



**CareScience  
Complication and  
Complication Morbidity Risk Models**

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## Part I: Complications

### I. Significance

Inpatient complications are a relevant quality measure for most patient populations, causing avoidable harm to patients and adding significant cost. They range from trivial to significant and are estimated to account for 24-30% of patient care costs, 20-25% of unscheduled readmissions, 14-30% of patient length of stay, and 10-12% of inpatient mortality.<sup>1</sup>

For the performance improvement statistician, inpatient complications present advantages as a quality measure. Due to their high rate of frequency (30% across hospitals on average), they offer greater measurement sensitivity than the more common measure of mortality, which occurs in only 3% of inpatient cases per year and often suffers from small number problems. Unlike mortality, complications are also a relevant outcome measure for most disease groups. (Mortality fails to be a meaningful performance measure for many patient populations such as *hip/knee replacement* patients, *asthma* patients, etc due to its low incidence.) Additionally, complications offer the advantage of being a more direct consequence of the care process than other outcome measures, offering actionable opportunities for quality and financial improvement.

### II. Measurement Challenge

The challenge with measuring complications is the difficulty observing them and their dependence on good documentation and coding consistency. Traditionally, complications have been tracked using chart reviews during which clinicians pull and review individual patient charts. These time-consuming reviews are expensive and laborious and consequently unsuitable for large scale data analysis.

Identifying complications through mining of ICD-9 diagnosis codes in administrative data is also problematic. Secondary diagnoses of complications are often missing their complication "linking codes," making it difficult to determine whether a secondary diagnosis represents a complication. Furthermore, facilities vary in the rigor of their coding practices including use of "present on admit" diagnosis identifiers.<sup>2</sup> Up- and down-coding biases also exist for certain complications based on financial reimbursement and performance appraisal, masking "true" complication rates.

### III. CareScience Comorbidity-Adjusted Complication Model

In light of the challenges surrounding complication tracking, Premier has developed a unique decision-theoretic complication model that uses Comorbidity-Adjusted Complication Indices

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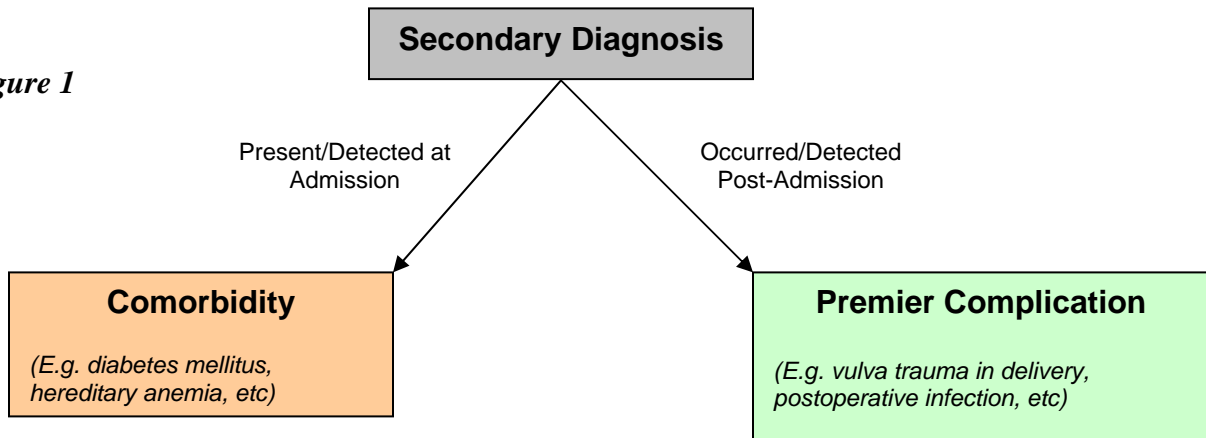
<sup>1</sup> Brailer DJ, Kroch E, Pauly MV, Huang J. Comorbidity-Adjusted Complication Risk: A New Outcome Quality Measure, *Medical Care* 1996; 34:490-505.

<sup>2</sup> Secondary diagnosis "Present on Admission" identifiers do not exist in public datasets, eliminating their possible use in analyses of these datasets.

(CACI) to distinguish complications from comorbidities.<sup>3</sup> This model assumes a nonstandard definition of complications, defining them as conditions that occur or are detected during a patient's hospital stay. By this construction, complications do not necessarily imply iatrogenic events or physician negligence. Nevertheless, the occurrence of these conditions or the failure to detect them upon admission alters the course of the patient's care process.

The exact complement of Premier's complications are comorbidities. These conditions pre-exist or are noted upon the patient's hospital admission, allowing consideration of them during planning of the patient's care.

**Figure 1**



### 3.1 Comorbidity-Adjusted Complication Indices (CACI)

Complications are derived from secondary diagnosis codes.<sup>4</sup> Ideally, they should be recorded as binary outcomes, however, there is no definitive way to classify most diagnoses as complications in all instances. A diagnosis may be considered a complication in one case but a comorbidity in another. The timing of a diagnosis further complicates classification of complications. A diagnosis that was captured during an inpatient stay does not necessarily indicate its development after admission. Although chart reviews are a reliable way to supplement this information, they are unsuitable for large-scale data processing efforts.

Premier has developed a set of Comorbidity-Adjusted Complication Indices (CACIs) wherein each index or CACI approximates the probability that a secondary diagnosis is a complication given an accompanying principal diagnosis. For example, the CACI for a secondary diagnosis of *congestive heart failure* with a principal diagnosis of *simple pneumonia* is 20%. For 20% of patients with this principal-secondary diagnosis pair, the *congestive heart failure* emerged during their inpatient stay. For the remaining 80% of patients, the *congestive heart failure* was present at the time of admission.<sup>5</sup>

<sup>3</sup> Ibid.

<sup>4</sup> Occasionally, complications are coded as principal diagnoses. Obstetrics patients are one such example.

<sup>5</sup> Premier complications and comorbidities are complementary events so that  $\text{Prob}(\text{SDx Z is a complication given PDx A}) + \text{Prob}(\text{SDx Z is a comorbidity given PDx A}) = 1$

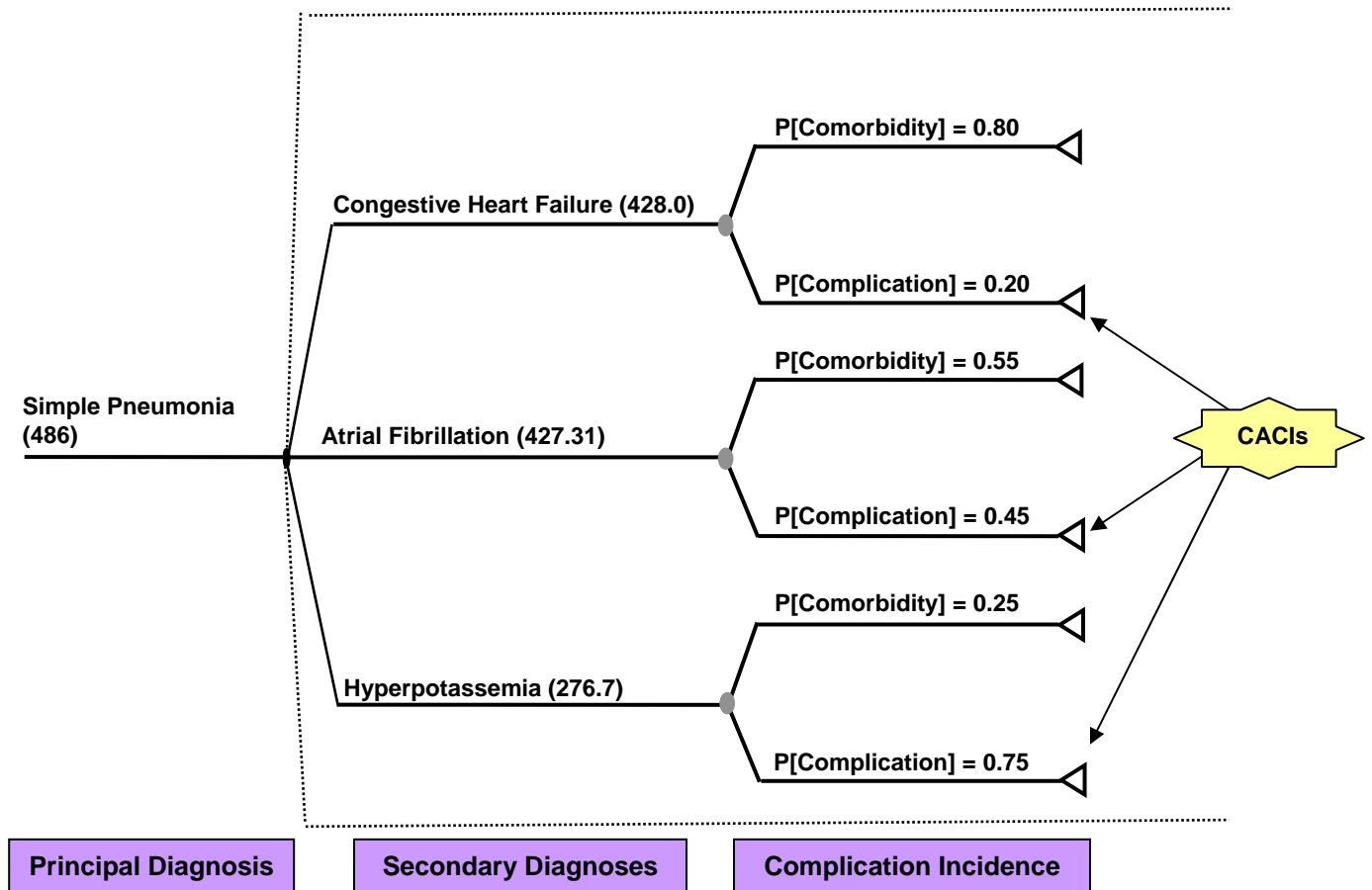
**Figure 2: Secondary Diagnoses**

<u>PURE COMORBIDITY</u>	<u>COMORBIDITY OR COMPLICATION</u>	<u>PURE COMPLICATION</u>
CACI = 0% across all PDxs	0% < CACI < 100%	CACI = 100% across all PDxs
(E.g. diabetes mellitus, hereditary anemia, etc)	(E.g. urinary tract infection, CHF, etc)	(E.g. vulva trauma in delivery, postoperative infection, etc)

Secondary diagnoses with CACIs of 0% across all principal diagnoses can be considered pure comorbidities or chronic conditions. Accordingly, secondary diagnoses with CACIs of 100% across all principal diagnoses can be viewed as pure complications.

CACIs exist for every principal-secondary diagnosis pair combination and are assigned *ex ante* by Delphi panels of physicians.

**Figure 3: CACI Assignment Example**



### 3.1.1 Calculating Raw Complication Rates from CACI

Under the CACI system, raw complication rates are defined as the probability of having at least one complication. Complications are calculated (imputed) as

$$1 - \prod_j (1 - p_{ij}), j = 1, 2, \dots, m$$

where  $m$  is the number of secondary diagnoses, and  $p_{ij}$  is the probability of complication for the  $j$ th secondary diagnosis given principal diagnosis  $i$ .

*Figure 4: Raw Complication Rate Example for Patient Z*

#### Patient Z

**Principal Diagnosis = Simple Pneumonia (486)**

Secondary Diagnosis (SDx)	Probability SDx is a Complication	Probability SDx is NOT a Complication
Congestive Heart Failure (428.0)	0.20	0.80
Atrial Fibrillation (427.31)	0.45	0.55
Hyperpotassemia (276.7)	0.75	0.25

- Probability that Patient Z had NO complications:  
 $0.80 \times 0.55 \times 0.25 = 0.11$
- 1- Prob of having NO complications = Prob of having AT LEAST 1 complication:  
 $1 - 0.11 = 0.89$
- There is an 89% chance that Patient Z had at least 1 complication during his inpatient stay.
- Therefore, Patient Z's raw complication rate is 89%.

#### *Caveats for Calculating Raw Complication Rates*

Newborns as defined by principal diagnosis are excluded from complication analyses. Also, for obstetrics patients, both secondary and principal diagnosis codes are considered in their complication calculations due to current coding practices. Finally, if the first three-digits of a patient's secondary diagnosis code are equal to the first three-digits of his principal diagnosis code, the secondary diagnosis code is excluded from his complication calculation.

### 3.1.2 CACI Maintenance

CACIs must periodically be reevaluated as a result of changes in medical practice, contestations, or additional information such as "present on admission (POA)" data. CACIs are selected for review through a screening process involving high volume, identification by internal clinicians, disputability, and immediate importance. Panels of external practicing physicians are assembled to review the CACIs through iterative rounds of surveys in a Delphi format using current CACIs and "Present on Admission" rates as reference. The panel's final consensus CACIs are reviewed by internal clinicians and then implemented into the CareScience complications model.

## IV. CareScience Complication Risk Model

The purpose of the CareScience Complication Risk Model is to generate the expected or "standard" complication rate ("risk" rate) under typical care in an inpatient setting, given the patient's health status and relevant characteristics. Patient-level complication risk is assessed via a stratified multiple regression model with the following functional form:

$$y_{ijk} = x_{ijk}\beta_k + \varepsilon_{ijk}, \forall ijk$$

where  $y_{ijk}$  is the complications risk rate at patient level  $i$ , provider  $j$ , and principal diagnosis  $k$ .  $x_{ijk}$  is a vector of patient characteristics and socioeconomic factors.  $\beta_k$  is the marginal effect of the independent variables on the complications outcome measure, and  $\varepsilon_{ijk}$  is the random error component of the model. The strata ( $k$ ) are roughly based on 3-digit level ICD-9-CM diagnosis codes. Rare and insignificant diagnoses are rolled up into broad diagnosis groups, which are defined in the ICD-9-CM book. A total of 140 disease strata are analyzed.

### 4.1 Independent Variables

The following patient characteristics and socioeconomic factors comprise the set of regressors (i.e. classes of independent variables) used in the CareScience Complication Risk Model.

1. **Age** (*quadratic form*)
2. **Sex** (*female, male, unknown*)
3. **Race** (*white, black, other, unknown*)
4. **Hispanic flag**
5. **Income** (*median household income within a zip code reported by US Census Bureau*)
6. **Distance traveled** (*the centroid-to-centroid distance between the zip code of the household and the zip code of the hospital or provider, represented as a relative term*)
7. **Principal diagnosis** (*terminal or three digit ICD-9-CM code, where statistically significant*)
8. **Comorbidity-Adjusted Complication Risk (CACR)<sup>6</sup> comorbidity scores** (*count of comorbidities within each of five severity categories on the CACR Likert scale*)

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<sup>6</sup> Brailer DJ, Kroch E, Pauly MV, Huang J. Comorbidity-Adjusted Complication Risk: A New Outcome Quality Measure, *Medical Care* 1996; 34:490-505.

9. **Cancer status** (*benign, malignant, carcinoma in situ, history of cancer, derived from secondary diagnoses*)
10. **Chronic disease and disease history** (*terminal digit ICD9-CM diagnosis codes, such as diabetes, renal failure, hypertension, chronic GI, chronic CP, obesity, and history of substance abuse*)
11. **Valid procedure** (*terminal ICD9-CM procedure codes, where clinically relevant and statistically significant*)
12. **Admission source** (*Physician Referral, Clinic Referral, HMO Referral, Transfer from a Hospital, Skilled Nursing Facility or Another Health Care Facility, Emergency Room, Court/Law Enforcement, Newborn - Normal Delivery, Premature Delivery, Sick Baby, or Extramural Birth, Unknown/Other*)
13. **Admission type** (*Emergency, Urgent, Elective, Newborn, Delivery, Unknown/Other*)
14. **Payor class** (*Self-pay, Medicaid, Medicare, BC/BS, Commercial, HMO, Workman's Compensation, CHAMPUS/FEHP/Other Federal Government, Unknown/Other*)
15. **Discharge disposition** (*Home or Self Care, Short-term General Hospital, Skilled Nursing Facility, Intermediate Care Facility, Other Type of Institution, Home under Care of Organized Home Health Service, Left against Medical Advice, Discharged Home on IV Medications, Expired, Unknown/Other*)

Risk factors used in the CareScience risk assessment model are tailored to specific patient subpopulations and outcomes. The use of the following risk factors may vary depending on the specific subpopulation and outcome evaluated:

- significant CACR comorbidities
- defining procedures
- diagnosis detail

#### 4.1.1 CACR Comorbidity Scores

CACR comorbidity scores are derived from principal and secondary diagnosis codes. Secondary diagnoses are first categorized according to a five point Likert scale of increasing severity (A-E) where E is most severe.<sup>7</sup> Comorbidities are calculated for each severity level as

$$N_{is} = \sum_{p_{ij} \in S} (1 - p_{ij}), \quad S = A, B, \dots, E$$

where  $N_{is}$  is the expected number of comorbidities of severity  $s$  for a patient with principal diagnosis  $i$ ,  $p_{ij}$  is the CACI probability of complication for the  $j$ th secondary diagnosis given principal diagnosis  $i$ , and  $S$  is one of the severity levels, A-E.

Common chronic diseases enter the model as dummy variables separate from comorbidities. Both comorbidities and chronic diseases are constrained to be non-negative coefficients in the model calibration.

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<sup>7</sup> Severity ratings are assigned by an internal panel of clinicians.

### **4.1.2 Valid Procedures**

Strictly speaking, a procedure is not a patient characteristic but rather a provider care choice. For example, two physicians may opt to pursue two different yet equally effective courses of treatment for the same patient. Although procedures represent the discretion of the care provider, they can signal important information about the patient's overall health status. Certain procedures can serve as effective proxies for lab reports and treatment history that are not available in the current database, as well as for other unobservable critical factors. To be included in the model, procedures must be designated as "valid" for the patient's particular disease stratum. Additionally, the timing of certain procedures relative to the patient's hospital admission must be considered. Valid procedures are grouped into one of two categories based on timing criteria.

Each disease stratum has a unique set of valid procedures. If a procedure falls into Category 1, timing of the procedure is not considered, and the analytic program simply searches for the procedure's corresponding coefficient. (Procedures failing to be statistically significant are not included in the model and have no impact on the risk score.<sup>8</sup>)

If a procedure is mapped to Category 2, inclusion of the procedure in the model depends on the procedure's timing during the inpatient stay. If the procedure occurs within a critical time period from the patient's hospital admission, the procedure is included in the model. If not, the procedure is excluded. The critical time windows for Category 2 procedures are assigned by internal panels of clinicians.

For several disease strata, the risk model does not incorporate valid procedures. These groups include DRGs 103, 480, 481, 495, 512, and 513.

### **4.1.3 Missing Independent Variables**

As with most large databases, some records may lack one or more independent variables. Dismissing these records completely from the analysis may eliminate important patient information and in turn shrink the base sample size. This is particularly true for public data sets where missing data elements are more common. Recognizing that independent variables have varying impacts on risk scores, the risk model is designed to tolerate missing values to some extent.

#### ***Zero Tolerance***

Principal Diagnosis and Age are mandatory elements in the risk assessment model. Patient records missing any of these required elements are excluded from the model.

#### ***Conditioned Tolerance***

For most categorical variables, such as Admission Source, there is an 'Unknown' category designated for unrecognizable or missing values. Among the categories, 'Unknown' statistically

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<sup>8</sup> See Sections 5.4 and 5.5 on Model Selection.

has the greatest probability of having the highest counts, since missing data are due to random errors. In risk modeling, the largest and most common category is often used as the reference group. Assigning the 'Unknown' category as the reference group is thus justifiable, however, a high proportion of 'Unknown' values risks diluting the real characteristics of the reference group.

Due to tight quality control, 'Unknown' values are very rare in private client data. In public data, however, the missing portion ranges from a couple of percent to around ten percent. It is therefore necessary to check the distribution of the data before calibration. In general, the 'Unknown' values should not represent more than one third of the entire sample in order to be used as the reference group.

### ***Value Proxy***

Income and Relative Distance are derived from zip code information. In the case of Income, the patient's residence zip code is used. For Relative Distance, both the patient's residence zip code and the hospital zip code are employed. If the patient's zip code is missing, the average Distance and Income of all patients in that hospital will be applied. In cases where both patient and hospital zip codes are unavailable, the Relative Distance is set to 1, and the national average income is applied.

## **V. Data Source and Model Calibration**

Premier employs three main data sources: MedPAR, All-Payor State data, and private client data. All three datasets are calibrated separately.

### ***5.1 MedPAR Data***

MedPAR consists of approximately 12 million inpatient visits that are covered by Medicare each year. These fiscal year data are generally consistent and updated annually with roughly a one-year lag time. (e.g. Fiscal year 2004 data were available at the end of 2005.) MedPAR covers all U.S. states and territories and is publicly available. Unsurprisingly, many research projects and publications are based on MedPAR. MedPAR covers around one-third of all hospital inpatients, almost all of which are 65 and older. Consequently, some specialties such as Pediatrics and Obstetrics are practically absent.

### ***5.2 All-Payor State Data***

All-Payor State data include all inpatients regardless of payor type or other restrictions, thus providing an advantage over MedPAR. Additionally, All-Payor State data contain a larger volume: roughly 20 million records from around 2700 hospitals. Despite these advantages, the data set has limitations. The most noticeable of these is that the data are less geographically representative. All-Payor State data come from fewer than 20 states located mostly on the coasts. In addition to this handicap, the data set lacks a continuum of data for each of the states, since changing regulatory laws often affect the availability of states' data from year to year. This

lack of continuous data can severely limit the feasibility of longitudinal studies. Additionally, because State data is released by individual states with their own data specifications, the data are often inconsistent across states. As a result, All-Payor State data require significant internal resources to validate and improve its quality. The two-year lag time in release prevents All-Payor State data from being chosen as the model's calibration database, because the standards of hospital care are in constant flux (reflected in part by new codes appearing every year to reflect changes in diagnosis, procedure, DRG, etc). Despite the aforementioned limitations, All-Payor State data remains a good choice for hospital ranking because of its volume and completeness of disease segments. It also serves as a reference data set for Premier's private data.

### ***5.3 Private Client Data***

In addition to the public data sets, Premier collects private data from clients. Client data are submitted in compliance with Premier's Master Data Specifications (MDS), ensuring its consistency and quality. The data are updated frequently with three to six months lag and offer much richer content that allows exploration of new model specifications. Annually, there are around two million records from 140 hospitals dispersed in 35 states. Because the client base is continually changing, the number of hospitals and records may fluctuate each year. The quality and richness of the client data make it an ideal calibration database despite its significantly smaller size than the two public data sets.

### ***5.4 Model Selection for Private Client Data***

To avoid overfitting, CareScience's model calibration employs Stepwise Selection for private client data with critical significance set at 0.10. Variables are added to the model one at a time with the computational program selecting the variable whose F statistic is the largest and also meets the specified critical significance. After a variable is added, the stepwise method inspects all variables in the model and deletes any whose F statistic fails to meet the specified significance threshold. Once the check is made and the necessary deletions accomplished, another variable is added to the model. This process effectively reduces the possibility of multicollinearity caused by highly correlated independent variables. The stepwise process ends when the F statistics for every variable outside the model fail to meet the significance threshold while the F statistics for every variable within the model satisfy the significance criterion.

Due to the selection criteria, the number of selected independent variables ranges from several to dozens, depending on the disease. The R-Square of the model may be smaller than that of a full model without restriction but are far more robust than an overfitted full model. For out-of-sample predictions, robust parameter estimates generate more reliable risk scores.

Chronic conditions and comorbidities are restricted to positive-only parameter estimates due to their clinical attributes.

### ***5.5 Model Selection for Public Data***

Public data sets are always calibrated on themselves. Because their parameter estimates are not used for out-of-sample predictions, a full model is preferred as it provides a higher R-Square.

## VI. Performance Assessment

Provider performance can be assessed for virtually any patient grouping (e.g. hospital-level, physician-level, principal diagnosis, DRG, procedure, etc.) through aggregation and comparison of the model's raw and risk complication rates. Positive deviations, as calculated below, indicate worse than expected (average) performance while negative deviations indicate better than expected (average) performance.

$$\text{Complication Deviation}_i = \frac{1}{n} \left( \sum_{i=1}^n \text{Raw Rate}_i - \sum_{i=1}^n \text{Risk Rate}_i \right), \quad i = 1, 2, \dots, n$$

where  $n$  is the number of patients in the  $i$ th patient group.

Statistical significance tests can be used to determine whether complication deviations indicate reliable areas for opportunity. Premier performance reports flag deviations significant at 75% and 95% confidence levels.

**Figure 5: Computing Complication Risk Rates and Deviations Example**

### Principal Diagnosis: Simple Pneumonia (486) Sample Patient Characteristics

Patient	Dependent Variable	Independent Variables							
	Raw Complication Rate (%)	Age	Age <sup>2</sup>	Gender Female=0 Male=1	Income	Comorbidities Severity A	Comorbidities Severity B	Chronic Condition 250.x2	...
1	96	42	1764	1	\$40,000	2	1	0	...
2	72	55	3025	1	\$55,000	1	2	0	...
3	64	63	3969	0	\$39,000	4	3	1	...
4	80	66	4356	0	\$25,000	3	3	1	...

### Principal Diagnosis: Simple Pneumonia (486)

Independent Variable	Coefficient (Parameter Estimate)
Age	0.00068
Age <sup>2</sup>	0.0000084
Gender	0.01707
Income	0.000000117
Comorbidities Severity A	0.03553
Comorbidities Severity B	0.08394
Chronic Condition 250.x2	0.00875
...	...

### Patient-Level Risk:

$$\begin{aligned} \text{Complication Risk} &= b_0 + b_1(\text{age}) + b_2(\text{age}^2) + b_3(\text{gender}) + b_4(\text{income}) + \dots \\ &= 0.15 + 0.00068(\text{age}) + 0.0000084(\text{age}^2) + 0.01707(\text{gender}) + 0.000000117(\text{income}) + \dots \\ &= 0.15 + 0.00068(42) + 0.0000084(1764) + 0.01707(1) + 0.000000117(40,000) + \dots = 0.2392 \end{aligned}$$

- Patient 1 has a 23.9% chance of developing at least 1 complication during his inpatient stay.

(Continued next page...)

**Provider-Level Risk:**

Patient	Complication Raw Rate (%)	Complication Risk Rate (%)
1	96	24
2	72	56
3	64	35
4	80	40
5	50	17
6	30	35
<b>SUM</b>	<b>392</b>	<b>207</b>

Raw Rate = 392%/6 = 65%

Risk Rate = 207%/6 = 35%

- **Complication Deviation = 65% - 35% = 30% (excess complication)**

## VII. Validation Studies

Validation studies have shown that the CareScience Complication Risk Model yields similar results to chart reviews at the aggregate level, particularly for surgically treated patients.<sup>9</sup>

### 7.1 Azimuddin et al – Colorectal Surgery Comparison

A study by Azimuddin et al<sup>10</sup>, which examined 270 major colorectal operations over 21 months, showed that Premier’s predicted distribution of comorbidities was similar to the actual occurrences in 15 of 17 categories of procedures. The overall incidence of complications obtained by physician review was 47% (actual), compared with 46% predicted by Premier. Additionally, the CareScience Complication Risk Model was on target for most of the underlying complication distribution detail.

### 7.2 Hover –Comparison at St. John’s Health System

Alex Hover at St. John’s Health System compared the results of CareScience’s Complication Risk Model against chart reviews for nine high volume conditions including *Coronary Bypass Graft, Laminectomy, Hysterectomy, Total Joint Replacement, Small and Large Bowel Resection, Gastrointestinal Hemorrhage, Congestive Heart Failure, Pneumonia, and Cesarean Section*.<sup>11</sup>

<sup>9</sup> Azimuddin K, Rosen L, Reed JF. Computerized Assessment of Complications after Colorectal Surgery. *Diseases of Colon & Rectum* 2001; 44:500-505.

<sup>10</sup> Ibid.

<sup>11</sup> Hover A. Evaluation of CaduCIS Manager for Nine High Volume Conditions at St. John’s Health System. Medical Management Services, St. John’s Health System. 1999.

Hover's study found that the CareScience model calculated an average of 88.1% of secondary diagnoses as preexisting with a range of 81.6-95.8% across 8 of the high volume conditions (CABG excluded). This correlated well with the nurse chart review that identified an average of 87.4% secondary diagnoses as preexisting across the 8 conditions with a range of 75-95.9%. Hover's team concluded that use of the CareScience Complication Risk Model would save significant resources from reviewing charts manually.

### **7.3 Comparison of CACI Rates to Present on Admission Rates**

The Premier Research Team conducted a comparison of CACI predicted raw complication rates against Present on Admission (POA) data for two large California hospitals. The results of the study showed that for ~75% of principal-secondary diagnosis pairs, the CACI-POA difference is less than 10% and that the average CACI rate is almost identical to the POA rate. The CACI to POA Pearson correlation was 64%.

The case-weighted CACI rate was higher than that of POA, and the CACI variability was less than that of POA.

## **Part II: Complication Morbidity**

### **VIII. Significance**

Premier's complication measure encompasses the full spectrum of harm from inpatient events with virtually no consequence to those that are life-threatening and cause significant suffering and cost. For performance improvement efforts, however, complications in this latter category often offer the greatest opportunities and clinical relevance. Premier's complication morbidity measure identifies this subset of inpatient events with severely adverse impacts on care processes and patient well-being.

### **IX. CareScience Complication Morbidity Model**

Within the CareScience model, morbidity is defined as the severity of a patient's complications and is grouped into 5 severity levels, 'A' to 'E.' These categories represent a Likert scale with 'A' denoting events having trivial or no effect on care processes and 'E' reserved for events precipitating radical departures from standard treatment. Complications in categories 'D' and 'E' represent truly severe conditions that jeopardize patient well-being and are considered 'morbid' complications. They are measured separately under the label 'morbidity' and often result in organ failure, unscheduled ICU admission, rescue procedures, and significant increases in length of stay.

Most common secondary diagnoses fall into categories 'B' or 'C,' while categories 'D' and 'E' are less common.

**Figure 6: Premier Morbidity Ratings**

Morbidity Rating	Clinical Impact	% of All Complications	Cost per Complication	Marginal Mortality
<b>A</b>	<b><u>NONE or TRIVIAL</u></b> <i>(E.g. diarrhea NOS, dysphagia, etc)</i>	37%	\$1,027	0%
<b>B</b>	<b><u>MINOR</u></b> departure from standard course of treatment <ul style="list-style-type: none"> <li>• 1 or 2 day increase in LOS</li> </ul> <i>(E.g. hypothyroidism, leiomyoma, etc)</i>	23%	\$2,433	0.7%
<b>C</b>	<b><u>MODERATE</u></b> departure from standard course of treatment, requiring active intervention <ul style="list-style-type: none"> <li>• unscheduled ICU admission</li> <li>• 1 or 2 day increase in LOS</li> </ul> <i>(E.g. coagulation defect, pleural effusion NOS, etc)</i>	19%	\$6,849	3.8%
<b>D MORBID</b>	<b><u>MAJOR</u></b> departure from standard course of treatment <ul style="list-style-type: none"> <li>• 50% risk of temporary impairment</li> <li>• unscheduled ICU admission</li> <li>• 3+ day increase in LOS</li> </ul> <i>(E.g. septicemia, acute respiratory failure, etc.)</i>	15%	\$14,490	8.5%
<b>E MORBID</b>	<b><u>RADICAL</u></b> departure from standard course of treatment <ul style="list-style-type: none"> <li>• 50% risk of impairment</li> <li>• unscheduled ICU admission</li> <li>• doubling LOS</li> </ul> <i>(E.g. cardiac arrest, coma, anoxic brain damage, etc)</i>	6%	\$36,300	18.4%

Brailer DJ, Kroch E, Pauly MV, Huang J. Comorbidity-Adjusted Complication Risk: A New Outcome Quality Measure, Medical Care 1996; 34:490-505.

### 9.1 Morbidity Assignments

Morbidity ratings are assigned by internal panels of clinicians at the terminal digit-level of diagnosis codes. For instance, uncomplicated type I diabetes mellitus (250.01) is classified as category ‘B’ while type I diabetes mellitus with neuro manifestation (250.61) is considered more severe and thus grouped into category ‘C.’

There are currently 514 secondary diagnosis codes with morbidity assignments, accounting for approximately 80% of all secondary diagnoses. Diagnosis codes lacking a morbidity assignment are not dropped from morbidity analyses but are instead grouped into an ‘unspecified’ category labeled ‘U.’ As the morbidity assignments’ normal distribution suggests, category ‘U’ diagnoses generally share similar characteristics as the most common categories ‘B’ and ‘C.’

### 9.1.1 Calculating Raw Morbidity

Morbidity is calculated as the probability of having at least one morbid complication. Mathematically, it is computed like complications, however, only secondary diagnoses rated ‘D’ or ‘E’ are included in the calculation.

$$1 - \prod_j (1 - p_{ij}), j = 1, 2, \dots, n$$

where  $n$  is the number of secondary diagnoses with morbidity ratings of ‘D’ or ‘E’, and  $p_{ij}$  is the probability of complication for the  $j$ th secondary diagnosis given principal diagnosis  $i$

Since only a subset of complications are considered in morbidity calculations, morbidity rates are always less than (or equal) to their corresponding complication rates.

*Figure 7: Raw Morbidity Rate Example for Patient Y*

**Patient Y**  
**Principal Diagnosis = Acute Myocardial Infection (410)**

Secondary Diagnosis (SDx)	Probability SDx is a Complication	Probability SDx is NOT a Complication	Morbidity Rating	Morbid
Type II Diabetes Mellitus w/ Renal Manifestation (250.40)	0	1	C	
Glaucoma NOS (365.9)	0	1	B	
Urinary Tract Infection (599.0)	0.64	0.36	B	
Congestive Heart Failure (428.0)	0.55	0.45	D	✓
Respiratory Failure (518.81)	0.76	0.24	D	✓

- Probability that Patient Y had NO morbid complications:  
 $0.24 \times 0.45 = 0.108$
- 1- Prob of having NO complications = Prob of having AT LEAST 1 morbid complication:  
 $1 - 0.108 = 0.892$
- There is an 89.2% chance that Patient Y had at least 1 morbid complication during his inpatient stay.

- Therefore, Patient Y's raw morbidity rate is 89.2%.

## X. CareScience Complication Morbidity Risk Model

The CareScience Complication Morbidity Risk Model is estimated with the same functional form, regressors, and data requirements as the Complication Risk Model except that the dependent variable is restricted to morbid complications. Please see sections IV and V for information on independent variables, calibration, and data.

## XI. Performance Assessment

As with complications, provider performance for morbidity can be assessed for virtually any patient grouping (e.g. hospital-level, physician-level, principal diagnosis, DRG, procedure, etc.) through aggregation and comparison of the model's raw and risk rates. Positive deviations indicate worse than expected (average) performance while negative deviations indicate better than expected (average) performance:

$$\text{Complication Morbidity Deviation}_i = \frac{1}{n} \left( \sum_{i=1}^n \text{Raw Rate}_i - \sum_{i=1}^n \text{Risk Rate}_i \right), \quad i = 1, 2, \dots, n$$

where  $n$  is the number of patients in the  $i$ th patient group.

Statistical significance tests can be used to determine whether complication morbidity deviations indicate reliable areas for opportunity. Premier performance reports flag deviations significant at 75% and 95% confidence levels.

**Figure 8: Computing Complication Morbidity Risk Rates and Deviations Example**

**Principal Diagnosis: Acute Myocardial Infarction (410)**

**Sample Patient Characteristics**

Patient	Dependent Variable	Independent Variables							
	Raw Morbidity Rate (%)	Age	Age <sup>2</sup>	Gender Female=1 Male=0	Income	Comorbidities Severity A	Comorbidities Severity B	Chronic Condition 250.x2	...
1	76	61	3721	1	\$25,000	3	2	0	...
2	88	55	3025	1	\$22,000	1	3	0	...
3	63	63	3969	0	\$75,000	4	3	1	...
4	71	70	4900	1	\$20,000	3	4	0	...

**Principal Diagnosis: Acute Myocardial Infarction (410)**

Independent Variable	Coefficient (Parameter Estimate)
Age	Not Significant
Age <sup>2</sup>	0.00000147
Gender	0.00682

Income	-0.000000129
Comorbidities Severity A	Not Significant
Comorbidities Severity B	0.00866
Chronic Condition 250.x2	0.0285
...	...

**Patient-Level Risk:**

$$\begin{aligned} \text{Morbidity Risk} &= b_0 + b_1(\text{age}^2) + b_2(\text{gender}) + b_3(\text{income}) + \dots \\ &= 0.039 + 0.00000147(\text{age}^2) + 0.00682(\text{gender}) - 0.000000129(\text{income}) + \dots \\ &= 0.039 + 0.00000147 (3721) + 0.00682 (1) - 0.000000129 (25000) + \dots = 0.582 \end{aligned}$$

- Patient 1 has a 58.2% chance of developing at least 1 morbid complication during her inpatient stay.

**Provider-Level Risk:**

Patient	Morbidity Raw Rate (%)	Morbidity Risk Rate (%)
1	76	58
2	88	70
3	63	40
4	71	80
5	50	17
6	30	40
<b>SUM</b>	<b>378</b>	<b>305</b>

Raw Rate = 378%/6 = 63%

Risk Rate = 207%/6 = 51%

- **Complication Morbidity Deviation = 63% - 51% = 12% (excess morbid complication)**

## XII. Relationship to Other Quality Outcomes

Risk-adjusted rates of 177 Pennsylvania hospitals show that complication morbidity is uncorrelated with mortality (0.02) and only loosely correlated with complications (0.26).<sup>12</sup> These low correlations justify the use of multiple performance indicators for assessing quality of care.

*Figure 9: Pearson Correlations*

Outcome	Mortality	Complications
Complication Morbidity	0.02	0.26
Complications	-0.01	-

<sup>12</sup> Pauly MV, Brailer DJ, and Kroch EA. The Corporate Hospital Rating Project: Measuring Hospital Outcomes from a Buyers Perspective, *American Journal of Medical Quality*, **11**(3):112-122.

