

RUG III Category	Nursing Index	Medical Ancillary Index	Therapy Index	Nursing Component	Med. Ancillary Component	Therapy Component	Therapy Non-Case-Mix Component	Non-Case-Mix Component	Total Rate
CBC	0.99	2.17		\$61.88	\$101.08		\$12.10	\$59.32	\$234.38
CBD	0.99	1.6		\$61.88	\$74.53		\$12.10	\$59.32	\$207.83
CBE	0.99	0.89		\$61.88	\$41.46		\$12.10	\$59.32	\$174.76
CBF	0.99	0.59		\$61.88	\$27.48		\$12.10	\$59.32	\$160.78
CCA	0.91	2.17		\$56.88	\$101.08		\$12.10	\$59.32	\$229.38
CCB	0.91	2.17		\$56.88	\$101.08		\$12.10	\$59.32	\$229.38
CCC	0.91	2.17		\$56.88	\$101.08		\$12.10	\$59.32	\$229.38
CCD	0.91	1.6		\$56.88	\$74.53		\$12.10	\$59.32	\$202.83
CCE	0.91	0.89		\$56.88	\$41.46		\$12.10	\$59.32	\$169.76
CCF	0.91	0.59		\$56.88	\$27.48		\$12.10	\$59.32	\$155.78
CDA	0.84	2.17		\$52.50	\$101.08		\$12.10	\$59.32	\$225.00
CDB	0.84	2.17		\$52.50	\$101.08		\$12.10	\$59.32	\$225.00
CDC	0.84	2.17		\$52.50	\$101.08		\$12.10	\$59.32	\$225.00
CDD	0.84	1.6		\$52.50	\$74.53		\$12.10	\$59.32	\$198.45
CDE	0.84	0.89		\$52.50	\$41.46		\$12.10	\$59.32	\$165.38
CDF	0.84	0.59		\$52.50	\$27.48		\$12.10	\$59.32	\$151.40
CEA	0.83	2.17		\$51.88	\$101.08		\$12.10	\$59.32	\$224.38
CEB	0.83	2.17		\$51.88	\$101.08		\$12.10	\$59.32	\$224.38
CEC	0.83	2.17		\$51.88	\$101.08		\$12.10	\$59.32	\$224.38
CED	0.83	1.6		\$51.88	\$74.53		\$12.10	\$59.32	\$197.83
CEE	0.83	0.89		\$51.88	\$41.46		\$12.10	\$59.32	\$164.76
CEF	0.83	0.59		\$51.88	\$27.48		\$12.10	\$59.32	\$150.78
CFA	0.75	2.17		\$46.88	\$101.08		\$12.10	\$59.32	\$219.38
CFB	0.75	2.17		\$46.88	\$101.08		\$12.10	\$59.32	\$219.38
CFC	0.75	2.17		\$46.88	\$101.08		\$12.10	\$59.32	\$219.38
CFD	0.75	1.6		\$46.88	\$74.53		\$12.10	\$59.32	\$192.83
CFE	0.75	0.89		\$46.88	\$41.46		\$12.10	\$59.32	\$159.76

RUG III Category	Nursing Index	Medical Ancillary Index	Therapy Index	Nursing Component	Med. Ancillary Component	Therapy Component	Therapy Non-Case-Mix Component	Non-Case-Mix Component	Total Rate
CFE	0.75	0.59		\$46.88	\$27.48		\$12.10	\$59.32	\$145.78
IAR	0.69	0.51		\$43.13	\$23.76		\$12.10	\$59.32	\$138.31
IBR	0.67	0.51		\$41.88	\$23.76		\$12.10	\$59.32	\$137.06
ICR	0.57	0.51		\$35.63	\$23.76		\$12.10	\$59.32	\$130.81
IDR	0.53	0.51		\$33.13	\$23.76		\$12.10	\$59.32	\$128.31
BAR	0.68	0.64		\$42.50	\$29.81		\$12.10	\$59.32	\$143.73
BBR	0.65	0.64		\$40.63	\$29.81		\$12.10	\$59.32	\$141.86
BCR	0.56	0.64		\$35.00	\$29.81		\$12.10	\$59.32	\$136.23
BDR	0.48	0.64		\$30.00	\$29.81		\$12.10	\$59.32	\$131.23
PAR	0.77	0.64		\$48.13	\$29.81		\$12.10	\$59.32	\$149.36
PBR	0.72	0.64		\$45.00	\$29.81		\$12.10	\$59.32	\$146.23
PCR	0.7	0.64		\$43.75	\$29.81		\$12.10	\$59.32	\$144.98
PDR	0.65	0.64		\$40.63	\$29.81		\$12.10	\$59.32	\$141.86
PER	0.64	0.64		\$40.00	\$29.81		\$12.10	\$59.32	\$141.23
PFR	0.51	0.64		\$31.88	\$29.81		\$12.10	\$59.32	\$133.11
PGR	0.5	0.64		\$31.25	\$29.81		\$12.10	\$59.32	\$132.48

RUG III Category	Nursing Index	Medical Ancillary Index	Therapy Index	Nursing Component	Med. Ancillary Component	Therapy Component	Therapy Non-Case-Mix Component	Non-Case-Mix Component	Total Rate
PHR	0.49	0.64		\$30.63	\$29.81		\$12.10	\$59.32	\$131.86
PIR	0.46	0.64		\$28.75	\$29.81		\$12.10	\$59.32	\$129.98
PJR	0.46	0.64		\$28.75	\$29.81		\$12.10	\$59.32	\$129.98

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The models described here focus on those upper RUG-III categories that are reflective of the skilled care needs of Medicare

beneficiaries. However, since there are a small number of beneficiaries in the research data base who may be classified into one of the lower RUG-III levels, we also applied the

WIM and UWIM models to the Impaired Cognition, Behavior, and Physical Function categories. Almost all the beneficiaries in these three levels of the RUG-III hierarchy

grouped into the two lowest non-therapy ancillary index levels. In fact, in the UWIM model, 90 percent of the Impaired Cognition, 87.8 percent of the Behavior and 85 percent of the Physical Function observations fell into the lowest level of the non-therapy ancillary index. In these analyses, we did

find a relationship between costs and the index value for these beneficiaries. However, including these groups in the model resulted in minimal additional improvement in statistical performance (See Table 7).

While these groups have not been included in the refinements proposed in this rule, we

will include these RUG-III categories in additional analyses using the full PPS data base. Based on the results, we will review the applicability of the non-therapy ancillary index to the Impaired Cognition, Behavior, and Physical Function categories.

TABLE 7.—STATISTICAL PERFORMANCE OF POTENTIAL RUG-III REFINEMENTS—MODEL DESCRIPTION

Model description	Number of groups	R-squared validation sample (test sample)	
		Ancillary charges (percent)	Total costs (percent)
UWIM—Unweighted index model applied to Extensive Services residents (includes new category “Extensive Services and Rehabilitation”) jkand to Rehabilitation, Special Care, and Clinically Complex residents.	58 plus a four-group ancillary add-on system.	10.9 – 12.6	17.1 – 18.0
UWIM—ALL-Unweighted index model applied to all residents (including new “Extensive Services and Rehabilitation” category).	58 plus a four-group ancillary add-on system.	10.9 – 12.7	17.1 – 18.2

Data sources: Medicare claims, Minimum Data Set 1995–1997.

G. RUG-III Medications Data

Although the bulk of the development and analysis of potential RUG-III refinements to date have been based on Medicare claims data, the Section U drug cost data holds unique promise as a source of detailed information on the drug use of particular beneficiaries. In the coming months, once the characteristics of these new data are more fully understood, we plan to use Section U drug cost data to analyze the behavior of high-cost individuals as well as the potential effects of case mix refinements.

1. Creation of MDS-Based Drug Cost Measures

The following types of pricing are available in the Medispan Master Drug Data Base: Average wholesale price (AWP), Direct Price, Wholesaler Acquisition Cost, HCFA Federal Financial Participation (FFP) limit price, Average AWP, and the generic equivalent average price. While we translated the medications listed on the MDS with NDC codes to therapeutic classes and sub-classes, we needed to cross-link the two data systems to identify the cost of the medications. We used the average wholesale price (AWP) for medication costs for several reasons. The AWP is a national figure and not subject to regional influence resulting from purchasing contracts and other local market factors. This helps to account for the cost of dispensing. Using AWP is conservative when the price of a medication is relatively low or high, and AWP is not subject to institutional cost-shifting. Additionally, AWP, compared to other pricing options, was found to yield the lowest amount of missing cost data.

In evaluating the drug regimens of beneficiaries in our sample, we realized that because of the way some drugs are packaged, the AWP price may reflect a price for multiple doses. Examples include injectables, inhalants, elixirs, and other drugs that indicated a multi-day supply in the drug description. We generated a printout of all potential problems of this sort. A clinical pharmacist reviewed the potential appropriateness of multiple use and long-acting dosage forms and unique treatment

regimens for bundling. The Physician Desk Reference, the Red Book and other sources were used in addition to the documented AWP to determine a likely constant by which to divide the cost for each potential problem. In many instances, not enough information was available to make an appropriate estimate. In these cases, the drug cost remained as indicated by the AWP.

While we were able to successfully map NDC codes to drug names (nested within therapeutic classes and sub-classes), successfully matching to a drug cost required more information. Specifically, assigning an AWP to a drug requires both the strength of the drug administered and complete information regarding the frequency with which the medication was administered. Unfortunately, many of the NDC codes included in the MDS data did not include information regarding strength.¹ For example, we may know that a beneficiary received aspirin, but we do not know if it was 80 mg, 325 mg, or some other strength. As a result, we have substantial missing cost data. Because of the extent of missing data, we opted to impute the drug costs as opposed to excluding cases for which we did not have complete drug cost information. Analyses of the extent of missing data revealed that missing data did not vary by RUG group, State, year, or type of medication.

Nonetheless, by imputing missing drug costs, we have introduced random variations in the data that were not generated by the underlying process that we are attempting to model. Consequently, variables that explain variance in non-missing data will have no explanatory power for imputed data. The coefficients on these variables will, therefore, be biased toward zero. This bias will be small if the proportion of total variance attributable to imputation is small. However, variables explicitly or implicitly used in the imputation process may have explanatory power with regard to the imputed values. For example, if the RUG group is implicitly used

as part of the imputation process, it theoretically could explain more of the variance in the dependent variable simply because RUG was used as part of the imputation algorithm. The coefficients of the variables used to impute cost data may be amplified relative to other coefficients in the explanatory models. Depending on the correlation between the RUG groups and other variables, these coefficients will also be biased in unpredictable ways. This problem could be small if the between-group variance is small (overall variance can be broken down into between-group and within-group components). Given the potential for introducing bias in our models, we opted to create two imputation algorithms.

2. RUG-Based Imputation Method

We assigned drug costs based on NDC codes recorded on Section U of the MDS evaluation forms using the following algorithm. First, if the NDC code was listed among the approximately 150,000 codes tracked by Medispan, we used the pricing information collected by Medispan. If the NDC code was not listed, but the exact name of the generic drug was listed, we calculated pricing as follows. In those instances where the RUG code (as calculated for our recording purposes and provided on the “raw” data files) was observed among beneficiaries using the drug, if only one cost was associated with the drug, it was used. If multiple costs were associated, the most likely cost was chosen based on the distribution of observed costs among beneficiaries. If the RUG code was not observed, we applied the process to a pooled distribution over all of the medication codes observed among all of the MDS records for all of the beneficiaries. If we could not match the exact generic name, we sought a match for the leading words in the generic name, and if matched, we applied the same approach (that is, selecting the most likely drug cost based on the RUG distribution). In cases where no reasonable match could be found, no price was assigned to the medication. This algorithm was iterative over the observed distribution among beneficiaries.

¹ The MDS instruction manual references NDC codes which do not contain drug strength information.

3. State and Year-Based Imputation Method

Because of our concerns regarding bias, we implemented a similar, but alternative algorithm to estimate the drug costs based on data contained in Section U of the MDS. We thought that missing data might vary systematically by State owing to differing data collection procedures (and software) among States. Further, we considered that coding of drugs might have improved over time. If both assumptions were true, the pattern of missing data would vary systematically through time and place. It follows that an imputation method based on time and place would be reasonable. If the NDC code was not listed among the 150,000 Medispan codes, but the exact name of the generic drug was listed, we calculated pricing as follows. If only one cost was associated with the drug within a given State and year, it was used. If multiple costs were associated, we chose the most likely cost based on the distribution of observed costs among beneficiaries. If we could not match the exact generic name, we sought a match for the leading words in the generic name, and if matched, we applied the same approach (that is, selecting the most likely drug cost using the State and year). In cases where no reasonable match could be found, no price was assigned to the medication. As with the RUG-based imputation measure, this algorithm was iterative over the observed distribution among beneficiaries.

During the course of initial analyses, we noted discrepancies between costs as measured by MDS Section U and costs as measured by SNF claims. The discrepancies between the Section U-based drug cost measure and the drug cost measure estimated from SNF claims may be due to several factors. The pharmacy cost detail codes used from the SNF claim include treatments that would not necessarily be included on the Section U according to the MDS instructions. For example, radiation treatment supplies and other procedure-related drug supplies are clearly not included on Section U. Furthermore, while applying the cost to charge ratio for pharmacy charges might appear to estimate "costs", this adjustment may only capture the administrative step-down from the facility cost report since, in all but the largest facilities, consultant pharmacy firms supply all drugs to beneficiaries. The charge to the facility includes both its "cost" (from the pharmaceutical firm or supplier) as well as the value-added labor of the facility's consultant pharmacists who perform its drug utilization review, along with any mark-up that the consultant pharmacy contractor applies. These charges for services provided represent "costs" to the facility, and so applying the facility cost to charge ratio only discounts its administrative step-down. Finally, in most States and areas, the typical practice in nursing homes is for a new

admission to have a 30-day blister pack ordered for each specified drug the resident was taking upon admission to the nursing home. Since most residents came from the hospital where drugs are dispensed daily, they generally arrive at the nursing home with less than a one-day supply of medications. As a result, the transition and ordering of medications must be very quick. In turn, the "charge" for the drug will, in many instances, include drugs that may have already been changed by the 14th day of the stay, when the MDS Section U would be completed. The net result of this practice of delivering and billing for a full 30-day supply is a higher observed cost than would be produced by estimating per diem drug cost based on an enumeration of the drugs received.

Thus, we believe that Section U-based drug cost measures may eventually provide further insight into drug utilization patterns in the SNF population as these potential sources of data inconsistency yield to further analysis. However, in view of the delay in implementing the collection of medication data on the MDS, and given the current need to address and resolve these issues before proceeding, the analysis of potential RUG-III refinements described in this report was based on SNF claims data.

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