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Title

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Permalink

<https://escholarship.org/uc/item/28r3t7vc>

Journal

Medical Care, 51(8)

ISSN

0025-7079

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Publication Date

2013-08-01

DOI

10.1097/mlr.0b013e318298082f

Peer reviewed



Published in final edited form as:

Med Care. 2013 August ; 51(8): 740–747. doi:10.1097/MLR.0b013e318298082f.

Risk adjustment for health care financing in chronic disease: What are we missing by failing to account for disease severity?

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Abstract

BACKGROUND—Adjustment for differing risks among patients is usually incorporated into newer payment approaches, and current risk models rely on age, gender, and diagnosis codes. It is unknown the extent to which controlling additionally for disease severity improves cost prediction. Failure to adjust for within-disease variation may create incentives to avoid sicker patients. We address this issue among patients with chronic obstructive pulmonary disease (COPD).

METHODS—Cost and clinical data were collected prospectively from 1,202 COPD patients at Kaiser Permanente. Baseline analysis included age, gender, and diagnosis codes (using the Diagnostic Cost Group Relative Risk Score [RRS]) in a general linear model predicting total medical costs in the following year. We determined whether adding COPD severity measures—FEV₁, 6 minute walk test, dyspnea score, body-mass index, and BODE Index (composite of the other four measures)—improved predictions. Separately, we examined household income as a cost predictor.

RESULTS—Mean costs were \$12,334/year. Controlling for RRS, each ½ standard deviation worsening in COPD severity factor was associated with \$629 to \$1,135 in increased annual costs (all p<0.01). The lowest stratum of FEV₁ (<30% normal) predicted \$4,098 (95% CI \$576–\$8,773)

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Conflicts of Interest: No conflict of interest relevant to this article are reported.

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additional costs. Household income predicted excess costs when added to the baseline model ($p=0.038$), but this became non-significant when also incorporating BODE Index.

CONCLUSIONS—Disease severity measures explain significant cost variations beyond current risk models, and adding them to such models appears important to fairly compensate organizations that accept responsibility for sicker COPD patients. Appropriately controlling for disease severity also accounts for costs otherwise associated with lower socioeconomic status.

Keywords

chronic disease; COPD; financing; health care costs; health care markets; health care reform; risk adjustment; socioeconomic factors

INTRODUCTION

Risk adjustment by estimating expected costs is fundamental to many payment approaches developed over the last two decades, including capitated payment, cost-efficiency calculations in pay-for-performance programs, and shared saving determinations under accountable care organizations (ACOs).¹⁻⁴ The basic tenet of such adjustments is that providers should not be “penalized” for accepting responsibility for patients who are likely to use more healthcare resources. For example, ACOs with particular expertise in tertiary care should be properly compensated for accepting referrals of particularly ill patients, especially since specialized care is one of cornerstones of the U.S. healthcare system.⁵ For this reason, healthcare payers, including Medicare and private insurers, now employ risk-adjustment models that use age, gender, and previous diagnosis codes to estimate expected costs and reimburse accordingly.^{1,6} Measures of disease severity, however, are noticeably absent from these risk models, as are measures of patient socioeconomic status (SES) beyond Medicaid status. Indeed, the current ACO structure and payment approaches could exacerbate disparities because, for any given diagnosis, patients of lower SES tend to be sicker and utilize greater resources.^{7,8}

There has been little research on the extent to which clinical data beyond diagnosis codes and, in particular, disease-specific measures of severity-of-illness, can add to risk-adjustment. Clinical data, in the form of admission laboratory values, does improve the accuracy of short-term in-hospital mortality estimates.^{9,10} It also has been shown that self-reported health and functional status (such as the Physical Component Summary Scale) can improve predictive models, although such measures of health status are primarily research tools and unlikely to be collected as part of routine clinical practice. For ambulatory patients, little is known about whether disease-specific clinical data can be used to improve outcome prediction, and especially cost prediction, especially over a longer time horizon.

As a proof-of-concept study of how disease-specific severity measures might improve the ability to predict cost, we used the example of chronic obstructive pulmonary disease (COPD), the third leading cause of death in the United States.¹¹ We examined a variety of COPD severity measures and the extent to which these impacted cost predictions when added to a commonly-used risk adjustment model. Additionally, we analyzed whether adding COPD disease severity measures to risk adjustment models would attenuate any incentives that healthcare organizations may have to avoid lower SES patients. We used an existing cohort of COPD patients treated at Kaiser Permanente (KP), examining measures of COPD severity recognized to be clinically important for gauging disease severity.¹²⁻¹⁵

METHODS

Overview

We used data from FLOW, a longitudinal cohort study of 1,202 working-age COPD patients treated at KP in Northern California. Participants in the FLOW study had completed both structured telephone interviews and research clinic visits assessing a range of measures of COPD severity. We developed multivariable models to predict costs in which various measures of COPD-specific disease severity were added to a baseline model that included the Relative Risk Score (RRS) derived from the Diagnostic Cost Group (DxCG) model.^{1,3,6,16}

Patient Population

Patient recruitment details for the FLOW cohort have been described in detail.¹⁷ Briefly, key inclusion criteria were that patients be between 40-65 years old at baseline and receiving ongoing treatment for COPD.¹⁷ We identified all patients who met two criteria: [1] health-care utilization: having ≥ 1 ambulatory visits (routine or emergent), ED visits, or hospitalizations over the prior 12 months with a principal diagnosis code for COPD (ICD-9 codes 491, 492 or 496) and [2] medication prescription: having ≥ 2 prescriptions for a COPD-related medication during a 12-months window around the date of service for the COPD-related utilization in criterion 1 above. Baseline evaluation for FLOW participants took place between 2005 and 2007. The study was approved by the University of California, San Francisco Committee on Human Research and Kaiser Foundation Research Institute's institutional review board. All participants provided informed consent.

DxCG Relative Risk Score

The RRS was obtained from the prospective DxCG-Hierarchical Condition Category (HCC) model (Commercial algorithm, Version 6.2, Verisk Health, Boston, MA).¹⁶ The DxCG RRS is obtained from a regression model based upon historical International Classification of Diseases, 9th Revision, Clinical Modification (ICD9-CM) codes, which are assigned to condition categories, and allows for a limited number of interactions. Age and gender are also incorporated. The RRS is calibrated to an average score of 1.00. Thus, a score of 1.20, for example, indicates predicted costs over the coming 12 months that are 20% greater than average costs. The DxCG and the closely-related Center for Medicare and Medicaid Services (CMS)-HCC models have performed well in predicting costs in a variety of populations,¹⁸⁻²⁴ with DxCG-HCC model being commonly used by private insurers and the CMS-HCC model being used to risk-adjust Medicare capitated payments since 2004.^{1,6,25}

COPD Severity Measurements

COPD severity measures consisted of [1] forced expiratory volume in 1 second (FEV₁), [2] 6 Minute Walk Test (6MWT), [3] Modified Medical Research Council (MMRC) dyspnea scale, [4] body mass index (BMI), and [5] "BODE" Index.¹³ FEV₁, measured utilizing standard spirometry, is critical to diagnosing COPD and assessing its severity.¹² FEV₁ is commonly reported as "FEV₁ % predicted", which is FEV₁ as a percentage of that predicted by age, gender, and race; this might also be thought of as FEV₁ as a percentage of normal.²⁶ The 6MWT, which measures distance walked during 6 minutes of sub-maximal exercise, is also widely used as a clinical tool, is reimbursable under most insurances, and is simple to perform.^{13,15,27,28} The MMRC dyspnea scale assesses dyspnea on exertion using a single item with a 0-4 point response scale.^{14,29,30} Dyspnea severity is important in selection of COPD therapy and is used COPD staging systems, with the MMRC dyspnea scale being one of the most popular dyspnea measures.^{14,29,30} The BODE Index is a composite score that includes FEV₁ % predicted, 6MWT, MMRC dyspnea scale, and BMI.¹³ This index has been

shown in multiple cohorts to predict COPD outcomes.^{13,31-33} It has a possible range of 0 to 10, with FEV₁, 6MWT, and dyspnea each contributing between 0 and 3 points and BMI contributing up to 1 point (for BMI ≥ 21 indicative of cachexia).¹³

Annual Household Income

We measured SES as annual household income. Annual household income was ascertained during structured interviews and classified as: <\$20,000, \$20,000 to <\$60,000, \$60,000 to \$120,000, \$120,000.

Medical Cost Data

Total direct medical costs, including hospital, emergency department (ED), pharmacy, outpatient clinic, laboratory, radiology, pharmacy, durable medical equipment, and skilled nursing facilities use, were obtained for the 12 months following baseline assessment. The KP cost system generates fully allocated costs by patient, using standard step-down accounting methods and including overhead.^{34,35} Costs from non-KP providers (e.g., ED services and hospitalizations from outside KP), which generally represents a small percentage of costs (8.2% in this sample), were determined from charges obtained from databases that track bills sent to KP.

Health Outcomes

We also examined whether the COPD-specific factors improved prediction of either all-cause hospitalization or COPD-related hospitalization in the 12 month period following baseline. COPD-related hospitalizations were defined as those with a principal ICD-9 discharge diagnosis code for COPD (491, 492, or 496). The rationale for this analysis was two-fold: (1) to examine the generalizability of our findings, because calculation of actual costs may differ among provider organizations, whereas measurement of health outcomes can be standardized, and (2) to investigate whether COPD-specific factors might impact risk-adjusted health outcomes, which themselves are important as quality metrics in pay-for-performance programs and ACOs.^{2,36}

Statistical Analysis

All analyses used Stata/IC version 12.1 (College Station, TX). Total costs were approximately log-normally distributed (see Figure, Supplemental Digital Content 1); we utilized a general linear model (GLM) with a gamma response probability distribution and a log-link function.³⁷⁻³⁹ A gamma response probability distribution was chosen based on modified Park test results.³⁹

In the baseline GLM model, RRS was the sole predictor. Each COPD severity factor was then added separately. The RRS predictions were positively skewed, reflecting the skewed nature of underlying costs; log-transformation of RRS produced an approximately normal distribution (see Figure, Supplemental Digital Content 2), and RRS was log-transformed as a predictor to improve model fit (assessed using Akaike's Information Criterion).⁴⁰ The relationship between log-transformed RRS and log-transformed total costs was approximately linear (see Figure, Supplemental Digital Content 3).

For each COPD-specific factor measured on a continuous scale (i.e., all except BMI), we determined, from the model parameter estimates, the incremental cost in absolute dollars that would be expected for any given individual when that person's COPD-specific factor changed from the mean for the population to $\frac{1}{2}$ standard deviation (SD) worse than the mean (i.e. indicated greater COPD severity), holding RRS constant at its mean value.^{37,39} We selected $\frac{1}{2}$ SD because this generally corresponds to the minimum clinically important difference (MCID).^{41,42} For example, the MCID for the 6MWT is approximately 54 meters,

while the $\frac{1}{2}$ SD from the 6MWT in our sample was 60 meters.⁴³ For the purposes of measuring COPD severity by BODE Index, BMI is categorized into low (≤ 21) or not low (>21), and thus we presented the incremental cost of having BMI ≤ 21 vs BMI >21 . We also calculated the model R^2 , based on the squared correlation between fitted and observed values, for the baseline model including only RRS as well as for models with additional COPD severity factors.⁴⁴ The F-test was used to test the statistical significance of changes in model R^2 with the addition of disease severity factors in each model in question.

To provide more concrete insight into the incremental costs of the sickest COPD patients, above and beyond that predicted by RRS, we compared those with the worse health status as measured by FEV₁, 6MWT, and MMRC dyspnea scale to the remainder of the population. We selected thresholds for categorization *a priori* based on logical cut-points. Specifically for FEV₁, we compared those with Global Initiative for Chronic Obstructive Lung Disease (GOLD) Stage 4 (i.e. FEV₁% predicted $<30\%$) to those with better FEV₁.¹⁴ For 6MWT, we selected the lowest threshold specified by the BODE criteria, comparing those with <150 meters walked to those with better performance.¹³ For MMRC dyspnea scale, we compared those with the worst health status on this scale (i.e. 4 points) to those with lower dyspnea; this cut-point was also utilized by the originators of the BODE Index.^{13,29,30}

We utilized multivariable logistic regression in our analysis of whether COPD-specific factors predicted all-cause hospitalization, using RRS in the baseline model and investigating whether each COPD-specific factor was predictive of hospitalizations when controlling for RRS. We also examined the overall predictive accuracy of the various logistic regression risk models by calculating a concordance index (c-index), which is the area under the receiver-operating characteristics curve.⁴⁵

We examined whether annual household income was associated with future costs when added to the baseline model including RRS. In this analysis, patients with income $< \$20,000$ were used as the referent group for comparison to other income groups. In a second model, we then added the BODE Index, a composite measure of COPD severity, to RRS and income; we thus examined the association between income and future costs after controlling not only for RRS but also COPD severity. For both models (with and without controlling for BODE Index), we performed tests for trend across the income groups, using the linear contrast method and excluding subjects who refused to report income, as well as the F-test of homogeneity across income groups.⁴⁰

RESULTS

Patients' baseline characteristics are shown in Table 1. Mean costs per patient over 12 months were \$12,334 (SD=\$26,861). The distribution of BODE Index scores and costs and RRS by BODE Index are available in an on-line supplement (see Table, Supplemental Digital Content 4). When RRS was used as the only cost predictor, it was highly significant ($p<0.001$). When FEV₁, 6MWT, dyspnea scale, BMI, and BODE Index were added to the baseline model with RRS, each was also statistically significant ($p<0.01$ for all) (Table 2). For the continuous measures, each $\frac{1}{2}$ SD worsening predicted between \$629 and \$1,135 in excess annual costs above that predicted by RRS, while BMI ≤ 21 was associated with \$6,412 in additional annual expenditures. Improvements in model R^2 were small but statistically significant ($p<0.01$ for all changes in model R^2).

Those in the worst strata of FEV₁, 6MWT, and dyspnea scale had substantially higher predicted costs than those with better performance, after controlling for RRS (Figure 1). Being in FEV₁ GOLD Stage 4 (FEV₁ $<30\%$ normal) ($n=112$) predicted \$4,098 per patient in annual incremental costs (95% CI \$576 – \$8,773; $p=0.019$). Walking less than 150 meters

on 6MWT (n=62) predicted an extra \$8,146 in annual costs (95% CI \$2,546 – \$16,219; p=0.002). A dyspnea scale score of 4 (n=409) predicted \$3,850 in excess costs (95% CI \$1561 – \$6,588; p<0.001).

Among the cohort, 206 subjects (17%) were hospitalized in the 12 months following baseline study. Hospitalizations for 52 subjects (4.3%) were COPD-related. Each disease severity factor was associated with increased risk of both all-cause hospitalization and COPD-related hospitalization, after controlling for RRS (p<0.05 for all) (Table 3). For the outcome of all-cause hospitalization, the estimated C-indices for models with disease severity measures, at 0.68 to 0.70, were only marginally higher than the estimated C-index for the model including only RRS, at 0.67. For the outcome of COPD-related hospitalization, the estimated C-indices with disease severity measures were between 0.72 and 0.82, as compared to 0.69 for the model with only RRS (Table 3). Similarly, point estimates for odds ratios associated with disease severity factors were higher for the outcome of COPD-related hospitalization than for all-cause hospitalization.

When household income was added to the baseline model containing RRS but no disease severity factors, higher incomes were associated with lower cost (Table 4). For example, as compared to those with annual income<\$20,000, predicted annual medical costs were \$3,382 lower in the group with annual income \$120,000 (p=0.039). The test for trend across income groups was statistically significant (p<0.05). The F-test yielded p<0.05, rejecting the null-hypothesis of homogeneity across income groups. When controlling additionally for BODE Index, however, the association between SES and predicted costs was no longer statistically significant.

DISCUSSION

These analyses demonstrate that disease-specific measures substantively explain observed variability in costs above and beyond standard risk adjustment modeling relying on age, gender, and diagnosis codes alone. We show this in the context of COPD, but the concept that disease severity measures may add predictive power to diagnosis code-based predictions may be relevant to a wide variety of chronic diseases. These findings highlight the potential for healthcare providers to be held responsible for costs based on metrics that do not fully account for known causes of variation in resource utilization and cost. Moreover, the excess costs associated with disease-specific measures were not trivial. If current risk-adjustment models were used to predict cost, our data suggest there would be a heavy penalty incurred by providers who treat patients with the most severe COPD, since patients with FEV₁ GOLD Stage 4, for instance, incurred an average of more than \$4,000 in excess costs annually beyond that predicted by RRS. Although the improvements in model R² from adding COPD-specific factors were small in absolute terms, the R² of the baseline model (including only RRS) itself was not high at 0.21, illustrating the challenges of predicting future costs. Indeed, although model R² values from diagnosis-based risk adjustment methods have been found to be similarly low or even lower in other populations, the application of these methods is felt to be important to prevent adverse risk selection.^{19,21,22} Furthermore, it is not necessary that risk adjustment achieve especially high accuracy in cost prediction to be effective. Rather, the goal is to minimize the potential for risk selection and convince physicians and provider organizations that selecting risk is neither necessary nor worthwhile. Thus any improvement in R² may be meaningful, especially if the possibility of losses in dollar terms might reduce the willingness of provider organizations to accept the sickest patients and when such improvements are achieved specifically by adding to risk models the variables that physicians use to assess disease severity.

At the same time, our findings point the way towards a solution, since we show that cost modeling improves through the inclusion of quantitative measures that potentially could be culled from medical records. Indeed, with the current movement toward electronic health records (EHR), incorporating clinical measures into risk prediction is likely to become more practical on a large scale.⁴⁶ As we reimagine our EHRs and define what constitutes “meaningful use”,⁴⁶ these findings suggest that making disease severity measures accessible for the purposes of risk adjustment should be one goal. It is important to note, however, that although this study used measures that are recommended and often used to establish the severity of COPD,^{12,15,27,28} our data were not in fact obtained in the course of routine clinical practice. In large part, this is because at KP (and with most current EHRs), data such as FEV₁ or 6MWT distance are currently entered as text, rather than structured fields, making them difficult or impossible to cull electronically.^{47,48} Therefore, as much as providing impetus for including disease-specific measures in risk adjustment, this research also should provide motivation for health delivery organizations and EHR vendors to facilitate entering these critical data into EHRs in standardized formats.

The analysis of the predictive association of SES on medical costs demonstrates another potential mechanism for adverse risk selection. It may well be impractical to utilize household income for the purposes of risk adjustment; indeed, the fact that 8% of our sample refused to provide their income is testament to the difficulty of obtaining such data. Nonetheless, this does not change the reality that organizations that care for lower income patients may be unfairly assessed or compensated based on currently-employed risk-adjustment formulas. Indeed, current risk-adjustment techniques may disincentivize ACOs, for example, from building a referral base or advertising in poorer communities. Whether proxy measures of income might correct this problem was beyond the scope of the current work. Moreover, multiple other socioeconomic factors, including race and education, may be associated with costs, and controlling for disease severity may not entirely eliminate the predictive association between household income and medical costs. However, this analysis does suggest that controlling for disease severity may potentially be one means of reducing the incentives to avoid lower SES patients.

Our study has important limitations. It was conducted among working age adults, which may limit its generalizability to wider COPD populations. Overall, the population we analyzed was younger and had less advanced COPD than certain published cohorts,^{13,31} although average COPD severity assessed by BODE Index was higher than in other cohorts.^{32,33} The study also was conducted within a single health maintenance organization, and our cost estimates therefore are not generalizable to the U.S. population of persons with COPD. However, the goal of our study was not to estimate costs differentials to be adopted for payment, but rather to demonstrate that there are significant within-disease cost variations that are not predicted using diagnosis codes alone, but that would be predictable by clinical organizations that had detailed clinical data. Since that was our goal, it is a strength of the study that all patients were of limited age range and received their care in a single provider organization, because these study characteristics reduce the likelihood that the variations in utilization and costs we observed were due to variation in patterns of care among providers or age groups. To implement our observation about the impact of severity on cost into a payment policy would require further research that would generate estimates of the impact of severity on cost from a nationally representative sample of providers caring for a cohort of patients of all ages. Next, we acknowledge that we examined the impact of adding disease severity factors only to a prospective risk model; retrospective, concurrent, or “hybrid” models also play a role in risk adjustment but were not examined.²⁴ Additionally, we relied on ICD-9 codes as reflected in KP computerized data but did not check their concordance with actual clinical data through chart reviews. Indeed, further work is also required to determine the extent to which adding disease-specific clinic factors to risk-

adjustment methodologies might alter the behavior of clinicians in obtaining this information; for example, previous work has suggested that the introduction of diagnostic codes into Medicare prospective payment systems led to diagnostic inaccuracies that “gamed the system” to increase provider payments.⁴⁹

An additional limitation is that our cohort may not have maximized the variations in income, given that all were members of KP. Nonetheless, we did show an association between income and costs, even in a cohort that may be more homogenous than others, and this association diminished when controlling for COPD severity. Moreover, the demographic and socioeconomic characteristics of KP members are similar to Northern California as a whole (with KP covering 25% to 30% of the regional population), and KP also covers patients receiving Medicaid.⁵⁰ As such, it is largely representative of the locally insured marketplace.

In summary, we demonstrate the substantial impact disease-specific clinical measures have on predicted costs among COPD patients, even after risk-adjustment using diagnosis codes. Although clinical measures need to be made more easily accessible for cost prediction, we convincingly show that COPD severity measures, in absolute dollar terms, meaningfully impact costs. Incorporating disease-specific measures into risk models is important to encourage providers to accept responsibility for sicker COPD patients. Additionally, incorporating these measures may reduce the financial disadvantages faced by organizations that care for lower SES populations. This is likely to become increasingly important with the growth of ACOs, expected under the Affordable Care Act, and the application of risk-adjustment more broadly.⁴ Simultaneously, it is likely to become easier to implement with the growth of EHRs. Caution must therefore be taken about the extent to which currently-employed risk adjustment methods may adequately control for disease severity while further work to incorporate clinical measures is conducted.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

We thank G. Thomas Ray, MBA for assistance with the acquisition of cost data.

Funding/Support: Dr. Omachi was supported by NIH-NHLBI K23 HL102159. Dr. Blanc and the FLOW Study were supported by NIH-NHLBI R01 HL077618 and the UCSF Bland Lane Flight Attendants Medical Research Institute (FAMRI) Center of Excellence on Secondhand Smoke CoE2007. This project was also supported in part by the National Center for Research Resources and the National Center for Advancing Translational Sciences, National Institutes of Health, through UCSF-CTSI Grant Number UL1 RR024131. Its contents are solely the responsibility of the authors and do not necessarily represent the official views of the NIH.

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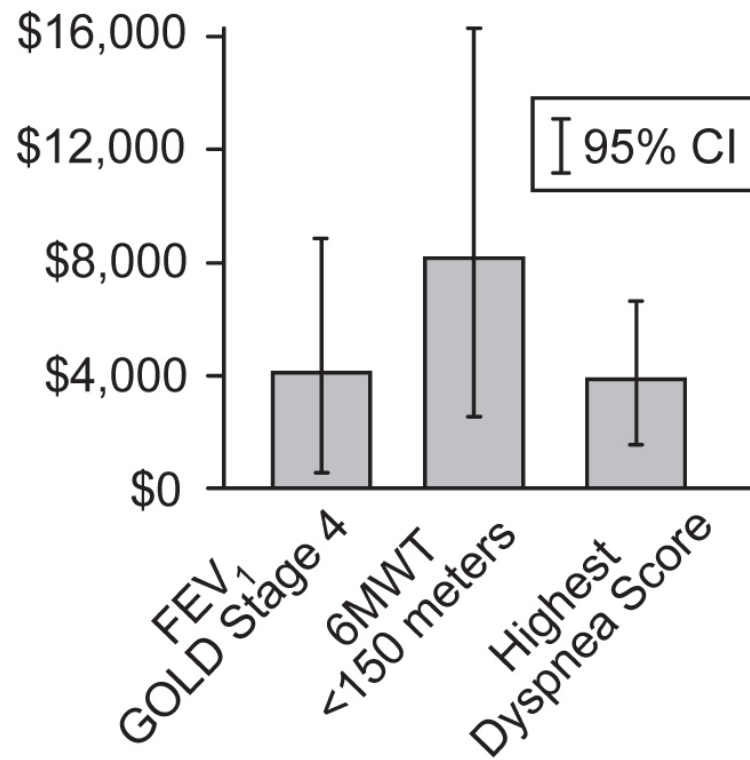


Figure 1. Excess Annual Costs Predicted by Worst COPD Severity*

*Controlling for the diagnosis-based DxCG Relative Risk Score, comparing the worst COPD severity classifications to all others.

Table 1

Characteristics of 1202 patients with COPD

	N (%) or Mean \pm SD
Age, years	58.2 \pm 6.2
Female gender	691 (57.5%)
Annual Household Income	
<\$20,000	129 (10.7%)
\$20,000 to \$60,000	523 (43.5%)
\$60,000 to \$120,000	354 (29.5%)
\$120,000	98 (8.2%)
Refused to provide	98 (8.2%)
FEV ₁ % predicted [†]	62% \pm 23%
6 Minute Walk Test Distance, meters	403 \pm 121
MMRC Dyspnea Score	2.3 \pm 1.5
Body-Mass Index (BMI)	
BMI > 21	1129 (93.9%)
BMI \leq 21	73 (6.1%)
BODE Index [*]	2.9 \pm 2.4
DxCG Relative Risk Score	5.1 \pm 5.3

* BODE Index consists of FEV₁ % predicted, 6 Minute Walk Test distance, MMRC dyspnea scale, and BMI (with BMI \leq 21 indicating higher COPD severity)

[†]“FEV₁ % predicted” is FEV₁ as percentage of that predicted by age, gender, and race (i.e. as a percentage of normal).

Table 2

COPD-specific factors add incremental value in predicting future costs among COPD patients above and beyond DxCG Relative Risk Score ^{*}

	Predicted Incremental Cost Per Year (95% CI)	p-value	Model R ² [‡]
FEV ₁ % predicted [†]			
Additional cost per ½ SD (11.7%) decrement in FEV ₁	\$629 (\$197, \$1,079)	p=0.004	0.22
6 Minute Walk Test Distance [†]			
Additional cost per ½ SD (60 meter) decrement in distance walked	\$1,135 (\$689, \$1,600)	p<0.001	0.24
MMRC dyspnea scale [†]			
Additional cost ½ SD (0.75 point) increment in scale	\$696 (\$251, \$1,161)	p=0.002	0.24
Body-Mass Index [†]			
Additional cost associated with having BMI ≥ 21	\$6,412 (\$1,627, \$13,141)	p=0.005	0.22
BODE Index [†]			
Additional cost per ½ SD (1.2 point) increment in scale	\$982 (\$547, \$1,436)	p<0.001	0.24

^{*} Each row above presents results from a separate general linear model in which total medical costs was the outcome and DxCG Relative Risk Score was used as a covariate along with the predictor of interest from the table row above.

[†] Higher scores on the MMRC dyspnea scale and BODE Index indicate more severe COPD. In contrast, lower FEV₁ % predicted, lower 6 Minute Walk Test distance, and Body-Mass Index ≥ 21 indicate more severe COPD.

[‡] R² from model including DxCG Relative Risk Score and the listed COPD-specific factor. R² for model including only DxCG Relative Risk Score was 0.21.

Table 3

COPD-specific factors predicted increased risk of both all-cause hospitalization COPD-related hospitalization, above and beyond that predicted by DxCG Relative Risk Score *

	All-Cause Hospitalization		COPD-Related Hospitalization	
	OR (95% CI) p-value	C-Index [†]	OR (95% CI) p-value	C-Index [†]
FEV ₁ % predicted				
Per ½ SD (11.7%) decrement in FEV ₁ % predicted	1.09 (1.004, 1.18) p=0.039	0.68	1.81 (1.49, 2.16) p<0.001	0.81
6 Minute Walk Test Distance				
Per ½ SD (60 meter) decrement in distance walked	1.23 (1.15, 1.33) p<0.001	0.70	1.31 (1.17, 1.48) p<0.001	0.76
MMRC dyspnea scale				
Per ½ SD (0.75 point) increment in scale	1.15 (1.06, 1.25) p=0.001	0.69	1.56 (1.30, 1.87) p<0.001	0.77
Body-Mass Index				
Associated with having BMI ≥ 21	2.37 (1.32, 4.28) p=0.004	0.69	2.91 (1.16, 7.30) p=0.023	0.72
BODE Index				
Per ½ SD (1.2 point) increment in scale	1.23 (1.13, 1.33) p<0.001	0.70	1.71 (1.46, 2.00) p<0.001	0.82

* Results from separate multivariable logistic regressions in which either all-cause hospitalization or COPD-related hospitalization was the outcome and DxCG Relative Risk Score (RRS) was used as a covariate along with the predictor of interest from the table row above.

[†] C-index (area under the receiver operator characteristics curve) for the baseline model with RRS was 0.67 for the outcome all-cause hospitalization and 0.69 for the outcome of COPD-related hospitalization.

Table 4

Annual household income as a predictor of medical costs above and beyond DxCG Relative Risk Score (RRS)

	Predicted Incremental Cost Per Year (95% CI)	p-value
Controlling only for DxCG RRS *		
<\$20,000	[Referent]	N/A
\$20,000 to \$60,000	-\$2,064 (-\$4,044, +\$558)	0.11
\$60,000 to \$120,000	-\$2,819 (-\$4,698, -\$291)	0.031
\$120,000	-\$3,382 (-\$5,542, -\$206)	0.039
Refused to provide	+\$677 (-\$2,789, +\$5,710)	0.74
Controlling for DxCG RRS and BODE Index †		
<\$20,000	[Referent]	N/A
\$20,000 to \$60,000	-\$1,717 (-\$3,731, +\$942)	0.19
\$60,000 to \$120,000	-\$2,028 (-\$4,075, +\$724)	0.14
\$120,000	-\$2,348 (-\$4,799, +\$1,257)	0.17
Refused to provide	+\$342 (-\$2,902, +\$5,066)	0.86

* Test for trend across income groups, excluding group refusing to provide income, yielded $p=0.028$, and F-test for homogeneity of income groups yielded $p=0.038$.

† After additionally controlling for BODE Index, test for trend across income groups, excluding group refusing to provide income, yielded $p=0.16$, and F-test for homogeneity of income groups yielded $p=0.33$.