and management tool. The CRGs were developed to include explicit severity of illness subclasses that describe the extent and progression of an individual's condition.

The CRGs are Based on Standard Claims Data

The data used in the clinical definition of the CRGs is limited to data routinely available in standard claims processing systems. The data used to assign the CRG is limited to age, sex, diagnoses, procedures, site of service, date of service and provider type. Restricting the data used in the definition of the CRGs to data that is readily available allows CRGs to be widely used. Data currently not routinely collected, such as pharmaceuticals, may be useful for defining future versions of CRGs

if the inclusion of these additional data result in an improvement in the clinical accuracy and statistical performance of the CRGs.

Separate Methodology for Computation of Payment Weights

The CRG payment weights are a relative measure of the future cost of individuals in each CRG. The process of establishing the relative CRG payment weights is relatively straight-forward and basically involves computing the average future cost of individuals assigned to the CRG. For example, suppose two years of historical data were available. CRGs would be assigned based on the demographic and clinical information in the first year. CRG payment weights would be computed as the average expenditures in the second year for individuals assigned to each CRG based on the first year data. The first year is used to assign the CRG and the second year is used to compute the CRG payment weight. The separation of the CRG clinical model and the CRG payment weights allows payers to compute their own payment weights while using the standard CRG clinical model.

Payment Weights Subdivided into Cost Components

The specific categories of expenditures included in capitated payment arrangements can vary. For example, pharmacy costs may be "carved out" of the capitated rate. The CRG payment weights can be expressed in terms of the cost components that make up the payment weight (e.g., pharmacy, physician, hospital, laboratory, etc.) so that the proportion of the payment weight that is associated with each cost component is known. For example, a capitated payment arrangement negotiated with a managed care organization might exclude pharmacy expenditures which could be paid on a capitated basis

to a separate organization. CRG payment weights excluding pharmacy and separate CRG pharmacy payment weights can be generated to support such a payment arrangement. The separation of the clinical model and payment weights and the relatively straight-forward method for computing the CRG payment weights (i.e., the average values) provides great flexibility in establishing capitated payment arrangements. Such flexibility is not necessarily available in other risk adjustment systems. For example, risk adjustment systems based on regression models require different regression equations be developed for each cost component.

Aggregation of CRGs

The number of individuals covered by payers can vary considerably. While payment weights are available with CRGs, most payers will compute their own payment weights. In order to facilitate CRG use, CRGs are consolidated into three tiers of aggregation. Each successive tier of aggregation has fewer CRGs. Payers that wish to compute their own payment weights but have relatively few covered individuals can use a highly consolidated tier of CRG aggregation in order to have a sufficient number of covered individuals to compute a payment weight. Within each successive aggregation of CRGs distinct severity of illness levels are maintained. The severity of illness of an individual is an essential part of description of the individual's condition. Not only are the multiple tiers of aggregation important for flexibility in establishing payment weights, but they are also essential for developing an effective management information system based on CRGs. Since the successive consolidations of CRGs are formed in a hierarchical manner, upper management can receive highly aggregated reports while clinicians can receive a correspond-

ing set of reports that contain more detail. CRGs contain the flexibility to provide the payer or provider the level of detail that corresponds to their needs.

Separate Payment Adjustments for Nonclinical Factors

The CRG payment weights reflect the relative costliness of individuals due to their clinical condition as measured through the disease and treatment information available on claims data. There are other factors that may also contribute to health services utilization and expenditures but such factors are not included in the CRG definitions in order to preserve the clinical nature of CRGs and their value as a communications tool. For example, the payment status of an individual (e.g., dually eligible for Medicare and Medicaid) may have an impact on the health expenditures of the individual. Dual eligibility may be a proxy measure for various risk factors such as low income. Separate adjustments to the payment weights can be made to recognize the impact of such nonclinical factors on healthcare expenditures.

Stop Loss or Reinsurance Payment Specific to the Condition of the Individual

In capitated payment arrangements, it is not uncommon for there to be stop loss or reinsurance provisions. Such arrangements are usually expressed in the form of a fixed threshold for an individual or for specific procedures. Thus, all expenditures for an individual, which exceed a pre-specified amount, are totally or partially paid by the stop loss or reinsurance carrier. Of course, the cost of a stop loss or reinsurance policy can vary greatly depending on the level of the threshold. A fixed threshold is arbitrary and makes little sense from a clinical perspective. A \$50,000 threshold is too high for a healthy individual and is too low for a high severity

of illness individual who has diabetes, congestive heart failure and emphysema. Ideally, the threshold would be specific to the individual's condition and only a relatively small percentage of individuals would qualify for additional payment. Condition specific thresholds promote meaningful case management programs and can potentially reduce the cost of stop loss or reinsurance policies by limiting their applicability to individuals whose expenditures are extreme relative to their capitated payment rate and not relative to an arbitrary threshold.

Support Internal Management Systems

Capitated payment arrangements place the majority of financial risk on the providers of care. The underlying assumption is that since providers are responsible for the delivery of care, they can respond to the incentives to control costs inherent in a capitated payment system. The success of any payment system that is predicated on providing incentives for cost control is almost totally dependent on the effectiveness with which the incentives are communicated to providers. Payers need to express the payment arrangements in a form that communicates the incentives in the system in a manner and at a level of detail that promotes effective management responses. Given the impact that the method of payment can have on patient care, it is not only in the best interest of payers to promote effective management, it is their obligation. CRGs were explicitly designed to be a tool for management. Indeed, CRGs are really a management tool that can also be used as the basis of establishing capitated payment rates. The key distinction between a management tool and payment method relates to the ability of the provider to use the information to take action in response to the incentives in the system. Thus, a manage-

ment tool communicates information in a form and at a level of detail that can lead to specific positive actions. As the Medicare PPS clearly demonstrated, the effectiveness of any incentive-based payment system is greatly enhanced if the payment method is simultaneously a management tool. To illustrate the difference, suppose for individuals with diabetes the capitated payments are 25 percent lower than the provider's expenditures. While this is obviously useful information for identifying a problem, it does not give the provider any real information on the precise source of the problem or the actions that can be taken to correct the problem. In contrast, suppose the payment system also provided the following information.

The higher costs for diabetic individuals are due to unusually high expenditures for inpatient care combined with uncommonly low expenditures for pharmacy and outpatient laboratory services for severity of illness level 1 and 2 diabetic individuals. Further, a higher than expected percentage of severity of illness level 1 and 2 diabetic individuals over time become severity level 3 or 4.

Clearly, the above information raises specific questions concerning the monitoring and preventive care being provided to low severity diabetic individuals. A capitated payment system that communicates information similar to the information illustrated above, gives providers a basis for management action and an effective response to the incentives in the system.

The CRG payment system is summarized in Figure 4. The development of CRGs and their use in a capitated payment system has been patterned on the experience with DRGs. CRG, like DRGs, were developed from a clinical perspective

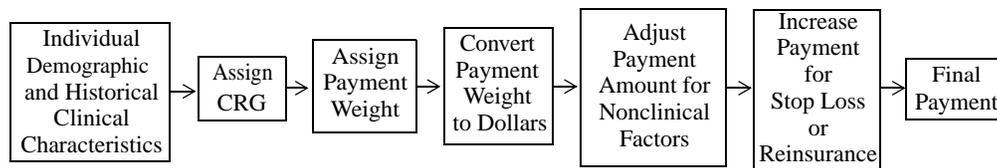


Figure 4. CRG Payment System

to be a management tool that can also be used as the basis of a payment system. As illustrated in Figures 2 and 3, the payment systems based on CRGs and DRGs are structurally similar.

Overview of CRG Clinical Logic

The CRG clinical logic is based on a five phase process.

Phase I: A disease profile and history of past medical interventions is created

Phase II: For each organ system, the most significant chronic disease under active treatment is identified

Phase III: For each organ system, the severity of illness level of the most significant chronic disease under active treatment is determined

Phase IV: The most significant chronic disease(s) under active treatment and its (their) associated severity of illness level are combined to determine the overall base CRG and severity of illness level for the individual

Phase V: The overall base CRG and severity of illness level are consolidated into three successive tiers of aggregation

The five phase process for determining the CRG assignment for an individual is based on precise, hierarchically structured and detailed clinical logic. In particular, the development of clinical logic for identifying individuals with multiple interacting comorbid diseases and their associated severity of illness level has been emphasized.

Phase I: Creation of a Disease Profile and History of Past Medical Interventions

The International Classification of Diseases, 9th Revision, Clinical Modifications (ICD-9-CM) is used to code not only diseases, but also signs, symptoms, findings and other factors influencing health status. There are 12,697 codes in the current version of ICD-9-CM (hereafter referred to as disease codes). Each of the disease codes is categorized into one of 31 mutually exclusive and exhaustive categories referred to as Major Disease Categories (MDCs). The diseases in each MDC correspond to a single organ system (e.g., respiratory system, digestive system, etc.) or etiology (e.g., malignancies, systemic infectious diseases, etc.). With the exception of malignancies and multiple trauma, which were each assigned to their own MDC, diseases that included both a particular organ system and a particular etiology (e.g., urinary tract infection) were assigned to the MDC corresponding to the organ system involved. Systemic infectious diseases such as septicemia were assigned the systemic infections disease MDC. Some diseases are considered catastrophic (e.g., persistent vegetative state) and are assigned to a catastrophic MDC. The 31 MDCs are listed in Table 1.

The diseases in each MDC are further subdivided into Episode Disease Categories (EDCs). There are a total of 533 mutually exclusive and exhaustive EDCs across the 31 MDCs. Each EDC is assigned to

1	Neurologic Diseases
2	Ophthalmalmic Diseases
3	Otolaryngologic Diseases
4	Cranio-facial Anomalies
5	Pulmonary Diseases
6	Heart and Cardiac Vascular Diseases
7	Peripheral and Noncardiac Vascular Diseases
8	Digestive Diseases
9	Hepatobiliary and Pancreatic Diseases
10	Musculoskeletal Diseases
11	Connective Tissue Diseases
12	Skin, Subcutaneous Tissue and Breast Diseases
13	Diabetes Mellitus
14	Endocrine and Metabolic and Thyroid Diseases Except Diabetes Mellitus
15	Genitourinary Diseases
16	Male Reproductive Diseases
17	Female Reproductive Diseases
18	Pregnancy, Childbirth and the Puerperium
19	Newborns and Neonatal Diseases
20	Mental Retardation and other Developmental and Cognitive Diseases
21	Hematologic Diseases
22	Malignancies
23	Systemic Infectious and Parasitic Diseases
24	Mental Health Diseases
25	Substance Abuse
26	Poisoning and Toxic Effects of Drugs
27	Burns
28	Factors Influencing Health Status and other Contact with Health Services
29	HIV Disease
30	Trauma
31	Catastrophic Diseases

Table.1 List of Major Disease Categories (MDCs)

one of six EDC types. Four of the EDC types relate to chronic diseases and two of the EDC types relate to acute diseases. There are several disease progressions that are considered chronic. A disease is classified as chronic if the duration of the disease is life long (e.g., diabetes). Diseases which have a prolonged duration, but for which a cure (i.e., no evidence of the disease) is possible, are considered chronic (e.g., malignancies). Life long or prolonged diseases controlled by medication or other means (e.g., hypertension) are also considered chronic. A disease is classified as acute if the duration of the disease is short and the disease would naturally resolve (e.g., pneumonia) or a treatment exists which cures the disease (e.g., fractured leg). Signs, symptoms and findings (e.g., chest pain) are also considered acute. The six EDC types of are defined as follows:

Dominant Chronic EDCs

Serious chronic diseases which often result in the progressive deterioration of an individual's health and often times lead to or significantly contribute to an individual's debility, death and future need for medical care (e.g., congestive heart failure, diabetes).

Moderate Chronic EDCs

Serious chronic diseases which, usually do not result in the progressive deterioration of an individual's health but can significantly contribute to an individual's debility, death and future need for medical care (e.g., asthma, epilepsy).

Minor Chronic EDCs

Minor chronic diseases can usually be managed effectively throughout an individual's life with typically few complications and limited effect upon an individual's debility, death and future need for medical care (e.g., migraine headache, hearing

loss) However, minor chronic diseases may be serious in their advanced stages or may be a precursor to more serious diseases (e.g., hyperlipidemia).

Chronic Manifestation EDCs

A manifestation or acute exacerbation of a chronic disease (e.g., diabetic neuropathy). The chronic manifestation EDC describes the manifestation or acute exacerbation (i.e., the neuropathy) and indicates the presence of the underlying chronic disease (i.e., diabetes). In addition, they are used to identify uncommon, but distinct diseases within a more frequently occurring EDC and are used in determining the severity level of the EDC and for management reporting.

Significant Acute EDCs

Serious acute illness which can be a precursor to or place the individual at risk for the development of chronic disease (e.g., chest pain) or can potentially result in significant sequelae (e.g., head injury with coma). In the CRG logic, an acute illness is only classified as a significant acute illness if it occurred in the most recent six month period.

Minor Acute EDCs

Minor acute illnesses or events that may be mild or more serious but are self limiting, are not a precursor to chronic disease, do not place the individual at risk for the development of chronic disease and do not result in significant sequelae (e.g., fractured arm, common cold, appendicitis).

Of the 533 EDCs, 60 are dominant chronic (DC), 65 are moderate chronic (MC), 40 are minor chronic (C), 99 are chronic manifestation (CM), 151 are significant acute (SA) and 118 are minor acute (A). In the CRG clinical logic, the categorization of an EDC as chronic or acute is an

important distinction because individuals who have chronic EDCs from multiple organ systems (i.e., MDCs) are assigned to a distinct set of CRGs. For example, individuals who have both congestive heart failure (CHF) and chronic obstructive pulmonary disease (COPD) form a separate CRG, and individuals who have CHF, COPD and diabetes form another CRG.

Some diseases that are generally considered chronic can, under certain conditions, be an acute disease. For example, congestive heart failure is generally considered a chronic disease. However, congestive heart failure that occurs in children is usually associated with an underlying congenital anomaly and reflects the status of the underlying anomaly. Therefore, in children congestive heart failure is considered an acute disease. The one exception is congestive heart failure due to rheumatic fever which is always considered chronic. In the CRG logic, there are also some diseases generally considered chronic that are only categorized as chronic under certain conditions. For example, hypertension is generally considered a chronic disease. However, because there is the possibility that a single high blood pressure reading could be miscoded as hypertension, hypertension is considered an acute disease unless the hypertension occurs at least twice over a period of time that spans at least 90 days.

Within each MDC the dominant, moderate and minor chronic EDCs are ranked hierarchically in terms of their relative contribution to an individual's need for medical care, debility and death. Chronic EDCs which result in progressive deterioration of an individual's health are ranked highest in the chronic EDC hierarchy. Dominant chronic EDCs are always ranked higher in the EDC hierarchy than moderate or minor chronic EDCs and moderate chronic

EDCs are always ranked higher than minor chronic EDCs. Table 2 contains the EDCs, the disease type and the chronic EDC rank for the heart and cardiac vascular system MDC.

Procedures performed in hospitals are reported using ICD-9-CM procedure codes. Professional services and procedures performed in an ambulatory setting are reported using Current Procedural Terminology (CPT) and HCFA Common Procedure Coding System (HCPCS). All procedure codes were categorized into 382 mutually exclusive and exhaustive categories referred to as Episode Procedure Categories (EPCs). The EPCs have limited use in the CRG clinical logic. Only 75 of the EPCs are used in the CRG logic. The EPCs are used to identify individuals who are dependent on some medical technology (e.g., mechanical ventilation), who had a procedure that is indicative of advanced disease (e.g., leg amputation for a diabetic) or who had a procedure that has long term sequelae (e.g., heart transplant). The occurrence of these EPCs creates a chronic EDC that specifies a history of the procedure (e.g., history of heart transplant). In the CRG assignment logic, no distinction is made between chronic EDCs associated with the history of a procedure and chronic EDCs associated with a disease.

The use of procedures in the CRGs is very limited. The primary use of procedures is to indicate more advanced disease in the severity of illness leveling (e.g., a diabetic with circulatory complications who requires an above-the-knee amputation). It was recognized that the inclusion of some procedures in the CRGs could result in higher future payments for individuals who had one of these procedures, thus theoretically, creating the financial incentive for MCOs to perform more pro-

Rank	Type	EDC
1	DC	Major Congenital Heart Diseases
2	DC	Moderate Congenital Heart Diseases
3	DC	Congestive Heart Failure
4	DC	Major Chronic Cardiac Diseases
5	DC	Cardiac Valve Diseases
6	DC	History of AMI
7	DC	Angina
8	MC	Atrial Fibrillation
9	MC	Cardiac Dysrhythmia
10	MC	History of CABG
11	MC	History of PTCA
12	MC	History of Cardiac Device
13	MC	Coronary Atherosclerosis
14	MC	Hypertension
15	C	Ventricular and Atrial Sept Defects
16	C	Minor Chronic Cardiac Diseases
	CM	History of Defibrillator
	CM	Unstable Angina
	CM	Moderate Hypertension
	CM	Myocardopathy
	CM	Pulmonary Hypertension
	CM	Graft Atherosclerosis
	SA	Cyanosis
	SA	Ventricular Tachycardia
	SA	Complete Heart Block
	SA	Shock
	SA	Cardiac Arrest
	SA	AMI Except Subendocardial
	SA	Hypotension
	SA	Tachycardia/Palpitation
	SA	Moderate Acute Cardiac Diseases
	SA	Chest Pain
	SA	Subendocardial AMI
	SA	Minor Hypertension
	SA	Pediatric CHF
	A	Atrial Flutter
	A	Cardiac Inflammation
	A	Minor Acute Cardiac Diagnoses
	A	Malfunction Coronary Bypass Graft
	A	Complications CV Device, Implant, Graft
	A	Malfunction CV Device, Implant, Graft
	A	Malfunction Vascular Graft

DC = Dominant Chronic
MC = Moderate Chronic
C = Minor Chronic
CM = Chronic Manifestation
SA = Significant Acute
A = Minor Acute

Table 2. EDCs for the Circulatory MDC

cedures. However, there is no real substance to such a concern because the increase in future payments is small relative to the cost of the procedure. It is unlikely that any fiscally prudent MCO would incur substantial short-term costs in order to receive relatively small increases in long-term future payments. The other argument against the use of procedures is that MCOs which provide poor quality care that results in the need for the procedure (e.g., the diabetic only needed the above-the-knee amputation because of poor care) would receive additional future financial compensation. However, the financial incentive remains to avoid procedures since the future increases in payment will not cover the cost of the original procedure for an extended period of time. Further, there will be enrollment and disenrollment between MCOs and from other payment systems such as fee-for-service. It is essential that MCOs not have the financial incentive to avoid enrolling individuals with a history of a major procedure. The overall functioning of the system and access to care are better served when there is a recognition of the future costs of such individuals. Thus, there is a highly selective use of procedures in the CRGs because, on balance, financial incentives to avoid enrolling individuals with a history of certain major procedures was viewed as a more serious issue than potentially providing some additional future compensation for individuals who had a procedure that may have been avoidable.

Based on the individual's chronic disease profile and history of past medical interventions, the initial step in Phase I is to determine the EDCs and EPCs assigned to the individual. Once the EDCs and EPCs have been assigned, EDCs and EPCs are added or deleted based on the nature of and temporal relationship among

the EDCs and EPCs.

Chronic Manifestation EDCs Create Chronic EDCs

All chronic manifestation EDCs create a chronic EDC that specifies the underlying chronic disease associated with the manifestation or acute exacerbation. For example, the diabetic neuropathy chronic manifestation EDC creates the diabetes EDC.

Multiple Occurrences of an Acute EDC can Create Chronic EDCs

Selected acute EDCs that have multiple occurrences over a period of time create a chronic EDC that indicates the recurrence of the acute EDC. For example, if the acute EDC for urinary tract infection occurs at least three times over a period of time that spans at least 180 days, the chronic EDC for recurrent urinary tract infection is created.

Acute EDCs can Create Chronic EDCs

Selected acute EDCs can create a chronic EDC for the history of the significant acute EDC. For example, the significant acute EDC for Acute Myocardial Infarction (AMI) creates a chronic EDC for the history of the AMI. A history of a significant acute EDC is only created for significant acute EDCs that indicate a significant progression of an underlying disease (e.g., cerebrovascular accident (CVA)) or may have long term sequelae (e.g., hip fracture). The creation of a chronic EDC for the history of a significant acute EDC is sometimes dependent on the individual's age. For example, the acute EDC for hip fracture only creates the chronic EDC for history of hip fracture if the individual is 65 years or older.

Major Procedure EPCs can Create Chronic EDCs

Selected major procedures that are

indicative of advanced disease or have long term sequelae create a chronic EDC for the history of the major procedure. For example, the EDC for coronary bypass surgery creates the chronic EDC for history of coronary bypass surgery.

Temporal Relationship Between EDCs can Eliminate an EDC

If specific EDCs occur prior to the first occurrence of another specified EDC, the EDC is eliminated. For example, if the CVA EDC occurs prior to the first occurrence of the hemiplegia EDC, the CVA EDC is eliminated because the hemiplegia is a sequelae of the CVA. However, if a CVA occurs after the first occurrence of hemiplegia, the CVA EDC is not eliminated since it represents a second CVA. The temporal relationship between CVA and hemiplegia is the basis for determining whether there has been a second CVA.

Temporal Relationship Between EDCs and EPCs can Eliminate an EDC

If specific EDCs occur prior to the occurrence of a specified EPC, the EDC is eliminated. For example, if the angina EDC occurred prior to the coronary bypass EPC, the angina EDC is eliminated because the coronary bypass is expected to cure the angina. However, if angina occurs after the coronary bypass EPC, the angina EDC is not eliminated since it indicates that the coronary bypass was not successful or that the underlying coronary artery disease has progressed.

Temporal Relationship Between EPCs can Eliminate an EPC

If a specific EPC occurs prior to the occurrence of another specified EPC, the EPC is eliminated. For example, if a dialysis EPC occurs prior to a kidney transplant EPC, the dialysis EPC is eliminated because the kidney transplant is expected to eliminate the need for dialysis. However,

if dialysis occurs after the kidney transplant EPC, the dialysis EPC is not eliminated since it indicates that kidney transplant was not successful.

At the end of Phase I a complete list of EDCs and EPCs is created which describes the individual's disease profile and history of past medical interventions.

Phase II: Selection of Primary Chronic Disease(s)

In Phase II the EDC that represents the most significant chronic disease under active treatment, referred to as the primary chronic disease (PCD), is identified for each organ system (i.e., MDC). An underlying assumption of CRGs is that individuals with chronic diseases from multiple organ systems are especially at risk to have poor outcomes and require significant medical care. A single chronic disease (i.e., EDC) must first be selected from each major organ system (i.e., MDC) for the purpose of identifying the individuals with chronic disease in multiple organ systems.

The first step in Phase II is to reduce the number of chronic EDCs in an MDC that are candidates to be the PCD. Certain chronic diseases are secondary to (i.e., a by-product of or an integral part of) another chronic disease. For example, when systemic lupus and chronic nephritis are both present, the chronic nephritis is secondary to the systemic lupus and the primary disease is systemic lupus. In this example, chronic nephritis is never assigned as the PCD if systemic lupus is present. The initial step in selecting the PCD is to eliminate from consideration as the PCD chronic EDCs that are secondary to another chronic EDC.

The second step in Phase II is to select the PCD for each MDC. If only one chronic

EDC in an MDC remains after the chronic EDCs identified as secondary to another chronic EDC are eliminated, then that chronic EDC is the PCD for the MDC. If more than one chronic EDC remains in the MDC, then the PCD selection criteria contained in Table 3 is used to select the PCD. The selection criteria first considers chronic disease type. A dominant chronic EDC is always selected over a moderate chronic EDC and a moderate chronic EDC is always selected over a minor chronic EDC. This ensures, for example, that a dominant chronic EDC such as progressive neurological condition is always chosen as the PCD over a moderate chronic EDC such as epilepsy. If there are multiple chronic EDCs of the same type within the same body system, then the full logic of the PCD selection hierarchy in Table 3 is applied. The PCD selection hierarchy uses site of service, recency and duration of treatment to identify which chronic EDC is the most significant under active treatment. Within an EDC type treatment in a hospital within the most recent year is highest in the selection hierarchy followed by treatment in an ambulatory setting that had duration of at least 90 days within the most recent year. An underlying assumption of CRGs is that the diseases under active treatment have the greatest impact on the subsequent need for medical care, debility and death. If more than one chronic EDC of the same type meets the same PCD selection criteria, then the

EDC rank in the MDC is used to select the EDC to be the PCD. At the end of Phase II the PCD for each MDC that had at least one chronic EDC present has been determined.

Phase III: Assignment of Severity Level to Each Primary Chronic Disease

In Phase III the PCD from each MDC is assigned a severity of illness level which for brevity, is referred to as severity level or Sol. The severity level describes the extent and progression of the disease selected as the PCD. A high level of severity is indicative of a high degree of treatment difficulty and a need for substantial future medical care. The assignment of the severity level is specific to each PCD and takes into account factors associated with a more severe or advanced forms of the disease. This includes: a more severe form of the disease as identified through a chronic manifestation EDC (intractable epilepsy); comorbid chronic and acute EDCs from the same organ system (cardiac valve disease with congestive heart failure); age if it relates to a specific disease progression (age over 65 for history of hip fracture); chronic EDCs from other body systems when they are secondary to and caused by the PCD (nephritis for systemic lupus); acute EDCs from other body systems when they are specifically related or a reliable indicator of general health sta-

EDC Type	Site of Service	Recency of Treatment	Duration of Treatment
Dominant Chronic	Hospital	Last Year	
Dominant Chronic	Ambulatory	Last Year	90 days
Dominant Chronic			
Moderate Chronic	Hospital	Last Year	
Moderate Chronic	Ambulatory	Last Year	90 days

Table 3. Primary Chronic Disease (PCD) Selection Criteria

tus (acute infections, neurologic and gastrointestinal EDCs) and selected therapies or procedures if they are indicative of advanced disease or may have long term sequelae (history of coronary bypass disease).

All chronic EDCs have a severity leveling matrix, consisting of a list of EDCs and EPCs. Along with the list of EDCs and EPCs are the conditionality rules which for each EDC and EPC in the list specify the conditions that must be met in order for a specific severity level to be assigned. For example, an individual with a PCD of congestive heart failure who had been hospitalized with cardiac valve disease in the most recent year or had been treated at any site for a cardiac valvular disease in the most recent six months is considered to have congestive heart failure at severity level 4. However, if the individual had not been hospitalized for the cardiac valvular disease during the most recent year nor had been treated at any site for the cardiac valvular disease during the most recent six months, then the individual is considered to have congestive heart failure at severity level 3. Thus, the severity level associated with the cardiac valvular disease differs depending on conditionality rules relating to recency of treatment and the site of treatment. In addition to the recency and site of treatment, conditionality rules used in the severity leveling matrices can relate to the duration of treatment or the age of the individual. There is a unique severity leveling matrix for each chronic EDC.

The severity leveling matrix for congestive heart failure is shown in Table 4. The EDCs at severity level 4 are primarily acute cardiac events (shock, cardiac arrest, AMI, unstable angina and ventricular tachycardia) that either occurred recently or required inpatient care. In addition, severity level 4 includes the recent

occurrence of acute EDCs that are indicative of advanced congestive heart failure (pleural effusion). Comorbid cardiac diseases (cardiac valve disease, congenital heart disease, and major chronic cardiac diseases) that interact with the congestive heart failure and increase treatment difficulty are also included at severity level 4. Finally, EDCs and EPCs (tracheostomy) that relate to the dependence on a respirator are included at severity level 4.

Severity level 3 for congestive heart failure includes some of the same EDCs as level 4 (AMI, unstable angina, major chronic cardiac disease and congenital heart disease) but without a recent occurrence or requiring inpatient care. Other moderate chronic or significant acute cardiac or circulatory EDCs are included at severity level 3 (complete heart block, cardiac dysrhythmia, thrombophlebitis, atrial fibrillation, coronary atherosclerosis, pulmonary emboli, history of coronary bypass and history of defibrillator). Recent acute endocrine, metabolic and neurological problems are also included at severity level 3 since these significant acute diseases can increase the treatment difficulty of the CHF and worsen general health status. Finally, the presence of EPCs that are indicative of significant debility such as a hospital bed for the home or the need for a motorized wheelchair are included at severity level 3.

Severity level 2 for congestive heart failure includes some acute cardiac EDCs (chest pain, atrial flutter, stable angina and cardiac inflammation) plus some of the moderate cardiac or circulatory EDCs from severity level 3 (e.g., atrial fibrillation without the condition of having a duration of at least 90 days). Severity level 2 also includes a wide range of acute problems from other MDCs (e.g., infections, mental health diagnoses, skin diagnoses, etc.) that are indicative

Severity Level	EDC	Type	Recency	Site	Duration
4	Complex Cyanotic/Major Cardiac Septal Anomaly	DC	2 Years	Inpatient	
	Other Major Congenital Heart Diagnosis Except Valve	DC	2 Years		
	Valvular Disorder	DC	2 Years	Inpatient	
	Valvular Disorder	DC	6 Months		
	Unstable Angina	CM	1 Year		90 Days
	Unstable Angina	CM	1 Year	Inpatient	
	Acute Myocardial Infarction Except Subendocardial - Initial	MA	6 Months		
	Cardiac Arrest	MA	1 Year		
	Hypotension	MA	1 Year	Inpatient	
	Pleural Effusion	MA	1 Year		180 Days
	Respiratory Failure	MA	1 Year		90 Days
	Shock	MA	1 Year		
	Subendocardial Infarction - Initial	MA	6 Months		
	Ventricular Tachycardia	MA	1 Year		
	History of a High Risk of Mortality Event	MA	1 Year		
3	Complex Cyanotic/Major Cardiac Septal Anomaly	DC	2 Years		
	Other Cardiovascular Diagnosis - Major	DC	2 Years		
	Valvular Disorder	DC	2 Years		
	Atrial Fibrillation	MC	2 Years		
	Cardiac Device Status	MC	2 Years		
	Cardiac Dysrhythmia	MC	2 Years		90 Days
	Cardiac Dysrhythmia	MC	6 Months		
	Coronary Atherosclerosis	MC	1 Year		2 * 90 Days
	Defibrillator Status	CM	2 Years		
	Graft Atherosclerosis	CM	2 Years		
	Mechanical Complication of Cardiovascular Device/Implant/ Graft	CM	2 Years		
	Myocardiopathy	CM	2 Years		
	Pulmonary Hypertension	CM	2 Years		
	Unstable Angina	CM	1 Year		
	Acute Myocardial Infarction Except Subendocardial - Initial	MA	1 Year	Inpatient	
	Acute Neurological Diagnosis - Major/Extreme	MA	6 Months		
	Major / Extreme Infections	MA	1 Year		
	Moderate Infections	MA	6 Months		
	Complete Heart Block	MA	6 Months		
	Convulsion – NOS	MA	1 Year		90 Days
	Other Valvular Disorder	MA	6 Months		
	Pleural Effusion	MA	1 Year		
	Pulmonary Emboli	MA	6 Months		
	Respiratory Failure	MA	1 Year		
	Subendocardial Infarction - Initial	MA	1 Year	Inpatient	
	Thrombophlebitis	MA	1 Year		
	Metabolic / Endocrine	A	6 Months		

Table 4 Severity Leveling Matrix for Congestive Heart Failure

Severity Level	EDC	Type	Recency	Site	Duration
2	Angina	DC	6 Months		
	History of Myocardial Infarction	DC	2 Years		
	Coronary Atherosclerosis	MC	6 Months		
	Coronary Atherosclerosis	MC	1 Year		90 Days
	History of Coronary Artery Bypass Graft	MC	6 Months		
	History of Post Transluminal Coronary Angioplasty	MC	6 Months		
	Chronic Arteries & Veins Diagnosis - Minor	C	1 Year		90 Days
	Malfunction Coronary Bypass Graft	CM	6 Months		
	Obesity	CM	1 Year		
	Acute Gastrointestinal Diagnosis/Symptom - Major	MA	1 Year		
	Acute Gastrointestinal Diagnosis/Symptom - Moderate	MA	1 Year		
	Acute Myocardial Infarction Except Subendocardial - Initial	MA	1 Year		
	Acute Neurological Symptom/Diagnosis - Moderate	MA	6 Months		
	Atrial Flutter	MA	1 Year		90 Days
	Cardiac Inflammation	MA	1 Year	Inpatient	
	Cardiomegaly/Other Moderate Acute Cardiovascular Diagnosis	MA	1 Year		90 Days
	Chest Pain	MA	1 Year		90 Days
	Moderate Infections	MA	1 Year		90 Days
	Complete Heart Block	MA	1 Year		
	Convulsion - NOS	MA	1 Year		
	Cyanosis	MA	1 Year		
	Decubitus Ulcer	MA	1 Year		
	Subendocardial Infarction - Initial	MA	1 Year		
	Tobacco Use Disorder	MA	1 Year		90 Days
	Wheelchair	MA	1 Year		
	Hypovolemia	A	1 Year	Inpatient	
Nausea/Vomiting/Diarrhea	A	1 Year		90 Days	
Minor Infections	A	1 Year		90 Days	
1	Cardiac Dysrhythmia	MC	2 Years		
	Hypertension	MC	2 Years		
	Chronic Cardiovascular Diagnosis - Minor	C	1 Year		
	Ventricular/Atrial Septal Defect	C	1 Year		
	Malignant/Other Significant Hypertension	CM	2 Years		
	Acute Myocardial Infarction Except Subendocardial - Subsequent/Unspecified	MA	1 Year		
	Cardiac Inflammation	MA	1 Year		
	Cardiomegaly/Other Moderate Acute Cardiovascular Diagnosis	MA	1 Year		
	Chest Pain	MA	1 Year		
	Congestive Heart Failure - Age Less Than 18 Years	MA	1 Year		
	Hypertension NOS/NEC	MA	1 Year		
	Subendocardial Infarction - Subsequent/Unspecified	MA	1 Year		
	Tachycardia/Palpitation	MA	1 Year		
	Acute Cardiovascular Diagnosis - Minor	A	1 Year		
	Malfunction Vascular Graft	A	1 Year		
	Other Complication Due to Cardiovascular Device/Implant/Graft	A	1 Year		
	Reaction to Cardiovascular Device/Implant/Graft	A	1 Year		

Table 4 Severity Leveling Matrix for Congestive Heart Failure (Continued)

of general health status. Finally, an extended list of history of significant cardiac procedures (e.g., cardiac pacemaker) and EPCs related to medical supplies that are indicative of debility (e.g., walker, commode) are included at severity level 2.

If none of the EDCs and EPCs and associated conditions in severity levels 2 through 4 are present, then the congestive heart failure PCD is assigned severity level 1. For completeness, all the EDCs in the heart and cardiac vascular MDC that are not used in severity levels 2 through 4 are included in level 1 in the severity leveling matrix for congestive heart failure. However, since severity level 1 is the default severity level, it can be assigned without any of the EDCs listed in level 1 being present.

The number of severity levels specified in the severity leveling matrix varies across EDCs. Minor chronic EDCs and nondominant/nonmetastatic malignancy EDCs have only two severity levels specified because of the limited clinical spectrum of these diseases. All dominant chronic, moderate chronic and metastatic malignancy EDCs have four severity levels.

The severity level for a PCD is determined based on the following steps:

1. From the complete list of EDCs and EPCs created in Phase I, the subset of EDCs and EPCs that are present in the severity leveling matrix for the PCD are identified
2. For each EDC and EPC identified in step 1, the conditionality rules in the severity leveling matrix are evaluated and the severity level for each EDC and EPC is determined
3. The severity level for the PCD is equal to the highest severity level associated with any of the EDCs and EPCs from step 2

Since the same EDCs and EPCs can be used in the severity leveling matrix for PCDs in more than one MDC, it is possible that the same EDC or EPC could determine the severity level for more than one PCD. In order to avoid this possibility the severity level for each PCD is determined with the constraint that no EDC or EPC can determine the severity level (i.e., be the EDC or EPC used in step 3) of more than one PCD.

Phase IV: Determination of the Base CRG and Severity Level for the Individual

At the end of Phase III all PCDs are assigned a severity level. Based on the PCDs and EPCs that are present, the individual is assigned to one of nine CRG statuses. The CRG status is assigned hierarchically starting with catastrophic. The highest status in the hierarchy, for which the status criteria are met, is assigned as the CRG status.

Catastrophic Conditions

Catastrophic conditions include long term dependency on a medical technology (e.g., dialysis, respirator, TPN) and life-defining chronic diseases or conditions that dominate the medical care required (e.g., persistent vegetative state, cystic fibrosis, AIDS, history of heart transplant).

Dominant and Metastatic Malignancies

A malignancy that dominates the medical care required (e.g., brain malignancy) or a nondominant malignancy (e.g., prostate malignancy) that is metastatic.

Dominant Chronic Disease in Three or More Organ Systems

Dominant chronic disease in three or more organ systems is identified by the presence of three or more dominant PCDs.

Significant Chronic Disease in Multiple Organ Systems

Significant chronic diseases in multiple organ systems is identified by the presence of two or more PCDs of which at least one is a dominant or moderate PCD. PCDs that are a severity level 1 minor chronic disease are not considered a significant chronic disease and are not used to identify the presence of significant chronic disease in multiple organ systems, but minor PCDs that are severity level 2 minor chronic diseases are used.

Single Dominant or Moderate Chronic Disease

Single dominant or moderate is identified by the presence of a single dominant or moderate PCD.

Minor Chronic Disease in Multiple Organ Systems

Minor chronic disease in multiple organ systems is identified by the presence of two or more minor PCDs.

Single Minor Chronic Disease

A single minor chronic disease is identified by the presence of a single minor PCD.

History of Significant Acute Disease

A history of significant acute disease is identified by the presence within the most recent six month period of one or more significant acute EDCs or significant EPCs with no PCDs present.

Healthy

A healthy status is identified by the absence of any PCDs or significant acute EDCs or EPCs.

Once the CRG status is determined, the base CRG and overall severity level of the individual is determined. The logic for determining the base CRG and overall severity level for the individual is dependent on the CRG status of the individual.

CATASTROPHIC CONDITIONS

First in the CRG status hierarchy are catastrophic conditions, either associated with long term dependence on medical technology or life-defining chronic diseases or conditions that dominate the medical care required. All conditions that are considered catastrophic are ordered hierarchically (e.g., renal dialysis is higher in the catastrophic hierarchy than history of heart transplant). If there is more than one catastrophic condition present, the catastrophic condition that is highest in the catastrophic hierarchy is assigned as the base CRG. For each catastrophic condition there is a four level severity leveling matrix that is specific to the catastrophic condition. In addition, since individuals with a catastrophic condition can also have diseases in organ systems that are not directly related to the catastrophic condition, the severity is adjusted based on the presence of PCDs from organ systems unrelated to the catastrophic condition. The additional adjustment to the severity level is done to insure that the severity level of the catastrophic condition fully reflects to the total burden of illness. There are 11 catastrophic base CRGs, each of which is divided into four severity levels, for a total of 44 catastrophic CRGs.

DOMINANT AND METASTATIC MALIGNANCIES

Second in the CRG status hierarchy are dominant or metastatic malignancies. Certain malignancies (e.g., brain, pancreas, etc.) are similar to catastrophic conditions in that they are life defining and dominate an individual's medical care. Other malignancies (e.g., prostate, colon, etc.) do not dominate the future medical care required unless they are metastatic.

When multiple malignancies are present, the CRGs contain logic to identify the primary malignancy and any meta-

static sites (e.g., a bone malignancy is considered metastatic to a prostate malignancy). A malignancy is considered a metastasis if there is a related primary malignancy present. In addition to identifying a primary malignancy that has metastasized by the presence of a related secondary malignancy, there are also some conditions that indicate that a primary malignancy has likely metastasized (e.g., severe malnutrition, the need for a second course of chemotherapy).

For each dominant or metastatic primary malignancy there is a four level severity leveling matrix that is specific to the primary malignancy. In addition, since individuals with a dominant or metastatic primary malignancy can also have diseases in organ systems that are not directly related to the primary malignancy, the severity level is adjusted based on the presence of PCDs from organ systems unrelated to the primary malignancy. The additional adjustment to the severity level is done to insure that the severity level of the dominant or metastatic primary malignancy fully reflects the total burden of illness. Primary malignancies that are not dominant or metastatic are treated like any other disease and are included in the subsequent portions of the CRG status hierarchy. There are 23 dominant or metastatic malignancy base CRGs, each of which is divided into four severity levels, for a total of 92 dominant or metastatic malignancy CRGs.

DOMINANT CHRONIC DISEASE IN THREE OR MORE ORGAN SYSTEMS

Third in the CRG status hierarchy are dominant chronic diseases in three or more organ systems. Explicit combinations of three dominant PCDs are identified (e.g., congestive heart failure, diabetes and emphysema). The explicit

combinations of three dominant PCDs are ranked hierarchically. Individuals with three or more dominant PCDs are assigned to a base CRG that corresponds to the first match in the hierarchy. If the dominant PCDs do not match any of the explicit combinations, then the individual is assigned to a residual base CRG that corresponds to any combination of three dominant PCDs that are not explicitly specified in the hierarchy. Each base CRG that is comprised of three or more dominant PCDs is subdivided in six severity levels.

The severity level for the CRG is determined using the severity level for each of the PCDs that comprise the CRG. The criteria in Table 5 are used to assign the CRG severity of illness. The criteria in Table 5 are applied hierarchically from top to bottom. The severity level for the CRG is assigned based on the first criteria that is matched in Table 5. For example, if the three dominant PCDs that comprise the CRG have severity levels of 4, 4 and 2, then the severity level of the CRG would be 4. The severity level that results from Table 5 is generic, since the same Table 5 applies to all CRGs that are comprised of three or more dominant PCDs. The CRG severity level that results from the application of the generic criteria in Table 5 is further adjusted based on clinical criteria that is specific to that base CRG. For example, the generic severity level for the base CRG comprised of congestive heart failure, diabetes and emphysema is increased by one if the EDC for unstable angina is present and the unstable angina has been actively treated in the most recent six month period. Although unstable angina is often treated by performing coronary bypass surgery, an individual with diabetes and emphysema may be too ill to undergo surgical treatment resulting in a difficult to treat, severely ill individual.

CRG Severity Level	Severity Level of PCDs Comprising the CRG		
	4	3	2 or 1
6	3 or more		
5	2	1 or more	
4	2	None	1 or more
4	1	2 or more	
3	1	1	1 or more
3	1	None	2 or more
3	3 or more		
2	2		1 or more
2	1		2 or more
1	3 or more		

Table 5. Severity Levels for CRGs Composed of Three or More Dominant PCDs

There are 21 base CRGs for individuals with three or more dominant chronic diseases, each of which is divided into 6 severity levels for a total of 126 CRGs.

SIGNIFICANT CHRONIC DISEASE IN MULTIPLE ORGAN SYSTEMS

Fourth in the CRG status hierarchy are significant chronic diseases in multiple organ systems. For individuals who do not have three or more dominant chronic diseases but do have multiple chronic diseases with at least one dominant or moderate chronic disease, explicit combinations of two PCDs are identified (e.g., the dominant chronic PCDs for congestive heart failure and diabetes). Severity level 1 minor PCDs are not used in identifying combinations of two significant chronic diseases since they have minimal impact on the individual's need for medical care. The explicit combinations of two PCDs are ranked hierarchically. Individuals with two or more PCDs are assigned to a base CRG that corresponds to the first match in the hierarchy. If the PCDs do not match any of the explicit combinations, then a residual base CRG is assigned that corre-

sponds to any combination of two PCDs that are not explicitly specified in the hierarchy.

Each base CRG that is comprised of two PCDs is subdivided into 2, 4 or 6 severity levels. The number of severity levels depends on the PCDs that comprise the combination. A combination that is comprised of a nonmetastatic malignancy PCD and a severity level 2 minor PCD has only two severity levels, since nonmetastatic malignancies and minor PCDs have only two severity levels. A combination that is comprised of a dominant or moderate PCD and a severity level 2 minor PCD or a nonmetastatic malignancy PCD has four severity levels. All other combinations of PCDs have six severity levels. The severity level for the combination that comprises the CRG is determined using the severity level for each of the PCDs that comprise the combination. Since the individual PCDs that comprise the combination can be very different in terms of relative clinical significance (e.g., the combination of congestive heart failure and diabetes versus the combination of congestive heart failure and asthma) the criteria used to determine the severity level for the CRG is specific to the pair of PCDs that comprise the combination. Table 6 shows the severity levels for a CRG composed of the dominant PCD for diabetes and the dominant PCD for congestive heart failure.

Based on the criteria in Table 6, if the diabetes PCD is severity level 3 and the congestive heart failure PCD is severity level 4, the severity level for the CRG is 5. There are 9 different versions of assignment logic for determining the CRG severity level from the severity level of two PCDs. The different versions of the reflect the relative clinical significance of the two PCDs. If one of the PCDs has greater clinical significance the criteria gives more

CHF SoI Level	Diabetes SoI Level			
	4	3	2	1
4	6	5	4	4
3	5	4	3	3
2	4	3	2	2
1	3	2	2	1

Table 6. Severity Levels for the CRG that is Comprised of the PCDs for Congestive Heart Failure and Diabetes

weight to that PCD. The CRG severity level that results from the application of criteria like that in Table 6 is further adjusted based on additional clinical criteria that are specific to that base CRG. For example, the CRG severity level for the base CRG comprised of congestive heart failure and diabetes is increased by one if the PCD for chronic gastric ulcer is present and the chronic gastric ulcer has been actively treated in the most recent six month period. Since the gastric ulcer PCD is not a dominant chronic disease the individual is not assigned to one of the CRGs for three dominant chronic diseases. However, the chronic ulcer disease can complicate the treatment of the congestive heart failure and diabetes and, therefore, increases overall the severity level of the individual. There are 61 base CRGs for individuals with significant chronic disease in multiple organ systems, each of which is divided into 2, 4 or 6 severity levels for a total of 324 CRGs.

SINGLE DOMINANT OR MODERATE CHRONIC DISEASE

Fifth in the CRG status hierarchy is a single dominant or moderate chronic disease. These individuals have only one PCD which, therefore, becomes the base CRG (i.e., if the single PCD for the individual is diabetes, the base CRG is diabetes). The severity level for the CRG is the same

as the PCD severity level. The nondominant/nonmetastatic malignancy PCDs have two severity levels and all other moderate and dominant PCDs have four severity levels. There are 109 base CRGs for individuals with a single moderate or dominant chronic disease, each of which is divided into 2 or 4 severity levels for a total of 406 CRGs.

MINOR CHRONIC DISEASE IN MULTIPLE ORGAN SYSTEMS

Sixth in the CRG status hierarchy are two or more minor chronic diseases. Individuals with two or more minor chronic diseases are assigned to a single base CRG which has four severity levels based on the number of minor chronic PCDs present and the severity level of the minor chronic PCDs.

SINGLE MINOR CHRONIC DISEASE

Seventh in the CRG status hierarchy is a single minor chronic disease. These individuals have only one PCD. The base CRG is the same as the PCD. The severity level for the CRG is the same as the PCD severity level. There are 40 base CRGs for individuals with a single minor chronic disease, each of which is divided into 2 severity levels for a total of 80 CRGs.

HISTORY OF SIGNIFICANT ACUTE DISEASE

Eighth in the CRG status hierarchy is a history of significant acute disease. The individual has no PCDs present but has in the most recent six month period at least one significant acute EDC or significant EPC present. If the significant acute EDC (e.g., AMI) creates a chronic EDC for the history of the significant acute (e.g., history of AMI) then the individual would have a PCD present and, therefore, would not be assigned to the status for history of sig-

nificant acute disease. Thus, individuals with significant acute diseases with significant sequelae such as AMI are not included in this status. However, the significant acute diseases that are present in this status can be a precursor to chronic disease or place the individual at risk for the development of chronic disease (e.g., chest pain). Thus, although the individuals in the history of significant acute disease status do not have any chronic diseases, they are distinct from healthy individuals. Certain EPCs are also considered equivalent to a significant acute disease. For example, if the skin graft EPC is present, the individual is assigned to the history of significant acute disease status even if no significant acute EDCs are present. The performance of a skin graft is considered indicative of significant acute disease. There are six base CRGs for individuals with history of significant acute disease which include a CRG for multiple significant acute diseases from different MDCs. The six base CRGs are assigned hierarchically based on the number and duration of treatment of the significant acute diseases present. There are no severity levels assigned to the history of significant acute disease CRGs.

HEALTHY

The ninth and final status in the CRG status hierarchy is for healthy individuals who have no PCDs and no significant acute EDCs or EPCs in the most recent six month period. They may have minor acute EDCs present (e.g., upper respiratory infection) but are otherwise healthy. There is a single CRG for healthy individuals. The healthy status includes individuals who had no medical care encounters. It is possible that in any population, this includes a subset of individuals with chronic diseases who did not access the

medical care system during the time period used to assign the CRGs.

The nine CRG statuses are subdivided into a total of 273 base CRGs which, when subdivided into severity levels results in 1083 CRGs.

Phase V: Consolidation of CRGs into Three Successive Tiers of Aggregation

In order to facilitate CRG use, the 1083 CRGs are consolidated into three tiers of aggregation. Each successive tier of aggregation has fewer base CRGs. Across the CRG aggregations, the CRG status and the severity levels within the aggregated CRGs are maintained. Thus, the successive tiers of CRG aggregation maintain the CRG status and maintain the severity levels but reduce the number of base CRGs. Although the aggregation of CRGs reduces clinical precision, the successive tiers of aggregation maintain clinical meaningfulness. The successive tiers of aggregation take into consideration the future medical care needs and clinical similarity of the individuals assigned to the aggregated CRGs. The aggregated CRGs are referred to as ACRGs and the successive tiers of aggregation are referred to as ACRG1, ACRG2 and ACRG3, with ACRG3 being the highest level of aggregation. Table 7 summarizes the aggregation of CRGs into ACRGs.

As shown in Table 7 the number of base CRGs are 273, 93, 30 and 9 and the number of CRGs with severity levels are 1083, 370, 131 and 34 for CRG, ACRG1, ACRG2 and ACRG3, respectively. The process of aggregating CRGs into successive tiers of ACRGs is illustrated in Table 8 for the CRG status consisting of single dominant and moderate chronic diseases for the MDCs for heart and coronary vascular diseases, peripheral vascular and

CRG	CRG	ACRG1	ACRG2	ACRG3
<i>Catastrophic Conditions</i>				
Base	11	10	6	1
Sol Levels	4	4	4	6
Total	44	40	24	6
<i>Dominant and Metastatic Malignancies</i>				
Base	23	3	1	1
Sol Levels	4	4	5	4
Total	92	12	5	4
<i>Dominant Chronic Disease in Three or More Organ Systems</i>				
Base	21	7	2	1
Sol Levels	6	6	6	6
Total	126	42	12	6
<i>Significant Chronic Disease in Multiple Organ Systems</i>				
Base	61	24	8	1
Sol Levels	2,4,6	4,6	5,6	6
Total	324	134	47	6
<i>Single Dominant or Moderate Chronic Disease</i>				
Base	109	25	8	1
Sol Levels	2,4	2,4	2,5,6	6
Total	406	96	35	6
<i>Minor Chronic Disease in Multiple Organ Systems</i>				
Base	1	1	1	1
Sol Levels	4	2	2	2
Total	4	2	2	2
<i>Single Minor Chronic Disease</i>				
Base	40	21	2	1
Sol Levels	2	2	2	2
Total	80	42	4	2
<i>History of Significant Acute Disease</i>				
Base	6	1	1	1
Sol Levels	1	1	1	1
Total	6	1	1	1
<i>Healthy</i>				
Base	1	1	1	1
Sol Levels	1	1	1	1
Total	1	1	1	1
<i>Total</i>				
Base	273	93	30	9
Sol Levels	1,2,4,6	1,2,4,6	1,2,4,5,6	1,2,4,6
Total	1,083	370	131	34

Table 7. Number of Groups and Severity Levels for Clinical Risk Groups (CRGs) and Aggregated CRGs (ACRGs)

noncardiac vascular diseases and respiratory diseases. As shown in Table 8, in these three MDCs there are 24 base CRGs, each with 4 severity levels for a total of 96 CRGs. The aggregation CRGs to ACRG1s combines the MDCs for heart and cardiac vascular disease together with the MDC for peripheral vascular and non-cardiac vascular disease into circulatory diseases which is subdivided into the following four circulatory base ACRG1s.

- Congestive heart failure
- Dominant chronic circulatory diseases except CHF
- Moderate chronic circulatory diseases except hypertension
- Hypertension
- The CRGs in the respiratory system are aggregated into two base ACRG1s
- Dominant chronic respiratory diseases
- Asthma

Thus, the 24 base CRGs from these three MDCs are consolidated into six base ACRG1s. The severity level for the ACRG1 is the same as the severity level for CRG (e.g., if the severity for the angina CRG is level 3, the severity level for the ACRG1 for dominant chronic circulatory diseases except CHF is also level 3). Thus, the 96 CRGs in these three MDCs for the single dominant or moderate chronic disease status are aggregated into 24 ACRG1s.

The six base CRGs in ACRG1 are aggregated into a single ACRG2 for cardiopulmonary disease. However, because there is significant clinical diversity across the six ACRG1s, the number of severity levels in ACRG2 is expanded to six. The mapping of the four severity levels for the ACRG1s to the six severity levels for the ACRG2s is shown in Table 9. Severity level 6 for cardiopulmonary base ACRG2 is composed of ACRG1 severity level 4 congestive heart failure and ACRG1

severity level 4 dominant chronic respiratory diseases. The mapping of the ACRG1 severity levels to the ACRG2 severity levels reflects both the ACRG1 severity level and the relative clinical significance of the different base ACRG1s that are aggregated into a single base ACRG2.

In ACRG3 all base ACRG2s in the single dominant or moderate chronic disease status are aggregated into a single base ACRG3 with six severity levels. Similar to the severity level mapping between ACRG1 and ACRG2, there is a severity level mapping between ACRG2 and ACRG3 that reflects the relative clinical significance of the different base ACRG2s that are aggregated into the single base ACRG3.

The clinical logic in the five phase process for determining CRG assignment results in a severity adjusted set of mutually exclusive and exhaustive categories that differentiate the relative need for future medical care as well as debility and death. The multiple aggregations of CRGs provide the flexibility for CRGs to be used at a level of detail that corresponds to the needs of all users including payers and providers.

CRG Development Process

The development of the clinical logic of the CRGs was accomplished through a four-phase process.

Phase 1: Development of Overall CRG Algorithm

In Phase 1, the overall architecture of the CRGs was designed. The use of EDCs and EPCs as the basic building blocks of the CRGs, the creation of nine CRG statuses, the role of the PCD, etc. are examples of design decisions that define the overall architecture of CRGs. These

CRGs	ACRG1s	ACRG2s
Heart and Coronary Vascular Diseases 14 Base CRGs 4 Sol Levels 58 CRGs Peripheral and Noncardiac Vascular Diseases 3 Base CRGs 4 Sol Levels 12 CRGs Respiratory Diseases 5 Base CRGs 4 Sol Levels 20 CRGs	Circulatory Diseases 4 Base ACRG1s 4 Sol Levels 16 ACRG1s Respiratory Diseases 2 Base ACRG1s 4 Sol Levels 8 ACRG1s	Cardiopulmonary Diseases 1 Base ACRG2 6 Sol Levels 6 ACRG2s
DC Congestive Heart Failure DC Major Congenital Heart DC Moderate Congenital Heart DC Major Cardiac Diagnoses DC Cardiac Valve Diagnoses DC History of AMI DC Angina MC Atrial Fibrillation MC Cardiac Dysrhythmia MC History of CABG MC History of PTCA MC History of Cardiac Device MC Coronary Atherosclerosis MC Hypertension DC Peripheral Vascular Disease DC Moderate Artery and Vein Disease MC Leg Varicosities with Ulcer DC COPD and Bronchiectasis DC BPD/Major Lung Anomaly DC Significant Pulmonary Disease DC Tracheostomy Status MC Asthma	DC Congestive Heart Failure DC Major Congenital Heart DC Moderate Congenital Heart DC Major Cardiac Diagnoses DC Cardiac Valve Diagnoses DC History of AMI DC Angina DC Peripheral Vascular Disease DC Moderate Artery and Vein Diseases MC Atrial Fibrillation MC Cardiac Dysrhythmia MC History of CABG MC History of PTCA MC History of Cardiac Device MC Coronary Atherosclerosis MC Leg Varicosities with Ulcer MC Hypertension DC COPD and Bronchiectasis DC BPD/Major Lung Anomaly DC Significant Pulmonary Disease DC Tracheostomy Status MC Asthma	DC Congestive Heart Failure DC Major Congenital Heart DC Moderate Congenital Heart DC Major Cardiac Diagnoses DC Cardiac Valve Diagnoses DC History of AMI DC Angina DC Peripheral Vascular Disease DC Moderate Artery and Vein Disease DC COPD and Bronchiectasis DC BPD/Major Lung Anomaly DC Other Sig Chronic Pulmonary Diagnoses DC Tracheostomy Status MC Atrial Fibrillation MC Cardiac Dysrhythmia MC History of CABG MC History of PTCA MC History of Cardiac Device MC Coronary Atherosclerosis MC Leg Varicosities with Ulcer MC Hypertension MC Asthma

Table 8. Aggregation of Cardiopulmonary CRGs into ACRGs for the CRG Status Consisting of a Single Dominant or Moderate Disease

Base ACRG1	ACRG2 Severity Level					
	1	2	3	4	5	6
Congestive Heart Failure			1	2	3	4
Dominant Chronic Circulatory System Diseases except CHF		1	2	3	4	
Dominant Chronic Respiratory Diseases			1	2	3	4
Moderate Chronic Circulatory System Diseases except Hypertension	1	2	3	4		
Hypertension	1	2	3	4		
Asthma	1	2	3	4		

Table 9. Mapping of ACRG1 Severity Level to ACRG2 Severity Level for Cardiopulmonary Diseases

design decisions were formulated into an algorithm that constitutes the steps associated with the assignment of a CRG. The criteria for the design of the algorithm for assigning a CRG was strictly clinical. The focus was to create an algorithm that would permit conditional and complex clinical characteristics to be specified. The premise was that the clinical characteristics are dependent on the nature and extent of an individual's underlying diseases. In particular, the ability to identify individuals with disease in multiple organ systems, along with an explicit specification of severity of illness was emphasized. In essence, the CRG algorithm provides a means of combining detailed clinical distinctions into a meaningful overall clinical description. The diversity and complexity of the clinical issues required an algorithm that could reflect the unique clinical characteristics of each disease and each combination of diseases.

Phase 2: Clinical Parameterization of the CRG Algorithm

Once the overall CRG algorithm was developed, it needed to be parameterized by specifying the actual clinical detail. In this phase, the EDCs were defined, the ICD-9-CM disease codes were assigned to each EDC, etc. The initial parameterization of the CRG algorithm was done independently by two separate clinical groups.

The clinical research team at 3M HIS parameterized the CRG algorithm with a primary focus on the adult and elderly populations. A clinical team at the National Association of Children's Hospitals and Related Institutions (NACHRI) parameterized the CRG algorithm with a primary focus on the pediatric population and a secondary focus on the Medicaid disabled population. NACHRI had previously developed a classification of congenital and chronic health conditions which it used as the starting point for the parameterization of the CRG algorithm.²⁴ While there was ongoing communication between the two clinical groups and both clinical groups worked within the structure of the CRG algorithm, the actual parameterization of the CRG algorithm was done relatively independently. This process provided a cross validation of the initial clinical parameterization. All decisions on the initial parameterization of the CRG algorithm were made on a clinical basis without any review of historical expenditure data. Outside clinical specialists were frequently consulted. The focus of the clinical decisions was on the identification of clinical characteristics that impacted an individual's future need for medical care, debility and death.

Phase 3: Review Clinical Parameterization of the CRG Algorithm with Historical Data

Based on the initial clinical parameterization of the CRG algorithm, the initial CRGs were assigned to the three analysis databases which covered three very distinct population groups. For Medicare and the employed population databases, the initial CRGs were assigned based on the first two years of data. Expenditures in the third year of data were used as a measure of the impact of specific clinical characteristics on the future healthcare needs of an individual. Since, in general, individuals with high healthcare expenditures have significant disease, third year expenditures were used as a proxy for the individual's clinical condition. The third year expenditures were for review purposes only. Final decisions were always clinical. For the Medicaid database, CRGs were assigned based on the first year of data and expenditures in the second year were used as the measure of future healthcare needs.

Detailed CRG analysis reports were produced which examined the impact of a wide range of clinical characteristic on individuals with specific diseases and combinations of diseases. For example, the reports examined the impact on subsequent expenditures of the occurrence of pneumonia in an individual with emphysema. The impact of pneumonia was examined under various conditions such as having occurred in the most recent six months, or having occurred multiple times. The impact of pneumonia in an individual with both emphysema and congestive heart failure was examined separately. Thus, the reports were extremely detailed and examined almost every conceivable combination of diseases and disease conditions (e.g., occurred within most recent six months). Based on the initial review of the data, the clinical parameterization of

the CRG algorithm was modified, the CRGs were reassigned to the data, the CRG analysis reports were reproduced and the CRG analysis reports were reviewed again. Thus, the process of finalizing the parameterization of the CRG algorithm was highly iterative. The complete process was repeated multiple times.

The review of the subsequent expenditures for specific clinical characteristics sometimes produced statistical results for which there was no clinical rationale. Statistical results that were clinically unreasonable were not used as a basis for modifying the parameterization of the CRG algorithm. If clinically unreasonable statistical results occurred with high frequency, additional confirmation was obtained from outside clinical experts in the specialty area. The 3M HIS clinical staff utilized data from the Medicare and employed population data, while the NACHRI clinical staff utilized data from the Medicaid and employed population data. The end result of the process was a clinical model that had been extensively reviewed with historical data.

Phase 4: Integration of Parameterization of the CRG Algorithm

Since 3M HIS and NACHRI clinical staffs had parameterized the CRG algorithm relatively independently, there were differences between the two parameterizations (e.g., the severity level to which a particular clinical characteristic is assigned.) In Phase 4, a final unified parameterization of the CRG algorithm was developed through a consensus process between the two clinical staffs.

The final parameterization of the CRG algorithm that resulted from the four-phase process constitutes the full clinical logic of the CRGs. The four-phase process took 42 months to complete. Phase I required

six months, Phase 2 required twelve months, Phase 3 required eighteen months and Phase 4 required six months. The iterative process of successive clinical evaluations of historical data was patterned after the process that was used in the original development of the DRGs.

Data Used in Development of CRGs

Databases from a Medicare, Medicaid and privately insured population were used in the development of the CRGs. The data from all three populations met the following conditions.

- Eligibility information was available
- Claims data from all care settings was available
- The claims data could be linked from each eligible individual
- There were multiple years of claims data available
- Diagnostic, procedure and expenditure information was available on each claim

The availability of eligibility information was essential in order to identify individuals who had continuous eligibility over the period of time covered in the analysis. For example, suppose two years of data were available and that the data from the first year is used to assign the CRGs for predicting expenditures in the second year. An individual who was only eligible in the first year could not have any reported expenditures in the second year, and would need to be excluded from the analysis. Conversely, an individual who was eligible in both years, but had no claims in the first year, would still need to be assigned a CRG (i.e., healthy) for the purpose of predicting year 2 expenditures. Indeed, individuals who had no claims for the entire analysis time period, but who were eligible during the entire analysis period, must be included in the database.

In all three databases identifiers for individuals and providers were encrypted to ensure confidentiality.

MEDICARE DATA

Data for the Medicare component of the analysis came from the Medicare Standard Analytical Files (SAF), which is a five percent sample of Medicare beneficiaries. The SAF contains all claims for the institutional components of inpatient care, outpatient care, hospice care, skilled nursing facility (SNF) and hospital outpatient care, as well as professional and ancillary claims. Eligibility information was available from a separate beneficiary file. All data were linkable at the beneficiary and provider level. Data from 1991 to 1994 were included in the analysis database. The criteria for inclusion in the analysis database were:

- Noninstitutionalized
- Continuous Part A and Part B eligibility for the analysis period
- No HMO enrollment for the analysis period
- No indication of another primary or payer

Beneficiaries who are long-term institutionalized can exceed their lifetime Medicare benefits and therefore all their claims data may not be available. Continuous Part A and Part B coverage was required in order to insure that claims from all care settings were available. Beneficiaries enrolled in an HMO or with another primary payer may not have all their claims data available and were therefore excluded from the analysis. Beneficiaries who met the eligibility criteria but had no claims for the entire analysis period were included in the analysis.

The first three years of data were used in the development of the CRGs (i.e.,

1991-1993) and the last three years of data (i.e., 1992-1994) were used to validate the CRGs. The criteria used for inclusion in the analysis were applied separately to each of the three year periods. In addition, in each of the three year periods, beneficiaries who died in the first two years of the period or were born in the last year of the period were excluded from the analysis. A total of 1,330,458 beneficiaries were included in the analysis database for the 1991-1993 period and 1,325,568 beneficiaries were included in the analysis database for the 1992-1994 period.

Submitted and paid charges were included in the Medicare database. Submitted charges are the actual charges submitted to Medicare by the provider. Paid charges are the charges actually paid by Medicare and exclude deductibles and coinsurance paid by the beneficiary. Medicare paid charges also include geographic adjustments.

PRIVATELY INSURED POPULATION DATABASE

Data for the privately insured population component of the analysis came from a commercial insurance database which included working individuals and their dependents and retirees not yet Medicare eligible. The commercial insurance coverage included full range of benefits which were paid primarily on a fee-for-service basis. Complete eligibility information was available and all data was linkable for each eligible individual.

Data from 1992 to 1995 were included in the analysis database. The criteria used for inclusion in the analysis database were:

- Continuous eligibility for the analysis period
- No HMO enrollment for the analysis

period

- No indication of another primary payer
- Age less than 65 years old for the analysis period

Individuals who met eligibility criteria but had no claims for the entire analysis period were included in the analysis. The first three years of data (i.e., 1992-1994) were used in the development of the CRGs and the last three years of data (i.e., 1993-1995) were used to validate the CRGs. The criteria used for inclusion in the analyses were applied separately to each of the three year periods. In addition, in each of the three year periods, individuals who died in the first two years of the period or were born in the last year of the period, were excluded from the analysis. A total of 253,116 individuals were included in the analysis database for the 1992-1994 period and 246,186 individuals were included in the analysis database for the 1993-1995 period. Both submitted and allowed charges were included in the database. Allowed charges are the charges approved for payment by the insurance carrier. Paid charges were not included in the database because they reflected negotiated discounts which was considered proprietary information.

MEDICAID DATA

The state of Washington Medicaid claims database was used for the Medicaid component of the analysis. Data from fiscal years 1992 and 1993 were included in the analysis database. Complete eligibility information was available and all data was linkable for each beneficiary. The Medicaid database presented a problem not encountered in either the Medicare or privately insured population database. Medicaid beneficiaries change eligibility status frequently. Thus, it was not feasible to restrict the criteria for inclusion in the

analysis database to those beneficiaries who were continuously eligible for the entire two years. The criteria used for inclusion in the analysis database were:

- Noninstitutionalized
- Not Medicare-Medicaid dually eligible
- Non-HMO enrollee
- Valid age for newborn and obstetric diagnoses to avoid co-mingling of claims for mothers and newborns at time of birth

In addition, criteria were established to insure that only beneficiaries that had sufficient claims experience were included in the analysis database:

- Minimum eligibility for at least 6 months in both 1992 and 1993 except for newborns in 1992
- Newborns in 1992 were required to have at least 2 months eligibility in 1992

Medicare-Medicaid dually eligible individuals were excluded because all their claims data would not be included in the Medicaid database. A problem encountered in the Medicaid data related to the claims for newborns being reported with the identification number of the mother. Therefore, edits relating to diagnosis consistency with age were used to exclude beneficiaries with obstetrical care who potentially had co-mingled newborn claims. This exclusion criteria resulted in a somewhat higher proportion of female Medicaid beneficiaries being excluded from the analysis. Beneficiaries were required to have at least six months of eligibility in both 1992 and 1993. The one exception was newborns who were only required to have two months of eligibility in 1992 and six months in 1993 in order to be included in the analysis database. There were 242,816 Medicaid beneficiaries who were included in the analysis database. Two-thirds of the Medicaid beneficiaries

were children and one-sixth were disabled.

The measure of expenditures for analysis of the Washington Medicaid data was submitted charges. For recipients with less than 12 months of eligibility in 1993, the submitted charges were annualized based upon the beneficiaries months of eligibility. An indication of whether an individual died was not present in the Medicaid database.

Capitated Payment Models

The classification system for risk adjustment is only one component of a capitated payment system. The actual performance of CRGs can only be evaluated in the context of the full design of the capitated payment system. Operationally, the important issue is the overall performance of the complete capitated payment system under real world conditions. The evaluation of a classification system for risk adjustment in isolation from the other components of the capitated payment system and under idealistic conditions, is not very meaningful. For example, up-to-date data are almost never available at the time the capitated rates are set. The data available for determining the risk adjustment will usually be at least six months to a year old. Further, data from all sites of service may not be available (e.g., physician office data). In addition, providers or payers may obtain some form of stop loss or reinsurance policies in conjunction with the capitated payment arrangement. Therefore, the evaluation of the performance of a risk adjustment system should replicate these real world conditions. A series of capitated payment simulations using CRGs for risk adjustment have been performed that examine alternative configurations of the components of a full capitated payment system.

In order to risk adjust using CRGs, historical claims data must be available. The historical claims data is used for the following two purposes.

- The computation of the CRG payment weights
- The assignment of the CRGs used for risk adjustment

The CRGs assigned for risk adjustment in combination with the CRG payment weights are used as the basis for the establishment of the risk adjusted capitated payment rates. As an example of the use of the historical data, assume that a payer has historical data from year 1 and 2 available, but has no data from year 3 available due to delays in claims submission and claims processing. Also, assume that the risk adjusted capitation rates for year 4 need to be established prior to the beginning of year 4. Further, assume that the payer does not want to use exogenous CRG payment weights and wants to compute CRG payment weights from its own historical data. As illustrated in Figure 5, the two years of historical data are used to establish the payor specific CRG payment weights and set the CRG risk adjusted capitated rates for year 4 based on the following steps:

1. Using the claims data from year 1, a CRG is assigned to each individual
2. Based on the CRGs assigned in step 1, the average expenditures in year 2 for the individuals assigned to each CRG are computed and used as the basis of the CRG payment weights
3. A CRG for each individual is assigned using the claims data from year 2 (alternatively the claims data from both year 1 and 2 can be used to reassign the CRG)
4. Using the CRG payment weights from step 2 and the CRG assignments from

step 3, the risk adjusted CRG capitated payment rates for each individual for year 4 are established

5. The CRG capitated payment rates for year 4 established in step 4 are adjusted for inflation, age/sex and any applicable nonclinical adjustment factors

As demonstrated in the above steps, if a payer wants to set its own CRG payment weights, it must have two years of historical data available.

From a data perspective, there are three key issues.

Data Lag

Due to delays in claims submission and claims processing, the data available for assigning the CRGs will always lag behind the point in time at which the capitated rates are set. In the above example, the data lag was one year. Operationally, it is difficult to have data lag less than six months. The data lag is a crucial issue for any disease-based risk adjustment system. Long data lags reduce the accuracy of any disease-based risk adjustment systems such as CRGs.

Data Duration

In the above example, the duration of the data used to assign the CRGs for risk adjustment was one year (i.e., year 2). A full two year duration could have also been used (i.e., years 1 and 2). In general, the expectation is that a longer data duration should give a more complete profile of an individual's history of diseases and medical interventions which in turn, should result in more accurate CRG assignment. However, it is also possible that older data may have a negative effect by incorporating into the CRG assignment diseases and medical interventions that are no

Data Used to Assign CRGs for Computation of Payment Weights	Expenditures Used for Computation of Payment Weights		
	Data Used to Assign CRGs for Risk Adjustment	Data Unavailable	Predicted Expenditure
Year 1	Year 2	Year 3	Year 4

Figure 5. Data Used to Set Year 4 Capitation Rates

longer significant. Indeed, in the determination of the CRG severity level, less significance is attributed to diseases that have no recent occurrences.

Data Completeness

In the above example, data from all care settings, including inpatient and ambulatory, were assumed to be included in the historical data. Data from all settings are not always available. Inpatient data is almost always available but ambulatory data may not be available. Institutionally based ambulatory data, such as from hospital outpatient departments, tends to be more readily available than noninstitutional data such as from physician's offices. The unavailability of ambulatory data is a potentially serious problem. Many chronic diseases that never result in hospitalization can have a significant impact on the individual's health and need for healthcare services. Indeed, most healthcare is rendered outside of the hospital and relatively few individuals are hospitalized in any given year.

In addition to data lag, duration and completeness, a capitated payment system must also address the issues of the calculation of payment weights, payment death proration, age/sex adjustment and stop/loss and reinsurance.

Calculation of Payment Weights

The calculation of the CRG payment weights is relatively straightforward. If two years of historical data are available, the CRG payment weights are computed as the average year 2 expenditures in each CRG for individuals assigned to CRGs based on year 1 data. In computing the average year 2 expenditures, there are two computational issues. Individuals who die in the second year only have a partial year of expenditures. To compensate, the year 2 expenditures for individuals who die during year 2 can be set to the expenditures in the 12 months prior to death. Since the expenditures in the last months before death are often quite high, the use of the expenditures in the 12 months prior to death provides a more accurate estimate of the annual expenditures than is obtained by annualizing the partial expenditures in year 2. The expenditures from 12 months prior to death are only used in the computation of the payment weights and are not used to adjust the predicted expenditures in the capitated payment period. In addition, since a few high expenditure individuals can have a disproportionate impact on the average value, the average should be computed with extreme expenditure values excluded. A better estimate of the average is obtained when indi-

viduals with extreme expenditure values are excluded. Typically, the identification of extreme expenditure values is accomplished by taking the log of expenditures and eliminating from the computation of the average value all individuals with expenditure values that exceed a specified number of standard deviations (1.75 was used) above the mean. This is the same computational method that Medicare uses to compute the DRG payment weights. The exclusion of individuals with extreme expenditure values applies only to the computation of the CRG payment weights. Individuals with extreme expenditure values are included in all other analysis.

Payment Death Proration

In addition to being an issue in the computation of CRG payment weights, deaths are also an issue for determining the proportion of the capitated amount to be paid for an individual. Based on the CRG, a capitated payment amount is established for each individual. Typically, one-twelfth of the capitated amount is paid monthly. Thus, if an individual dies, the full capitated amount for that year is not paid. Instead, the capitated payment is reduced in proportion to the number of months in the year that the individual lived (e.g., if the individual dies in the third month, payment is equal to one-fourth of the annual capitated amount). Since individuals who die tend to incur high expenditures prior to death, the reduction in the capitated payment may increase the difference between actual expenditures and capitated payment for individuals who die.

Age/Sex Adjustment

CRGs do not include an explicit age/sex adjustment. Age and sex are sometimes used within the CRG clinical model (e.g.,

CHF in a child is an acute disease and in an adult CHF is a chronic disease). However, age and sex were only used to differentiate diseases that were fundamentally distinct based on the age or sex of the individual. A separate set of age/sex adjustment factors were computed for adjusting the CRG capitated rates for age and sex. The age/sex adjustment factors were computed separately for each status because the impact of age or sex can vary considerably depending on the health of the individual. For example, the age and sex of an individual has a greater relative impact on the future healthcare needs for a healthy individual than for an individual with a metastatic malignancy. The age/sex adjustment factors are computed in conjunction with the computation of the CRG payment weights. For this analysis age was subdivided into nine categories. (the specification of age categories can vary depending on the population covered). Within each status, the average expenditures are computed for individuals in each of the age/sex categories. The average expenditures for each of the 18 age/sex categories is then divided by the overall average expenditure in the status to determine the age/sex adjustment factors for the status. The status-specific age/sex adjustment factors can then be used to adjust the CRG capitated amount for age and sex.

Stop Loss and Reinsurance

Capitated payment arrangements can include provisions for either stop loss or reinsurance. Under a stop loss, if expenditures for an individual exceed a specified threshold (e.g., \$100,000), all expenditures above the threshold are paid under the stop loss policy separate from the capitated payments. From the perspective of the capitated payment system, a stop loss

means that no individual has expenditures that exceed the stop loss threshold. In other words, all expenditures for an individual above the threshold are excluded from the capitated payment system. In order to simulate a stop loss in a CRG-based capitated payment system, the expenditures for each individual are capped at the stop loss threshold (i.e., if expenditures exceeded the threshold, the expenditure amount would be set equal to the threshold). Using the capped expenditures, the CRG payment weights and age/sex adjustments would be computed and used to establish capitated payment amounts. In evaluating the performance of a CRG payment system with stop loss, the capitated payments would be compared to the capped expenditures in the predicted year. In essence, a stop loss reduces the amount of expenditures covered by the capitated payment.

In a reinsurance model, the amount of expenditures covered by the capitated payment system is not reduced, but the amount of the capitated payments is increased for individuals with high expenditures. In order to compensate for the additional reinsurance payments, the standard CRG payment amounts are decreased in order to maintain budget neutrality. The reinsurance model is equivalent to the outlier policy used in the Medicare DRG-based PPS. In the reinsurance model, the computation of the payment weights and age/sex adjustments is unaffected by the reinsurance. The total payment for an individual is computed as follows:

$$\left[\text{CRG Payment} \right] + \left[\text{Reinsurance Percentage} \right] * \left\{ \left[\text{Actual Expenditure} \right] - \left[\text{CRG Payment} \right] - \left[\text{Reinsurance Threshold} \right] \right\}$$

If the difference between the expenditures and the CRG capitated payment exceeds the reinsurance threshold, then payment is increased by an amount equal

to the reinsurance percentage times the amount by which the difference between the actual expenditures and CRG capitated payment exceeds the reinsurance threshold. For example, suppose the reinsurance threshold is \$100,000 and the reinsurance percentage is 50 percent. If, for an individual, the expenditure is \$200,000 and the CRG capitated payment is \$60,000, then the expenditure exceeds the capitated payment by \$140,000, which is \$40,000 above the reinsurance threshold. Fifty percent of the \$40,000 would be added to the CRG capitated payment as a reinsurance payment (i.e., total payment is \$80,000). The key feature of reinsurance is that it is applied on a CRG-specific basis. Thus, the reinsurance is only applicable if the CRG capitated payment falls below actual expenditures for the individual by an amount that exceeds the reinsurance threshold. The incentive for the provider to control costs remains strong since the provider must take a loss equal to the insurance threshold before it becomes eligible for reinsurance payments. However, the reinsurance limits the possibility of an extreme loss from any one individual.

A series of CRG payment simulations were performed with various configurations of data lag, data duration, data completeness, payment death proration, age/sex adjustment, stop loss and reinsurance. No nonclinical adjustment factors were used in the simulations nor were any geographical cost of living adjustments. All payment simulations were performed on a budget neutral basis (i.e., the CRG capitated payment amounts were multiplied by a budget neutrality factor that insured the overall aggregated payments equaled overall aggregated expenditures).

The most common statistical measure used to compare risk adjustment systems

is reduction of variance (R^2), which measures the proportion of variation that is explained by a risk adjustment system. R^2 provides a summary measure of the extent to which the risk adjustment system is able to predict the value of future expenditures. R^2 ranges between 0 and 100 and measures the percentage of variation in future expenditures explained by the risk adjustment system. Thus, an R^2 of 10.15 would mean that 10.15 percent of the variation in future expenditures is explained by the risk adjustment system. The CRG payment simulations are compared using R^2 .

CRG Payment Simulations Using Medicare Data

Medicare paid charges were used as the measure of expenditures. In order to provide a reference value for R^2 , Table 10 includes the R^2 values from the data used in the development of CRGs. Table 10 also examines the impact of the payment death proration. The values in the first four rows of Table 10 specify which years of data were used for payment weights and pre-

dicted expenditures. In the development of CRGs, years 1 and 2 of the data were used to assign the CRGs for predicting year 3 expenditures. The payment weights used in the prediction were based on year 3 expenditures. In a regression context, this would be equivalent to developing the regression equation to predict year 3 expenditures based on independent variables from years 1 and 2 and then using the resulting regression equation to predict year 3 expenditures. The R^2 without payment death proration is 14.15. No payment death proration means that the full CRG capitated payment is paid even if the individual dies during year 3. If the CRG capitated payment is prorated based on the number of months the individual was alive in year 3, then the R^2 decreases to 12.11. The decrease in R^2 due to the payment death proration reflects that individuals who die have high expenditures and that the payment death proration lowers payments for individuals who die. In the development data, even though individuals who died in year 3 only incur expenses for part of the year, they still have average actual

	Development Database	Validation Database	Validation Database with Independent Payment Weights
Years of Data Used to Assign CRGs for Payment Weights	1,2	2,3	1,2
Year of Expenditures Used to Compute Payment Weights	3	4	3
Years of Data Used to Assign CRGs for Prediction	1,2	2,3	2,3
Year of Expenditures Predicted	3	4	4
R^2 with no Payment Death Proration	14.15	12.55	11.94
R^2 with Payment Death Proration	12.11	10.93	10.79

Table 10. R^2 of CRGs for Development and Validation Databases for Medicare Population

expenditures that are nearly three times higher than individuals who lived. The payment death proration lowers payments for individuals who have high actual expenditures. Thus, the R^2 decreases since the payment death proration increases the difference between actual expenditures and payment.

From a policy perspective this result raises the issue of whether a provider should be entitled to the full annual capitated payment amount even if the individual dies. However, since virtually all capitated payment arrangements use monthly rather than annual payments, all payment simulations will be performed using the payment death proration.

In the development of the CRGs, data from year 4 was not used and was reserved for validation. In the validation column in Table 10, years 2 and 3 of the data are used to assign the CRGs for predicting year 4 expenditures. The CRG payment weights used in the prediction were based on year 4 expenditures. In a regression context, this would be equivalent to taking the regression equation developed to predict year 3 expenditures and recalculating the regression coefficients based on year 4 expenditures without altering the variables used in the equation, and then using the resulting regression equation to predict year 4 expenditures. For the year 4 validation data, the R^2 with payment death proration is 10.93 which is a 9.7 percent decrease from the R^2 of 12.11 in the year 3 development data.

The development and validation R^2 values were computed using CRG payment weights derived from the same year as the expenditures being predicted. If the CRG payment weights were developed from a year other than the year for which the expenditures are being predicted, then the

R^2 may decrease due to differences in the payment weights over time. In the last column in Table 10, years 2 and 3 of the data were used to assign the CRGs for predicting year 4 expenditures. The CRG payment weights used in the prediction were based on year 3 expenditures for CRGs assigned using years 1 and 2 of the data. In a regression context, this would be equivalent to developing the regression equation to predict year 3 expenditures based on independent variables from years 1 and 2 and then using the resulting regression equation to predict year 4 expenditures. For the year 4 validation data with independent (year 3) CRG payment weights, the R^2 with payment death proration is 10.79 which is a 1.3 percent decrease from the R^2 of 10.93 for the year 4 validation data.

The base simulation model used for the CRG payment simulations is based on the year 4 validation data using year 3 CRG payment weights with the payment death proration. Thus, payment weights are developed from the prior year's data and are applied prospectively to the prediction year with capitated payments paid on a monthly basis. This model is the most realistic from an actual implementation perspective.

The age/sex adjustment had minimal impact on the R^2 for the Medicare population. The R^2 of the base CRG payment simulation increased from 10.79 to 10.85 when the status specific age/sex adjustment was included. This is not surprising since a detailed clinical model should reduce the need for additional age/sex adjustment. Since for Medicare data the age/sex adjustment had minimal impact on R^2 across all the CRG payment simulations, all payment simulation results will be reported without age/sex adjustment.

Impact of Data Duration, Data Lag and Data Completeness

Table 11 contains the R^2 value for different data durations, data lags and data completeness for the Medicare population. The base simulation model for all entries in Table 11 uses payment weights computed from year 3 expenditures to predict year 4 expenditures, with payment death proration and with no age/sex adjustment. Thus, the last entry in Table 10 corresponds to the first entry in Table 11. In the column labeled “complete” in Table 11 both inpatient and ambulatory data are used to assign the CRGs for prediction. If the data duration is reduced from two years to one year (i.e., only year 3 data instead of year 2 and 3 data is used to assign the CRGs for prediction), the R^2 increases slightly from 10.79 to 10.89. If there is a six month lag in the data used to assign the CRG for prediction, there is a 16.9 percent reduction in R^2 from 10.10 to 8.39. A six month data lag with a one year duration means that the data from months 19-30, instead of from months 25-36, are used to assign the CRGs for prediction. If the data lag is a full year, the reduction in

Data Used to Assign CRGs for Prediction				
Duration	Lag	Complete	Inpatient Only	Ambulatory Only
24	0	10.79	8.63	9.96
12	0	10.89	7.59	10.04
12	6	8.39	5.25	8.05
12	12	6.56	4.30	6.23

Table 11. R^2 for Base Simulation Model with Different Data Durations, Data Lags and Data Completeness for the Medicare Population

R^2 is 35.0 percent from 10.10 to 6.56. Thus, data lag is a critical issue. A capitated payment system should always use the most recent data possible for risk

adjustment. A six month data lag is probably the shortest possible data lag that can be achieved operationally. Because of the substantial impact of the data lag on R^2 , the evaluation of the performance of any risk adjustment system should always be based on data lagged for at least six months.

In the column labeled “Inpatient” in Table 11, the data used to assign the CRGs for prediction is limited to only inpatient data. Using only inpatient data reduces the R^2 for a data duration of two years with no data lag by 20 percent, from 10.79 to 8.63. If the data duration is reduced to one year, the R^2 is reduced by another 12.1 percent from 8.63 to 7.59. Although a shorter data duration did not negatively affect R^2 when complete data was used to assign the CRGs for prediction, it does when only inpatient data is used to assign the CRGs for prediction. Since most individuals are never hospitalized, a longer data duration is needed to expand the number of individuals for whom data is available. When the ambulatory data is also available the longer data duration is not needed. A six month data lag further reduces the R^2 for inpatient only data by 38.8 percent from 7.59 to 5.25. The impact on R^2 of the data lag is greater with only inpatient than it is with complete data (30.9 percent reduction in R^2 versus 16.9 percent reduction in R^2 , respectively). With a one year data duration with a six month data lag, there is a 37.4 percent difference in R^2 between complete data (8.39) and inpatient only data (5.25). The same payment weights were used for all the simulations in Table 11. The computation of the payment weights was based on CRGs assigned using complete data. If the CRGs assigned to compute the payment weights also use only inpatient data, there is an

additional slight reduction in R^2 . For example, with a one year data duration with a six month data lag, the R^2 is reduced from 5.25 to 4.91 if the payment weights are also based on CRGs assigned using only inpatient data.

In the column labeled “Ambulatory” in Table 11, the data used to assign the CRGs for prediction is limited to only non-inpatient data. Hospital data and physician claims for hospital care are excluded from the data used to assign the CRGs for prediction. Using only ambulatory data reduces the R^2 compared to complete data by less than 8 percent across all combinations of data durations and data lags. Thus, for the Medicare population, the ambulatory data provides a more complete description of an individual for the purpose of the prediction of future expenditures than does inpatient data.

Stop Loss and Reinsurance

Tables 12 and 13 examine the impact of a stop loss and reinsurance on R^2 for the Medicare population. The simulation model used in Tables 12 and 13 utilizes a

Stop Loss	Data Used to Assign CRGs for Prediction		
	Complete	Inpatient Only	Ambulatory Only
None	8.39	5.25	8.05
50,000	10.63	6.56	10.14
100,000	10.07	6.39	9.62
250,000	9.46	6.07	9.05

Table 12. R^2 for Base Simulation Model with One Year Data Duration, Six Month Data Lag and Stop Loss for the Medicare Population

one year data duration and a six month data lag (line three in Table 11). When complete data is used to assign the CRGs for prediction, a \$50,000 stop loss

increases the R^2 by 26.7 percent from 8.39 to 10.63. The R^2 is reduced slightly if the stop loss is increased to \$100,000 and \$250,000. The pattern is similar if the data used to assign the CRGs for prediction is limited to only inpatient or ambulatory data. The stop loss of \$50,000 and \$100,000 applies to 0.93 and 0.12 percent of the individuals, respectively. A stop loss of \$250,000 affects only 27 individuals. In a stop loss simulation the expenditures above the stop loss are excluded from the capitated payment system (i.e., the expenditures are capped at the stop loss value).

In the reinsurance simulations, the capitated payment is increased for individuals for whom the difference between payment and expenditures exceeds the reinsurance threshold. The R^2 under a reinsurance model will increase dramatically because additional payment is provided for individuals whose capitated payment is significantly below actual expenditures. A large portion of the R^2 is due to the reinsurance as opposed to the risk adjustment. Therefore, payment simulations with reinsurance are not useful for comparing risk adjustment systems, but are useful for demonstrating the impact that increasing payment for a relatively few individuals can have on R^2 . Table 13 contains the R^2 values for various reinsurance models. When complete data is used to assign the CRGs for prediction, a reinsurance model with a \$25,000 threshold with a 90 percent reinsurance percentage increases R^2 from 8.39 to 59.00. Even a reinsurance model with a \$250,000 threshold and a 50 percent reinsurance percentage more than doubles R^2 from 8.39 to 18.06. The pattern is similar if the data used to assign the CRGs for prediction is limited to only inpatient or ambulatory data. The percent of individuals for whom the reinsurance

Reinsurance		Data Used to Assign CRGs for Prediction		
Threshold	Percentage	Complete	Inpatient Only	Ambulatory Only
None	None	8.39	5.25	8.05
25,000	50	51.57	37.27	52.74
25,000	90	59.00	46.97	59.89
50,000	50	33.62	22.60	34.17
50,000	90	38.31	27.73	38.76
100,000	50	22.86	14.89	22.93
100,000	90	25.55	17.61	25.56
250,000	50	18.06	11.69	17.94
250,000	90	19.79	13.44	19.63

Table 13. R² for Based Simulation Model with One Year Data Duration, Six Month Data Lag and Reinsurance for the Medicare Population

applies is approximately 2.8, 0.09 and 0.009 percent for a reinsurance threshold of \$25,000, \$50,000 and \$100,000, respectively, and is fairly consistent across CRGs assigned using complete, inpatient and ambulatory data. A reinsurance model with a \$250,000 reinsurance threshold only applies to between 24 and 26 individuals depending on the data used to assign the CRGs. From a payment policy perspective, some form of a reinsurance would greatly reduce the level of risk associated with a capitated payment system. Medicare included outlier payment in the inpatient PPS system to reduce the financial risk to hospitals. Since the relative financial risk associated with an inpatient admission is less than the financial risk associated with a capitated payment, it would be reasonable for Medicare as well as other payers to consider some form of reinsurance (i.e., outliers) in the design of their capitated payment system.

Applying CRGs to Retrospective Data

The R² results have focused on the application of the CRGs to predict future healthcare expenditures. CRGs could also be applied retrospectively. Table 14 con-

tains the R² values for CRGs applied retrospectively to the development and validation data. For the development data, data from years 2 and 3 are used to assign the CRGs for predicting year 3 expenditures. For the validation data, data from years 3 and 4 are used to assign the CRGs for predicting year 4 expenditures. The R² values for the development data are 40.72 and 38.09 with no payment death proration and with a payment death proration, respectively. For the validation data, the R² values are 35.66 and 33.54 with no payment death proration and with a payment death proration, respectively. The standard CRGs with no changes were applied to the retrospective data. The CRG definitions could have been altered specifically for retrospective analysis. CRGs make limited and restricted use of procedures. Since in a retrospective application the expenditures for a procedure occur in the same year as the data used to assign the CRGs, an expanded use of procedures in the CRG definitions could significantly increase the retrospective R² value. However, this would be somewhat tautological since it essentially would be using the services rendered to predict the expenditures associated with those ser-

	Development Database	Validation Database
Data Used to Assign CRGs for Payment Weights	2,3	3,4
Expenditures Used to Compute Payment Weight	3	4
Data Used to Assign CRGs for Prediction	2,3	3,4
Expenditures Predicted	3	4
R ² with no Payment Death Proration	40.72	35.66
R ² with Payment Death Proration	38.09	33.54

Table 14. R² for CRGs Applied Retrospectively to the Development and Validation Data for the Medicare Population

vices. In addition, some acute illnesses have a significant impact on resource use in the year of occurrence, but have only minimal or modest implications for future resource use. The CRG definitions used in the prospective and retrospective analysis were identical.

A capitated payment system could be designed to include both prospective and retrospective payments. Such a system would blend together the prospective and retrospective CRG payment amounts for an individual to arrive at a composite capitated payment rate for the individual (sometimes referred to as partial capitation).²⁵ For example, if complete data with a one year duration and a six month data lag (i.e., the third line in Table 11) were used to set the prospective CRG capitation rates and complete data with payment death proration were used to set the retrospective CRG capitation rates (i.e., the last entry in Table 14), then the capitated payment for an individual could be computed as 50 percent of the prospective rate plus 50 percent of the retrospective rate. The R² for this blended prospective and retrospective capitated payment system is 27.06 which is more than a three-fold increase over the R² of 8.39 for a purely prospective system. Operationally, this could be achieved by paying the prospective rate during the course of the year and

then reconciling the aggregate payments when the data for the year becomes available. The problem with this approach is the administrative effort associated with the reconciliation process. This blended payment approach is essentially how the first DRG PPS in New Jersey was implemented.²⁶ The DRG payment rate for a hospital was set at a percentage of the standard statewide DRG payment rate plus the complementary percentage of the hospital's actual cost in the DRG. The hospital's actual cost in a DRG could not be determined until the end of the year. Thus, the determination of the final aggregate payments required a reconciliation process. It was not uncommon for a final reconciliation to be completed more than a year after the year to which the rates applied.

ACRG Aggregation

All the R² results have been reported at the CRG level which means that 1,083 separate payment rates are established. Alternatively, the R² could have been computed at the ACRG1, ACRG2 or ACRG3 level. Table 15 contains the R² values for both at the CRG and ACRG3 level for CRGs assigned using complete data (see Table 11). The ACRG3 level requires that only 34 payment rates be established. The

CRGs and ACRG3s for prediction were assigned with a one year data duration and a six month data lag. The R² for the ACRG3 level is 3.2 percent lower than the R² for the CRG level (i.e., 8.39 versus 8.12). Thus, for the Medicare population there is only a slight loss in R² associated with the aggregation to the ACRG3 level.

Duration	Lag	CRG	ACRG3s
24	0	10.79	10.38
12	0	10.89	10.51
12	6	8.39	8.12
12	12	6.56	6.35

Table 15. R² Using Data from All Settings for CRGs and ACRG3s with Different Data Durations and Data Lags for the Medicare Population

Predictive Ratio and Deciles

The evaluation of the performance of CRGs in a capitated payment system has utilized the R² statistic. The predictive ratio can also be used as an evaluation statistic. The predictive ratio is computed as the average CRG payment divided by the average expenditures (i.e., paid charges for the Medicare data) in the prediction year. Since the payment simulations are performed on a budget neutral basis, the predictive ratio across the entire database will be 1.0. However, the predictive ratio can be examined for subsets of the database. A predictive ratio greater than one means that in the prediction year, payments are greater than actual expenditures. A predictive ratio of 1.2 means that CRG payments are 20 percent higher than actual expenditures. Conversely, a predictive ratio of 0.8 means that CRG payments are only 80 percent of actual expenditures.

Table 16 contains the predictive ratio of CRG payments to expenditures by CRG status for the standard simulation model

with a one year data duration and a six month data lag. The predictive ratio for individuals determined to have been healthy six months prior to the start of the prediction year is 0.5334. Thus, the healthy individuals are significantly underpaid. This is not unexpected since some healthy individuals will get sick in the prediction year causing higher expenditures than would be expected if they remained healthy. Conversely, the sickest individuals with catastrophic conditions, dominant or metastatic malignancies and dominant chronic disease in three or more organ systems have a predictive ratio of 1.3820, 1.2742 and 1.2557, respectively. The source of the high predictive ratios for the sickest individuals is the six month data lag used to assign the CRGs for prediction. If there were no data lag the predictive ratio for the three sickest statuses would be 1.3026, 1.0899 and 1.1129, respectively. However, no data lag is not operationally feasible. While a six month data lag was used to assign the CRGs for prediction, no data lag was used to assign the CRGs that were used to compute the payment weights. If a six month data lag was also used to assign the CRGs for computing the payment weights, then the predictive ratios for the sickest individuals are 1.0777, 1.0911 and 1.0374, respectively. Since over time, some healthy individuals get sick and the health of some very sick individuals improves, using lagged data tends to compress the payment weights which results in predictive ratios closer to one for the sickest individuals. However, lagging the CRG assignment for computation of the payment weights while improving the predictive ratios, slightly lowers the R² (8.22 versus 8.39). In addition, in order to use payment weights that are computed based on lagged data would require a user to have at least two-and-a-half years of historical

CRG Status	Count	Average Expenditure	Average CRG Payment	Predictive Ratio
Healthy	357,982	2,080	1,109	0.5334
History of Significant Acute Disease	38,856	2,788	2,880	1.0329
Single Minor Chronic Disease	123,147	2,695	2,522	0.9358
Minor Chronic Disease in Multiple Organ Systems	26,643	2,967	2,637	0.8886
Single Dominant or Moderate Chronic Disease	348,251	3,810	3,735	0.9802
Significant Chronic Disease in Multiple Organ Systems	354,103	6,475	6,817	1.0529
Dominant Chronic Disease in Three or More Organ Systems	36,189	11,807	14,826	1.2557
Dominant and Metastatic Malignancies	32,477	8,981	11,444	1.2742
Catastrophic Conditions	7,920	29,647	40,971	1.3820

Table 16. Predictive Ratio by CRG Status for Base Simulation Model with 12 Months Data Duration and 6 Months Data Lag for the Medicare Population

data available. As this discussion indicates, data lags are a crucial issue for evaluating the performance of a capitated payment system.

The results by status have significant practical implications. In a capitated payment system with inadequate risk adjustment, there are significant financial incentives to avoid enrolling and to disenroll sick individuals. Conversely, there are significant financial incentives to enroll, and keep enrolled healthy individuals. It is unlikely that an MCO could make a better determination of which individuals are healthy and which are sicker than the categorization provided by the CRG status and severity levels. Thus, it would be difficult for the MCO to engage in financially advantageous selective enrollment and disenrollment when the capitated rates are expressed in terms of CRGs. Indeed, the financial incentive in a CRG capitated payment system are completely reversed. In a CRG payment system, the MCO will lose money by enrolling healthy individuals and make money by enrolling the sick. The greatest profit opportunities for an MCO in a CRG-based payment system are associated with providing cost-effective care for the sickest individuals.

Table 17 contains the predictive ratio by expenditure decile. Expenditure deciles are computed by rank ordering the actual expenditures for each individual and then dividing the individuals into 10 equal-sized subgroups. Thus, the first expenditure decile contains the 10 percent of individuals with the lowest expenditures, while the tenth expenditure decile contains the 10 percent of individuals with the highest expenditures. The deciles can be based on expenditures in the prediction year or expenditures in the year prior to the prediction year. The expenditure deciles for the prediction year in Table 17 reflect the enormous concentration of expenditures in relatively few individuals. Figure 2 showed that 73.5 percent of Medicare beneficiaries consume 7.6 percent of program expenditures, while 9.8 percent of beneficiaries consume 68.4 percent of program expenditures. The prediction year expenditure deciles in Table 17 almost exactly mirror these results with the first seven expenditure deciles (i.e., 70 percent of the individuals in the Medicare database) constituting 7.8 percent of year 4 actual expenditures, while the tenth expenditure decile constitutes 65.3 percent of year 4 actual expenditures. All indi-

Prediction Year Deciles				Prior Year Deciles		
Expenditure Decile	Average Expenditure	Average CRG Payment	Predictive Ratio	Average Expenditure	Average CRG Payment	Predictive Ratio
1	0	1,741	-	2,009	1,694	0.8429
2	29	2,380	82.1567	2,123	1,901	0.8953
3	138	3,057	22.1303	2,593	2,662	1.0264
4	283	3,598	12.6980	2,899	3,115	1.0743
5	496	4,093	8.2491	3,349	3,603	1.0757
6	859	4,583	5.3350	3,951	4,085	1.0340
7	1,630	4,917	3.0164	4,586	4,639	1.0114
8	3,522	5,176	1.4696	5,254	5,113	0.9733
9	8,335	5,936	0.7121	6,573	6,493	0.9878
10	28,742	8,555	0.2977	10,698	10,732	1.0032

Table 17. Predictive Ratio by Expenditure Deciles for Base Simulation Model with 12 Month Data Duration and 6 Month Data Lag for the Medicare Population

viduals in the prediction year first expenditure decile have no expenditures in year 4 and so a predictive ratio can not be computed. The predictive ratio for the prediction year lower expenditure deciles is quite high (e.g., 82.15 for the second expenditure decile) and low for the prediction year tenth expenditure decile (0.29). For prior year expenditure deciles the predictive ratios are much closer to 1.0

Table 18 contains the predictive ratios for each payment decile which are computed by rank ordering the payments in the prediction year for each individual and then dividing the individuals into 10 equal-sized subgroups. The predictive ratios for the lower three payment deciles in Table 18 are relatively low, ranging from 0.354 to 0.6033. The predictive ratio for the tenth payment decile is relatively high at 1.4018. While expenditure or payment deciles represent a method for comparing risk adjustment systems they have limited operational significance.

Payment Weights

The CRG payment weights used to predict year 4 expenditures are based on year 3 expenditures. Table 19 shows the 34 payment weights for the ACRG3 tier of aggregation (see Table 7). As shown in Table 19, the ACRG3 payment weights within each status increase monotonically

Payment Decile	Average Expenditure	Average CRG Payment	Predictive Ratio
1	2,970	1,050	0.3534
2	1,863	1,124	0.6033
3	2,393	1,227	0.5128
4	2,853	2,344	0.8216
5	3,014	2,607	0.8948
6	3,690	3,340	0.9052
7	4,206	4,077	0.9693
8	5,051	5,093	1.0033
9	6,602	7,115	1.0777
10	11,392	15,968	1.4018

Table 18. Predictive Ratio by Payment Deciles for Base Simulation Model with 12 Month Data Duration and 6 Month Data Lag for the Medicare Population

CRG Status	Severity Level					
	1	2	3	4	5	6
Healthy	0.2009					
History of Significant Acute Disease	0.4993					
Single Minor Chronic Disease	0.4266	0.5867				
Minor Chronic Disease in Multiple Organ Systems	0.4666	0.6540				
Single Dominant or Moderate Chronic Disease	0.5256	0.7189	0.9370	1.1841	2.0850	3.7962
Disease in Chronic Multiple Organ Systems	0.8857	1.4277	2.1845	2.9002	3.6478	6.1852
Dominant Chronic Disease in Three or More Organ Systems	1.3768	1.8098	2.5294	3.6102	4.9347	6.6154
Dominant and Metastatic Malignancies	1.4912	2.4280	4.0026	5.3719		
Catastrophic Conditions	1.5661	2.7608	5.3801	9.0080	10.8938	13.2945

Table 19. ACRG3 Payment Weights by Severity Level for the Medicare Population

across the severity levels. Across the 35 ACRG3s, there is a 66 fold difference in payment weights from 0.2009 for healthy individuals to 13.2945 for individuals with severity level 6 catastrophic conditions. To illustrate the payment weights at the CRG level, Table 20 contains the payment weights for individuals with diabetes melli-

tus (DM), congestive heart failure (CHF) and chronic obstructive pulmonary disease (COPD). Within each CRG, the payment weights increase monotonically across the severity levels. For individuals with only a single one of these three chronic diseases, the CRG payment weights range from 0.5953 to 2.2961. For

CRG	Severity Level					
	1	2	3	4	5	6
DM	0.5953	0.7797	0.9246	1.3985		
CHF	0.8950	0.9782	1.1783	1.7863		
COPD	0.8426	1.0144	1.3077	2.2961		
COPD & DM	0.9925	1.1082	1.4112	1.7560	2.2504	3.3735
DM & CHF	1.0632	1.2664	1.6494	2.0645	2.6528	3.6650
COPD & CHF	1.0956	1.4792	1.7433	2.2875	2.8244	3.8638
DM & COPD & CHF	1.4588	2.1968	2.5539	3.2849	4.2358	5.7845

Table 20. CRG Payment Weights by Severity Level for Individuals with DM, CHF and COPD for the Medicare Population

individuals with two of these chronic diseases, the CRG payment weights range from 0.9925 to 3.8638. For individuals with all three of these chronic diseases, the CRG payment weights range from 1.4588 to 5.7845. The differences in payment weights illustrates the substantial impact that specific combinations of multiple chronic disease and severity of illness can have on future healthcare needs.

CRG Payment Simulations Using Privately Insured Population Data

As with the Medicare database, year of 4 of the privately insured population database was reserved for validation. Unfortunately, when the year 4 data was used for validation, significant problems with the year 4 data were discovered. The average allowed charges across the four years of data were \$1,643, \$1,837, \$1,763 and \$1,336 for the years 1992 through 1995, respectively. There was a 24 percent drop in allowed charges between 1994 and 1995. It was discovered that due to a change in carriers, the field in the database for allowed charges for 1995 actually contained paid charges with discounts applied. As a result of this discrepancy the fourth year of data could not be used for validation. Therefore, the analysis of the privately insured population data was limited to the development data. Allowed charges were used as the measure of expenditures for the privately insured pop-

ulation data. Table 21 contains the R² values for the development data. Data from years 1 and 2 were used to assign the CRGs for computation of the payment weights and for predicting year 3 expenditures. The prospective R² values in Table 21 for the privately insured population are equivalent to the R² values in the first column of Table 11 for the Medicare data. The retrospective R² values are equivalent to the R² values in the first column of Table 14 for the Medicare data.

In contrast to the Medicare data, the payment death proration resulted in only a small decrease in R² (approximately 3 percent for prospective models). This result is expected since relative to a Medicare population, the privately insured population has relatively few deaths (deaths in a privately insured data are often underreported). The aggregation to ACRG3 resulted in a more substantial decrease in R² (approximately 25 percent for prospective models) than was observed in the Medicare data. Although age/sex adjustment would be expected to be more significant in the privately insured population, there was a negligible increase in R² at the CRG level when the age/sex adjustment is applied. However, at the ACRG3 level, there was a more substantial increase in R² from the age/sex adjustment (approximately 8.5 percent for prospective mod-

	Payment Death Proration	CRG		CRG3	
		Age/Sex Adjustment		Age/Sex Adjustment	
		Without	With	Without	With
Prospective	Without	12.13	12.21	8.75	9.49
	With	11.80	11.87	8.46	9.18
Retrospective	Without	33.27	33.52	24.71	25.06
	With	32.66	32.83	24.08	24.40

Table 21. R² for Development Database for Privately Insured Population

els). Thus, age/sex adjustment has a greater impact at the less clinically precise ACRG3 level. The retrospective R² for the privately insured population data shows patterns similar to the prospective R² except that the decrease in R² as a result of the aggregation to ACRG3 was greater for the retrospective data (approximately 25 percent). The prospective R² results are slightly lower for the privately insured population (11.80) than for the Medicare population with payment death proration (12.11). The retrospective R² results are 14.2 percent lower for the privately insured population (32.66) than for the Medicare population (38.09) with payment death proration.

The base simulation model for the CRG payment simulation for the privately insured population uses age/sex adjustment and payment death proration. Table 22 contains the R² values for different data durations and data lags. Reducing the data duration for the data used to assign the CRG for prediction increases R² slightly from 11.87 to 12.10. This is similar to the Medicare data in which R² also increased slightly with a shorter data duration. Adding a six month data lag to the data used to assign the CRG for prediction reduces the R² by 29.2 percent from 12.10 to 8.57. As with the Medicare data, the data lag has a substantial impact on R². Since operationally, it is not possible to implement a capitated payment system

Duration	Lag	R ²
24	0	11.87
12	0	12.10
12	6	8.57

Table 22. R² for Base Simulation Model with Different Data Durations and Data Lags for the Privately Insured Population

without a data lag, the payment simulations for the privately insured population data are all based on a one year data duration and a six month data lag.

Stop Loss	R ²
None	8.57
50,000	9.31
100,000	8.85
250,000	8.62

Table 23. R² for Base Simulation Model with Different Data Durations and Data Lags for the Privately Insured Population

Table 23 contains the R² values with stop loss. A \$50,000 stop loss increases the R² by 8.6 percent from 8.57 to 9.31. Table 24 contains the R² values with reinsurance. A reinsurance model with a \$25,000 threshold with a 90 percent reinsurance percentage increases R² from 8.57 to 68.36. Even a reinsurance model with a \$100,000 threshold with a 50 percent reinsurance percentage increases R² to 24.39. The impact of stop loss and reinsurance is consistent with the results from the Medicare population.

Table 25 contains the predictive ratios by

Reinsurance		R ²
Threshold	Percentage	
None	None	8.57
25,000	50	63.59
25,000	90	68.36
50,000	50	43.90
50,000	90	48.44
100,000	50	24.39
100,000	90	27.44
250,000	50	10.63
250,000	90	11.19

Table 24. R² for Based Simulation Model with One Year Data Duration, and 6 Month Data Lag and Reinsurance for the Privately Insured Population

CRG Status	Count	Average Expenditures	Average CRG Payment	Predictive Ratio
Healthy	203,158	1,256	1,249	0.9945
History of Significant Acute Disease	11,672	2,532	2,523	0.9663
Single Minor Chronic Disease	13,070	3,166	3,187	1.0065
Minor Chronic Disease in Multiple Organ Systems	752	4,345	4,362	1.0037
Single Dominant or Moderate Chronic Disease	20,094	3,886	3,932	1.0118
Significant Chronic Disease in Multiple Organ Systems	3,555	7,353	7,331	0.9969
Dominant Chronic Disease in Three or More Organ Systems	46	13,117	13,818	1.0534
Dominant and Metastatic Malignancies	804	11,672	11,618	0.9954
Catastrophic Conditions	165	27,563	29,984	1.0879

Table 25. Predictive Ratio by CRG Status for Base Simulation Model with 12 Months Data Duration and 6 Months Data Lag for the Privately Insured Population

CRG status. The predictive ratios for the privately insured population data show a similar pattern to the Medicare data except that the predictive ratios are closer to one for the privately insured population. Healthy individuals tend to have a predictive ratio that is less than one (0.9945) while the sickest individuals tend to have predictive ratios greater than one (1.0879, 0.9954 and 1.0534 for the catastrophic conditions, dominant or metastatic malignancies and dominant chronic disease in three or more organ systems, respectively). The number of individuals by CRG status illustrates the substantial differences in the privately insured and Medicare populations. In the privately insured population, 80.2 percent of the individuals are healthy, while in the Medicare population, only 27 percent are healthy.

Table 26 contains the predictive ratios by prediction year and prior year expenditure deciles and Table 27 contains the predictive ratios by payment deciles. The pattern for the prediction year expenditure deciles for the privately insured population is similar to the Medicare population. The prior year expenditure deciles for the privately

insured population tend to be above one for the lower deciles and below one for the higher deciles which is opposite the pattern for the Medicare population. The payment deciles for the privately insured population while having the same general pattern as the Medicare data, are overall closer to a value of one.

CRG Payment Simulations Using Medicaid Data

Since the Medicaid data contained only two years of data, the payment simulations that could be performed were limited. Submitted charges were used as the measure of expenditures for the Medicaid data. Since individuals who died were not identified in the Medicaid database, no payment death proration could be made. The R² result from the Medicaid data are 20.11 with age/sex adjustment and 19.71 without age/sex adjustment. The high R² value reflects the bipolarity of Medicaid population which includes a high proportion of relatively healthy mothers and children and a substantial number of relatively sick

Prediction Year Deciles				Prior Year Deciles		
Expenditure Decile	Average Expenditures	Average CRG Payment	Predictive Ratio	Average Expenditure	Average CRG Payment	Predictive Ratio
1	0	1,259	-	249	1,227	4.9226
2	0	1,359	-	964	1,355	1.4058
3	2	1,265	-	1,136	1,291	1.1365
4	78	1,250	16.0787	948	1,223	1.2393
5	205	1,386	6.7444	1,111	1,305	1.1747
6	395	1,562	3.9499	1,339	1,482	1.1068
7	686	1,792	2.6121	1,784	1,714	0.9608
8	1,194	2,107	1.7646	2,258	2,043	0.9049
9	2,406	2,532	1.0525	3,189	2,528	0.8105
10	12,680	3,133	0.2471	4,736	3,476	0.7339

Table 26. Predictive Ratio by Expenditure Deciles for Base Simulation Model with 12 Month Data Duration and 6 Month Data Lag for the Privately Insured Population

Expenditure Decile	Average Expenditure	Average CRG Payment	Predictive Ratio
1	527	506	0.9601
2	582	579	0.9947
3	990	838	0.8471
4	1,046	1,106	1.0581
5	1,317	1,358	1.0312
6	1,625	1,627	1.0014
7	1,917	1,807	0.9428
8	2,084	1,960	0.9606
9	2,298	2,435	1.0599
10	5,260	5,427	1.0318

Table 27. Predictive Ratio by Payment Deciles for Base Simulation Model with 12 Month Data Duration and 6 Month Data Lag for the Privately Insured Population

and disabled beneficiaries. Table 28 contains the predictive ratios by CRG status with age/sex adjustment. In the Medicaid data, 70 percent of the beneficiaries are healthy in contrast to 80.2 percent and 27 percent for the privately insured and Medicare populations, respectively. The predictive ratios are close to one across all CRG

status in part because there is no data lag.

Comparison of CRGs to other Risk Adjustment Systems

A precise comparison of the performance of risk adjustment systems is very difficult. R² results can vary considerably depending on the following factors:

- Extent of data editing
- Expenditures used (e.g., submitted, allowed or paid)
- Independence of data (development data or validation data)
- Payment proration for deaths
- Nonclinical adjustments (e.g., eligibility status)
- Duration of data used to compute risk adjustment
- Length of the data lag used to compute risk adjustment
- Comprehensiveness of data used to compute risk adjustment (e.g., inpatient only)

The extent of data editing is important

CRG Status	Count	Average Submitted Charge	Average Payment	Predictive Ratio
Healthy	177,225	1,192	1,177	0.9873
History of Significant Acute Disease	20,316	2,316	2,307	0.9921
Single Minor Chronic Disease	16,558	3,541	3,538	0.9993
Minor Chronic Disease in Multiple Organ Systems	1,516	5,179	5,101	0.9851
Single Dominant or Moderate Chronic Disease	26,853	5,725	5,822	1.0169
Significant Chronic Disease in Multiple Organ Systems	9,318	12,838	12,796	0.9967
Dominant Chronic Disease in Three or More Organ Systems	305	29,615	28,373	0.9581
Dominant and Metastatic Malignancies	539	27,380	27,647	1.0097
Catastrophic Conditions	991	28,003	29,254	1.0447

Table 28. Predictive Ratio by CRG Status for Medicaid Population

because the edits applied to the data determine which individuals and, therefore, which expenditure values are included in the computation of the R^2 value. For example, if any of the data edits is based on the magnitude of the charges (e.g., \$500,000 in charges in the prediction year with no significant illnesses present in the prediction year) then the data editing eliminates the individuals who are the most difficult to predict, thus improving the R^2 value. R^2 values from the database used in the development of the risk adjustment system will be higher than the R^2 obtained when the risk adjustment system is applied to an independent validation database. Since deaths tend to be expensive, any adjustments to the expenditures or payments for individuals who die can significantly affect R^2 . The inclusion of nonclinical adjustment factors (e.g., eligibility status) will increase R^2 . As demonstrated in Table 11 the data duration, data lag and data completeness have a significant impact on R^2 .

PRINCIPAL INPATIENT DIAGNOSTIC COST GROUPS (PIP-DCGS)

PIP-DCGs are a linear model that was developed through regression analysis.²⁷ The diagnosis and procedures used in PIP-DCGs are limited to those that occur in an inpatient setting. With a few exceptions, only diagnoses that are the principal diagnosis from a hospital stay are used in the PIP-DCGs. The PIP-DCGs used 16 diagnosis groups, age and sex, plus non-clinical factors (reason for initial Medicare coverage such as disability and Medicaid eligibility) to establish risk adjusted payment rates. HCFA has proposed the PIP-DCGs be used as the basis of risk adjusting Medicare capitated payments beginning in 2000.²⁸

The PIP-DCGs were developed from HCFA's 5 percent Standard Analytic File for the calendar years 1995 and 1996. PIP-DCGs used paid charges in their development and validation. The reported R^2 results for the PIP-DCGs are from the development database. The expenditures for individuals who died, were annualized

and in the computation of the R^2 the individuals who died were weighted by the fraction of months they were alive. This process of annualizing expenditures and weighting individuals is difficult to interpret from a real world operational perspective. The CRG model simply reduces the capitated payment in proportion to the number of months the individual was alive and leaves actual expenditures unaltered. It is not clear what impact artificially inflating actual expenditure has on R^2 . The PIP-DCG evaluation results used inpatient data only and were based on a one year data duration. The data was not lagged.

In order to compare PIP-DCGs, the CRGs were assigned based on year 2 data and used to predict year three data (i.e., the development data). The payment weights were based on year 3 expenditures. The CRGs used for prediction and weight computation were based on inpatient data only. No data lag was used. Actual paid charges were the prediction variable and the age/sex adjustment was applied. In addition to computing the R^2 for a CRG payment system configured in the above manner, the data was also split into two equal samples and the payment weights were derived from one of the samples and used to compute payments for the other sample.

For the full PIP-DCG model, which includes Medicaid eligibility and reason for initial Medicare coverage such as disability, the R^2 is 6.26. For the PIP-DCG model without reason for initial Medicare coverage and Medicaid eligibility, the R^2 is 5.80. The R^2 results for CRGs and ACRG3s are contained in Table 29. The R^2 results are shown both with and without the payment death proration because the PIP-DCG analysis altered the actual expenditures in

	Without Payment Death Proration		With Payment Death Proration	
	Full	Split	Full	Split
CRG	10.21	9.65	8.76	8.26
ACRG3	9.83	9.67	8.37	8.23

Table 29. R^2 for CRGs for Comparison to PIP-DCGs for the Medicare Population

the computation of the R^2 and there is not an exact parallel in the CRG model. The R^2 values in Table 29 are comparable to the R^2 values in Table 10 for the full development data (i.e., 14.15 and 12.11 without and with payment death proration, respectively). The difference in the results in Table 29 from the ones in Table 10 is the use of only inpatient data for assigning the CRGs for prediction and for payment weight computation, the use of a one year data duration instead of a two year data duration and the application of the age/sex adjustment. With payment death proration the CRGs have an R^2 that is 51 percent higher (8.76 versus 5.80). Caution should be used in interpreting these results since the databases and payment models are not identical.

The comparison of PIP-DCGs and CRGs has been under idealized conditions and does not provide comparative performance results under real world operational conditions. In particular, no data lag was used. Table 11 showed the substantial impact that a six month data lag has on R^2 . Medicare has proposed that the PIP-DCGs will be assigned based on data that is six months old, but there is no reported evaluation of the impact of this data lag on the performance of PIP-DCGs. If PIP-DCGs had been developed based on data that was lagged six months, it is likely that the weighting factors in the PIP-DCG model would be substantially different.

HIERARCHICAL COEXISTING CONDITIONS (HCC)

In contrast to PIP-DCGs, HCCs utilize data from all settings (not just inpatient data), utilize all diagnoses from a hospital stay, assign an individual to multiple disease groups and may or may not use non-clinical factors depending on the precise version of the HCCs used. In HCCs, risk adjustment is accomplished by computing a score that is based on the sum of weighting factors across all clinically distinct disease groups to which an individual is assigned. HCCs have been tested on Medicare,²⁹ Medicaid³⁰ and privately insured population data.³⁰ Table 30 summarizes the R² results for HCCs on the three data sources. It is important to recognize that the HCC scoring and weighting factors are tailored to each of these three data sources. Thus, there is a separate and distinct HCC model for each of these data sources. The reported R² values for HCCs in Table 30 are from the development databases, used paid charges as the prediction variable for the Medicare and Medicaid data and allowed charges for the privately insured population, used a one year data duration, used no data lag and used the same death adjustment that was used in the PIP-DCGs.

In order to compare CRGs to HCCs, CRGs were assigned using year 2 data and used to predict year 3 data (i.e., the development data). The payment weights

were based on year three expenditures. The CRGs for prediction and weight assignment were based on full data including inpatient and outpatient. Actual paid charges were the prediction variable for Medicare data, allowed charges for the privately insured population and submitted charges for Medicaid data. No data lag was used and the age/sex adjustment was applied. In contrast to HCCs, the identical CRG clinical logic is applied across all three data sources.

Table 30 contains the R² values for HCCs and CRGs. The reported HCC R² values are for the version of HCCs that does not use any nonclinical factors. The R² values for CRGs are slightly different from the development R² values reported in Table 10 for Medicare because only one year of data was used to assign the CRGs for prediction and the age/sex adjustment was applied. The R² for CRGs for Medicare with the payment death proration are 35 percent higher than HCC (12.11 versus 8.97). For the privately insured population, the R² for CRGs with payment death proration is 23.5 percent higher (12.10 versus 9.80). The HCC R² values are slightly higher for the Medicaid population (21.50 versus 20.11). However, the Medicaid data is the most difficult to compare due to significant partial eligibility and the inability to identify deaths. Separate modifications were made to the HCC model, specifically

	Medicare	Privately Insured	Medicaid
HCCs with Expenditure Death Adjustment	8.97	9.80	21.50
CRGs without Payment Death Proration	14.14	12.49	20.11
CRGs with Payment Death Proration	12.11	12.10	-

Table 30. Comparison of Prospective R² Results for HCCs and CRGs

for each of these populations. Indeed, when the HCC model developed for privately insured population is applied to a Medicaid database, the R^2 value decreases.

In addition to PIP-DCGs and HCCs, Ambulatory Care Groups (ACGs)²¹, the Disability Payment System (DPS)³², and the Health Insurance Plan of California (HAC)³³ are other risk adjustment models that have been developed. ACGs is the most prominent, having been in use longer. ACGs were originally designed to predict the cost of ambulatory care. They have since been expanded to include inpatient diagnoses and to be used for prospective risk adjustment. Reported R^2 for the ACG system for the Medicare data is in the range of 5.5 to 6.3.

Summary

CRGs are risk groups that can be used as the basis of risk adjustment in a capitated payment system and also are sufficiently clinically precise enough that they can be used as a management tool for MCOs. The CRGs are a clinical model in which each individual is assigned to a single mutually exclusive risk group which relates the historical clinical and demographic characteristics of the individual to the amount and type of healthcare resources that individual will consume in the future. Since the CRGs are clinically based, they create a language that links the clinical and financial aspects of care. Thus, CRGs are designed to serve as the foundation of management systems which support care pathways, product line management and case management.

The development of CRGs utilized extensive historical healthcare data from Medicare, Medicaid and privately insured

population databases. The CRGs were developed through a highly iterative process that combined extensive clinical input with evaluation and verification from historical data. The performance of CRGs across a wide range of capitated payment system configurations was simulated. The statistical performance of the CRGs is superior to any risk adjustment system in the market. Thus, CRGs are an effective means of risk adjusting capitated payments. Just as important as their use for risk adjusting capitated payment, CRGs are also an effective management tool. The key distinction between a management tool and payment method relates to the ability of the provider to use the information to take action in response to the incentives in the system. Thus, a management tool communicates information in a form and at a level of detail that can lead to specific positive actions. The effectiveness of any incentive-based payment system such as capitation is greatly enhanced if the payment method is simultaneously a management tool.

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