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Development of a comorbidity index using physician claims data

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Abstract

Important comorbidities recorded on outpatient claims in administrative datasets may be missed in analyses when only inpatient care is considered. Using the comorbid conditions identified by Charlson and colleagues, we developed a comorbidity index that incorporates the diagnostic and procedure data contained in Medicare physician (Part B) claims. In the national cohorts of elderly prostate (n = 28,868) and breast cancer (n = 14,943) patients assessed in this study, less than 10% of patients had comorbid conditions identified when only Medicare hospital (Part A) claims were examined. By incorporating physician claims, the proportion of patients with comorbid conditions increased to 25%. The new physician claims comorbidity index significantly contributes to models of 2-year noncancer mortality and treatment received in both patient cohorts. We demonstrate the utility of a disease-specific index using an alternative method of construction employing study-specific weights. The physician claims index can be used in conjunction with a comorbidity index derived from inpatient hospital claims, or employed as a stand-alone measure.

Keywords: Comorbidity; Claims data; Administrative data; Medicare; Breast cancer; Prostate cancer

1. Introduction

Comorbidities are coexisting medical conditions that are distinct from the principal diagnosis or the primary illness for which the patient seeks health care services [1–3]. Comorbidities can be either chronic diseases or acute illnesses, and can increase a patient's total burden of illness [3,4]. Compared to patients who do not have these conditions, patients with comorbid illnesses may be at greater risk of complications or death, less able to tolerate particular medical procedures, and less responsive to therapy [1,3]. Furthermore, physicians may factor the presence of particular comorbidities into decisions concerning the most appropriate medical treatments for patients. For example, studies involving breast and prostate cancer patients have found that patients with more comorbidities receive less aggressive treatment for their tumors, even after controlling for patient age and cancer stage [5,6]. The reluctance to pursue a course of aggressive therapy, particularly surgery, in patients with a high burden of comorbid conditions likely stems from their substantially increased risk of complications and death [7].

The complexity of comorbidity data and its potential for creating unwieldy analyses has led to the development of summary comorbidity measures such as the Charlson index [8,9]. Based on medical record review, Charlson and colleagues developed a weighted index measure of comorbidity that was shown to predict 1-year all-cause mortality in a cohort of 559 hospitalized medical service patients and 10-year non-breast cancer mortality in cohort of 685 breast cancer patients. The index is comprised of 19 conditions, each of which is assigned a weight according to its potential for influencing mortality. Charlson and colleagues used as weights the adjusted hazard ratios (referred to in their article as "relative risks") from a stepwise proportional hazards model, rounded to the nearest integer. The patient's comorbidity index, the sum of the weighted comorbidities, takes into account both the number and seriousness of the conditions. A higher score on the Charlson index indicates a greater burden of comorbid disease.

Deyo *et al.* [10] adapted the Charlson index for use with the ICD-9-CM diagnostic and procedure codes available in administrative datasets, and demonstrated the utility of this adapted measure in predicting risk of poor outcomes for patients following lumbar spine surgery. The Deyo adaptation involves searching a patient's hospital claims data for the presence of certain ICD-9-CM diagnosis and procedure

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codes corresponding to the Charlson comorbid conditions. An important limitation of the Deyo/Charlson comorbidity measure, however, is that it was developed and validated on the basis of inpatient hospital care. To date, studies that have used the measure have included only data from the inpatient setting [11–13]. It is possible that important comorbidities recorded on outpatient claims are missed in analyses when only inpatient care is considered [11,14], particularly because an estimated 80% of Medicare beneficiaries are not hospitalized in a given year [15]. Because of the ongoing shift toward delivery of health care services exclusively in outpatient settings, consideration of comorbidities recorded in outpatient claims is of particular importance when assessing treatment patterns in more recent years.

This article describes the development of a comorbidity measure using Charlson's conditions, the diagnostic and procedure data contained in Medicare physician (Part B) claims, and a new methodologic approach. Although other validated comorbidity measures such as the Kaplan-Feinstein index [16] and Index of Coexistent Disease [5] are available, we chose to build upon the Charlson index because of its wide use with claims data. The new measure is validated by assessing whether comorbidity information derived from physician claims significantly contributes to models of short-term noncancer mortality in national cohorts of elderly breast and prostate cancer patients. Prior studies [10,17–21] also have demonstrated the utility of the Charlson comorbidity index, developed as a prospective means of evaluating risk of death, in predicting such nonmortality outcomes as complications, length of stay, and charges. In this study, we also evaluate whether inclusion of physician claims data significantly contributes to models of type of cancer treatment received in breast and prostate cancer patients. Finally, we propose a method of index construction that avoids arbitrary thresholds for condition exclusion and uses a scale more closely related to the model that produces the condition weights.

2. Methods

2.1. Data sources

Data for this study were derived from two sources: 1) the National Cancer Institute's Surveillance, Epidemiology, and End Results (SEER) program, and 2) Medicare claims.

2.1.1. SEER

The SEER program is a National Cancer Institute-funded, population-based system of cancer registries. Data on all cancers except nonmelanoma skin diagnosed in individuals who reside in the SEER reporting area at the time of diagnosis are gathered by the SEER registries [22]. Data reported to SEER include the date of cancer diagnosis, reporting source, age at diagnosis, tumor stage and grade, patient demographic characteristics, whether the patient has a prior history of cancer, and type of surgery or radiation therapy planned or given within the first 4 months of diagnosis. Patients in the SEER system are subsequently followed to determine survival status and cause of death, with data on cause of death obtained from the National Center for Health Statistics. Eleven SEER sites, covering nearly 14% of the U.S. population, were included in this study: Atlanta, Connecticut, Detroit, Hawaii, Iowa, Los Angeles, New Mexico, San Francisco/Oakland, San Jose/Monterey, Seattle/Puget Sound, and Utah.

2.1.2. Medicare

Medicare files used in the analysis include: 1) Master enrollment file, with information about Part A and Part B entitlement, health maintenance organization (HMO) enrollment status, and demographic characteristics for each Medicare beneficiary; 2) Part A inpatient hospitalization files, containing a summarized record of each hospital inpatient stay, including date of admission and discharge and up to 10 diagnoses and 10 procedures recorded using ICD-9-CM codes [23]; and 3) Part B physician, supplier, and outpatient facility files. Data from physician claims include a Common Procedure Terminology (CPT) code [24] for each billed procedure. Each CPT code must be accompanied by an ICD-9-CM diagnosis code that describes the reason for the service. Data were available for 100% of Medicare beneficiaries.

2.1.3. Dataset linkage

SEER and Medicare records have been linked to provide a database for studying the utilization of health services and costs involved in cancer care delivery. This linkage, described in detail elsewhere [25], presently includes cancer diagnosed through 1993. In the linkage, 93% of SEER-recorded cancer cases among the elderly were successfully merged with Medicare enrollment data.

2.2. Case selection

From the SEER–Medicare-linked dataset, we identified 35,615 men diagnosed with prostate cancer and 17,724 women diagnosed with breast cancer in any of 11 SEER areas during the period January 1, 1992 through December 31, 1993. To optimize the likelihood of identifying comorbidities recorded in inpatient hospital and physician claims in the 12 months prior to diagnosis, eligible patients were age 66 or older at diagnosis and continuously enrolled in both Part A and Part B of Medicare. Patients whose cancer was diagnosed by autopsy or on death certificates ($n = 356$ prostate; $n = 89$ breast) were excluded. Also excluded were patients whose Medicare claims data were incomplete, including those enrolled in health maintenance organizations (HMOs) in any month within the 12-month period prior to diagnosis with cancer ($n = 6405$ prostate; $n = 2699$ breast). The final study cohorts comprised 28,868 men with prostate cancer and 14,943 women with breast cancer.

2.3. Identifying comorbid conditions

ICD-9-CM diagnostic codes recorded in Medicare claims during the 12-month period prior to the patient's di-

agnosis with breast or prostate cancer were searched for the comorbid conditions identified by Charlson *et al.* [9] as significantly influencing mortality. The month of diagnosis was excluded to avoid identifying complications or conditions directly resulting from cancer treatment as comorbidities. Although solid tumors and leukemia and lymphoma are comorbid conditions in the Charlson idex, we excluded the diagnostic codes corresponding to these conditions because of our focus on studying comorbidity in cancer patients. ICD-9-CM diagnostic codes from Part B clinical laboratory, diagnostic imaging, and durable medical equipment claims also were excluded to maximize the likelihood that clinician-assigned codes would be used. Furthermore, because of the concern that the accuracy of the diagnoses recorded in Part B claims has not been established, ICD-9-CM diagnostic codes corresponding to comorbid conditions in physician claims were examined for each patient. If a code appeared only once in physician claims during the year prior to the patient's cancer diagnosis and an identical code was not present in inpatient hospital claims, the condition was excluded from calculation of comorbidity indices. Likewise, if a code appeared more than once in physician claims within a 30-day period but never appeared again in either inpatient hospital or physician claims, the condition was excluded. The rationale for requiring a condition to appear on more than one physician claim is supported by prior studies showing poor agreement between medical records and administrative claims in the diagnostic information recorded [26,27].

2.4. Developing weights for new comorbidity measures

Weights for two new comorbidity indices, Inpatient Claims and Physician Claims, were obtained by fitting for each cohort a single Cox proportional hazards model with 2-year mortality from causes other than cancer as the dependent variable. Patients who died of cancer within the 2-year follow-up period or who were alive as of December 1994 were treated as censored cases. Survival was measured as the number of months surviving during the follow-up period, which commenced with the month of diagnosis. Both models incorporated dichotomous indicators (1 = condition present; 0 = condition absent) for each Charlson condition as explanatory variables, and reflected whether the condition was identified in inpatient hospital claims, or in physician claims only (and not appearing in inpatient hospital claims). Thus, for each condition, indicators for inpatient hospital and physician claims were mutually exclusive. We used this approach because an inpatient hospital claim is nearly always accompanied by a physician claim, and attributing the same condition to both the inpatient hospital and physician claims indicators poses conceptual and computational difficulties. Patient age at diagnosis, a continuous measure, was included as an additional explanatory variable. Modeling was carried out using a randomly selected half of each patient cohort (i.e., "development"datasets). Unlike the approach of Charlson and colleagues [9], we used the estimated coefficient values (rather than adjusted hazard ratios) as weights in the new Inpatient Claims and Physician Claims indices.

2.5. Calculating comorbidity measures

For each patient cohort, we computed three comorbidity measures: 1) the Charlson index; 2) Inpatient Claims index; and 3) Physician Claims index. We calculated the Charlson index from comorbid conditions identified in inpatient hospital claims and using Charlson's method [9]. Thus, adjusted hazard ratios were obtained from the multivariate Cox models described in the previous section. Only conditions with an adjusted hazard ratio of 1.2 or greater were retained. Adjusted hazard ratios were then rounded to the nearest integer. The integer weights were multiplied by their corresponding condition indicators and summed to create the index.

In contrast, the Inpatient Claims and Physician Claims indices were constructed by multiplying each dichotomous condition indicator by its corresponding estimated coefficient and then summing over all conditions to create an index or risk score [28]. The Inpatient Claims index was derived from comorbid conditions identified in inpatient hospital claims, while the Physician Claims index was derived from comorbid conditions found in physician claims but not appearing in inpatient hospital claims. Summing the estimated coefficients rather than exponentiated coefficients (i.e., hazard ratios) results in a scale for the comorbidity measures that is consistent with the Cox proportional hazards and logistic regression models in which the measures are used [20].

2.6. Assessing comorbidity measures—predicting mortality

For each patient cohort, the remaining half of the dataset not used in developing weights for comorbidity indices was employed to assess the indices' predictive ability. Cases in these "test" datasets (n = 14,429 prostate; n = 7,472 breast) were used to fit Cox proportional hazards models with 2-year noncancer mortality as the dependent variable and age and the comorbidity index of interest as explanatory variables. A base model that included age but not comorbidity also was fit. Similar to the models used in obtaining condition weights, patients who died of cancer within the 2-year follow-up period or who were alive at the end of this period were treated as censored cases. Survival was measured in months. The validity of the proportional hazards assumption was assessed for each model by plotting residuals and examining survival curves. The likelihood ratio test was used to compare nested models. Two-way interaction between the Inpatient Claims and Physician Claims indices was tested in models containing both measures, in both cohorts. These interaction terms were not statistically significant.

2.7. Assessing comorbidity measures—predicting treatment

The "test" halves of the breast and prostate cancer datasets were used in logistic regression models predicting treat-

ment type. The C-statistic, which measures the area under the receiver operating characteristic (ROC) curve, was used to assess model fit [3]. Because a greater range of initial treatment options is available to prostate and breast cancer patients with early stage disease, these analyses were restricted to patients with early stage cancer, defined as local or regional in the prostate and stages I or II in the breast cohort. Receipt of less aggressive versus more aggressive therapy was the outcome of interest. For the prostate cancer cohort, patients who received nonsurgical management were compared to those who underwent radical prostatectomy. For the breast cancer cohort, patients who received breast-conserving surgery without radiation therapy were compared to those who underwent mastectomy or breast-conserving surgery with radiation therapy.

In both patient cohorts, age at diagnosis, race, education, geographic region, and the Inpatient Claims and Physician Claims comorbidity indices were included as explanatory variables. In addition, the prostate cancer treatment model included tumor grade, while the breast cancer treatment model included tumor stage. Age and the comorbidity indices were treated as continuous measures. Race was a categorical variable (white, black, other). Education, also a categorical variable, was estimated from 1990 U.S. Census data linked to SEER–Medicare through the patient's census tract of residence. The percentage of adults residing in the census tract who had failed to attain a high school diploma was used as a proxy measure of educational attainment. Education categories were defined as: 35–100% of adults have completed high school (high attainment); 20–34.9% have completed high school (medium attainment); and $<$20% have completed high school (low attainment). Geographic region was defined as the SEER area in which the patient resided at the time of diagnosis and initial treatment. Prostate tumor grade consisted of three ordinal categories that represent less to more aggressive cell growth and are based on the SEER grading system: well differentiated (corresponds to Gleason score 2–4), moderately differentiated (Gleason score 5–7), and poorly differentiated (Gleason score 8–10). Two ordinal categories were used to capture breast tumor stage (Stage I and Stage II) according to the tumor-node-metastasis (TNM) staging system [29]. Two-way interaction between the Inpatient Claims and Physician Claims comorbidity indices was assessed in both cohorts and was not statistically significant in either treatment model.

3. Results

Table 1 displays condition prevalences, estimated coefficients, and hazard ratios for comorbidities appearing in inpatient hospital or only in physician claims for the prostate cancer cohort. To facilitate comparison to Charlson's original weights (see Table 1, Charlson *et al.* article), this table also includes the study-derived hazard ratios for these comorbid conditions rounded to the nearest integer, according to the method of Charlson *et al.* [9]. Diabetes, chronic pulmonary disease, and congestive heart failure are the most commonly occurring conditions. Prevalences are higher in physician than in inpatient hospital claims for some but not all conditions. Coefficients and hazard ratios could not be estimated for moderate/severe liver disease and AIDS due to the rarity of these conditions (less than 10 cases each in inpatient hospital and physician claims). Study-derived hazard ratios obtained for seven conditions identified in inpatient hospital claims [diabetes, cerebrovascular disease, paralysis, peripheral vascular disease, acute myocardial infarction (MI), renal disease, and diabetes with complications] were similar to those obtained by Charlson *et al.* [9] in that the rounding procedure yielded identical weights. Study-derived hazard ratios differed from those obtained by Charlson *et al.* for seven conditions (the study-derived hazard ratio appears first and the hazard ratio reported by Charlson *et al.* second): chronic pulmonary disease (2.1 vs. 1.4), congestive heart failure (2.1 vs. 1.3), old MI (0.9 vs. 1.4), ulcer disease (0.7 vs. 1.4), dementia (1.1 vs. 1.4), rheumatologic disease (2.8 vs. 1.4), and mild liver disease (2.4 vs. 1.4). Had Charlson's method been used in constructing the Inpatient Claims and Physician Claims indices in the prostate cohort, three conditions (old MI, ulcer disease, and dementia) would have been excluded from the Inpatient Claims index, and one condition (old MI) from the Physician Claims index, because their hazard ratios were less than 1.2.

Condition prevalences, estimated coefficients, and hazard ratios for comorbidities appearing in inpatient hospital or only in physician claims for the breast cancer cohort are shown in Table 2. As with the prostate cohort, diabetes, chronic pulmonary disease, and congestive heart failure are the most commonly occurring conditions. For most conditions, the estimated coefficients and hazard ratios for conditions recorded in inpatient hospital claims are of greater magnitude than those identified only in physician claims. The rarity of moderate/severe liver disease and AIDS in inpatient hospital and physician claims and of old MI in physician claims precluded estimation of coefficients and hazard ratios for these conditions. Study-derived hazard ratios for conditions identified in inpatient hospital claims were similar to those obtained by Charlson *et al.* [9] for peripheral vascular disease and diabetes with complications but differed from the hazard ratios obtained by Charlson *et al.* [9] for 12 conditions: diabetes (1.7 vs. 1.4), chronic pulmonary disease (2.3 vs. 1.4), congestive heart failure (2.2 vs. 1.3), cerebrovascular disease (0.9 vs. 1.4), paralysis (3.4 vs. 1.9), acute MI (1.1 vs. 1.4), old MI (2.7 vs. 1.4), renal disease (3.8 vs. 1.5), ulcer disease (1.0 vs. 1.4), dementia (1.15 vs. 1.4), rheumatologic disease (2.5 vs. 1.4), and mild liver disease (3.3 vs. 1.4). If we had used Charlson's method to construct the Inpatient and Physician Claims indices in the breast cohort, four conditions each would have been excluded from the Inpatient Claims index (cerebrovascular disease, acute MI, ulcer disease, and dementia) and from the

Table 1
Condition prevalences, coefficients, and hazard ratios for comorbidities derived from Medicare data for the prostate cohort ($N = 14,439$), with comparison to hazard ratios obtained using the Charlson *et al.* method

	Inpatient Claims			Physician Claims			Charlson
Comorbid condition	Prevalence	Coefficient	Hazard ratio[a]	Prevalence	Coefficient	Hazard ratio[a]	Hazard ratio[a,b]
Diabetes	2.0%	0.39	1.48	6.9%	0.30	1.35	1
Chronic pulmonary disease	3.3%	0.74	2.11	4.5%	0.50	1.66	2
Congestive heart failure	2.3%	0.73	2.08	2.3%	0.86	2.36	2
Cerebrovascular disease	2.0%	0.32	1.37	1.4%	0.42	1.53	1
Paralysis	0.6%	0.61	1.84	0.9%	0.95	2.59	2
Peripheral vascular disease	1.0%	0.34	1.41	1.2%	0.40	1.50	1
Acute myocardial infarction	0.8%	0.23	1.26	0.3%	1.22	3.40	1
Old myocardial infarction	0.8%	0.09	0.92	0.4%	0.17	1.19	0
Moderate/severe renal disease	0.5%	0.72	2.05	0.5%	1.11	3.05	2
Diabetes with complications	0.2%	0.53	1.70	0.6%	0.89	2.44	2
Ulcer disease	0.4%	−0.34	0.71	0.3%	0.51	1.67	0
Dementia	0.3%	0.12	1.13	0.2%	0.90	2.45	0
Rheumatologic disease	0.1%	1.01	2.75	0.6%	0.35	1.42	3
Mild liver disease	0.1%	0.89	2.44	0.1%	1.80	6.06	2

[a] Derived from a Cox proportional hazards model with 2-year noncancer mortality as the dependent variable and age and comorbid conditions identified in inpatient and physician claims as the explanatory variables.
[b] Rounded to the nearest integer, following the method of Charlson *et al.* [9].

Physician Claims index (paralysis, acute MI, ulcer disease, and rheumatologic disease), because their hazard ratios were less than 1.2.

Ninety-two percent of prostate and 93% of breast cancer patients had Charlson scores of zero, while 91% of prostate and 92% of breast cancer patients had Inpatient Claims scores of zero. When physician claims are considered, the proportion of patients with a comorbidity score of zero drops to 75% in both cohorts. Descriptive statistics for the Charlson index and Inpatient and Physician Claims indices, with nonzero values exponentiated for comparison to the Charlson index, are provided in Table 3. In both cohorts, the mean Charlson score is lower than the mean Inpatient Claims score, reflecting the differences in weights between the two measures, while the mean Physician Claims scores exceed those of the inpatient-derived measures, indicating that physician claims contain major comorbid conditions not present in inpatient claims for many patients.

Cox proportional hazards models assessing the contribution of the three comorbidity measures to prediction of 2-year noncancer mortality in the "test" half of the prostate cancer cohort are shown in Table 4. Comparing the models shows that each index—Charlson, Inpatient Claims, and Physicians Claims—contributes to prediction of mortality. Likelihood ratio test results demonstrate that incorporation of the comorbidity index measure derived from physician claims in a model with the Inpatient Claims index (Model 5) significantly improves model fit [Model 5 vs. Model 3; χ^2 =

Table 2
Condition prevalences, coefficients, and hazard ratios for comorbidities derived from Medicare data for the breast cohort ($N = 7,471$), with comparison to hazard ratios obtained using the Charlson *et al.* method

	Inpatient Claims			Physician Claims			Charlson
Comorbid condition	Prevalence	Coefficient	Hazard ratio[a]	Prevalence	Coefficient	Hazard ratio[a]	Hazard ratio[a,b]
Diabetes	2.3%	0.52	1.67	7.5%	0.65	1.92	2
Chronic pulmonary disease	2.4%	0.83	2.29	3.9%	0.84	2.31	2
Congestive heart failure	2.3%	0.76	2.15	2.7%	0.74	2.09	2
Cerebrovascular disease	1.4%	−0.09	0.92	1.6%	1.10	3.01	0
Peirpheral vascular disease	0.5%	0.23	1.26	1.5%	0.75	2.12	1
Paralysis	0.4%	1.23	3.41	0.1%	−0.08	0.93	3
Acute myocardial infarction	0.5%	0.05	1.05	0.3%	−0.99	0.37	0
Old myocardial infarction	0.4%	1.00	2.72	0.1%	—	—	3
Moderate/severe renal disease	0.4%	1.34	3.83	0.4%	1.20	3.31	4
Diabetes with complications	0.2%	0.64	1.89	0.5%	0.36	1.44	2
Ulcer disease	0.2%	0.03	1.03	0.4%	−0.65	0.52	0
Dementia	0.3%	0.14	1.15	0.6%	1.07	2.92	0
Rheumatologic disease	0.2%	0.92	2.50	1.2%	−0.45	0.64	3
Mild liver disease	0.1%	1.19	3.29	0.1%	1.63	5.10	3

[a] Derived from a Cox proportional hazards model with 2-year noncancer mortality as the dependent variable and age and comorbid conditions identified in inpatient and physician claims as the explanatory variables.
[b] Rounded to the nearest integer, following the method of Charlson *et al.* [9].

Table 3
Descriptive statistics for the Charlson index and exponentiated inpatient and physician claims indices

	Prostate cohort (N = 14,429)			Breast cohort (N = 7,472)		
	Charlson[a]	Inpatient claims[b]	Physician claims[b]	Charlson[a]	Inpatient claims[b]	Physician claims[b]
Mean Score	0.20	0.23	0.31	0.20	0.24	0.44
Median Score	0	0	0	0	0	0
Score Range	0–10	0–27.0	0–20.6	0–9	0–23.7	0–18.3

[a] The Charlson index was constructed from adjusted relative risks rounded to the nearest integer.
[b] The inpatient and physician claims indices were constructed from estimated Cox regression coefficients. Nonzero values were exponentiated to obtain relative risk estimates for comparison with the Charlson index.

119.2, $P < 0.0001$]. Although the inpatient comorbidity measure has a greater impact in predicting mortality as evidenced by its larger hazard ratio, the contribution of the physician claims comorbidity measure is positive and statistically significant. This model would assign to a 66-year-old man with chronic pulmonary disease and congestive heart failure an inpatient comorbidity score of 1.47 (=0.74 + 0.73 from Table 1). Unlike a Charlson score, the score directly translates to a hazard ratio through exponentiation. Thus, the hazard of dying within 2 years of diagnosis for this hypothetical patient would be 4.3 times ($=e^{1.47}$) greater than for a comparable 66-year-old with an inpatient comorbidity score of zero. If these same conditions had been identified in physician claims only with no other conditions detected using either inpatient or physician claims, the model would assign a physician claims comorbidity score of 1.36 (=0.50 + 0.86 from Table 1). When compared to men with inpatient and physician claims comorbidity scores of zero, the hazard of dying within two years of diagnosis for this patient would be 3.9 times ($=e^{1.36}$) greater.

Table 5 displays Cox proportional hazards models assessing the contribution of comorbidity measures to prediction of 2-year noncancer mortality in the "test" half of the breast cancer cohort. Comparison of the models shows the Charlson, Inpatient Claims, and Physician Claims comorbidity indices each to contribute to prediction of mortality. Once again, likelihood ratio test results demonstrate that incorporation of the comorbidity measure derived from physician claims in a model with the Inpatient Claims index (Model 5) significantly improves model fit [Model 5 vs. Model 3; $\chi^2 = 53.9$, $P < 0.0001$]. Using this model for prediction reveals the hazard of dying within 2 years of diagnosis for a 66-year-old woman with an inpatient comorbidity score of 1.40 because of congestive heart failure and diabetes with complications to be four times greater than that of a comparably aged woman with an inpatient comorbidity score of zero. If this hypothetical 66-year-old woman had an inpatient comorbidity score of zero but a physician claims comorbidity score of 1.10 due to these same comorbid conditions, her hazard of dying would be three times higher than for a woman of similar age with comorbidity scores of zero.

Finally, logistic regression results from models that include both the Inpatient Claims and Physician Claims indices in prediction of less aggressive prostate and breast cancer treatment are displayed in Tables 6–8. In the prostate cancer treatment model, an increased comorbidity score is indicative of a reduced likelihood of undergoing radical prostatectomy for both measures. Holding constant age at diagnosis, tumor grade, race, education, geographic region, and comorbidity measured from physician claims, a one-unit increase in the inpatient comorbidity index conveys 2.5 times greater odds of receiving nonsurgical treatment for early stage disease. A

Table 4
Comparison of comorbidity indices: predicting 2-year noncancer mortality in prostate cancer patients (N = 14,429), SEER–Medicare, 1992–1993

	Coefficient	Hazard ratio	95% CI	Model −2 log likelihood
Model 1				15113.4
Age	0.10*	1.10*	1.09–1.11	
Model 2				14926.5
Age	0.09*	1.10*	1.09–1.11	
Charlson index	0.34*	1.40*	1.34–1.45	
Model 3				14921.0
Age	0.09*	1.10*	1.09–1.11	
Inpatient claims index	0.96*	2.61*	2.33–2.91	
Model 4				14984.7
Age	0.09*	1.10*	1.09–1.11	
Physician claims index	0.91*	2.49*	2.18–2.86	
Model 5				14801.8
Age	0.09*	1.09*	1.08–1.10	
Inpatient claims index	0.93*	2.53*	2.27–2.83	
Physician claims index	0.88*	2.41*	2.10–2.77	

*$P < 0.0001$.

Table 5
Comparison of comorbidity indices: predicting 2-year noncancer mortality in breast cancer patients ($N = 7,472$), SEER–Medicare, 1992–1993

	Coefficient	Hazard ratio	95% CI	Model −2 log likelihood
Model 1				6715.0
Age	0.09*	1.10*	1.09–1.11	
Model 2				6637.7
Age	0.09*	1.10*	1.08–1.11	
Charlson index	0.31*	1.36*	1.29–1.44	
Model 3				6641.6
Age	0.09*	1.10*	1.08–1.11	
Inpatient claims index	0.84*	2.31*	1.97–2.72	
Model 4				6662.9
Age	0.09*	1.09*	1.08–1.11	
Physician claims index	0.66*	1.94*	1.65–2.28	
Model 5				6587.7
Age	0.09*	1.09*	1.08–1.10	
Inpatient claims index	0.85*	2.35*	2.00–2.77	
Physician claims index	0.67*	1.95*	1.66–2.29	

*$P < 0.0001$.

one-unit increase in the physician claims comorbidity score increases the odds of receiving less aggressive therapy by a factor of 2.1, all else held constant.

Similar to the prostate model, an increased inpatient comorbidity score in the breast cancer treatment model is indicative of a greater likelihood of undergoing less aggressive therapy (breast conserving surgery only). An increased physician claims comorbidity score also predicts receipt of less aggressive therapy. As with the prostate cohort, the magnitude of the odds ratio for the inpatient claims measure is greater than that of the physician claims measure. Odds ratios for both indices are of somewhat smaller magnitude in the breast cancer than in the prostate cancer treatment models.

4. Discussion

The Charlson comorbidity index, adapted for use with administrative datasets [10,20], has been shown to predict a variety of patient outcomes, including mortality, postoperative complications, length of stay, and hospital charges [10,17–21]. The Charlson index, however, was developed and validated on the basis of inpatient hospital care [9]. We developed a new index measure of comorbidity derived from physician (Medicare Part B) claims data in two separate cohorts of elderly cancer patients, using 16 conditions identified as prognostically important by Charlson *et al.* [9]. The index was assessed independently and in the presence of a similarly constructed comorbidity index derived from inpatient hospital (Medicare Part A) claims. To evaluate the contribution of the Physician Claims index beyond the comorbidity information available in inpatient claims, we employed an algorithm that requires searching inpatient claims to ensure that each patient's physician claims comorbidity index is comprised of conditions recorded in physician claims but not appearing in inpatient claims. When only Medicare hospital (Part A) claims were examined, less than 10% of patients

Table 6
Contribution of comorbidity indices to prediction of receipt of less aggressive treatment in nonmetastatic prostate (nonsurgical vs. radical prostatectomy)[a,c] and early stage breast cancer patients (breast conserving surgery only vs. mastectomy or breast-conserving surgery with radiation therapy), SEER–Medicare, 1992–93[b,c]

	Prostate cancer treatment ($N = 11,170$)		Breast Cancer Treatment ($N = 5,438$)	
	Odds Ratio	95% CI	Odds Ratio	95% CI
Inpatient claims index	2.51**	1.90–3.32	1.88**	1.52–2.33
Physician claims index	2.13**	1.66–2.73	1.30*	1.07–1.56
Intercept Only −2 Log Likelihood:	13194.1		4873.4	
Model −2 Log Likelihood:	10073.4		4305.8	
C-Statistic:	0.82		0.74	

[a] Radical prostatectomy is defined as subtotal/simple prostatectomy, radical/total prostatectomy, or cystoprostatectomy.

[b] Breast-conserving surgery is defined as segmental/subtotal mastectomy, lumpectomy, quadrantectomy, tylectomy, wedge resection, nipple resection, excisional biopsy, or partial mastectomy not otherwise specified. Mastectomy is defined as subcutaneous mastectomy, simple mastectomy, modified radical mastectomy, or mastectomy not otherwise specified. Radiation therapy is defined as beam radiation, radioactive implants, radioisotopes, beam radiation combined with implants or isotopes, or radiation not otherwise specified.

[c] Other model covariates included age, tumor stage or grade, race, SES, and geographic region.

*$P < 0.01$; **$P < 0.0001$.

had comorbid conditions identified. By incorporating physician claims, the proportion of patients with comorbid conditions increased to 25%, illustrating the potentially important contribution of physician claims data to the measurement of comorbidity.

Using Cox proportional hazards models, we estimated study-specific weights for incorporation in comorbidity measures derived from inpatient hospital and physician claims in both patient cohorts, with 2-year noncancer mortality as the outcome of interest. Unlike the methodology of Charlson *et al.* [9], we used the estimated coefficients obtained from these models rather than the exponentiated coefficients (i.e., hazard ratios) as weights for the conditions in the indices, and did not exclude conditions from comorbidity indices based on an arbitrary threshold. This approach permits the direct transformation of an individual's comorbidity score into an estimated hazard ratio through exponentiation. Furthermore, it results in comorbidity measures with distributional properties that are consistent with the Cox proportional hazards and logistic regression models in which they are commonly applied.

We compared the study-derived hazard ratios for 14 conditions identified in inpatient hospital claims to Charlson's hazard ratios and found these to be dissimilar for seven conditions in the prostate and 12 conditions in the breast cancer cohort. Furthermore, comparison of estimated coefficients between the two patient cohorts revealed differences in magnitude for many conditions, in inpatient as well as physician claims. These findings may reflect differences in the patient cohorts examined in this study compared to Charlson's study, as well as the increased acuity of hospitalized patients in the 1990s compared to the 1984 cohort of medical service patients used in the development of Charlson condition weights [9]. Moreover, our models used 2-year noncancer mortality as the dependent variable, whereas Charlson used 1-year all-cause mortality. Also, because cause of death was obtained from death certificates in this study and medical records in Charlson's study, differences in estimates may be due in part to errors in ascertaining cause of death from these data sources, especially death certificates [30,31]. In addition, it is likely that different weights for the 16 conditions considered and more sensitive comorbidity measures would have been obtained had we been able to assess mortality over a longer period of follow-up than 2 years. Our results clearly support the contention that researchers should not rely on Charlson's weights but rather examine their own data to establish weights for comorbid conditions [18,20,32].

Negative coefficients, suggesting a protective association between the condition and mortality outcome measure, were obtained for certain comorbid conditions in both cohorts. For example, negative coefficients for ulcer disease in the prostate and for cerebrovascular disease in the breast cancer cohort in inpatient claims and for paralysis, acute MI, ulcer disease, and rheumatologic disease in the breast cancer cohort in physician claims were obtained. We did not exclude these conditions from the inpatient and physician claims comorbidity indices for three reasons. First, the conditions had been identified by Charlson *et al.* as important comorbidities and a primary goal of this study was to examine Charlson's approach with contemporary data. Second, one must be circumspect about interpreting individual coefficients because they were obtained from multivariate models in which all conditions were entered simultaneously. Third, our main intent in creating the comorbidity indices was to obtain a risk score or ranking of the patients in each cohort, not to assess conditions individually.

We showed that comorbidity information derived from physician claims contributes to models of short-term mortality and aggressive therapy receipt in prostate and breast cancer patients independently and in the presence of a comorbidity index derived from inpatient hospital claims. The contributions of the physician claims measure to assessment of mortality and aggressive therapy receipt in both cohorts were somewhat more modest than those of the inpatient hospital measure, even though individual hazard ratios were of greater magnitude in physician than in inpatient claims for some conditions. This finding may be explained by the greater prevalence of the condition in physician claims, resulting in a stronger association between the condition and mortality outcome measure. Second, application of the rule-

Table 7
Contribution of comorbidity indices to prediction of treatment (nonsurgical vs. radical prostatectoy) in prostate cancer patients with nonmetastatic disease, SEER–Medicare, 1992–93 ($N = 11{,}170$)[a]

	Odds ratio	95% CI
Age	1.25	1.25–1.27
Well differentiated	1.00	—
Moderately differentiated	0.36****	0.31–0.42
Poorly differentiated	0.34****	0.29–0.40
Unknown differentiation	1.80**	1.26–2.56
White	1.00	—
Black	1.82****	1.46–2.27
Other	1.29*	1.07–1.56
High SES	1.00	—
Medium SES	1.22***	1.09–1.37
Low SES	1.28**	1.07–1.53
Connecticut	1.00	—
Atlanta	0.29****	0.22–0.38
Detroit	0.53****	0.43–0.64
Hawaii	0.29****	0.20–0.41
Iowa	0.44****	0.35–0.54
Los Angeles	0.19****	0.16–0.23
New Mexico	0.26****	0.20–0.34
San Francisco	0.27****	0.21–0.34
San Jose	0.27****	0.20–0.35
Seattle	0.25****	0.20–0.31
Utah	0.13****	0.10–0.16
Inpatient claims index	**2.51****	**1.90–3.32**
Physician claims index	**2.13****	**1.66–2.73**

Intercept Only −2 Log Likelihood: 13194.1
Model −2 Log Likelihood: 10073.4
C-Statistic: 0.82

[a] Radical prostatecomy is defined as subtotal/simple prostatectomy, radical/total prostatectomy, or cystoprostatectomy.

*P < 0.01; **P < 0.005; ***P < 0.001; ****P < 0.0001.

Table 8
Contribution of comorbidity indices to prediction of treatment (breast-conserving surgery only vs. mastectomy or breast-conserving surgery with radiation therapy) in early stage breast cancer patients, SEER–Medicare, 1992–93 ($N = 5{,}438$)[a]

	Odds ratio	95% CI
Age	1.11****	1.09–1.12
Stage I	1.00	—
Stage II	0.43****	0.37–0.51
White	1.00	—
Black	1.79***	1.31–2.46
Other	1.08	0.76–1.54
Connecticut	1.00	—
Atlanta	0.46****	0.31–0.68
Detroit	0.64****	0.49–0.83
Hawaii	0.51	0.25–1.02
Iowa	0.38****	0.28–0.50
Los Angeles	0.83	0.64–1.07
New Mexico	0.46**	0.28–0.74
San Francisco	0.40****	0.29–0.56
San Jose	0.39****	0.25–0.60
Seattle	0.56****	0.41–0.75
Utah	0.48**	0.31–0.73
Inpatient claims index	**1.89****	**1.52–2.33**
Physician claims index	**1.30***	**1.07–1.56**

Intercept Only −2 Log Likelihood: 4873.4
Model −2 Log Likelihood: 4305.8
C-Statistic: 0.74

[a] Breast-conserving surgery is defined as segmental/subtotal mastectomy, lumpectomy, quadrantectomy, tyletomy, wedge resection, nipple resection, excisional biopsy, or partial mastectomy not otherwise specified. Mastectomy is defined as subcutaneous mastectomy, simple mastectomy, modified radical mastectomy, or mastectomy not otherwise specified. Radiation therapy is defined as beam radiation, radioactive implants, radioisotopes, beam radiation combined with implants or isotopes, or radiation not otherwise specified.

*$P < 0.01$; **$P < 0.005$; ***$P < 0.001$; ****$P < 0.0001$.

out algorithm (i.e., requiring more than one occurrence of the diagnostic code) when identifying conditions in physician claims may have resulted in a stronger association. Furthermore, the nature of medical care is changing, with very ill patients increasingly likely to be treated on an outpatient basis with no inpatient hospitalizations and similar condition-specific hazard ratios for patients treated in inpatient and outpatient settings a possible consequence.

A potential limitation of the study involves the use of Medicare claims data. Because Medicare data allow only a limited number of diagnostic codes to be recorded, important comorbidities may have been missed due to insufficient space. Some evidence suggests that comorbidities tend to be underreported in administrative datasets [4,33–36], although one study demonstrated the equivalence of claims-based and chart-based Charlson comorbidity indices [37]. We believe that use of both inpatient hospital and physician claims is a strength of this study because the likelihood of identifying comorbid conditions is increased. However, the accuracy of the diagnostic codes contained in administrative datasets, particularly those recorded in Medicare Part B claims, needs to be validated [2,38]. Also, in constructing comorbidity measures that incorporate outpatient care, we considered only those comorbid conditions identified by Charlson *et al.* [9] as significantly influencing mortality. Other comorbid conditions may be important contributors to prediction of mortality and/or treatment patterns. For example, obesity has been shown to influence breast cancer survival [39], and contributes to the risk of a number of chronic conditions such as diabetes, hypertension, and heart disease, which also influence survival. Cardiac arrhythmias, valvular disease, coagulopathy, and alcohol and drug abuse are among the conditions not represented in the Charlson index that have been identified as potentially important comorbidities [40].

Our approach to identifying conditions in physician claims to include in the physician claims comorbidity index was conservative. We required more than one occurrence of a diagnostic code outside of a 30-day window for a condition identified only in physician claims to be incorporated in the physician claims index. However, we also conducted our analyses without this restriction, and obtained similar results in terms of the performance of the physician claims index in the mortality and treatment models in both patient cohorts. Inclusion or exclusion of the month of diagnosis when identifying comorbid conditions for the inpatient and physician claims comorbidity indices also had minimal effect on study results.

Others have attempted to improve upon the Charlson index [18,20]. This study, however, is the first documented attempt to develop a Charlson-like comorbidity measure using the diagnostic and procedure data contained in Medicare Part B claims. As advances in medical technology result in more care being delivered exclusively in the outpatient setting [41], consideration of comorbid conditions recorded in physician claims becomes particularly critical. Only a minority of Medicare beneficiaries are hospitalized in a given year, but approximately 90% have some contact with the health care system during the same period [15,42]. This study demonstrates the utility of a physician claims comorbidity index in assessing short-term mortality and treatment choice in two distinct cohorts of cancer patients. We provide a methodology for constructing the index and recommend its use in conjunction with a comorbidity index derived from inpatient hospital claims, although it can be employed as a stand-alone measure. Future studies should explore whether results are replicable in other patient populations, and whether the measure has utility in predicting outcomes other than short-term mortality and initial therapy. For example, the physician claims-derived comorbidity measure may contribute to models examining longer term therapy, or receipt of such adjuvant treatments as chemotherapy or hormonal therapy. Moreover, the physician claims-derived comorbidity measure may have utility in assessing treatment type for conditions other than breast and prostate cancer. In addition, the merits of alternative risk-adjustment methods that account for a broader array of comorbid conditions should be examined.

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