

## **PROMETHEUS PAYMENT MODEL**

The PROMETHEUS Payment model is an ambitious attempt at creating a patient-centered payment for health care services that would split apart technical and probability risks (currently compressed and indistinguishable in either fee for service or capitation payments) and assign responsibility for the former to providers and the latter to insurers. The payment model's foundational element is an Evidence-informed Case Rate (ECR), which is a bundled price for a severity-adjusted, typical episode of care for any patient-provider-payer triad *after* an episode is triggered. Under grants from the Commonwealth Fund and the Robert Wood Johnson Foundation, we used a large national medical and pharmacy claims dataset consisting of over 4.5 million covered lives to model ECRs for 21 acute & chronic medical conditions and inpatient & outpatient procedures. Electronic medical records data or results of laboratory or radiology tests were not available to us.

### What are ECRs?

ECRs are patient-centered episodes of care for the treatment of an illness or condition, or for an inpatient or outpatient procedural event, severity-adjusted to that patient. They include all covered services related to the care of the condition as determined by tested, medically accepted clinical practice guidelines or expert opinion. They are time-delimited and are built to identify “typical” services, from services associated with potentially avoidable complications (PACs).

By separating base (typical) care from care of complications, we bifurcate the total variation in the price of care into the portion of that total variation that is caused by patient factors and typical care of the patient, and the portion that is caused by provider management failures leading to potentially avoidable complications. The base set reveals itself to be the appropriate one from which to develop the patient health status factors that require an adjustment in the intensity of services to care for that patient, as well as the base from which to create a risk-adjusted bundled price for an episode. The cost of caring for potentially avoidable complications forms the basis for the ECR-specific PAC allowance that is made available to all episodes, irrespective of occurrence of complications, creating a strong incentive for providers to decrease complications.

### How are ECRS constructed?

For each ECR, the following steps are followed:

1. Clinical Logic (Defining the boundaries of an ECR): This step is developed initially using clinical guidelines or expert opinion. It is then validated using empirical data that is shared with the clinical working group. The definitions are further refined

based on the outputs and clinical discussion and the final set of rules and definitions are created for the various components of an episode.

In this step we define 1) the triggers for a condition or procedure, 2) the time windows for the episode including look-back and look-forward periods, 3) what claims and services are considered relevant for the episode, 4) what constitutes “typical” care that is routinely expected to be delivered to a patient with or without co-morbidities or other factors that naturally increase the intensity of services and are outside the control of the provider (e.g. admission of a patient for an AMI through the emergency room), 5) what patients should be excluded from the episode (denominator exclusions), 6) what claims should be excluded from the episodes (numerator exclusions), 7) what variables should be used for risk adjustment, and 8) what are standard complications to be expected and would be considered potentially avoidable for the condition / procedure under study.

We consider PACs as indicators of health system failure that cause gaps in quality of care. We categorize them into three types:

- PACs related to the index condition. This would include an adverse event directly related to the index medical condition or procedure either during the index stay or a subsequent ED visit or hospitalization. An example would be respiratory failure during the index stay in a patient admitted with pneumonia, or wound infection in a patient with hip replacement.
- PACs related to comorbidities. If one of the patient’s controlled comorbid conditions is exacerbated during the episode time window or requires a subsequent ED visit or hospitalization. For example, an ED visit for an asthma attack in a patient with diabetes or one discharged for pneumonia.
- PACs related to patient safety failures. Examples are bed sores, line sepsis, adverse drug events, drug interactions etc.

The ABMS / Brookings have a strong process developed along with the PCPI Clinical Working Groups to define the clinical logic on an episode-by-episode basis. Clinical experts from various specialties who participate in the care of a condition / procedure are invited to the table to provide clinical guidance and input and to develop a consensus where published clinical guidelines are lacking. The Prometheus starter set of episodes will be vetted through this clinical logic process.

2. Development of the SAS Metadata: The clinical logic defined above is translated into code-sets for each ECR to convert the clinical definitions to a SAS metadata set that can be read into the SAS programs for episode construction.

We use the International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) codes, and the American Medical Association’s Current Procedural Terminology (CPT®) codes for diagnoses and procedures for medical claims, and the National Drug Codes (NDC) for pharmacy claims.

We heavily leverage the Agency for Healthcare Research and Quality (AHRQ)'s Clinical Classification Software (CCS) as a means of grouping ICD-9-CM diagnosis and procedure codes, and the CCS for CPT classification to group CPT codes into Prometheus defined super-categories. This helps group similar conditions and procedures into relatively homogenous meaningful, clinical categories to increase the strength of the variables for further analysis.

Separate SAS Metadata sets exist for each ECR® that map the ICD-9 diagnosis codes, the procedure codes, the CPT codes, the revenue codes as well as the NDC codes to the triggers, the typical, PACs as well as exclusion codes within each ECR®. The code-sets are taken back to the clinical working group for a final review before implementing into the SAS programs. Steps 1 and 2 could be performed to some extent during the same clinical session and the code-sets verified separately.

3. Episode Construction Logic: In this step we define the analysis plan, the methods and parameters to build an episode and to create the analytical dataset for risk-adjustment. This step once finalized, should be consistent across all conditions within an episode type. This step uses a series of sub-steps:
  - a. *Data Cleaning and Preparation*: Here rules are defined to 1) determine how to treat claims that straddle the episode start or end date, 2) what claims are considered as cost outliers, 3) what claims are considered as invalid for the episode due to missing data elements e.g. missing gender, missing costs.
  - b. *Enrollment / Eligibility criteria*: For each episode type we define the enrollment and eligibility criteria, so if a member has enrollment gaps then they are considered as having incomplete data and are dropped from the analysis.
  - c. *Trigger rules and other exclusion criteria*: For each episode type we define what claim type would be a valid claim to have the trigger codes present, determine if there are any trigger exclusions, how to treat emergency room claims, hospital deaths, cases that left against medical advice, age criteria, multiple of bilateral procedure exclusions.
  - d. *Building the episode*: All claims during the episode time window, for members that meet the inclusion criteria, are aggregated together to create the complete set of services within the episode. This includes inpatient facility claims and associated inpatient professional claims (linked as +/- 2 days from the date of admission and discharge of an inpatient stay claim), outpatient facility claims, outpatient professional services, as well as claims for laboratory, radiology, and other ancillary services. Readmissions as well as associated admissions (including skilled nursing facilities (SNF) and home health (HH) claims) during the episode time window are also aggregated with the episode. Pharmacy claims are identified using a unique member identifier and aggregated within an episode based on the prescription fill date and logic to verify that it is a valid pharmacy claim for the episode time window.

Claims with medical diagnosis or procedural codes for services not directly related to care for the index condition are excluded, as are claims for major

surgical procedures which suggest that the index condition is at a different acuity level requiring surgical intervention (e.g., coronary artery bypass graft in a setting of CAD or AMI). In such cases a procedural episode starts to keep the index episode more homogenous with regards to clinical as well as financial risk. Pharmacy claims with NDC codes not relevant to the episode are also removed. The remaining claims are considered “relevant” – and are separated into claims related to (a) typical care or (b) potentially avoidable complications (PAC) depending on whether they carry a PAC code in any of the diagnosis fields or had a procedure code that was related to services provided for a complication.

- e. *Validity Testing:* After the episodes are constructed, the SAS programs are run on the developmental database and the outputs are taken back to the Clinical Working Groups and studied for 1) the number of episodes that were triggered as compared to the prevalence of the condition or procedure in the literature, 2) drops in counts at every level of the episode construction to look for significant loss in episode counts and any need to refine the clinical codes or the logic, 3) average episode costs as compared to that in the literature, 4) the typical costs and the PAC costs, and 5) the types of PACs, their frequency of occurrence and the costs associated with them. This enables a validity testing with both empirical and clinical feedback into the clinical logic as well as the episode construction process to decide if any changes should be made to the trigger definitions, exclusion criteria, assignment of codes, or the episode construction architecture itself.
4. Risk-Adjustment Logic: The goal of the modeling effort is to determine the extent to which the different types of variation that are embedded into any episode of medical care – the risks inherent to the patient and the risks imputed by providers in the management of the patient’s care – could be sufficiently segregated to create clear and unambiguous accountability for the effective and efficient management of a patient’s care.

For each of the episodes, we use “allowed amounts” as the dependent variable to create the episode predicted price. These are the pre-adjudicated costs that account for the reimbursable amount (the reimbursed amount plus the patient portion of costs) for all the claims selected as “typical” for the episode. Only “typical” claims are used for the modeling exercise to adjust for the warranted variation in costs related to patient characteristics. We do not use PAC claims for risk-adjustment because these are events and services that are unwarranted and we do not want to adjust away costs associated with these services.

We create separate risk-adjustment models for up to three separate components based on the episode type: 1) inpatient facility, 2) outpatient facility, and 3) professional & other claims (here all other services are aggregated together for the purposes of modeling into one dataset containing inpatient professional, outpatient professional, pharmacy, lab, radiology and other ancillary claims). The results of the three models are then brought together as a complete predicted episode price.

This approach removes the incentive to provide care in a given location (inpatient vs. outpatient) and lets the provider choose the type and place of services that would lead to the most cost-effective care. In addition, there may be comorbid conditions that modify the costs of care in the inpatient setting that are different than the risk modifiers in the outpatient setting, hence the need for separate models. Moreover, the inpatient facility claims have their own coding rules and a hospital confinement often comes with a bundled cost (allowed amount) on a single line item, but risk factors and services on separate line items that provide a different challenge for modeling. On the other hand, the professional claims are individually available with cost and services on a line-by-line basis and can be linked using the member ID.

In addition, we chose to use pharmacy data to adjust for severity, since we found in the claims data, physicians do not use diagnosis codes completely, so pharmacy data helped enhance the risk-adjustment process and capture additional comorbidities.

#### Unit of Analysis:

The unit of analysis is the component of episode being modeled e.g. inpatient facility (stay model), outpatient facility, or professional, pharmacy and other services (PFO) model. It contains all “typical” claims that are relevant to that component of the episode. It is important to exclude claims for potentially avoidable complications (PACs) since costs related to these services should not have occurred and we do not want to adjust away or justify the occurrence of complications.

#### Dependent Variable:

The dependent variable is cost. We use the “allowed amount” field for costs since it usually represents the reimbursed amount to the providers along with the patient portion of the costs and does not vary with the members benefit design or utilization of services. We remove outlier ECRs by truncating the selected claims at the 1st and 99th percentile value for costs. The distribution of cost was examined, and was transformed using the log transformation (Ln) to reduce the skewness in cost data.

#### Independent Variables:

A separate list of independent variables is created for each ECR specific to the severity indicators and comorbidities for the condition under study. The list of “risk factors” or “cost modifiers” consists of patient demographic factors, hospital or provider characteristics, geographic area indicators, comorbidities, procedures or diagnostic tests performed, and pharmacy variables to the extent this information is available in the database. Variables are often grouped together into relatively homogenous risk categories. Frequency of occurrence of variables often determines if the variable needs to be entered alone or should be combined with other variables to ensure they are not lost from the modeling exercise. A difference in cost using univariate analysis (with or without a variable) often determines whether a given variable will be presented to the multivariable stepwise analysis. The variables selected in the inpatient model may be different from those used in the outpatient model depending on the implications of each variable to cost in various settings. The

statistical modeling determines whether or not a variable should be included in the final models.

### Statistical Methods

To measure the association between each categorical independent variable and cost, a bivariate analysis using the t-test (or analysis of variance (ANOVA) if the independent variable has more than 2 levels) was performed on Ln cost. Means, standard deviations and other descriptive statistics was transformed back and reported on the original scale.

For the “typical” cases and services analysis, we used the ordinary least squares regression (OLS; also known as multiple linear regression) analysis for developing the ECR multivariable models.

Multiple linear regression is a statistical method for measuring associations between a set of independent variables and a continuous outcome such as cost. This method has the following advantages: (a) widely used and accepted, (b) easy to understand, (c) relatively easy to explain to non-statisticians, (d) transparent, and (e) several different model selection methods are available in SAS (e.g. Schwarz Criterion, automated variable selection procedures such as stepwise).

The linear regression models are of the following form:

$$\text{Ln } Y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \beta_3x_3 + \dots + \beta_px_p + \epsilon$$

Where

Ln Y is the natural log of costs for the “typical” care and services

$\beta_0, \beta_1, \dots$  are the regression coefficients

$x_1, x_2, \dots$  are the independent variables; these variable include demographics, and comorbidities

$\epsilon$  is the error term

This model assumes that the  $\epsilon$  term is independent, normally distributed with mean 0 and constant variance.

### Model Selection Criteria

The question of which model is the “best” is often not a straightforward one.

Generally, the “best” model is the one that strikes a balance between being clinically plausible, fitting the data well, and yet not being overly complex (i.e. not having a large number of parameters in the model). An effective model selection process is one that combines both clinical input as well as statistical evidence (e.g. model building statistics). The process described below used a combination of clinical review and model building statistics.

Variables are first examined univariately. Variables which are clinically plausible, have a minimum number of 30 cases per category, and the t-test p-value for the association between the variable and Ln cost was  $<0.5$  are placed in the pool of candidate independent variables. Some of these candidate variables are reclassified as “force” variables, i.e. variables that should be in all models due to their clinical importance. Multiple linear regression with the stepwise variable selection procedure

is used to select from the remaining candidates. The p-values to enter and exit the model are set at 0.05. The stepwise procedure works by fitting a model with only the forced variable in the model. Then the procedure computes an F statistic for each candidate independent variable. The F statistic is the F statistic that would be obtained if only that variable were added to the model. The variable with the lowest F statistic p-value that is less than 0.05 is put in the model, and then the model is refit. New F statistics are computed for the remaining candidate variables, and again the one with the lowest F statistic p-value below 0.05 is added to the model. This process continues until no other candidates have F statistic p-values  $<0.05$ . If, at any time during the process, the p-value for the F statistic of any variable in the model goes above 0.05, that variable is removed from the model unless the variable is a force variable.

The resulting model is reviewed for clinical plausibility. Variables are selected if they were clinically important, their coefficients are in the right direction and magnitude, and their variance inflation factor (VIF) is low suggesting no evidence of multicollinearity. The models are re-run with the selected variables. This process of model fitting, clinical review, and refitting is continued until a clinically plausible model is identified.

#### Regression Diagnostics:

Once a model is selected, the assumptions of the linear regression model are verified. As mentioned above, this model assumes that the errors,  $\epsilon_i$ , are independent, normally distributed random variables with mean 0 and constant variance. Residual analysis was performed to verify these assumptions. If the residual analysis does not meet the linear regression assumptions, a Box-Cox transformation is performed on the data and the lambda that has the best regressions diagnostics is selected.

#### Bootstrap Validation:

The above model is run using stepwise selection with SLE (significance level for model entry) = 0.05 and SLS (significance level for staying in model) = 0.05 on 200 bootstrap samples, and a record is kept of how many times each variable is selected in the 200 model runs. A bootstrap sample is created by sampling with replacement from the full dataset until a sample of the same size as the full dataset is drawn. Any variables that were forced into the model above are also forced in the 200 bootstrap models. Any variable that enters into less than 160 bootstrap models (80% of the models) is dropped.

#### Final Model:

Variables which do not consistently perform as significant predictors in at least 75% of the 200 bootstrap validations are dropped. The final step is to run the model cleanup algorithm as in Step 4 one last time. The reason for doing this is that removal of some variables may cause perturbations in the sign of other variables, if there exists some correlation between these variables. The resulting model is the final model.

Retransformation Bias:

Because cost is log-transformed before it is modeled, there is a bias that occurs when one tries to back-transform predicted LN(ALLOW) into the original units. This results in systematic underpayment and the cumulative effect can be substantial. For this reason a Bias Correction Factor (BCF) is calculated as the ratio of the total actual costs in dollars (of all patients that went into the model) to their predicted costs. Multiplying the predicted cost by this BCF assures that there will be no systematic under or over-prediction of cost on the user's data set.

5. Pricing the Base Services (Core Pricing): A foundational element of Prometheus is that the base set of services should include all the services that are recommended by Clinical Practice Guidelines or expert opinion as laid out by the Clinical Working Groups. For chronic conditions, such core services were listed with input from Clinical Working Groups and their costs estimated. A “gaps-in-care” analysis is performed on a patient-by-patient basis to study the underuse of core services and to identify the gaps in care-coordination. This kind of analysis could be an add-on to the logic to understand variation in costs of “typical” care with regards to underuse.
6. Limitations of Episode Construction and Risk-adjustment analysis:
  1. Models are only as good as the data.
  2. We're using claims data from specific populations to estimate costs which will possibly be used for other populations. These cost estimates may not apply to all populations.
  3. Claims data are messy with incomplete or incorrect diagnosis codes being used and there is limited clinical information that can only be obtained through patient chart reviews such as information on body weight, BP, smoking status etc.
  4. Socio-economic and other factors such as educational level, family support, access to healthcare etc., which may impact costs are not available in most administrative databases but are very important for severity adjustment.
  5. Laboratory data is not available to us – it has been shown to add a lot of value to administrative data for risk-adjustment purposes to assess the severity of a patient's disease.
7. Limitations of Clinical Guidelines:

Work to date suggests clinical guidelines are necessary, but not always sufficient, to create a base ECR. Guidelines can use language that defers to a doctor's discretion, such as, “Use treatment X, when appropriate.” This can make it difficult to determine the resources necessary to provide recommended care. Where the best available evidence or expert consensus does not provide sufficient information, empirical data must be used to fill in knowledge gaps. In these cases, data modeling will help to determine where ECRs can provide sufficient flexibility to physicians without having significant impact on the final episode price. For example, clinical guidelines are often not specific in detailing the amount of case management and follow-up required to treat a given condition. However, if the final episode price is not sensitive to wide variation in follow-up time, this becomes much less of an issue. Alternatively,

examining cost data with high compliance rates may show a more consistent approach to case management as done by best-practice providers.

8. SAS package (SAS software): The clinical logic as depicted by the SAS Metadata, the episode construction logic in the form of SAS programs and macros as well as the logic for risk-adjustment has been assembled in a SAS package that has been made available in part as a free-ware downloadable from the website [www.hci3.org](http://www.hci3.org). The complete SAS packages are available on signing of a licensing agreement ensuring that data sharing happens among users. To date, over 12 health plans, three of them national health plans have run their data through the Prometheus software. Their feedback is that the SAS software is very user-friendly and automates all components mentioned above.

9. Future Development:

Conversion to ICD-10 codes: Since ICD-10 codes will be incorporated into claims in the next few years, the SAS metadata sets will be updated to map the ICD-9 codes to ICD-10. New trigger rules may be more appropriate than mapped ones based on the guidance from the Clinical Working Groups. AHRQ is coming up with an updated CCS categories based on ICD-10 codes and will be creating a new CCS to CPT mapping (personal communication with Anne Elixhauser from AHRQ). Prometheus will leverage the AHRQ classification software to the extent possible to minimize the effort involved in creating new metadata sets. Additionally, since the SAS Metadata set is a stand-alone piece of the SAS package and is created independent of the other components of the SAS programs, this change from ICD-9 to ICD-10 will cause minimum disruption of the episode grouper logic.

10. Examples: The tables below provide examples of output reports that are constructed from the episode construction effort. Detailed reports for each of the 21 ECRs are available on the website [www.hci3.org](http://www.hci3.org)

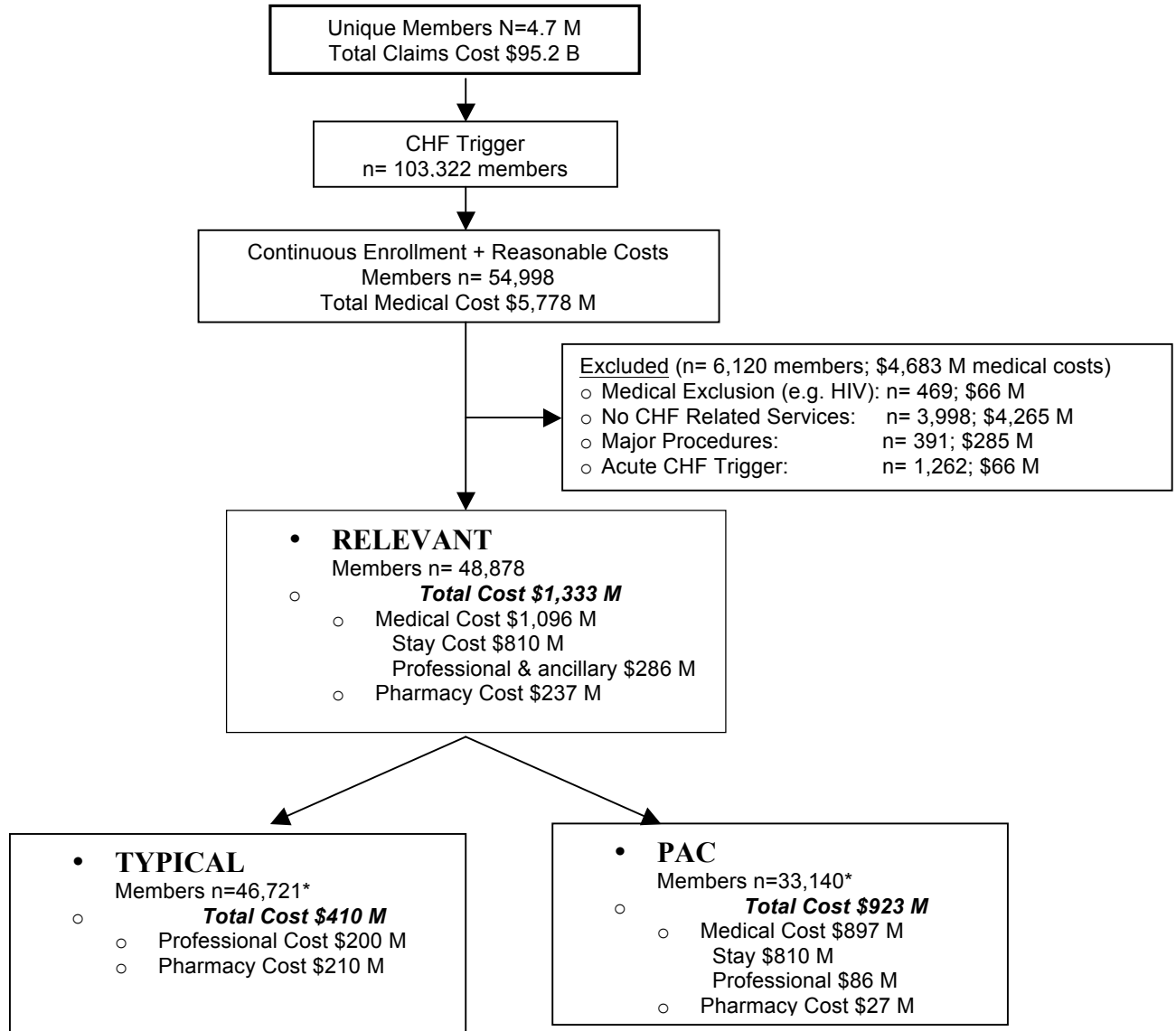
**Table 1: Acute Myocardial Infarction (AMI) ECR Definition Summary**

	<b>Definition</b>
Trigger Codes*	The patient has an <u>inpatient facility claim</u> with any of these ICD-9-CM diagnosis codes as the principal diagnosis: 410.xy, y=0,1
Episode Time Window	From the index admission date to 30 days after index discharge date
Enrollment / eligibility requirement	Duration of episode (duration of index hospital stay and 30-day look-forward period) with no any gap
Patient Exclusions	<ol style="list-style-type: none"> <li>1. Continuous enrollment requirement not met</li> <li>2. Age &lt; 18 or Age &gt;= 65 years</li> <li>3. Discharge status is left against medical advice</li> <li>4. In-hospital death</li> <li>5. Does not have both an inpatient and professional index claim at the relevant case level (orphan episode)</li> </ol>
Claim/Episode charge exclusions	<ol style="list-style-type: none"> <li>1. Remove PFO<sup>†</sup> claims if the claim charges are missing, &lt; \$10, or &gt;\$1,000,000</li> <li>2. Remove Stay claims if claim charges are missing, &lt; \$50, or &gt;\$1,000,000</li> <li>3. Remove Pharmacy claims if claim charges are missing, &lt; \$1, or &gt;\$1,000,000</li> <li>4. Remove episode if total medical charges for the episode are &lt; \$20 or &gt; \$1,000,000</li> <li>5. Remove episode if total pharmacy charges for the episode are &lt; \$1 or &gt; \$1,000,000</li> </ol>
Medical exclusions	HIV, cancer, suicide, end-stage renal disease (ESRD), pregnancy and newborn conditions
Procedural exclusions	Exclude claims with select major or irrelevant surgical procedures as indicated in the “all codes” workbook, transplants etc.
Potentially Avoidable Complications (PACs) – this includes CMS defined hospital acquired conditions (HACs), AHRQ’s patient safety indicators and more	<p>Index hospitalizations could also have a PAC if they are one of three types:</p> <ol style="list-style-type: none"> <li>1. PACs related to the anchor condition: The index stay is regarded as having a PAC if during the index hospitalization the patient develops one or more complications such as cardiac arrest, ventricular fibrillation, cardiogenic shock, etc. that may result directly due to AMI or its management.</li> <li>2. PACs due to Comorbidities: The index stay is also regarded as having a PAC if one or more of the patient’s controlled comorbid conditions is exacerbated during the hospitalization (i.e. it was not present on admission). Examples of these PACs are diabetic emergency with hypo- or hyperglycemia, GI hemorrhage, lung complications, need for tracheostomy, etc.</li> <li>3. PACs suggesting Patient Safety Failures: The index stay is regarded as having a PAC if there are one or more complications related to patient safety issues. Examples of these PACs are septicemia, other infections, phlebitis, deep vein thrombosis, pulmonary embolism or any of the CMS-defined hospital acquired conditions (HACs).</li> </ol> <p>All readmissions during the one-month episode time window are considered as PACs.</p>
Type of model(s) developed	<ol style="list-style-type: none"> <li>1. Inpatient facility model: Model for age &lt;65</li> <li>2. Professional, outpatient facility, pharmacy &amp; all other claims model: Model for age &lt;65</li> </ol>

\* x = any digit from 0-9 inclusive or blank, y is as indicated.

†PFO: Professional, outpatient facility, ancillary and other claims.

Figure 1: Flow Diagram for CHF cases



\* Categories are not mutually exclusive. That is, a patient can have both a typical and a PAC episode.

Table 2. Construction of severity-adjusted evidence-informed case rate (ECR) for typical care for congestive heart failure (CHF) for three hypothetical patients

Predictor <sup>1</sup>	Number of Episodes with Variable	Percent Episodes (N=45,787)	Coefficient on Ln Scale <sup>2</sup>	Hypothetical Patient Scenarios		
				Patient 1	Patient 2	Patient 3
Intercept	45,787	100.0%	7.3049	1	1	1
Age: < 50 vs. 50-64	782	1.7%	-0.0687	0	0	0
Age: 65-79 vs. 50-64	15,813	34.5%	0.1330	0	0	0
Age: >= 80 vs. 50-64	23,411	51.1%	-0.0059	0	0	0
Heart valve disorders	4,506	9.8%	0.1463	0	1	1
Coronary atherosclerosis and other heart disease	19,652	42.9%	0.2072	0	1	1
Carditis, Cardiomyopathy	4,058	8.9%	0.1294	0	1	1
Conduction disorders	3,723	8.1%	0.2003	0	1	1
Eye, ENT, oral procedures	615	1.3%	0.4293	0	1	1
Diagnostic cardiac catheterization, coronary arteriography	882	1.9%	0.4524	0	1	1
DME, visual and hearing aids	9,104	19.9%	0.4552	0	0	0
Cardiac ablation, pacemaker or cardioverter/defibrillator	680	1.5%	0.6575	0	0	0
Statins and other anti-lipid agents	6,581	14.4%	0.2161	0	1	1
Bronchodilators and other antiasthmatics	15,574	34.0%	0.2345	0	0	1
Antiarrhythmic agents	6,100	13.3%	0.2274	0	0	1
Inhalers and respiratory agents	7,376	16.1%	0.2061	0	1	1
Antacids and drugs for other oral and GI problems	27,060	59.1%	0.2915	0	1	1
Diuretics	36,548	79.8%	0.2469	0	1	1
Other cardiovascular agents	13,975	30.5%	0.1697	0	0	1
Beta-Blockers	31,234	68.2%	0.2322	0	0	1
ACEI, ARB, anti-renin drugs	29,454	64.3%	0.1672	0	1	1
Calcium channel blocking agents	16,172	35.3%	0.1672	0	0	1
Antiplatelet agents, thrombin inhibitors	11,699	25.6%	0.2214	0	1	1
Antidepressants	16,569	36.2%	0.1940	0	0	1
Severity-adjusted Price of ECR <sup>3</sup>				\$1,488	\$27,418	\$93,341

<sup>1</sup> Predictors of episode costs from a multiple linear regression model. Professional, outpatient facility and pharmacy costs were modeled on the natural log scale. The models included patient demographic, medical comorbid conditions, procedures performed, and pharmacy use.

<sup>2</sup> All coefficients were significantly different from 0 at the 0.05 level. The adjusted R-square was 41.9%

<sup>3</sup> To calculate the severity-adjusted price of the ECR by model, sum the estimates for the intercept and desired predictors (sumP) and compute  $e^{(\text{sumP})}$ .

Table 3: Evidence-informed core services and prices

Evidence-Based Services	CIP Database	CHF		CAD		Diabetes		Hypertension	
	Unit price	N	Price	N	Price	N	Price	N	Price
<b>Physicians</b>									
PCP-new	\$178	1	\$178	1	\$178	0	\$0	0	\$0
PCP-established	\$104	5	\$519	3	\$312	4	\$416	4	\$416
Cardiology/ Pulmonologist	\$242	3	\$726	1	\$234	0	\$0	1	\$121
Endocrinologist	\$242	0	\$0	0	\$0	0.1	\$24	0	\$0
Ophthalmologist	\$242	0	\$0	0	\$0	1	\$242	0	\$0
<b>Ancillary</b>									
Diabetes Educator	\$104	0	\$0	0	\$0	1	\$104	0	\$0
Cardiac Rehab	\$35	12	\$422	0	\$0	0	\$0	0	\$0
Emergency Room	\$469	0	\$0	0	\$0	0.1	\$47	0	\$0
<b>Diagnostics / Lab</b>									
Echo transthoracic	\$458	2	\$917	1	\$458	0	\$0	0	\$0
Electrocardiogram	\$58	2	\$116	1	\$58	0	\$0	1	\$58
Chest x-ray	\$90	2	\$180	1	\$90	0	\$0	0	\$0
Lung function test	\$35	2	\$70	0	\$0	0	\$0	0	\$0
metabolic panel	\$30	6	\$177	1	\$30	0	\$0	1	\$30
Lipid panel	\$70	2	\$139	1	\$70	2	\$139	1	\$70
Liver Function Tests	\$60	2	\$121	1	\$60	1	\$60	0	\$0
Microalbumin, quantitative	\$16	2	\$32	1	\$16	0	\$0	1	\$16
HbA1c	\$51	0	\$0	0	\$0	3	\$154	0	\$0
Potassium	\$37	0	\$0	0	\$0	1	\$19	0	\$0
Creatinine	\$75	0	\$0	0	\$0	2	\$113	0	\$0
<b>Est. Evidence-Based Costs</b>			<b>\$3,597</b>		<b>\$1,505</b>		<b>\$1,317</b>		<b>\$710</b>

<sup>1</sup> All specialists are computed at the same rate: cardiologist, pulmonologist, endocrinology, ophthalmologist.