Financial Analysis; Obesity

Identifying Patients at Risk for High Medical Costs and Good Candidates for Obesity Intervention

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Abstract

Purpose. *To develop a risk-scoring tool to identify in a base year patients likely to have high medical spending in the subsequent year and to understand the role obesity and obesity reduction may play in mitigating this risk.*

Design. *Cross-sectional analysis, using commercial claims and health risk assessment data.*

Setting. *United States, 2004–2009.*

Subjects. *Panel of 192,750 person-year observations from 116,868 unique working-age employees of large companies.*

Measures. *Probability of high medical expenses (80th percentile or above) in the following year; adjusted body mass index (BMI).*

Analysis. *Generate risk scores by modeling the likelihood of high next-year expenses as a function of base-year age, sex, medical utilization, comorbidities, and BMI. Estimate the effect of simulated bariatric intervention on patient risk scores.*

Results. *Individuals with higher BMI were more likely to be categorized in the very high risk group, in which the average annual medical expense was $8621. A weight-loss intervention transitioning a patient to the next lower obesity class was predicted to reduce this risk by 1.5% to 27.4%—comparable to hypothetically curing a patient of depression or type 2 diabetes.*

Conclusion. *A logistic model was used to capture the effect of BMI on the risk of high future medical spending. Weight-loss interventions for obese patients may generate significant savings by reducing this risk. (Am J Health Promot 2014;28[4]:218–227.)*

Key Words: Obesity, Medical Spending, Health Care Spending, BMI, Weight Control, Risk Score, Prevention Research. Manuscript format: research; Research purpose: instrument development, modeling/relationship testing; Study design: nonexperimental; Outcome measure: other financial/economic; Setting: clinical/health care; state/national; Health focus: weight control; Strategy: education; Target population age: adults; Target population circumstances: education/income level

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PURPOSE

The prevalence of obesity is rising in the United States. In 2010, nearly 36% of adults in the United States aged 20 years or older were classified as obese (body mass index [BMI] > 30 kg/m^2),[1] compared to 13% in 1962 and 31% in 2000.[2] The growing prevalence of obesity has, and will continue to have, serious consequences on national health because of obesity's connection with chronic health conditions, including type 2 diabetes, gallbladder disease, coronary heart disease, high cholesterol, and high blood pressure.[3,4]

Rising prevalence of obesity and obesity-related conditions increase indirect costs[5–7] and direct medical spending,[8–10] and the trends are worsening. In just one decade, incremental medical spending for obese patients relative to normal-weight patients rose from 37% to 42%, which amounted to an increase in the mean spending difference between the groups from $1145 in 1998 to $1429 in 2006 (2008 dollars).[8,9] Perhaps even more alarming is the impact of obesity at a societal level: obesity was responsible for 27% of the rise in inflation-adjusted health spending between 1987 and 2001,[10] and medical costs of obesity could have accounted for as much as $147 billion in 2008, that is, 9.1% of all medical spending.[9]

Given these trends, a number of risk-adjustment models for predicting patient health care expenditures have been developed with the intent of forecasting which patients are at increased risk of high medical spending. Depending on available data and intended audience, a variety of factors

are used to adjust for risk, including, but not limited to, comorbidity indicators, self-reported health, pharmacy claims, demographic information, and utilization counts.[11–16] For example, some models only use utilization counts to represent patient health; these models are fairly simple but consequently also limited in the associations on which they shed light.[11,16] Utilization counts are a good representation of disease severity (e.g., using more resources implies a worse health state),[17] yet on their own they do not distinguish between the potential expenditure burdens of varying comorbidities. For example, models using only prescription counts will give the same weight to a patient taking an angiotensin-converting enzyme (ACE) inhibitor for high blood pressure as a patient taking an ACE inhibitor for heart failure. Other models are more complex and based on claims data; these models tend to include patient comorbidities or comorbidity indices and are more applicable to payers.[12,13]

Risk-adjustment models based on claims data have reasonable predictive power; however, they often lack key predictors. For example, weight-related metrics (e.g., BMI) are generally not included as predictors, likely because these metrics are not available in most claims datasets. Even though obesity is often associated with certain clinical conditions such as diabetes, chronic obstructive pulmonary disease, or heart failure and thus these conditions can partially account for the effect of obesity, claims-based models are not apt to capture the impact of the rising prevalence of obesity directly.[18] The model presented here was designed to fill this gap in the literature.

In this study, insurer claims data were linked to health risk assessment data to determine the relationship between BMI, demographic variables, and comorbidities in the base year and health care expenditures in the following year. From these estimated relationships we derived a score measuring a patient's risk of belonging to the top quintile of medical spenders in the next year. These individual patient scores will add to payers' ability to identify patients with the greatest risk of high medical spending in the following year and optimally apply care programs for lowering that risk. For example, using the risk-scoring tool, payers can determine which patients have elevated risk of high spending as a result of their weight and suggest coverage strategies that include appropriate bariatric interventions to lower the patients' weight—and consequently their risk of high future spending.

METHODS

Design

Our study drew on data from the Thomson Reuters MarketScan Commercial Claims and Encounters (CCAE) and Health Risk Assessment (HRA) Databases for 2004–2009. Thomson Reuters constructed the databases by collecting information from companies using their decision support tools, all of which were large U.S. employers. The CCAE database included data on all inpatient, outpatient, and prescription claims, including diagnoses, length of stay, prescribed medications, and spending variables. The HRA database contained self-reported information about employees' health and behaviors, including BMI, smoking status, and individuals' plans to take steps in the future to improve their health. Additionally, person-level identifiers were included in the MarketScan database, which allowed linking information for the same person across years and datasets.

Sample

We focused on employees with both BMI and claims data available in a given year and with medical spending data available for at least 1 year beyond. Women who were pregnant at any time in 2004–2009, based on an International Classification of Diseases, Ninth Revision, code of V22 or V23 in the CCAE file, were excluded during pregnancy and the following year because pregnancy would skew BMI measurement and costs. Underweight employees were also excluded. The unit of observation for our analysis was person-year with recorded current-year characteristics and next-year spending. Our sample contained 192,750 person-year observations from 116,868 unique individuals. We randomly selected and reserved 10% of the observations to create a validation sample that was used to evaluate the performance of the risk-scoring tool.

Measures

BMI is self-reported in the HRA. It is commonly recognized in the literature that height and weight are subject to reporting bias.[19–22] Therefore, we adjusted the BMI measure, applying methods similar to those in Burkhauser and Cawley[23] and Stommel and Schoenborn[24] to reduce the effect of reporting bias. The latter authors used a polynomial regression model of self-reported height and weight, along with age, gender, and other demographic variables, to predict measured BMI scores. Included variables accounted for 92% of the variation in BMI, and the resulting coefficients were used to estimate "adjusted" BMI scores.[24] Using the National Health and Nutrition Examination Survey, which included both self-reported BMI data and BMI data measured by trained examiners, we calculated the average differences between self-reported and measured BMI for a range of gender, age, and self-reported BMI groups. We applied these correction factors to calculate adjusted BMI. A sensitivity analysis using BMI unadjusted for reporting bias had a negligible effect on the final results compared to adjusted BMI; however, the known reporting bias of BMI justified the use of the adjusted measures in our base case analysis.

The adjusted BMI measures were used to create obesity classes. In the study, persons in a given year were labeled as underweight (BMI < 18.5 kg/m^2), normal weight (BMI 18.5–24.9 kg/m^2), overweight (BMI 25–29.9 kg/m^2), obese class I (BMI 30–34.9 kg/m^2), obese class II (BMI 35–39.9 kg/m^2), or obese class III (BMI > 40 kg/m^2).

As covariates, our model also included demographic controls such as age and gender, Elixhauser comorbidity measures (reported in full in Table 1),[25] and measures of current health care resource utilization such as indicators for inpatient or specialist visits and the number of outpatient visits that occurred in the current year as well as the number of months in the year covered by prescriptions.

Table 1
Odds Ratio of Belonging to Next Year's Top Medical Spending Quintile (N = 181,282)

Variable	Odds Ratio (95% CI)
Obesity class	
Normal weight	1.00
Overweight	1.109 (1.073,1.147)***
Obese class I	1.237 (1.186,1.289)***
Obese class II	1.312 (1.238,1.391)***
Obese class III	1.651 (1.545,1.764)***
Sex	
Female	1.00
Male	0.741 (0.720,0.764)***
Age bracket	
18–24	1.00
25–29	0.935 (0.836,1.046)
30–34	1.146 (1.028,1.277)*
35–39	1.313 (1.182,1.459)***
40–44	1.433 (1.292,1.589)***
45–49	1.586 (1.431,1.758)***
50–54	1.823 (1.643,2.023)***
55–59	1.890 (1.696,2.106)***
60–64	1.880 (1.664,2.124)***
Health care resource utilization	
Any inpatient visits	1.205 (1.115,1.302)***
Any specialist visits	1.039 (1.010,1.069)**
Number of outpatient visits	1.019 (1.018,1.019)***
Months supplied of Rx	1.043 (1.042,1.044)***
Elixhauser comorbidities	
Valvular disease	1.216 (1.079,1.371)**
Pulmonary circulation disorder	0.967 (0.673,1.388)
Peripheral vascular disorder	1.506 (1.235,1.835)***
Other neurological	3.169 (2.718,3.694)***
Chronic pulmonary disease	1.448 (1.348,1.554)***
Hypothyroidism	0.786 (0.736,0.840)***
Renal failure	1.587 (1.115,2.259)*
Liver disease	1.583 (1.343,1.867)***
Solid tumor without metastasis	1.840 (1.649,2.053)***
Rheumatoid arthritis/collagen vascular diseases	1.585 (1.376,1.825)***
Coagulation deficiency	0.989 (0.757,1.292)
Weight loss	1.315 (1.033,1.674)*
Fluid and electrolyte disorders	1.012 (0.859,1.192)
Blood loss anemia	1.041 (0.738,1.468)
Deficiency anemias	1.123 (1.022,1.234)*
Psychoses	1.664 (1.530,1.809)***
Depression	1.247 (1.155,1.345)***
Type 2 diabetes	1.164 (1.090,1.243)***
Hypertension	0.815 (0.782,0.850)***
Hyperlipidemia	0.960 (0.926,0.995)*
Congestive heart failure	0.793 (0.546,1.151)
Paralysis	1.189 (0.727,1.944)
Chronic peptic ulcer disease	1.337 (0.642,2.782)
HIV and AIDS	8.223 (5.456,12.39)***
Lymphoma	2.296 (1.480,3.563)***
Metastatic cancer	2.129 (1.298,3.492)**
Alcohol abuse	1.568 (1.147,2.144)**
Drug abuse	0.987 (0.591,1.646)
Type 1 diabetes	1.018 (0.291,3.555)

† Normal weight is BMI $\geq$ 18.5 and $<$ 25 overweight is BMI $\geq$ 25 and $<$ 30; obese class I is BMI $\geq$ 30 and $<$ 35; obese class II is BMI $\geq$ 35 and $<$ 40; obese class III is BMI $\geq$ 40. Results from a logistic regression model predicting spending next year at or above the 80th percentile. Comorbidities are binary coded. CI indicates confidence interval; Rx, prescription.

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Analysis

Designing the Risk-Scoring Tool. Because a small portion of the population has consistently incurred the bulk of health care costs over time,[26] identifying this group would provide the greatest opportunity for potential savings through targeted interventions. We used a logistic regression to model the probability that an individual would be among the top quintile of medical spending in the next year, as a function of the individual's age group, gender, obesity class, and current medical utilization and comorbidities. Spending variables in this study represented the total payments to providers, i.e., the total charges minus the cost adjustments and uncovered charges. We adjusted for inflation and reported in 2011 dollars, but we lacked data to control for geographic differences in wages. We estimated the model using a randomly selected part of our sample (training sample). Then, for each person-year in our training sample, we calculated a medical expenditure risk score (MERS), that is, the predicted likelihood of having spending at or above the 80th percentile in the following year.

To create a convenient risk-scoring tool, we sorted the MERS values in the training sample. A person in a given year was classified as very high risk, high risk, moderate risk, low risk, or very low risk based on the corresponding quintile of the predicted likelihood of high spending. For example, a person in the top quintile was classified as very high risk.

The validation sample was used to assess the performance of the risk-scoring method, as is consistent with validation approaches used in existing literature.[12,13,15] We noted the cutoff risk score values between different risk classes in the training sample. Using these cutoffs, we grouped person-years in the validation sample into very high risk, high risk, moderate risk, low risk, and very low risk categories. Then, we calculated the proportion of actual high spenders in each risk group to analyze the association between estimated risk score and high medical spending in out-of-sample data.

Assessing Implications. After creating the risk-scoring tool, we used the entire

Table 2
Descriptive Statistics for Full Sample and by BMI Group*

		BMI Group†				
	Total (N = 192,750)	Normal (N = 59,580)	Overweight (N = 73,459)	Obese I (N = 29,634)	Obese II (N = 10,945)	Obese III (N = 19,132)
Male, %	62.42	51.45	74.14	70.29	47.36	48.07
Age, y	42.54	41.13	42.95	43.59	43.88	42.94
Mean adjusted BMI	27.69	22.25	27.06	32.16	37.15	45.15
Comorbidities, %						
Diabetes without chronic complications	4.05	1.52	2.88	6.55	10.51	8.87
Diabetes with chronic complications	0.65	0.37	0.43	0.95	1.61	1.36
Hypertension, uncomplicated	11.41	5.22	10.92	17.33	22.41	17.13
Hypertension, complicated	0.34	0.15	0.34	0.51	0.61	0.54
Hyperlipidemia	15.69	10.89	16.93	19.86	19.52	17.23
Hypothyroidism	3.47	3.17	3.05	3.46	5.11	5.04
Chronic pulmonary disease	2.67	2.30	2.39	2.96	4.22	3.61
Depression	2.32	2.32	2.11	2.23	3.13	2.75
Medical utilization over past year						
No. outpatient visits, No.	18.4	17.11	16.97	20.03	23.56	22.44
Any inpatient visits, %	2.70	2.13	2.41	3.23	4.24	3.83
Any specialist visits, %	58.68	56.06	55.28	58.54	62.12	78.14
Time supplied Rx, mo	10.8	8.28	9.66	13.42	17.3	15.28
Medical spending, 2011 $	2975	2528	2691	3411	4197	4087

* BMI indicates body mass index; Rx, prescription.
† Normal is BMI 18.5–24.9, overweight is BMI 25–29.9, obese I is BMI 30–34.9, obese II is BMI 35–39.9, and obese III is BMI $\geq$ 40. BMI is adjusted to correct for self-reporting bias.

sample to assess relationships between BMI, risk scores, and high medical spending. First, we computed the proportion of very high risk person-years to all person-years in each obesity class to study the association between BMI groups and risk scores. Then, we calculated the average medical spending among person-years in each of the risk categories to analyze association between risk score and medical spending.

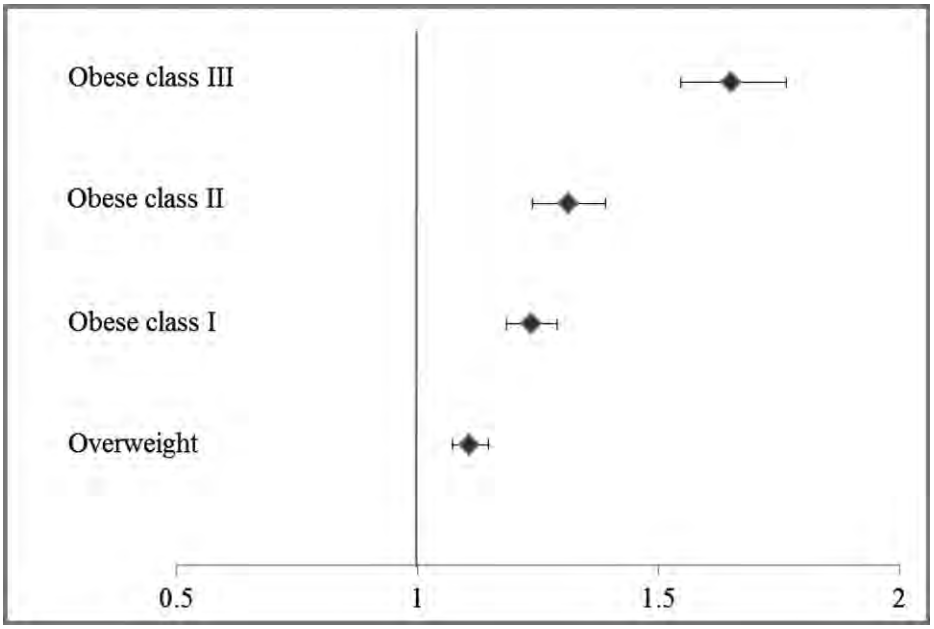
Given the concern about the high costs of obesity in the United States, we used our risk-scoring method to predict effects of bariatric intervention. Clinical data demonstrate that bariatric interventions (such as adjustable gastric bands) can transition patients to a lower obesity class.[27–30] Moreover, beyond reducing patients' BMI, weight loss interventions can further improve patients' general health.[28,29,31,32] However, as the literature lacks a consensus about the size of such improvements, we provided both an optimistic and a conservative estimate for the change in risk score associated with bariatric intervention. As a lower bound, we reduced patient BMI from one group (e.g., obese class III) to the next lower group (e.g., obese class II) , keeping the comorbidities and utilization variables fixed, and used our logistic regression model to predict the resulting change in average risk score for individuals in different starting BMI groups. As an upper bound, we assumed that as an individual transitioned to a lower BMI group, medical utilization and comorbidities would also change to reflect the average values in the new BMI group. We then predicted the resulting change in average risk score by initial BMI group.

Younger employees or employees with fewer comorbid conditions are less likely to become high spenders. Thus, the effect of bariatric intervention on the risk of high spending can be compared to the effects of age difference and certain comorbidities that similarly raise the risk of high spending. To present such comparisons, we simulated changes in age and comorbidities that would lead to a drop in risk score comparable to the estimated effect of bariatric intervention. Specifically, we simulated the effect of a drop in age by assigning everyone in the sample the mean age (more precisely, placing everyone in the corresponding age group), computing the mean risk score, and then reducing the mean age (more precisely, placing everyone in the new age group) and recomputing the risk score. We estimated the effect of alleviating comorbidities by calculating the average risk score for the subsample with a given comorbidity, removing the comorbidity, and recalculating the average risk score.

RESULTS

Table 2 provides descriptive statistics for the full sample and by BMI group. Consistent with previous studies,[3,4,9,33,34] our results show that individuals with higher BMI have greater medical utilization, a greater prevalence of comorbid conditions, and higher medical costs than normal-weight individuals. Table 1 shows the association between each covariate and the likelihood of belonging to the top medical spending quintile in the subsequent year via a logistic regression.

Figure 1
Odds Ratios of Belonging to Next Year's Top Spending Quintile, by Current BMI



Overweight is BMI $\geq$ 25 and $<$ 30; obese class I is BMI $\geq$ 30 and $<$ 35; obese class II is BMI $\geq$ 35 and $<$ 40; obese class III is BMI $\geq$ 40. Results are from a logistic regression model predicting spending next year at or above the 80th percentile. Reference group is normal-weight patients with BMI $\geq$ 18.5 and $<$ 25. BMI indicates body mass index.

For example, being male decreases the odds of belonging to the top medical spending quintile by 25.9% compared to being female; being in the age group of 40 to 44 years increases the odds of belonging to the top medical spending quintile by 43.3% compared to being in the age group of 18 to 24 years; and having one or more inpatient visits increases the odds of belonging to the top medical spending quintile by 20.5% compared to not having such a visit. As Figure 1 illustrates, even after controlling for age, gender, medical utilization, and comorbidities, obesity is strongly and significantly associated with an increased risk of high medical spending in the following year, and the higher the BMI, the greater the increase in risk. Overweight, obese class I, obese class II, and obese class III individuals are all significantly more likely to become high spenders in the following year than normal-weight individuals (odds ratio [OR] 1.109, 95% confidence interval [CI] 1.073–1.147; OR 1.237, 95% CI 1.186–1.289; OR 1.312, 95% CI 1.238–1.391; and OR 1.651, 95% CI 1.545–1.764, respectively; all estimates are with $p < .01$).

Table 3
Cutoff Values of the Predicted Probabilities of Belonging to the Top Spending Quintile in the Next Year

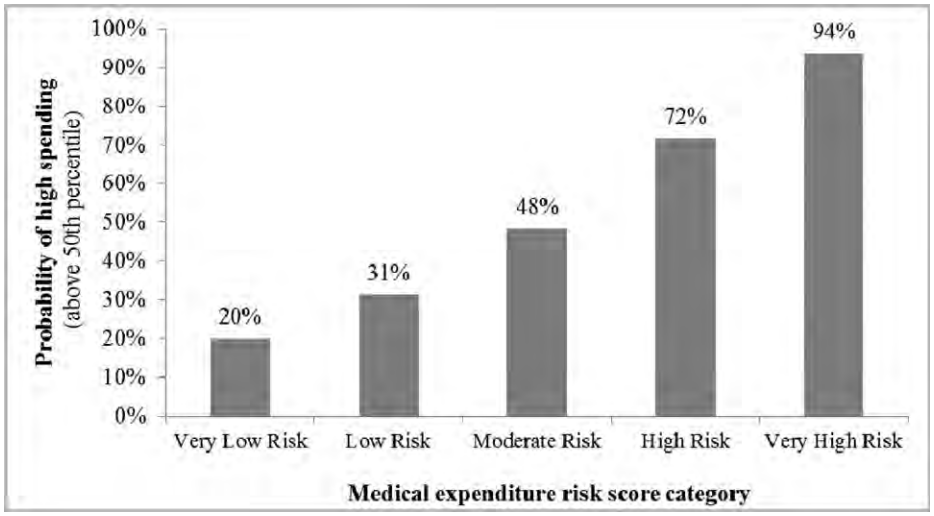
Risk Category	MERS Score Range	% of Training Sample	% of Validation Sample
Very low risk	0–7.9	20.00	20.05
Low risk	8.0–10.7	20.00	19.88
Moderate risk	10.8–15.9	20.00	19.60
High risk	16.0–30.1	20.00	20.41
Very high risk	30.2–100	20.00	20.05

Table 3 describes the distribution of the predicted likelihoods of belonging to the top spending quintile in the following year, using the training sample. We used these predicted likelihoods of high spending to sort the training sample into five equally sized groups. We then used the cutoff percentages between the groups to create our risk-scoring tool, which assigned each observation a risk group based on its predicted likelihood of high spending. The predicted chance of being in the top spending quintile in the subsequent year was less than 7.9% for the very low risk group; between 8.0% and 10.7% for the low risk group; between 10.8% and 15.9% for the moderate risk group; between 16.0% and 30.1% for the high risk group; and between 30.2% and 100% for the very high risk group.

Evidence presented in Figure 2 shows that individuals with high risk scores were substantially more likely to be high spenders in the following year (defined as health care spending above the 50th percentile). In the validation sample, 94% of person-years categorized as very high risk were actually high spenders in the next year, compared with 72% of person-years categorized as high risk and 48% of person-years categorized as moderate risk. This finding indicates that our risk-scoring tool can accurately predict high spending in the following year.

Our data demonstrate that individuals in all obesity classes have higher risk of high medical spending in the following year compared to normal-weight patients (BMI $\leq$ 25). Evidence in Figure 3 indicates that the proportion of very high risk patients was 48% in obese class III, 36% in obese class II, and 26% in obese class I, whereas only 14% of normal-weight patients were categorized as very high risk. If there were no association between obesity and high medical spending, we would expect patients in the top quintile of the spending distribution to comprise 20% of each obesity class. The fact that the proportion of very high risk patients in obese class III is 48% means that class III obesity is associated with a 140% increase in the likelihood of belonging to the top spending quintile compared to the average person. Similarly, class II obesity is associated with an 80% increase in the likelihood of belonging to the top spending quintile, whereas class I obesity is associated with a 30% increase in this likelihood.

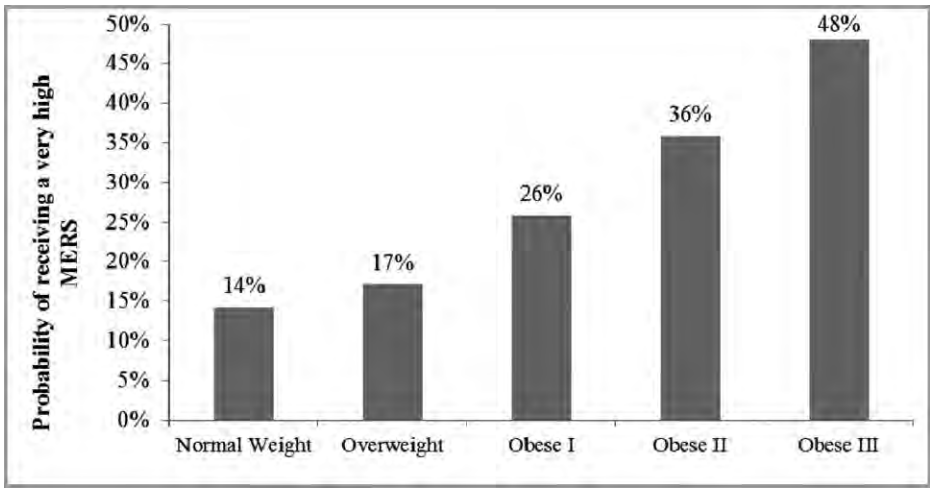
Figure 2
Probability of High Spenders, by Medical Expenditure Risk Score Category



As expected, the results also suggest that high risk individuals are considerably more costly from a payer perspective. Figure 4 shows that, on average, very low risk individuals spent $1016 in the following year, whereas low risk individuals spent $1662 and moderate risk individuals spent $2570. Transitioning from high to very high risk was associated with the steepest increase in average spending in the next year: $3770 for high risk individuals compared with $8621 for very high risk individuals, nearly a $5000 difference. Thus, focusing health care efforts on moving patients out of the very high risk category has the potential to reduce costs substantially for patients and payers. We expect that weight loss interventions that substantially reduce patients' BMI will reduce individuals' risk scores and their likelihood of high future medical spending.

To assess the possible consequences of a bariatric intervention, we predicted the drop in risk score associated with transitioning an obese individual to the next lower obesity class, as is typical under currently available bariatric interventions.[27–30] We estimated that obese class III individuals, whose starting average risk score was 39, would experience a 9.1% to 23.9% drop in risk score on average as a result of a weight loss intervention shifting them to obese class II. Obese class II individuals, with preintervention average risk score of 31, would experience a 1.5% to 25.5% drop on average as a result of a weight loss intervention shifting them to obese class I, whereas obese class I patients, with preintervention average risk score of 25, would experience a 2.7% to 27.4% reduction in risk score as a result of a weight loss intervention shifting them to overweight class. Our logistic regression revealed that the risk of high spending is also associated with age, gender, and health care resource utilization, as well as with the presence of a wide range of comorbidities. To compare the effects of changing obesity classes to changing age or comorbidities, we simulated the effects of theoretical shifts in patient health states. Our estimates show that patients moving from a health state with depression to a state without this diagnosis would experience an 8.8% drop in the risk score. Similar transitions from renal failure and type 2 diabetes to health states without these conditions would result in a 6.0% and a 4.5% drop in risk score, respectively. These estimates are reported in Figure 5.

Figure 3
Probability of Receiving a Very High Risk Score, by Obesity Class

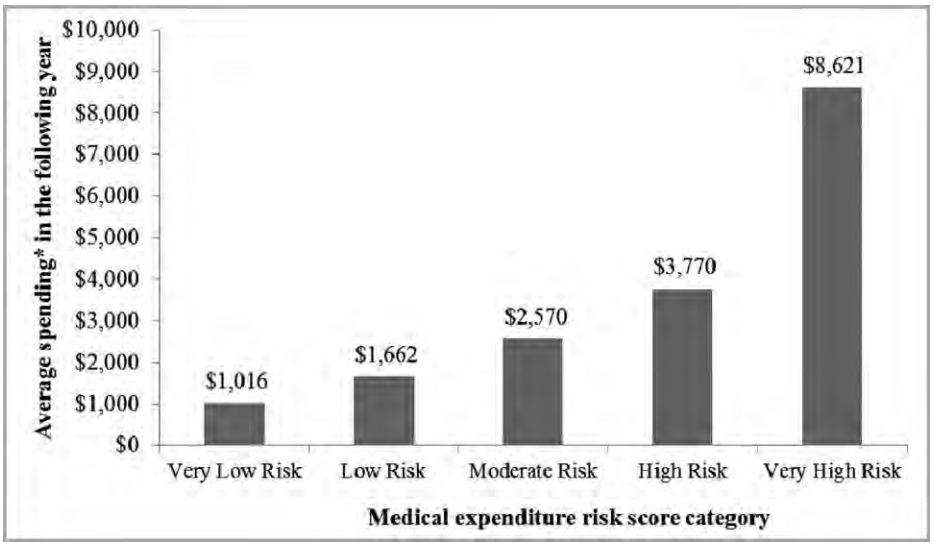


MERS indicates medical expenditure risk score.

DISCUSSION

Both obesity and medical spending have been rapidly increasing in the United States. This analysis demonstrated that these are not independent events; after controlling for age, sex, medical utilization, and comorbidities in the index year, obesity is still strongly and significantly associated with an

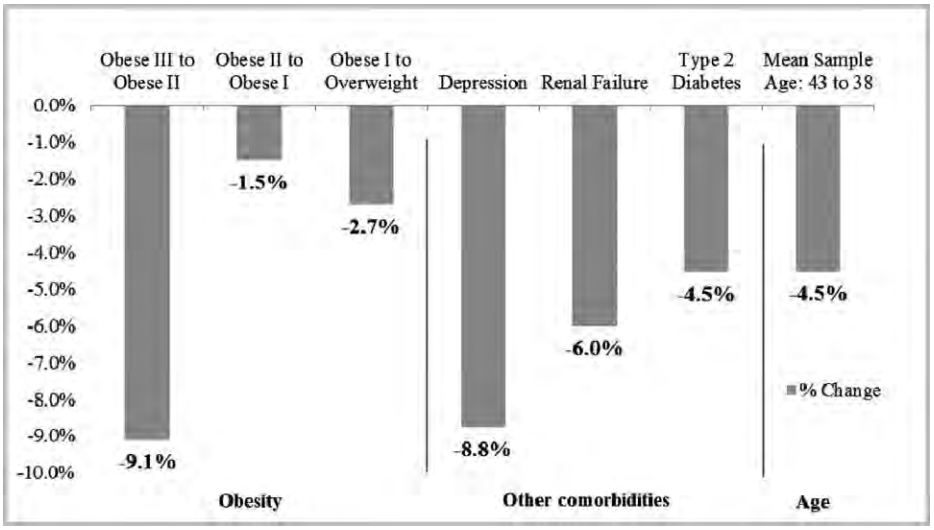
Figure 4
Average Spending in the Following Year, by Medical Expenditure Risk Score Category



Average spending is adjusted for inflation and reported in 2011 dollars.

increased risk of high medical spending in the following year. Compared to normal-weight individuals, the ORs for the risk of high medical expenditures in the following year are significantly higher than 1 at every level of obesity. Compared to normal-weight individuals, class III obesity is associated with risk of high spending at a rate similar to psychosis, greater than type 2 diabetes and liver disease, and lower than lymphoma, metastatic cancer, solid tumor, and other neurologic diseases.

Figure 5
Percentage Change in Average Risk Score From Simulated Comorbidity and Age Changes Comparable to Effects of Bariatric Interventions



Lower bound estimates.

Because health care spending is volatile, knowledge of current spending alone is not sufficient to predict future high-cost cases accurately,[35,36] yet the ability to predict future health care spending accurately is critical for both private and public insurers. Our analysis identified a wide range of conditions that are important indicators of high future spending, suggesting that a well-designed model is needed to make accurate predictions about future medical expenditures. Risk-scoring tools are useful for making such predictions, and clearly the accuracy of these predictions is linked to the value of these tools.

Appropriate and timely clinical interventions can lead to considerable savings in future medical spending; however, because of scare resources, decisions must be made to identify the best candidates for such interventions. Our estimates show that health care spending for patients in the lower risk categories was significantly less in the subsequent year than for patients in the risk categories one level higher. The largest spending increase between groups was roughly 225%—an increase from the high risk category to the very high risk category. Thus, risk-scoring tools can help to identify patients with the highest potential for cost savings and, in conjunction with clinical criteria, help to identify the better candidates for interventions.

Multiple risk-scoring tools described in the published literature have been developed to predict patients' future spending.[11–16] When well-developed models are combined with high-quality data, these tools have the ability to predict medical expenditures accurately and inform payers on appropriate case management strategies. However, as previously discussed, models that use only utilization counts or claims data as predictors of future medical spending tend to have certain limitations. For example, future spending estimates from models that include only health care utilization metrics may not fully account for

differences in disease burden across comorbidities, whereas models that only include comorbidity indices and diagnostic clusters tend to have lower predictive power.[11,16] As a correction for these limitations, Farley et al.[11] show that the predictive performance of models that include claims-based metrics can be strengthened with the inclusion of utilization counts as additional predictors. However, even with the improved predictive power, these models do not include indicators for patient weight, which has been shown to be correlated with higher spending[8,9] and which may enhance the predictive power of an obesity-specific model.

Our model is compelling because, in addition to combining utilization counts with claims data, we include a weight-related metric (BMI), which is usually not a predictor in risk-adjustment models. One exception to this pattern is the work of Baumeister et al.,[37] which includes BMI as a cardiovascular risk factor in a risk-scoring model. They find that BMI is correlated with baseline health care costs but is not a predictor of spending after 5 years. A possible explanation for the conflicting predictive significance of BMI between our study and that of Baumeister et al.[37] is the time frame for prediction. Our study focuses on predicting next-year spending. Weight can fluctuate in the short run, which implies that its predictive power would likely be stronger for 1-year spending than for 5-year spending.

One possibility for capturing potential health care savings is through interventions that reduce patients' BMI (a key predictor of an elevated MERS) and improve general health status. Papers such as the one by Adams et al.[38] show evidence of increased rate of diabetes remission and reduced risk of dyslipidemia and hypertension following bariatric interventions. Naturally, lower BMI and lower risk of comorbidities correspond to lower risk of high future spending.

In our paper, we considered a common bariatric surgery intervention that results in mean BMI reductions that are significant enough to move patients to a lower obesity class, i.e., obese class III individuals to obese class II, obese class II individuals to obese class I, and obese class I individuals to overweight. The predicted changes in MERS associated with such weight loss intervention are comparable to the predicted changes that would result from hypothetical shifts in patients' health states if it were possible to cure patients with depression, renal failure, or type 2 diabetes of their condition. The changes are also comparable to hypothetically lowering the mean age of the working-age reference population by 5 years, from 43 to 38 years. Correspondingly, a weight loss intervention with the mean estimated effects on BMI discussed above would move the average obese class II and obese class III patients from the very high risk category to the high risk category. As previously shown, transitioning patients away from the highest risk category is associated with a reduction in the subsequent year's medical expenditures. This would translate into large savings potential, given that 8.8% and 6.0% of adults aged 20 to 79 in the United States from 2007–2008 had BMIs in the obese class II and obese class III ranges, respectively.[39]

Bariatric surgery is not without risks or costs. The typical costs for bariatric surgery in 2004 ranged from $20,000 to $35,000.[40] Complications vary across different bariatric surgery interventions and may include gastrointestinal disturbances (e.g., leaking, loose stool, constipation),[41–43] bleeding,[41] and reoperation,[42–44] among others. However, as Michaud et al.[45] show, surgery is one of the most effective of the currently available methods of weight loss.

Other approaches to weight loss include behavioral change, especially in childhood,[46,47] and prevention. However, the evidence for successful behavioral change and weight loss for adults is mixed and the studies suffer several limitations, leading the U.S. Preventive Services Task Force to conclude that "the evidence is insufficient to recommend for or against the use of counseling of any intensity and behavioral interventions to promote sustained weight loss in overweight adults."[48] Prolonged pharmacotherapy is slightly more promising, but its discontinuation may lead to rapid weight regain.[49]

Success in preventing obesity and promoting healthier behaviors is also a product of the environment, including the family context, community, and societal influences. Full-service supermarkets with an array of fresh produce, for example, are often limited in poorer urban neighborhoods and rural communities. The U.S. Department of Agriculture estimates that 2.3 million U.S. consumers live more than a mile from a supermarket and do not have access to a car.[50] Even for those with adequate access, healthier diets cost more overall, creating incentives for low-income families to purchase higher-calorie, less–nutrient-rich, less-expensive food.[51,52] Neighborhoods and community matter as well to health; the prevalence of fast-food restaurants[53,54] or the lack of safe areas to exercise and play may contribute to sedentary lifestyles and poor diets, with resulting weight gain. Neighborhood influences weight through social networks and social capital as well. Epidemiological studies have documented that higher socioeconomic groups tending to eat a higher-quality diet[55] and therefore when lower–socioeconomic-status families move to better neighborhoods, they may be exposed to healthier habits.[56] The Moving to Opportunity experiment found that low-income adults who moved to lower-poverty neighborhoods were 4.6 percentage points less likely to have a BMI > 35 than those in the control group who remained in poor neighborhoods, and they were 3.4 percentage points less likely to have a BMI ≥ 40.[57] There was no significant effect on less extreme obesity, however.

In addition to access, marketing influences diets. The Federal Trade Commission found that the 44 companies surveyed in a seminal study spent more than $1.6 billion to promote food and beverages to children and adolescents in the United States in 2006. Carbonated beverages, restaurant food, and breakfast cereals accounted for 63% of the total marketing expenditures.[58,59] A meta-analysis by the Institute of Medicine revealed a correlation between advertising and later adiposity in children and teens.[60]

Limitations

Our study does have certain limitations. First, our sample may not be representative of the entire U.S. population because the sample is based on payroll records from a small number of large U.S. employers. Furthermore, the sample is linked to HRA data, which are voluntary and thus could introduce some level of selection bias. Second, our tool was limited to the variables available in the data. The literature shows that the omission of significant covariates can reduce the predictive power of the models[11]; however, the inclusion of BMI has significantly improved the predictive power of our model. Additionally, the interactions between the included comorbidities and obesity are unclear when calculating the effects of bariatric interventions. To account for this, we estimated both conservative and optimistic scenarios. Third, changes in medical technology may alter the effects of age, gender, and BMI risk over time; thus, our model may need to be updated in the future. Finally, we do not demonstrate causality, but we have clearly showed an association between our covariates and the MERS, which is sufficient for predicting future spending.

SO WHAT? Implications for Health Promotion Practitioners and Researchers

What is already known on this topic?

Obesity and medical spending are on the rise in the United States. Models have been developed to predict a patient's risk of high future spending using health care utilization and comorbid conditions; however, existing models generally omit weight-related measures. Because obese patients have higher medical spending compared to normal-weight individuals, it is useful to include a weight-related metric in prediction models to obtain an accurate assessment of a patient's risk of high medical spending.

What does this article add?

This article presents and applies a model to calculate a patient's risk of high medical spending in the subsequent year. Unlike past studies, it includes BMI in the risk-scoring model, along with more traditional metrics such as utilization counts and comorbidity measures, to predict the impact of obesity on a patient's risk of high future spending.

What are the implications for health promotion practice or research?

By estimating a patient's risk of future medical spending, our model can help identify patients who will likely gain the most benefit from relevant intervention strategies. For example, assuming that a bariatric intervention transitions the patient to the next lowest obesity class (e.g., class III to class II), we estimate a significant reduction in the patient risk score as a result of such intervention. Therefore, using appropriate clinical criteria and our risk-scoring tool to identify obese patients with the highest potential for cost savings, payers and providers can determine ideal candidates for intervention.

Future Directions and Conclusion

This study employed a risk-scoring tool to demonstrate that obesity is associated with a drastically increased MERS, reflecting an increased risk of high medical spending. Therefore, bariatric interventions that lower BMI have the potential to help patients and payers realize substantial cost savings. Specifically, the simulated impact, in terms of lowering future health expenditures, of interventions that transition patients to lower obesity classes is comparable to that of hypothetically curing patients with depression or type 2 diabetes of their respective conditions. Future research measuring the impact of reducing BMI on MERS after specific bariatric interventions is a logical next step.

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