Analysis of 2000-2009 Home Health Case-Mix Change

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1 Overview

In October 2000, the Centers for Medicare & Medicaid Services (CMS) implemented a prospective payment system for home health services provided to fee-for-service Medicare beneficiaries. Under the Home Health Prospective Payment System (HH PPS), Medicare payment for each 60-day episode of care is made based on wage levels in the patient's locale and on the episode's classification into a "home health resource group" (HHRG). In January 2008, the 80-group HHRG system was replaced by a 153-group system.[1] Refinement of the HHRG system was based on a four-equation model that accounted for the higher average costs associated with later episodes of care (third or higher) relative to early episodes of care. In both the 80- and 153-group HHRG models, patient classification is based on the patient's characteristics at the start of the episode, as well as the patient's use of rehabilitation therapy services (physical therapy, occupational therapy, or speech language pathology) during the episode. Each HHRG has an associated case-mix weight, which determines how much the payment for the specific episode is adjusted from the standardized base payment established for the current payment year.

Since implementation of the prospective payment system, there has been a steady increase in the average case-mix weight of Medicare home health patients. From 2000 – 2009, overall observed case-mix increased by 22.59% (see Table 4), and there have been increases in average case-mix every year since at least 2005 (the first year included in our analyses of case-mix change over time).

Given that case-mix assignment is based on patient assessments completed by home health agencies, there are questions about the extent to which these increases reflect real case-mix change that is associated with true changes in patient characteristics versus nominal case-mix changes attributable to changes in coding practices. Measuring the proportion of total case-mix change that is due to nominal versus real factors has important implications for establishing home health payment rates that are accurate and reasonable.

In this paper, we examine the changes in case-mix that occurred by 2009, updating analyses for the 2000-2008 period that were described in an earlier report.[2]

2 Data

Interim Payment System (IPS) Period Data

The IPS period data were used as our baseline period for predicting the relationship between covariates and case-mix. These data are from Federal Fiscal Year (FFY) 2000 (October 1, 1999 to September 30, 2000), the last 12 months when the Home Health Interim Payment System (IPS) was in effect. Since home health services were not yet paid on the per-episode basis used under HH PPS, we used Medicare home health claims to construct an analysis file of simulated 60-day episodes.

To assign case-mix weights to the simulated episodes, we needed the appropriate patient characteristic variables. These data were available from the Outcomes and Assessment Information Set (OASIS) assessment data collected on all Medicare and Medicaid home health patients, but the appropriate

[1] We expanded the case-mix variables included in the payment model by providing additional variables including scores for certain wound and skin conditions; and more diagnosis groups such as pulmonary, cardiac, and cancer diagnoses. Additional refinements were made to replace the previous single therapy visit threshold of 10 to three therapy thresholds (6, 14, and 20 visits)

[2] http://www.cms.gov/HomeHealthPPS/downloads/Analysis_of_Home_Health_Case_Mix_Change_2000_2008.zip

assessments needed to be matched to the patient's simulated payment episode. While the collection of OASIS on all Medicare home health patients began in July 1999, the data collection time points for each patient did not always match the starting points of our simulated payment episodes. This is because, at that time, OASIS assessments were conducted solely for outcomes monitoring purposes. When matching OASIS assessments to simulated payment episodes, we accepted any assessment within 14 days of the episode start date. If there were multiple qualifying assessments, we chose the closest start/resumption of care assessment for initial episodes, and the closest start/resumption or follow-up/recertification assessments for subsequent episodes. In approximately 18% of cases, no suitable OASIS assessment (close enough to a simulated payment episode start date) was available, and those episodes had to be excluded from the analysis.

Episodes with four or fewer visits were also excluded from the analysis because they would be considered low utilization payment adjustment (LUPA) episodes under PPS, and would not be paid using home health resource groups (HHRGs) in any case. The analysis file for the base period included episodes for a 10% sample of beneficiaries that represented 313,447 episodes. For episodes with OASIS assessments, an HHRG was assigned using the OASIS information, even though the actual claims for the services in the episodes were not paid using HHRGs.

HH PPS Period Data

The HH PPS period data consisted of analogous files from Calendar Years 2005, 2007 and 2009. These data were drawn from the Home Health Datalink file. This database includes 100% of Medicare fee-for-service home health episode claims from the start of HH PPS linked to matched OASIS assessments, data on other Medicare service use by the beneficiary, and additional data on provider and beneficiary characteristics. We used data for a 20% sample of Medicare home health users, selected based on beneficiary Medicare (HIC) number digits. This analysis file contained 864,461 episodes for 2005, 974,974 episodes for 2007 and 1,117,453 episodes for 2009. Since these were records from the PPS period, the actual paid HHRGs were available (based on the 80 HHRG payment model for 2005 and 2007 and the 153 HHRG model ("HHRG153") for 2009). In addition, we used the grouper program originally used in developing the 153 groups and their weights to assign the 2007 episodes to payment groups for the HHRG 153 model. In preparing the files, we corrected the HHRG and its associated case-mix relative weight in situations where claims-based information on number of allowed therapy visits during the episode was inconsistent with the submitted HHRG on the claim.

3 Methodology

Models

We used a three-equation approach to analyze case-mix changes between 2000 and 2009:

- ***2000 (IPS period)-2005:*** Using the 80 HHRG model and data from the IPS period, we estimated a regression-based, predictive model of individual case-mix scores (relative weights) based on measures of patients' demographic characteristics, clinical status, inpatient history, and Medicare costs in the time period leading up to their home health episodes. The regression coefficients from the IPS period model were applied to episodes from 2005, allowing us to estimate how much of the change in observed case-mix is attributable to changes in patient characteristics between the IPS period and 2005.
- ***2005-2007:*** We added several variables derived from Hierarchical Condition Categories (HCC) model to the 80 HHRG model that we estimated for the IPS period. Note that these HCC variables

are not available in the IPS period data. This model was estimated using 2005 data, and the regression coefficients from the model were applied to episodes from 2007 to calculate how much of the case-mix change between 2005 and 2007 is associated with changes in patient characteristics that occurred during this period.

- ***2007-2009:*** Using the 153 HHRG model and data from 2009, we estimated a model like the 2005 model. The coefficients from this model were applied to episodes from 2007 (using the 153 HHRG model), allowing estimation of how much of the 2007-2009 change in HHRG153 case-mix is associated with changes in patient characteristics observed between 2007 and 2009.

Calculating Real and Nominal Case-Mix Change for Each of the Three Periods

We classify the sources of case-mix change into two major types: real (predicted) and nominal (unpredicted).

- ***Real (predicted) change:*** This is change that is based on the relationship between patient characteristics included in the regression model and case-mix (i.e., coefficients from the regression model) and changes in the characteristics of patients over time (i.e., the change in mean values of the model predictor variables). Real case-mix change arises from variation in the underlying health status of patients, which is represented by predictor variables in the model.
- ***Nominal (unpredicted) change:*** This is the portion of case-mix change that cannot be explained by changes in patient characteristics included in the regression model. Nominal case-mix change is assumed to reflect differences over time in agency coding practices

Using the results from all three models, we calculate real and nominal case-mix change for 2000-2009. The specific steps are described below:

- ***Calculate real case-mix change for 2000-2005 (80 HHRGs):*** Using coefficients from the IPS period model (i.e., the first equation) and the mean values of model covariates for 2005, we calculated real case-mix change for the 2000- 2005 period. This was calculated as the sum across all model covariates of the regression coefficients multiplied times the change in the mean value of the covariate between the IPS period and 2005.
- ***Calculate real case-mix change for 2005-2007 (80 HHRGs):*** We calculated predicted case-mix change for 2005-2007 based on the regression coefficients from the second equation and the change in means that occurred between 2005 and 2007.
- ***Calculate real case-mix change for 2007-2009 (153 HHRGs):*** We calculated predicted case-mix change for the 2007-2009 period using coefficients from the regression model that we estimated using 2009 data (i.e., the third equation) and the change in mean values for 2007-2009. Note that, in this model, we used the 153 HHRG model for both 2007 and 2009.
- ***Calculate nominal case-mix change:*** For all three models, nominal case-mix change was calculated as the difference between total case-mix change in the period and real case-mix change.

Models to Examine Relationship between Patient Characteristics and Case-Mix

Using data from the baseline (IPS) period, 2005, and 2009, we estimated regression models of the following basic functional form:

$$\text{Relative Payment Weighti} = \alpha + \beta^{*}\text{Personal Characteristicsi} + \varepsilon\text{i}$$

where:

Relative Payment Weight for individual i is the relative payment weight for that individual's 60-day home health episode (based on the then-current 80 HHRGs for the IPS and 2005 models and the 153 HHRGs for the 2009 model);

α is a constant term (to be estimated);

β is a vector of coefficients (to be estimated);

Personal Characteristics is the vector of demographic and clinical variables for each individual; and

ε is an error term.

Our goal in estimating the models was to predict the case-mix weights, using variables that could be created using the available administrative data. As a result, we were not particularly concerned about redundancy among variables, as long as groups of variables make sense broadly as correlates of case-mix. Our interest was in achieving as much predictive power as possible from the variables taken together. The models included these covariates:

- ***Demographic variables:*** The demographic variables were included to control for any differences in case-mix determination associated with age, gender, and race/ethnicity. The following demographic variables were included:
  - Age (age groups 65 to 74, 75 to 84, 85 to 84, and 95 and above; age under 65 is the reference category);
  - Gender (male);
  - Race (White and African American; other, including Asian, Hawaiian/Pacific Islander, and Native American/Alaskan Native, is the reference category).

  In addition, the age variables were interacted with the gender and race dummy variables to fully exploit the potential differences of the effect on case-mix from the various demographic subgroups. There were a total of 19 demographic variables in the models.

- ***Measures of prior utilization:*** Prior hospital, inpatient rehabilitation, and SNF stays and days of care are likely to be associated with home health case-mix for a variety of reasons. For example, individuals with a recent rehabilitation facility stay may be recovering from an injury or fall and may require substantial amounts of care and further rehabilitation services as they continue to recover during their home health episodes. The models included measures of utilization of acute care hospital, long-term care hospital, inpatient rehabilitation facility, and Medicare skilled nursing facility in the period preceding the home health episode:
  - Acute-Care Hospital Days in Period 14 Days Preceding Home Health Episode
  - Acute-Care Hospital Days in Period 15 to 120 Days Preceding Home Health Episode
  - Long-Term-Care Hospital Days in Period 14 Days Preceding Home Health Episode
  - Long-Term-Care Hospital Days in Period 15 to 120 Days Preceding Home Health Episode
  - Rehabilitation Facility Days in Period 14 Days Preceding Home Health Episode
  - Rehabilitation Facility Days in Period 15 to 120 Days Preceding Home Health Episode

- Medicare Skilled Nursing Facility Days in Period 14 Days Preceding Home Health Episode
- Medicare Skilled Nursing Facility Days in Period 15 to 120 Days Preceding Home Health Episode

- ***Measures of patient living arrangements:*** Individuals who live with other people, especially spouses and close family members, may have lower home health care needs from third parties (home health agencies), resulting in lower home health resource use and lower case-mix, all else equal. For the IPS period, the model includes dummy variables indicating the patient's living status at home:
  - Patient Lives Alone
  - Patient Lives with Other (Not Family, Friends, Paid Help or Spouse)
  - Patient Lives with Other Family
  - Patient Lives with Paid Help
  - Patient Lives with Spouse

These living status variables were the only variables in the models that came from agency-reported OASIS data.

- ***Measures of patient's acute care hospital inpatient history:*** We examined the patient's acute care hospital inpatient history for the four years preceding the home health episode, considering the All Patient Refined Diagnosis Related Group (APR DRG) for the patient during his or her most recent inpatient stay.[3] Approximately 86-89% of beneficiaries with home health care episodes in the sample had a hospital stay during the look-back period. APR DRGs are designed to predict patient acuity and care needs in acute care hospital settings. To the extent that such acute care acuity and needs reflect the patient's need for more-intensive care in other settings (in this case, in home health settings), APR DRGs are reasonable proxy variables for home health resources need (i.e., home health case-mix). The models included dummy variables for the following:
  - The All Patient Refined Diagnosis Related Group (APR DRG) for the patient during his or her most recent inpatient stay.
  - Whether that APR DRG was procedure-based or medically-based.
  - The patient's expected risk of mortality at the time of the hospitalization (four levels – the reference group is patients with no APR DRGs– their relative mortality risk cannot be coded).
  - Interactions between the APR DRG and APR DRG severity level

Based on a patient's personal characteristics and comorbidities at the time of the hospital stay, each patient within each APR DRG is assigned to one of four severity levels in the APR DRG algorithm. The severity levels are specified in the models as interactions, because the APR DRG severity levels are developed individually for each APR DRG classification. Another reason for setting up the severity level effects as interactions in the regression is that this approach allows for interpreting the severity level effects relative to a severity level that serves as a reference group for each APR-DRG.

In cases where the four possible severity levels each met our sample size requirements, the reference group (labeled "any" in Appendix Table 1) is the highest severity level (i.e., extreme loss of function);

[3] The APR DRG system was developed in 1990 to address both the severity of illness and risk of mortality over all patient populations. The APR DRG system includes four severity of illness classes (minor, moderate, major or extreme loss of function) and risk of mortality subclass for each base diagnostic group (minor, moderate, major, and extreme).

then, to see the effect size of a given severity level, one adds the severity level interaction coefficient to the reference group coefficient. In other cases, the reference group will be an average effect of the severity levels whose indicator variables are left out of the model (note that there may be no sample observations for some severity levels). The procedure we used is described operationally in the bullet-points below.

We included all APR DRG variables and also the severity interactions in the model if there were at least 25 episodes[4] in the IPS period that were classified with that APR DRG severity level. APR DRG interactions that occurred in fewer than 25 episodes were not included in the models.

For each APR DRG the following steps were taken to determine which APR DRG/Severity interactions to include in the model:[5]

- Step 1: Identify all severity interactions that have occur in one or more episodes (maximum of 4 per APR DRG)
- Step 2: Identify all severity interactions that occur in at least 25 episodes (maximum of 4 per APR DRG)
- Step 3: If the number of interactions that occur in at least 25 episodes is smaller than the number of interactions that are observed in one or more episodes, drop all interactions that occur in fewer than 25 episodes. Then, include in the model all other interactions that occur in 25 or more episodes.
- Step 4: If all of the severity interaction terms for a given APR DRG that occur in at least one episode occur in 25 or more episodes, then we use the interaction term representing the highest severity level as the reference category and include in the model all the other interactions identified in Step 1.

As part of our analysis of 2000-2007 home health case-mix change, we consulted with clinical experts to review the findings for APR DRGs that had large changes in prevalence over time, soliciting input on whether there were “external” explanations for such changes (e.g. changes in coding guidelines) or whether the changes likely reflected actual changes in patient conditions. Based on this review, we combined APR DRGS 045 (CVA and precerebral occlusion with infarction) and 046 (non-specific (CVA and precerebral occlusion without infarction) The judgment of our clinical experts was that changes in coding directions suggested that some of the cases that would have been classified in APR DRG 045 in the base period would be classified in APR DRG 046 in the follow-up period, creating large changes in the frequency of each one that were not related to changes in patient condition. Therefore, it was decided to merge them for the analysis. Another decision was to drop APR DRG 468 (other kidney and urinary tract diagnoses, signs, and symptoms) from our models. This is because it appeared that changes in coding guidance, as well as changes (or lack of changes) in specification of the APR DRG in the grouper software produced large changes in frequency that appeared to be artifacts rather than related to actual

[4] The 25-episode cut off was selected to minimize the estimation of model coefficients with very few observations, which might result in imprecise estimates.

[5] We provide two examples to demonstrate the process. In the first example, for a particular APR DRG, severity level 1 occurs in 50 episodes, severity level 2 occurs in 75 episodes, severity level 3 occurs in 43 episodes, and severity level 4 occurs in 30 episodes. For that APR DRG, we include in the model severity levels 1, 2, and 3, and use severity level 4 as the reference category. In the second example, for a particular APR DRG, severity level 1 occurs in 120 episodes, severity level 2 occurs in 5 episodes, severity level 3 occurs in 20 episodes, and severity level 4 occurs in 60 episodes. For that APR DRG we include in the model severity levels 1 and 4, and use severity levels 2 and 3 as the reference group. The models also include indicator variables for the presence of each APR DRG.

changes in patient conditions. Since these issues could not be disentangled with a simple transformation (as with the CVA cases), this APR DRG was dropped from the analysis.

The models included a total of 848 APR DRG variables and interactions. Episodes with stays classified under an APR DRG that did not meet the sample size requirements are included in the models but not represented by an APR DRG variable. However, those episodes do have values for the variables representing the procedure- or medically- based classification and mortality risk variables. For the IPS period, 60.9% of episodes were classified as having had a medical APR DRG while 27.1% were classified as having had a procedure based APR DRG. The remainder of the sample did not have an acute hospitalization and thus no APR DRG information was available. For 2009, 62.4% of the sample was assigned a medically based APR DRG and 27.9% was assigned a procedure based APR DRG.

- Measures of home health agency ownership type: The models included dummy variables based on the agency's ownership type/type of control, as classified in CMS' Provider of Service (POS) file:
  - Free-standing, voluntary or non-profit
  - Free-standing, proprietary
  - Free-standing, government-owned
  - Facility-based, voluntary or non-profit
  - Facility-based, proprietary
  - Facility-based, government-owned
  - Other, voluntary or non-profit
  - Other, proprietary
  - Other, government-owned

The reference category is agencies with unknown agency ownership/control.

- ***Measures of Medicare Part A payments.*** After controlling for prior utilization, measures of Medicare Part A payments may proxy for the intensity of services in the period preceding the home health episode. The models included measures of Medicare Part A payments in the 120 days preceding the home health episode, by service type:
  - Acute-care hospital payments in 120 days preceding home health episode
  - Long-term-care hospital payments in 120 days preceding home health episode
  - Rehabilitation facility payments in 120 days preceding home health episode
  - Medicare SNF payments in 120 days preceding home health episode

Medicare payments between the IPS period and later periods vary partially due to the increases in Medicare payment rates made since the IPS period. To account for this, we inflated the IPS Medicare payment amounts using an inflation factor that was based on the aggregate effect of payment rate updates from IPS to 2007.[6] We took a similar approach and deflated the 2009 Medicare payment amounts to 2007 levels when computing the 2007 predicted case-mix using the 2009 model. To adjust payments, we divided the payments by the following constants.

6 The Medicare payment increases in each setting in each year were multiplied together, and then an annual average increase was calculated. The resulting average annual increases were then raised to the power of the average difference in years for episodes in the data files.

	IPS to 2007	2007 to 2009
• Acute care hospital:	1.252705187	0.96700
• Long-term care hospital:	1.194385134	0.99148
• Rehabilitation facility:	1.252727250	0.98400
• SNF:	1.284680344	0.96775

- ***HCC variables:*** The HCC model includes 70 HCCs, each of which is defined based on the presence of particular ICD-9-CM codes identified from Medicare claims data (inpatient and outpatient hospital claims and Part B Physician/Clinician claims). In the HCC model, each HCC has an associated payment weight. The payment weights for each resident's HCCs, along with the payment weights for their demographic and enrollment characteristics, are summed to calculate predicted expenditures. The HCC community risk score for each beneficiary is calculated based on expected expenditures for the patient divided by mean expenditures for all patients. We also included variables from the HCC model for whether disability was the original reason for Medicare entitlement; indicators for whether the individual is a Medicaid beneficiary (interacted with gender and original reason for Medicare entitlement); and several interaction terms between disability status and specific HCCs. Note that we tested models that use binary variables for each of the 70 HCCs instead of the HCC community score, but the final estimates of real case mix change are based on models that use the HCC community score. Models that used binary variables for each HCC had consistently lower predictions of real case-mix change than models that used the HCC community score. There were also a number of individual HCCs that had negative coefficients in our regression models, indicating that the presence of the HCC was associated with lower case-mix, adjusting for the other variables in the model. We tested both concurrent and prospective HCC model specifications.[7] (See Appendix Tables 1-3 for more details on the performance of alternative model specifications.) Note that while we tested several models in which the HCC variables replaced rather than supplemented the APR-DRG variables in the models, this approach was not pursued because of the poor statistical performance of these models.

Calculating Overall Real and Nominal Case-Mix Change for 2000-2009

After estimating the models, the results (coefficient estimates) were applied to data from 2005, 2007, and 2009. We calculated the following:

- ***Total case-mix change:*** We calculate the total difference in case-mix between the IPS period and 2009. This was based on the change in average case-mix between the two periods.
- ***Real case-mix change and the percentage of total change in case-mix that is real:*** This is the sum of real case-mix change for 2000-2005, 2005-2007, and 2007-2009. We divided the predicted change in case-mix by the total change in case-mix to calculate the percentage of the total change in case-mix that was real. As a percent, this equals the percentage change in total case-mix for the period multiplied times the proportion of the total case-mix change that is real.

[7] In the concurrent model, diagnoses from the year prior to the episode are used to create the HCC variables; in the prospective model, diagnoses from the year of the episode are used to create the HCC variables.

- ***Nominal (unpredicted) change in case-mix and percentage of total change in case-mix that is nominal (unpredicted):*** The unpredicted change in case-mix is calculated as the difference between the total and real change in case-mix. As a percent, the percent of nominal case-mix change from 2000-2009 is calculated by multiplying the overall percentage change in total case-mix times the proportion of the total case-mix change that is nominal.

While there may be observable or unobservable factors related to patient case-mix that were not included in the model, it is important to note that the omission of these variables affects estimates of case-mix change only if there were changes in the prevalence of these variables over time. Variables that remain constant over time do not contribute to real case-mix change regardless of how important they are in predicting case-mix level.

4 Results

Appendix Table 4 presents regression coefficients and mean values of model covariates for 2000, 2005, 2007, and 2009.

Changes in Patient Characteristics

We analyzed changes over time in the means of all of the variables included in the regression models. These changes may indicate differences in patient acuity and real case-mix change. Some notable differences in patient characteristics occurred between the two periods.

- Average acute care hospital days in the 14 days preceding the home health episode decreased from 2.26 in the IPS period, to 1.56 in 2007 and 1.28 in 2009. The average number of hospital days in the 15-120 days preceding the home health episode decreased from 4.07 in the IPS period to 3.29 in 2007 and 2.94 in 2009.
- The average number of SNF days in the 15-120 days preceding the home health episode increased from 2.77 in the IPS period to 3.84 days in 2009. There was little change in mean SNF days in the 14 days preceding the episode, which increased from 1.17 days in 2000 to 1.18 days in 2009.
- There were changes in the distribution of episodes by agency types:
  - The proportion of episodes for other proprietary home health agencies increased from 29.3% in the IPS period to 59.5% of episodes in 2009. There was also a large increase in the proportion of episodes for free-standing proprietary agencies, which increased from 4.06% in the IPS period to 7.9% in 2009.[8]
  - The percentage of episodes for facility-based non-profit agencies decreased from 29.9% in the IPS period to 10.9% in 2009.
  - The proportion of episodes for freestanding government agencies decreased from 3.9% in the IPS period to 1.4% in 2009.
- While the means of most of the APR DRG variables were low, there were large changes in the mean values of some APR DRG variables:

[8] About 84% of proprietary agencies are classified in the POS file as type "Other" – they are understood to be freestanding About 2% of proprietary agencies are identified as facility based (including hospital-based, SNF-based, and rehab-based); the others fall in categories also taken to be freestanding.

- The prevalence of episodes preceded by stays classified to renal failure was more than twice as high in 2009 (1.6%) than it was for the IPS period (0.67%).
- The proportion of patients who had cardiac defibrillator and heart assist implant was more than 100% higher in 2009 (0.34%) than in the IPS period (0.13%).
- The prevalence of coronary artery bypass without cardiac catheterization or percutaneous cardiac procedure was only about half as high in 2009 (0.55%) than in the IPS period (1.12%). The proportion of this APR DRG with minor severity decreased from 0.066% to 0.02%.
- The prevalence of knee joint replacement increased from 2.76% in the baseline period to 3.80% in 2009.
- The prevalence of knee replacement with major severity more than doubled between the IPS period and 2009, increasing from 0.14% to 0.32%.
- For all except the major severity level, the prevalence of heart failure decreased from the IPS period to 2009. The overall prevalence decreased from 6.07% in the IPS period to 4.53% in 2009.
- The prevalence of malfunction, reaction, complication of cardiac/vascular device or procedure with extreme severity more than tripled between 2000 and 2009, increasing from 0.019% to 0.081%.
- The prevalence of head trauma with a coma or hemorrhage increased from 0.09% in the IPS period to 0.252% in 2009.
- The prevalence of dorsal and lumbar fusion procedures for curvature of the back had an almost four-fold increase, from 0.008% to 0.032%.

Statistical Performance of Regression Models

We measured the statistical performance of the regression models using the adjusted R-squared statistic, a measure of the percentage of the variation in relative payment weight that is explained or predicted by variation in independent variables in the model, adjusting for the number of independent variables in the model.

- The adjusted R-squared of the IPS period model was 0.1894, indicating that almost 19% of relative payment weight variation was accounted for by the independent variables in the model.
- The adjusted R-squared of the 2005 model was 0.1685. Note that this is lower than the adjusted R-squared for the IPS model even though this model includes the HCC variables that could not be included in the IPS period model.
- The adjusted R-squared for the 2009 model was 0.1316. The goodness of fit for the 2009 model is lower that of the IPS and 2005 models. However, it should be noted that the adjusted R-squared statistics for the different models are not directly comparable with one another. The dependent variables are somewhat different (the 80-HHRG case-mix in the IPS and 2005 models and the 153-HHRG case-mix in the 2009 model).

Regression Coefficients

Because of the large number of independent variables used in these models, including the use of many interaction terms, the potential presence of multicollinearity means that the interpretation of individual regression coefficients should be approached with caution, as we have an imprecise estimate of the impact of independent changes in covariates. In a context where our goal is to predict the dependent variable, multicollinearity is not a problem because the predictions remain accurate. Nonetheless, there are several key model results worth noting:

Utilization in period preceding home health episode: In all three regression models, the coefficients on the variables indicating the number of acute care hospital, long-term care hospital, rehabilitation facility, and Medicare skilled nursing days in the 14 days preceding the home health episode and in the period 15 to 120 days prior were all positive and significant. This implies that having more days of care in these settings is associated with higher relative payment weights during the home health episode.

Patient's living arrangements: In all three models, living with paid help was associated with the highest case-mix level, followed by living with other family, and living with spouse. The coefficients for living alone (-0.07267 in the IPS period model) and living with paid help (0.12521 for the IPS model) were particularly interesting, in part because they identify the living arrangements associated with the lowest average case-mix (living alone) and highest average case-mix (living with paid help), after controlling for the other independent variables in the model. This likely reflects the higher care needs of those who have already hired live-in help to provide custodial care and services relative to those who live alone or with a family member.

Hospital inpatient history: Most of the individual APR DRG variables were not significant. Note that the analysis was not intended to identify and explain all individual effects of APR DRGs on home health episode relative payment weights. There are far too many variables, and interpreting them is complicated, given the inclusion of APR DRG and severity interactions, as well as the basic classification into either a medical APR DRG or a procedure APR DRG. That is, any measured impact of an APR DRG is understood to be relative to its basic classification. The purpose of including these variables was to capture the impact of the type and severity of an individual's most recent acute care hospital stay preceding the home health episode, after accounting for all other effects in the model.

Agency type: For all three models, the coefficient for freestanding voluntary/non-profit agencies was lower than the coefficient for freestanding proprietary agencies. Also, coefficients were lower for free-standing government agencies than for freestanding proprietary agencies.

Medicare payment amount: Adjusting for the other variables in the model, in all three models, there was a negative relationship between relative payment weight and acute care hospital payments in the 120 days preceding the home health episode and a positive relationship between relative payment weight and Medicare payments for rehabilitation facilities. For skilled nursing facilities, the coefficient was positive in 2000 and 2005 and negative in 2009. The coefficient for long-term care hospitals was close to zero in all three models. Each $1,000 increase in payments was associated with the following change in case-mix:

- Acute care hospital: -0.00206 (IPS) -0.00212 (2009)
- Long-term hospital: 0.00024 (IPS) 0.00005 (2009)
- Rehabilitation facility: 0.00199 (IPS) 0.00020 (2009)
- SNF: 0.00915 (IPS) -0.00160 (2009)

The negative coefficient on the acute care hospital expenditures measure may be because the model already includes variables that could be related to inpatient payments – e.g., variables for stays and days of care in each care setting, as well as APR DRG data for the most recent acute care hospital stay. Given the large number of independent variables in the models, it is difficult to interpret the coefficients on the payment variables. One possibility is that these variables, when added to the model alongside the related variables, might be a further measure of intensity of service – i.e., the amount of service provided per day. If services are more intensive in other settings, particularly acute care hospital settings, care needs following acute care stays in the home health setting could be lower. This result may not be surprising given that research conducted to support the development of the case-mix system found that hospital discharges were not associated with higher resource use in home health. As a result, in CMS's 80 HHRG system, a hospital discharge did not result in a higher case-mix weight whereas discharges from skilled nursing or rehabilitation stays did result in a higher case-mix weight.

Analysis of Case-Mix Change

We calculated predicted case-mix values for 2005, 2007, and 2009 using the approach described above. We combined results from analysis of these periods to produce an estimate of total real and nominal case-mix change for 2000-2009.

IPS Period-2005 Case-Mix Change

Most of the case-mix change that occurred between the IPS period and 2005 was not associated with changes in the prevalence of the independent variables included in the regression model and presumably reflects changes in nominal factors such as agency coding practices.

- The total change in case-mix between the IPS period and 2005was 0.1371, with average case-mix increasing from 1.0959 to 1.2331 (Table 1).
- Using the IPS model, predicted case-mix for 2005 was 1.1166, an increase of 0.0207 relative to the IPS period.
- Most of the observed case-mix change between the IPS period and 2005 is nominal change that was not predicted by the model. Our estimate is that 84.88% of the case-mix change that occurred between the IPS period and 2005 is unpredicted, while 15.12% is predicted (i.e., associated with changes in the mean values of covariates between the IPS period and 2005).
- Our best estimate is that there was a 10.62% nominal increase in case-mix between the IPS period and 2005, and a 1.89% real increase in case-mix.

2005-2007 Case-Mix Change

- Between 2005 and 2007, there was a 2.23% increase in average case-mix, which increased from 1.2331 to 1.2606 (Table 2).
- Using regression coefficients from the 2005 model, predicted case-mix for 2007 was 1.2392. Real case-mix change for the 2005-2007 period was 0.0061.
- Our estimate is that 23.23% of the 2005-2007 case-mix change is real and 77.77% is nominal. This translates to a 0.5% increase in real case-mix and a 1.74% increase in nominal case-mix.

2007-2009 Case-Mix Change

- Average case-mix increased from 1.2552 in 2007 to 1.3435 in 2009, an increase of 0.883 or 7.04% (Table 3). Note that the 2007 mean case-mix level reported in Table 3 differs slightly from that reported in Table 2 because the mean in Table 3 is based on the 153-HHRG model while the mean in Table 2 is based on the 80-HHRG model.
- Applying the regression coefficients from the 2009 model to mean values for 2007, real case-mix change between 2007 and 2009 is 0.0122. Predicted case-mix for 2009 is 1.2674.

- We estimate that 13.77% of the case-mix change that occurred between 2007 and 2009 is real, while 86.23% is nominal.
- Our estimate is that there was a 6.07% increase in nominal case-mix between 2007 and 2008 and a 0.97% increase in real case-mix.

2000-2009 Case-Mix Change

Combining results from Tables 1-3, we calculated the total amount of real and nominal change in case-mix from the IPS period through 2009.

- The total change in case-mix between the IPS period and 2009 was 0.2476, with average case-mix increasing from 1.0959 to 1.3435, a 22.59% increase (Table 4).
- Total predicted case-mix change for the 2000-2009 period was 0.0390. This was calculated as the sum of predicted case-mix change for 2000-2005 (0.0207), 2005-2007 (0.0061), and 2007-2009 (0.0122).
- Real (predicted) case-mix for 2009 was 1.1349. This equals the sum of average case-mix for the IPS period and the total predicted case-mix change for 2000-2009.
- Our estimate is 15.76% of the case-mix change that occurred between the IPS period and 2009 is real. This is estimated as the change in predicted case-mix between the IPS period and 2009 (0.0390) divided by the actual change in case-mix for this period (0.2476).
- Our estimate is that the remaining 84.24% of the case-mix change that occurred between the IPS period and 2009 is nominal case-mix change that is not due to changes in patient characteristics.
- Between 2000 and 2009, we estimate that there was a 3.56% increase in real case-mix and a 19.03% increase in nominal case-mix. The 3.56% real case-mix change estimate is calculated by multiplying the 22.59% change in total case-mix times our estimate that 15.76% of the total case-mix change is real. The estimate of a 19.03% increase is nominal case-mix is calculated as the 22.59% change in total case-mix times our estimate that 84.24% of the total case-mix change is nominal.

Drivers of Real Case-Mix Change

Either because their regression coefficient is close to zero, or because there was only a small change in mean values relative to the IPS period, most of the variables in the model add or subtract a trivial amount to the base year level of average case-mix. For the IPS-2005 model, only 21 out of 902 variables in the model predict a case-mix increase for 2005 of more than 0.01 or a decrease of more than 0.01 relative to the IPS period. For the 2007-2009 model, only 4 of the 921 variables in the model predict a case-mix change of this magnitude. The smaller number of variables associated with relatively large changes in predicted case-mix for the 2007-2009 model reflects the smaller change in means from 2007-2009 compared to IPS-2005.

We examined the variables in the model that were associated with real changes (either increases or decreases) in predicted case-mix for 2000-2009. Table 5 shows the variables associated with the largest increase in real case-mix for the study period. The table shows the predicted case-mix change for these variables for each model. The predicted case-mix change for each variable is calculated as the change in mean times the regression coefficient.

- The largest drivers of case-mix change were two ownership type variables: facility-based voluntary non-profit and other proprietary. Relative to the small group of agencies with unknown ownership type, predicted case-mix change was 0.0311 higher for facility-based voluntary agencies and -0.0203 lower for other proprietary agencies. Free-standing voluntary non-profit agencies were also associated with an increase in predicted case-mix, reflecting the negative regression coefficients and decreases in proportion of episodes provided by this agency type.

- Any hospitalization in the 14 days prior to the beginning of the home health episode was associated with lower case-mix in all three models. The mean of this covariate has decreased steadily over time, leading it to be associated with higher predicted case-mix (0.0140 for 2000-2009).

The mean of this covariate has decreased steadily over time and increased real case-mix in both models (0.0073 for the IPS-2007 period and 0.0013 for 2007-2008).

- The number of acute care hospital days in the 14 days preceding the episode was associated with higher case-mix. Because of the large decrease in mean hospital days (from 2.258 in the IPS period to 1.556 in 2007 and 1.281 in 2009), this variable led to a decrease in predicted case-mix (-0.0070 between 2000 and 2009). Similarly, acute care hospital days in the 15-120 days preceding the episode also led to a prediction of lower case-mix because of a decrease in mean hospital days combined with a positive regression coefficient.
- There was a substantial decrease in the proportion of patients with APR DRG 045 or 046 (CVA and preverbal occlusion with or without infarction). In all three regression models, this covariate had a large positive coefficient, meaning that the change in means led to a decrease in real case-mix. Knee joint replacement was the only other APR DRG item that was a driver of real case-mix. Knee joint replacement had a consistently positive regression coefficient and its prevalence has increased over time, leading to an increase in real case-mix.

Impact of HCC Variables on Estimates of Real Case-Mix

For this year's analyses, we added HCC variables to our analyses of case-mix change for 2005-2009 (the years for which HCC data were available). The addition of HCC variables is an important enhancement to our models. The HCCs cover a broad spectrum of health disorders and include conditions with significant expected health expenditures. Our analyses indicated that HCC variables were significantly related to case-mix levels and improved the statistical performance (R-square) of our models.

Overall, only one of the HCC variables (the interaction between CHF and COPD) was associated with real case-mix change of more than 0.0004 between 2005 and 2009 (Table 6). While the HCC community score was associated with higher case-mix (it had a regression coefficient of 0.0179 in the 2005 model and 0.0185 in the 2009 model), its mean value changed very little between 2005 and 2009. The average HCC score was 2.8553 in 2005 and 2.8775 in 2009, an increase of 0.78%. As a result, the HCC community score was associated with an increase in predicted case-mix of only 0.0004.

Overall, the addition of HCC scores led to slightly lower predicted case-mix for 2005-2007 (-0.0025) and slightly higher predicted case-mix for 2007-2009 (0.0012). Across 2005-2009, adding HCC scores to our models led to a 0.0013 decrease in predicted case-mix.

5 Discussion

Since implementation of the prospective payment system, there has been a steady increase in the average case-mix of home health patients. The overall observed case-mix increased by 22.59% between 2000 and 2009, with the average relative payment weight increasing from 1.0959 to 1.3435. The purpose of the analyses described in this report was to estimate the extent to which the observed increases in average case-mix were associated with changes in patient characteristics that reflect real case-mix change versus changes in agency coding practices or other nominal factors. We used data from the IPS period, 2005, and 2009 to estimate a regression-based, predictive model of individual case-mix weights based on measures of patients' demographic characteristics, clinical status, inpatient history, and Medicare costs in the time period leading up to their home health episodes.

The regression coefficients from these models were combined with information about the change in mean values of model covariates, allowing estimation of how much of the change in observed case-mix is attributable to changes in patient characteristics over time. We classified the sources of case-mix change into two major types: predicted and unpredicted. Real (or predicted) change is based on the relationship between patient characteristics and case-mix (i.e., coefficients from the regression model) and changes in the characteristics of patients over time (i.e., the change in mean values of the model covariates). Unpredicted (or nominal) change is the portion of case-mix change that cannot be explained by changes in patient characteristics. Nominal case-mix change is assumed to reflect differences over time in agency coding practices.

We estimate that there was a 19.03% nominal increase in case-mix between 2000- 2009. This nominal change reflects differences in agency coding practices and documentation. There was a 3.56% real change in case-mix that reflects treatment of more resource-intensive patients over time. This estimate is generally consistent with prior analyses that have found that only a small portion of the change in case-mix is associated with the observable factors that are included in our models. With each additional year of data that we have analyzed, the predicted average national case-mix weight has changed very little. This is largely because the variables (such as preadmission location, non-home health Part A Medicare expenditures, inpatient stay classification, and the HCC variables) that the models use to predict case-mix have remained relatively constant over time. Thus, even though many of these variables are associated with higher case-mix, they lead to only small changes in predicted case-mix. Many of the variables included in our models do not have a strong relationship to case-mix. At the same time, the actual average case-mix has continued to grow steadily. Thus, the gap between the predicted and actual has increased with each successive year of data.