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The Healthcare Costs of Overnutrition

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The Health Care Costs of Overnutrition:

A Disease-based and Instrumental Variables Approach

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ABSTRACT

Obesity is a growing problem globally and domestically. Obesity is related to several chronic and noncommunicable diseases such as hypertension, type II diabetes, coronary heart disease, and some cancers. Both obesity and its related diseases are forms of overnutrition, which is the excess intake of nutrients that causes increased body fat to the point of impaired health. Using data from the Medical Expenditure Panel Survey (MEPS) from 2008-2016, this paper is the first to estimate the causal effect of overnutrition on medical expenditure by examining the effect of overnutrition diseases on health care costs, correcting for the endogeneity bias of body fat in medical expenditure and reporting error in the MEPS by identifying individuals' BMI as an instrumental variable. I estimate that the marginal effect of overnutrition diseases on medical expenditure for individuals is $1,392.93 (in 2016 dollars), and the aggregate effect of overnutrition diseases on national health expenditures is $788.7 billion, or 23.9%, annually. I also estimate that overnutrition diseases are responsible for $287.1 billion, or 23.2% of Medicare and Medicaid health expenditures. My results indicate that the previous literature has underestimated the true impact of obesity and its related diseases on medical costs by not explicitly identifying the overnutrition diseases that are endogenous to obesity as the main explanatory variable.

I. INTRODUCTION

Over the past fifty years, the obesity rate has increased to epidemic proportions globally, where now 650 million adults are obese and 2 billion are overweight. Obesity is a major risk-factor for some of the leading causes of death: coronary heart disease, type II diabetes, stroke, and a number of cancers like breast and colon cancer. As a chronic disease itself, obesity is strongly associated with these other chronic diseases because they all stem from overnutrition. Poor diet and lifestyle choices cause overnutrition which is a form of malnutrition in which an imbalance of nutrient consumption[1] and expenditure leads to an excessive accumulation of body fat, especially intramyocellular lipids, which not only raises one's body mass but accelerates the development of atherosclerosis (high cholesterol), hypertension (high blood pressure), insulin resistance, and inflammation. With the adult obesity rate in the United States reaching 39.6% in 2016, it is becoming increasingly relevant to understand the effect of overnutrition on health care expenditure as a decline in the general health, quality of life, and productivity of people are threatened. Accurately measuring this relationship is especially important because i) it is a basic way of identifying the economic burden it poses to individuals' finances and insurance premiums, the expense of firms' group insurance contracts, and government spending on welfare programs like Medicare and Medicaid, and ii) if its attributable costs are significant, it may provide further incentive for individuals and countries to seek solutions that prevent and reverse these diseases.

The notion of obesity-related diseases can be vague, but it often refers to the diseases and medical outcomes caused by or associated with hypertension, atherosclerosis, insulin resistance, inflammation, endothelial dysfunction, and oxidative stress, all of which are highly associated with obesity. For this paper, the diseases and disease outcomes studied are atherosclerosis, hypertension, type II diabetes, coronary heart disease, breast cancer, colon cancer, heart attack, stroke, and other forms of heart disease and cancers[2]. While the relationship between obesity and each of these health risks vary, there is an abundance of evidence in the medical literature, namely by *Pi-Sunyer (2009)* and *Campbell (2017),* that suggests obesity is strongly correlated with each listed risk and that these health risks can be explained by overnutrition[3].

Recent research has estimated the effects of obesity on medical care costs through a two-part model that characterizes an individual's medical expenditure first by estimating the likelihood of medical care consumption and second by estimating the amount of medical care costs for those who have any costs. *Cawley and Meyerhoeffer (2010)* and *Qin and Pan (2015)* implemented instrumental variables (IV) to reduce endogeneity bias in the estimates and establish a causal relationship between BMI and medical expenditure. However, the underlying assumption of these methods, that obesity is the primary reason for increased expenditure in obese people, is flawed since obesity is merely a description of a person's weight to height ratio.

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[1] Overnutrition is not only eating too many calories. It also includes consuming certain nutrients, like dietary cholesterol, which promote disease.

[2] Other forms of heart disease and cancers are related to overnutrition, but the MEPS data does not distinguish between many of them. Nearly all forms of heart disease are affected by endothelial dysfunction which is attributable to diet choices (see *Barthelemes et al (2017)*). Other forms of cancer like rectum, endometrium, esophagus, pancreas, liver, and kidney are linked to overnutrition (see *Rock et al (2020)*).

[3] For the sake of organization, the References section at the end of the paper will include two distinct sections: economic literature and medical literature. Since there isn't any one study that comprehensively substantiates the medical claims in this paper, most citations will not be formally referenced in the text but can be found in the References.

The primary reason for increased expenditure in obese people is the presence of the diseases associated with obesity, like heart disease and type II diabetes, that cause people to spend money on medication and surgery. Obesity does not cause these overnutrition diseases, it is simply related to them. The root cause of overnutrition diseases are individuals' decisions regarding nutrition and exercise, so this paper improves upon the literature by using obesity-related diseases as the main explanatory variable with the individual's BMI as an instrumental variable reducing the endogeneity bias of body fat in medical expenditure and the reporting error that is unavoidable in the self-reported data collection method of the MEPS . By focusing on the effects of obesity-related diseases explicitly, the relationship between overnutrition and medical care costs is more accurately measured, and a causal link between obesity-related diseases and health care expenditure is drawn from the IV estimation. Through this disease-based and instrumental variable approach, I discover that past research has underestimated the effects of overnutrition on medical expenditure.

The remainder of the paper will be organized as follows: a literature review outlining the development of the methodology in the literature, a description of the data source and sample used in this paper, the empirical model and logic behind the choice of instrumental variable, tables and summaries of the main results including tests for the power, validity, and robustness of the IV, a discussion of the results in the context of previous research, the medical literature surrounding this topic, and implications for policy and future research, and the conclusion.

II. THE COSTS OF OBESITY

Due to its growing relevance globally, obesity's effect on health care and health care expenditures is becoming more widely studied. The standard method of measuring obesity is through the body mass index (BMI) which is calculated by dividing a person's weight (kg) by their height squared (m^2). A BMI between 18.5-24.9 is the healthy/normal range and a BMI above 30 is obese. The costs associated with obesity are either direct, the inpatient and outpatient medical costs as a result of obesity and its related diseases, or indirect, absenteeism, presenteeism, and opportunity costs. While some research has investigated the effects of obesity on indirect costs, the bulk of the literature focuses on estimating the associated direct costs. For example, *Colditz (1992)* use a prevalence-based approach to estimate the direct costs of obesity through the relative risk of contracting type II diabetes, coronary heart disease, gallbladder disease, hypertension, and breast and colon cancer which result in $39.3 billion or 5.5% of national healthcare expenditure in 1986. Updates to these estimates by *Wolf and Colditz (1998)* in which endometrial cancer and osteoarthritis were added to the direct costs as well as the indirect costs of excess physician visits, work-lost days, restricted activity days, and bed days, found that the total costs attributable to obesity are $99.2 billion, $51.64 billion of which are direct medical costs accounting for 5.7% of national healthcare expenditure in 1994. Both these papers use data from the National Health Interview Survey (NHIS) from 1986 and 1988-1994, respectively.

Improving on the estimation methodology, *Finkelstein et al. (2004)* provide state-level estimates of obesity's effect on total (including Medicare and Medicaid) medical expenditures using 1996-1997 NHIS data combined with data from the 1998 Medical Expenditure Panel Survey (MEPS) and the Behavioral Risk Factor Surveillance System through a four-part regression model. The state-level estimates range from $87 million (Wyoming) to $7.7 billion (California) for a national-level estimate at $75 billion; $17 billion financed by Medicare and

$21 billion by Medicaid. *Finkelstein et al. (2009)* estimate U.S. obesity costs across payers-- Medicare, Medicaid, and private insurers-- in separate categories for inpatient, non-inpatient, and prescription drug selling with MEPS data and an innovative two-part model (2PM). The first part estimates the probability of having a specific type of expenditure (*e.g.* inpatient) through a logit model, and the second part estimates total spending conditional on having positive spending from the first part through a generalized linear model (GLM) with a log-link and gamma distribution. The prevalence of obesity is responsible for $40 billion in increased spending from 1998 to 2006, and the difference in costs for obese versus healthy weight individuals is $1,145 in 1998 and $1,429 in 2006, a percent difference of 36.5% and 41.5%, respectively.

Utilizing the same 2PM, *Cawley and Meyerhoeffer (2010)* identify the BMI of a biological child as an instrumental variable to address the endogeneity of weight and to reduce the bias from reporting errors in the MEPS data. This instrument exploits genetic variation in weight yielding higher and more accurate estimates of obesity's effect on medical care costs. Without the IV, obesity is associated with a $676 increase in medical expenditure, but with the IV, the increase in cost between not being obese and being obese is $2,826 (in 2005 dollars). The annual national cost attributable to obesity is $168.4 billion which is 16.5% of medical care, which indicates that the previous research underestimated the effects of obesity by lacking a strong IV.

Qin and Pan (2015) publish the first comprehensive study of this topic in China using the 2PM, identifying the prevalence of obesity in the respondent's residential community as an IV. They contribute to the literature by using an IV+RE (random effects) model which further deals with the endogeneity problem by accounting for the longitudinal feature of a person's medical spending, with data from the China Health and Nutrition Survey 2000-2009. Comparing the effects of obesity in the 2PM, 2PM with an IV, and 2PM with an IV+RE, the highest estimates were in the IV+RE model indicating that unresolved endogeneity bias, even in the IV model, can cause significantly underestimated results. Overweightness, obesity, and their related ailments cause China to spend 24.35 billion yuan which is 2.46% of total health care expenditures.

III. DATA AND SAMPLE

Data Source

The data for this research is from the MEPS (Medical Expenditure Panel Survey) which collects nationally representative survey data from the U.S. civilian non-institutionalized population through an overlapping panel design. Data for each panel of households is collected for two calendar years in five rounds of interviews. The data has three components: (i) the Household Component, (ii) the Insurance Component, and (iii) the Medical Provider Component. The first covers the specific health services used by individuals and households, how often those services are used, the cost of the services, and the payment method used. The second covers Americans' access and use of different health insurance services. The third covers data collected on the medical care provided by physicians, hospitals, home health agencies, and pharmacies. I use data from the Household Component in the 2008-2016 waves of the MEPS, converting the medical costs in each year to 2016 dollars.

The data in the sample is limited to adults between the ages of 18 and 85 since the BMI range for body measure categories differs between children and adults. The weight and height of the individuals in the household are reported by one respondent, unless every adult is present, in which case they each report their weight and height. Individuals with BMIs greater than 60 and less than 12 or with medical expenditures in excess of $300,000 are excluded since these BMIs and expenditures are extreme outliers. Lastly, pregnant women are excluded since their BMI and medical costs are unrepresentative of their usual size and spending. In total, the sample in this paper is 174,428 observations.

Two measures of medical expenditures are used in the empirical models: total medical expenditures and public medical expenditures (those paid for by Medicare and Medicaid). These costs consist of spending on hospital inpatient care, ambulatory care, care provided in emergency departments, care provided in the patient's home, and the purchase of prescribed medications, which comprises all direct medical costs collected by the MEPS.

<u>Sample Description</u>

Descriptive statistics of the overnutrition diseases are reported in Table 4, descriptive statistics for key variables are outlined in Table 5, and descriptive statistics for all other variables are presented in Table 6. As a summary of the sample, 79% of adult men and women have some medical expenditures with an overall average expenditure of $4,578.88 (which includes those with no expenditure). About 20% of individuals use Medicare and about 16% use Medicaid[4]. The average expenditure for Medicare users is $1,345.38, $564.29 for Medicaid, and $4,578.88 for the general population. The average BMI is 28.08 which is in the upper half of the overweight BMI category. The average prevalence of obesity is 32% which is equivalent to the proportion of the sample who has a healthy BMI. Half of the sample has at least one overnutrition disease, with the most common diseases being atherosclerosis and hypertension at 30% and 33%, respectively.

IV. EMPIRICAL MODEL

With the time and resources, the preferred study of this topic would be to conduct a long-term randomized control trial in which a large group of people are divided into two groups. The control group would change nothing about their diet choices, other than the changes they normally would make, and the treatment group would adopt a whole food plant-based diet as recommended by *Ornish et al (1991), Esselstyn et al (2011), Barnard et al (2017), and Campbell et al (2017).* Research conducted in these papers found that whole food plant-based diet is effective at reversing and preventing coronary heart disease, type II diabetes, and cancer growth. The obesity rates, morbidity rates, and medical expenditures between the two groups would be tracked and then compared through a difference in differences model. In lieu of such a method, I rely on the methods outlined below.

The conventional method for estimating the effect of obesity on medical expenditures in the literature is through a two-part model, where the first part determines the probability of having positive expenditure and the second part determines the amount of expenditure conditional on having any. The equations for this model are:

$$P(y_i > 0 | X_i, V_i) = C(\gamma X_i + \alpha V_i + w_i) \quad (1)$$

$$y_i = \exp(\lambda X_i + \beta V_i) + z_i, \text{ for } y_i > 0 \quad (2)$$

[4] There is overlap in the use of Medicare and Medicaid. 14% of the sample only uses Medicare and 11% only use Medicaid to pay for their health care costs.

where y_i is the total expenditure of individual i incurred in the reported year of the MEPS. The main independent variable is X_i which takes a different form depending on the iteration of the model. For Table 1, it is a vector of the BMI categories "Obese" and "Healthy," for Table 2 it is a discrete variable for the overnutrition diseases, and for Table 3 it is a binary variable for overnutrition diseases in which 1 indicates having at least one disease and 0 indicates having no disease. The variable V_i is a vector of characteristics of each individual that are being controlled for.[5] The left-side of equation (1) is the probability of an individual having positive medical care costs given X_i and V_i, and it is estimated with a logit model. The right-side of equation (1) is the cumulative distribution function of the logistic distribution, with w_i as the error term. Equation (2) estimates the amount of expenditure incurred conditional on having positive expenditure, and it is estimated through a generalized linear model (GLM) with a gamma distribution and log link, where z_i denotes the error term. The parameters $\gamma, \alpha,$ and λ, β are the coefficients, representing the effect of an obese BMI, a healthy BMI, and presence of overnutrition diseases on the probability of positive expenditure and on the amount of conditional expenditure, respectively.

The 2PM is effective at capturing the correlation between BMI-measured health categories and expenditure. However, to form a causal relationship, the endogeneity bias related to weight as well as the reporting errors in the data must be corrected for. Past research by *Cawley and Meyerhoeffer (2010)* and *Qin and Pan (2015)*, have addressed this issue through the method of instrumental variables. These papers take an individual's BMI to be endogenous to the BMI of biological children and community members, which they use as instruments to better estimate the effect of the individual's BMI on their medical expenditure. While these approaches produced results significantly greater and more accurate than the previous literature and their own baseline models, they both suffer from the assumption that BMI is the cause of expenditure incurred by overweight or obese people, which I posit to be spurious since diseases are the chief cause of medical spending for overnutrition, not a person's weight to height ratio. This fundamental assumption in the literature is not corrected for by these IV-based papers.

By understanding that BMI exclusively measures the ratio of a person's weight to height, and not the status of endothelial function, any relationship obesity has with diseases like coronary heart disease and atherosclerosis is strictly correlational. This is further supported by the fact that many non-obese people, even healthy weighted people, suffer from diseases. Both obesity and its related diseases stem from the same root cause: poor diet and lifestyle choices. There is a vast body of medical literature[6] divulging the causal relationship between poor decision-making in regard to nutrition, primarily, but also exercise and stress management, that explains why people are obese and diseased with illnesses that only in the last seventy years have become commonplace. Since the economic literature measures the effect of obesity on expenditure through obesity's relationship to diseases, it is more logical and accurate to directly measure the effect of these diseases on expenditure, which decreases the omitted variable bias present in models where BMI is the main independent variable. I assert that the true intent of the previous literature is concerned with estimating not the effect of body size on expenditure per se, but rather the effect of the emerging global crisis of overnutrition on medical expenditures that is easiest to identify as an issue of body size. While the crisis can be broadly spoken of in terms of obesity, overnutrition can be more specifically analyzed by studying the effect of diseases on health expenditures. Considering that 32% of individuals in my sample are obese while 50% have an overnutrition disease, it is apparent that using obesity as the main explanatory variable to

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[5] Family size, region, age, gender, race, marital status, education attainment, employment, income.

[6] See the References section for an inexhaustive list.

determine the health care costs of the overnutrition epidemic is an inaccurate method. That is, obesity is a symptom of poor nutrition and lifestyle choices just like the diseases, yet the diseases are what cause people to purchase medication, undergo surgery, and suffer life-threatening medical events.

Therefore, to improve upon the literature, I substitute overnutrition diseases for BMI as the main explanatory variable. The diseases selected are atherosclerosis, hypertension, type II diabetes, coronary heart disease, breast cancer, colon cancer, other forms of cancer, coronary heart disease, other forms of heart disease, heart attack, and stroke. The medical literature supports these choices of diseases, as well as the strong likelihood of having the diseases for those who are obese versus those with a healthy BMI. This list is not exhaustive, for it is missing kidney disease, gallbladder disease, and osteoporosis which were unavailable in the MEPS data. Besides these missing diseases, the ones studied here are the most relevant and impactful diseases for studying increased expenditure in this topic.

Now, because body mass is related to and has a strong impact on the variation in the diseases between people, and since the significant effects of body mass on expenditure is indirect, affecting it only through diseases, it is appropriate to manage the endogeneity bias of diseases by using obesity as an instrumental variable, thus not only logically but quantitatively allowing the effect of diseases on expenditure to be causal. Moreover, this reduces the error caused by self-reported data since people who are underweight are more likely to over-report and people who are overweight are more likely to under-report their BMI. Due to the 2PM specifications, logit and GLM with log link and gamma distribution, and due to the nonlinear relationship between body mass and health quality (see *Xu (2015)*), rather than using BMI as the sole instrument, the BMI, BMI squared, and BMI cubed of the respondent are used as a set of instruments, following the method of *Cawley and Meyerhoeffer (2010)*.

All of the models control for the following regressors, except in instances when including the regressor poses obvious issues of collinearity: family size, census region (northeast, Midwest, south, and west), age (in the categories: 18-34, 35-44, 45-54, 55-64, and 65-85), gender, race (white, black, native American, Asian, pacific islander, and mixed), marital status, the highest level of education attainment (no high school diploma, high school diploma, some college, and college degree or higher), employment, and income.

V. RESULTS

Table 1. Baseline Estimates of the Marginal Effect of BMI on Medical Expenditure

		(1) Probability	(2) Amount
Total	Obese	0.039*	0.024*
		(0.0027)	(.0021)
	Healthy	-0.009	-0.012
		(0.0067)	(.0079)
Public	Obese	0.030*	0.025*
		(0.0021)	(.0031)
	Healthy	-0.006	-0.008
		(0.0072)	(.0131)

Notes to Table 1. Standard errors are in parentheses, and asterisks denote statistically significant results. The row titles "Total" and "Public" indicate the type of medical expenditure used as the dependent variable; where "Total" represents the expenditures of the entire sample, and "Public" represents the expenditures of the subpopulation who use Medicare and Medicaid. "Obese" and "Healthy" indicate the BMI category used for the main independent variable. The column titles "Probability" and "Amount" represent the two parts of the model; where "Probability" denotes the logit equation, and "Amount" denotes the GLM equation.

Although the primary contribution of this paper is on the effect of overnutrition diseases on medical costs with obesity as the IV, it provides useful context necessary to situating this paper in the literature to include the baseline 2PM with the categories of BMI-- obese and healthy-- as the independent variables. Table 1 estimates the baseline effect of BMI on medical expenditure with discrete variables Obese and Healthy representing the subpopulations with BMI in excess of 30 and inclusively between 18.5 and 24.9, respectively. The table outlines the marginal effect of BMI on total and public expenditures.

In column 1, obesity is associated with a 3.9% increase in likelihood of having any medical expenditure, while being healthy-weighted is associated with a 0.9% decrease in likelihood of having any medical expenditure, albeit insignificantly. Note that the probability and marginal effect of having a healthy BMI is statistically insignificant for both total and public expenditures. The probability of having positive public expenditure is 3.0% higher for the obese than for the non-obese and 0.6% less likely for the healthy.

In column 2, for those who have positive medical costs, obesity is associated with a 2.4% increase in total costs, while having a healthy weight is associated with a 1.2% decrease in total costs; such that, obesity implicates increased expenditure of $125.96 for every one point increase in BMI above 29 and having a healthy weight implicates decreased expenditure of $73.79 for every one point decrease in BMI below 25 but no less than 18.5. For public health care users, obesity is associated with a 2.5% marginal increase in health costs, $131.21, while a healthy weight is associated with a 0.8% marginal decrease, $52.22, in costs.

There appears to be a greater difference in both likelihood and amount of medical expenditure between the obese and healthy weighted in the general population than in the subpopulation of Medicare and Medicaid users. This may suggest that public health care users choose to use less health care services than people in the general population. However, considering that public health care users have a higher obesity rate at 36% as opposed to 33% in the general population and higher overnutrition disease rate at 76% versus 58%, it seems more likely that the difference in spending between the obese and healthy weighted is due to a difference in average relative healthiness between the general population and Medicare and Medicaid users. Because obesity and morbidity are more common among Medicare and Medicaid users, the people in this subpopulation have relatively similar overall health to one another than do people in the general population; such that, the difference in health care spending between obese and healthy weighted people are smaller than the difference in health care spending between obese and healthy weighted people in the general population. Of course, more research specifically on this topic will be needed to fully justify this observation.

Table 2. Baseline and IV Estimates of the Marginal Effect of Overnutrition Diseases on Medical Expenditure

	Baseline		IV
	(1)	(2)	(3)
	Probability	Amount	Amount
Total	0.920*	0.294*	0.513*
	(0.0107)	(0.0057)	(0.026)
Public	0.390*	0.250*	0.367*
	(0.0057)	(0.0075)	(0.031)

Notes to Table 2. Standard Errors are in parentheses, and asterisks denote statistically significant results. “Total” and “Public” as well as “Probability” and “Amount” serve their same respective purposes here as in Table 1. This table documents the results from the IV model in column 3.

In Table 2, the results from the 2PM with overnutrition diseases as the main independent variable and BMI as the instrumental variable are outlined. In column 1, the probability of having any medical care costs for those with overnutrition diseases is 92% more than those with no disease. For Medicare and Medicaid users, the increased likelihood is 39%. Comparing the baseline results from part one of the BMI model in Table 1 to the disease-variable model in Table 2, it is clear that the disease variable is a more powerful predictor of medical spending than BMI. That pattern is also present for the amount of spending, conditional on having positive expenditure.

In column 2, the marginal effect of overnutrition diseases increases total expenditure by 29.4%, $798.29, and increases public spending by 25%, $661.48, compared to those who do not have a disease. The baseline results alone indicate that the disease variable is a stronger way to measure the effect of overnutrition on health care costs compared to simply BMI.

In column 3, the marginal effect of overnutrition diseases causes 51.3% more expenditure for total spending, which is the same as $1,392.93 more than having no disease. For Medicare and Medicaid users, overnutrition diseases causes 36.7% or $971.05 in increased spending over not having any overnutrition diseases. By using obesity as an instrumental variable, I produce results that are considerably greater than the baseline estimates, and if my choice of instrument is valid in this model then it is likely that these high estimates are also more accurate.

Table 3. Baseline and IV Estimates of the Effect of Overnutrition Diseases on Medical Expenditure

	Baseline		IV
	Probability	Amount	Amount
	(1)	(2)	(3)
Total	1.467*	0.669*	1.339*
	(.017)	(.016)	(.074)
Public	0.809*	0.685*	1.457*
	(.015)	(.030)	(.130)

Notes for Table 3. Standard Errors are in parentheses, and asterisks denote statistically significant results. The main independent variable, overnutrition diseases is used as a binary variable for the model that produced these results. The "Probability" and "Amount" results are the increased effect of having some overnutrition disease(s) compared to having none. All row and column titles are used as in previous tables.

While Table 2 provides the marginal effect estimates of overnutrition diseases on medical expenditure, Table 3 includes the effect of overnutrition diseases on medical expenditure when the disease-variable is treated as a binary variable where 1 indicates having one or more overnutrition diseases and 0 indicates having no overnutrition diseases. In column 1, the likelihood of having any expenditure for those with some overnutrition disease is 146.7% greater than for those who do not. The likelihood of having positive expenditure for the diseased who utilize public health care is lower than the general population but still high at 80.9%. As stated previously, this lower positive probability is likely attributable to the higher morbidity rate among Medicare and Medicaid users compared to the general population.

In column 2, the baseline amount of increased expenditure for those with some overnutrition disease is relatively close between the total population and the public health care users at 66.9% and 68.5 %, respectively. In terms of dollars, having an overnutrition disease is associated with a $1,816.52 increase in expenditure for the general population and a $1,812.44 increase in expenditure for Medicare and Medicaid users compared to people without any overnutrition disease.

In column 3, the IV estimates are stated, and they are significantly higher than the baseline estimates. Having some overnutrition disease causes 133.9%, $3,635.75, increased expenditure in the general population and 145.7%, $3,855.08, increased expenditure in the subpopulation of public health care users compared to those without overnutrition diseases. The above results document the effects of overnutrition diseases on health care expenditure, but it does so without direct indication of which diseases are most common for people to develop, which are most prevalent for obese individuals, or which are most likely to be related to positive expenditure or high medical costs. To provide specificity of the nature of these diseases, there are four tables in the appendix that outline: descriptive statistics for each disease, the distribution of number of diseases in the sample, the likelihood of having specific diseases if an individual is obese, and baseline estimates of individual diseases on medical expenditure following the 2PM.

Power and Validity of the Instrument

For the IV results in Table 2 and Table 3 to be useful, the instrument set must be powerful and valid. Since the effects of overnutrition diseases on medical costs are estimated across total and public expenditure, the power of the instrument set must be tested in both parts of the 2PM across these two populations by using a weak identification test to determine whether the excluded instruments are correlated with the endogenous regressors. Following the test for power by *Stock, Wright, and Yogo (2002)*, the first stage F-statistic for each population specification is calculated and compared to the recommended minimum standard of power of F=10. The power of the F-statistics in each test exceed F=10 and their respective critical values suggesting that the instruments are powerful and unlikely to suffer from weak instrument bias. Although this test does not definitively prove that the instruments are powerful, it does provide some empirical evidence to suggest that they are powerful.

To test the validity of the IV models, both an overidentification and underidentification test are used. First, Hansen's test for over-identification is used to test the validity of the overidentifying restrictions of the instruments ensuring that the instruments are uncorrelated with the error term and the excluded instruments are rightfully excluded. GMM linear models are used to determine the J-statistics of the IV models with a chi-squared distribution with two degrees of freedom, and in each test the J-statistic is greater than zero and the p-value is greater than 0.1, thus I fail to reject the null hypothesis that the instruments are valid. Second, the Kleibergen-Paap LM statistic is used to test whether the equation is under-identified -- that the excluded instruments are correlated with the endogenous regressors. The LM statistics follow a chi-squared distribution with three degrees of freedom, and since the p-values in each test are less than 0.1, I reject the null hypothesis, which suggests that the instruments satisfy the relevance conditions.

Robustness Test

Beyond the power and validity tests, it is also valuable to conduct a robustness test. To ascertain the robustness of the results, I inspect the key assumption of the instrumental variable model. My analysis with the 2PM assumes that overnutrition diseases are endogenous to obesity, but if that assumption is untrue then the results may be spurious, and the effects of overnutrition diseases on medical costs may have been overestimated. To test the endogeneity of the disease-variable in Table 2 and Table 3, the Durbin score and Wu-Hausman F-statistic are calculated to estimate the effect of the disease-variable on both total expenditures and public expenditures. The Durbin score ranges between 27.16 and 189.25 and the Wu-Hausman F-statistic ranges between 27.18 and 189.45 in each test, and the p-values in each test are less than 0.05. This indicates that I should reject the null hypothesis that overnutrition diseases are exogenous to obesity; suggesting that it is likely that overnutrition diseases are endogenous to obesity. While it is impossible to conclude that this test fully proves that my assumption is sound, it does provide some evidence that my assumption is well-founded.

VI. DISCUSSION

This paper is the first to provide evidence of the causal relationship of overnutrition on medical care costs by explicitly analyzing the obesity-related diseases that are responsible for medical treatment with the use of instrumental variable estimation. The medical expenditure incurred by overnutrition diseases is approximately $292.8 million across the entire sample, which accounts for 23.9% of the total medical expenditure in the MEPS between 2008-2016, which is notably higher than the estimates of *Cawley and Meyerhoeffer (2010)* at 16.5% and all previous estimates in the literature. Overnutrition diseases are responsible for $122.1 million for the subpopulation of Medicare and Medicaid users, which is 23.2% of the total public expenditures in the MEPS during the same time frame. Assuming the sample, identification, and methods are generalizable to the national level, the cost of overnutrition diseases for the non-institutionalized population of adults in the U.S. account for approximately $788.7 billion of the total annual national health care expenditure for 2016. Likewise, the cost of overnutrition diseases for Medicare and Medicaid users is approximately $287.1 billion of the total annual Medicare and Medicaid expenditures.

I attribute the higher estimates of this paper to the difference in my identification of independent and instrument variables. Where the models in this paper primarily compare the differences in expenditure between the diseased and non-diseased, previous research compares the differences in expenditure between the obese and non-obese or the obese and healthy-weighted. Likewise, the instrumental variable differs from the previous literature, in that; the BMI of the individual is used as an instrument whereas the BMI of biological children or the BMI of community neighbors was previously used. Based on the way obesity is associated with medical spending, strictly through other diseases, and the endogeneity of the diseases in obesity, I believe the estimates produced by my choice of independent and instrumental variables are not only higher than past research but also more accurate.

Since my estimates are greater than estimates from previous research, it may seem suspicious that these models overestimate the effect of overnutrition diseases on medical costs. As demonstrated in the power and validity section of the paper, these high estimates are likely not caused by a weak or overidentified instrument. Obesity's effect on expenditure is primarily through obesity-related diseases and any direct effects it has on medical expenditures is insignificant. Moreover, considering that the leading causes of death are the diseases included in this paper, it is understandable that treatment for these diseases would not only be expensive but make up a sizeable portion of national medical costs, especially considering the prevalence of these diseases. In the sample, 50% of adults have at least one obesity-related disease and 28% have at least two. It is apparent that compared to obesity, an overnutrition disease variable is a much more powerful indicator of expenditure. Recall the results from Table 1 and Table 2 in which the increased likelihood at baseline of having positive expenditure if you are obese is 3.9% whereas overnutrition diseases increased likelihood by 92%, and the marginal expenditure increase of obesity was only 2.4% while overnutrition diseases were correlated with a marginal increase in expenditure of 29.4%.

Part of the motivation to study the effect of overnutrition on health care costs by focusing on the diseases, other than the increased accuracy, is that it allows for a closer study of the health economic effects of overnutrition than does focusing on obesity. There is a consensus in the medical community that the root of overnutrition, both for obesity and obesity-related diseases, is diet and lifestyle choices, with a strong emphasis on diet. Research by *Ornish et al (1991), Esselstyn et al (2011), Barnard et al (2017), and Campbell et al (2017),* found that by using a similar set of dietary parameters, a whole-food plant-based diet, atherosclerosis, hypertension, heart disease, type II diabetes, cancer growth, heart attacks, and strokes can be prevented and often times reversed. Focusing on the diseases rather than the body mass of people is better for researching the effects of overnutrition on health care costs because BMI is a much less robust measure of health than the diseases, and because not everyone who has the diseases are obese and not everyone who is obese has these diseases, studying the diseases specifically brings us closer to understanding the effects of particular diet and lifestyle choices on health care expenditure.

There are two policy implications of these results. The first is that these updated estimates to the literature further substantiate the need for government intervention to slow and reverse the overnutrition epidemic as now 50% of adults have some overnutrition disease which currently comprise 23.9% of total national health expenditures, which will likely continue to increase. If the evidence from the medical literature is correct, then policies that alter the dietary choices of Americans are a cost-effective route to decrease morbidity rates, thus decreasing expenditures. At the individual level, the same motivation to decrease morbidity rates by following the findings of the medical literature exists, as high Medicare and Medicaid taxes and hospital bills burden individual's finances, as well. Future research of this topic that conducts long-term randomized control trials in which the treatment group followed the whole food plant-based diet outlined in the obesity-related disease preventative and reversal literature would greatly enhance our understanding of the effectiveness of diet change on disease prevalence and medical expenditure.

The second policy implication is that because health care is the largest budget item of the U.S. government[7] and I estimate that 23.2% of the government's spending on health care is directly due to overnutrition disease, it could save the government, and ergo taxpayers, $287.1 billion annually to implement policies and simply adopt new behaviors that change diet choices.

VII. CONCLUSION

Assuming that a goal of individuals, insurance companies, and the government is to lower health care costs, and since obesity-related diseases are such an expensive part of health care, combating the growth rate of obesity and its related diseases would be a prudent strategy to take. In the United States, health care comprises the largest portion of government spending, and the health stock of individuals is incredibly valuable not only to the individual but to society as a whole. So, the choices people make to avoid diseases allow for increased productivity which benefits individuals and companies and therefore the macroeconomy, but it also allows people to enjoy a greater quality of life. Considering the high direct medical costs of obesity and obesity-related diseases and the threat these diseases pose on individuals' quality of life, it seems logical that solving the overnutrition epidemic would be of chief concern at the government and individual level. Insight from the medical literature on this topic as well as my own results strongly suggest that these non-communicable, chronic diseases are a function of individuals' choices. Commonly adopted dietary and lifestyle choices that are the standard behavior across

[7] The U.S. government spent $3.8 trillion in 2019

developed countries are fundamental to this topic. The preventability and reversibility of these diseases provides a basis for motivation to solve this problem because neither new technology nor new ideas are needed at the individual level. It seems well-informed decision making is sufficient to lower obesity, overnutrition disease rates, and lower health care expenditure.

Future research beneficial to the literature could explore the impact food choices have on overnutrition diseases and medical expenditure. One example of this would be to collect diet, health, and healthcare spending data from a city where some portion of the population follows a whole food plant-based diet and the other portion does not. Collecting such data from a population of a single city has the advantage of controlling some potentially confounding variables that would be present in a sample with people from different cities or states. A similar 2PM used in this paper could be applied to the sample collected with that methodology, and the results will more clearly articulate the effect diet has on overnutrition and medical spending. One potential city that could be studied in this manner is Loma Linda, California, where there is a large Seventh Day Adventist community where eating a plant-based diet is common as a religious practice.

VIII. APPENDIX

Table 4. Descriptive Statistics for Diseases (n = 174,428)

Variable	Mean	S.D.	Min	Max
Atherosclerosis	0.3	0.459	0	1
Hypertension	0.33	0.472	0	1
Type II Diabetes	0.1	0.298	0	1
Other Cancers	0.068	0.251	0	1
Breast Cancer	0.01	0.117	0	1
Colon Cancer	0.005	0.070	0	1
Coronary Heart Disease	0.05	0.227	0	1
Other Heart Disease	0.1	0.299	0	1
Stroke	0.04	0.192	0	1
Heart Attack	0.04	0.187	0	1

Table 5. Descriptive Statistics for Key Variables (n=174,428)

Variable	Mean	S.D.	Min	Max
Total Expenditures	$4,578.88	$12,368.80	0	$297,947.10
Positive Expenditures	0.79	0.406	0	1
Medicare Expenditures	$1,345.38	$6,803.40	0	$264,386.60
Positive Medicare	0.2	0.4000201	0	1
Medicaid Expenditures	$564.29	$4,314.79	0	$278,024
Positive Medicaid	0.16	0.3690329	0	1
Public Expenditures	$1,909.67	$8,364.91	0	$278,024
Positive Public	0.3	0.46	0	1
BMI	28.08	6.223	12.1	60
Obese	0.32	0.465	0	1
Healthy	0.32	0.466	0	1
Diseases	1.07	1.437	0	9
Diseases (Binary)	0.5	0.5	0	1

Table 6: Descriptive Statistics for Control Variables (n = 174,428)

Variable	Mean	S.D.	Min	Max
Male	0.47	0.499	0	1
Female	0.53	0.499	0	1
White	0.69	0.461	0	1
Black	0.2	0.399	0	1
Native	0.01	0.091	0	1
Asian	0.08	0.266	0	1
Pacific Islander	0.002	0.048	0	1
Multiple Races	0.02	0.139	0	1
Age: 18 - 34	0.32	0.465	0	1
Age: 35 - 44	0.18	0.388	0	1
Age: 45 - 54	0.19	0.391	0	1
Age: 55 - 64	0.15	0.359	0	1
Age: 65 - 85	0.16	0.363	0	1
Northeast	0.16	0.365	0	1
Midwest	0.19	0.395	0	1
South	0.38	0.485	0	1
West	0.27	0.443	0	1
HH Members: 1 - 2	0.5	0.5	0	1
HH Members: 3 - 5	0.43	0.496	0	1
HH Members: 6 - 10	0.07	0.248	0	1
No High School Diploma	0.22	0.42	0	1
High School Diploma	0.29	0.46	0	1
Some College	0.25	0.43	0	1
College Degree or Higher	0.23	0.42	0	1
HH Members: 11 - 15	0.001	0.034	0	1
Not Employed	0.37	0.483	0	1
Married	0.49	0.5	0	1
Income: Q1	0.26	0.436	0	1
Income: Q2	0.25	0.433	0	1
Income: Q3	0.25	0.432	0	1
Income: Q4	0.25	0.43	0	1
Year: 2008	0.13	0.338	0	1
Year: 2009	0.15	0.356	0	1
Year: 2010	0.13	0.34	0	1

Year: 2011	0.13	0.334	0	1
Year: 2012	0.08	0.27	0	1
Year: 2013	0.15	0.357	0	1
Year: 2014	0.14	0.35	0	1
Year: 2015	0.07	0.253	0	1
Year: 2016	0.14	0.351	0	1

Table 7. Distribution of Overnutrition Diseases

# of Diseases	# of People	% of Sample
1	37,497	21.50%
2	23,968	13.74%
3	13,562	7.78%
4	6,242	3.58%
5	3,615	2.07%
6	1,577	0.90%
7	523	0.30%
8	84	0.05%

Table 8. Baseline Estimates of the Effect of Individual Overnutrition Diseases on Medical Expenditure

Disease	Probability	Amount
Atherosclerosis	1.350*	0.342*
	(.021)	(.016)
Hypertension	1.334*	0.463*
	(.020)	(.015)
Type II Diabetes	2.037*	0.578*
	(.051)	(.022)
Other Cancers	1.217*	0.496*
	(.052)	(.025)
Breast Cancer	1.175*	0.485*
	(.145)	(.052)
Colon Cancer	1.710*	0.596*
	(.255)	(.087)
Coronary Heart Disease	1.524*	0.660*
	(.063)	(.028)
Other Heart Disease	1.216*	0.565*
	(.038)	(.021)

Stroke	1.366*	0.683*
	(.071)	(.033)
Heart Attack	1.529*	0.715*
	(.075)	(.034)
No Disease	-1.467*	-0.669*
	(.017)	(.016)

Notes for Table 8. Standard Errors are in parentheses, and asterisks denote statistically significant results. Each disease functions as the main independent variable, and the only disease variable, in its respective model. The last row contains the estimates for not having any disease, and it is serves to further juxtapose the difference in expenditure between the diseased and non-diseased.

Table 9. Probability of Having Specific Overnutrition Diseases for Obese

Atherosclerosis	0.645*
	(.012)
Hypertension	1.062*
	(.013)
Type II Diabetes	1.190*
	(.018)
Other Cancers	0.045*
	(.022)
Breast Cancer	0.157*
	(.044)
Colon Cancer	0.279*
	(.074)
Coronary Heart Disease	0.496*
	(.024)
Other Heart Disease	0.327*
	(.017)
Stroke	0.327*
	(.027)
Heart Attack	0.486*
	(.028)
No Disease	-0.850*
	(.013)

Notes for Table 9. Standard Errors are in parentheses, and asterisks denote statistically significant results. The structure of the models used for these results follows a different pattern from all previous tables. The main independent variable is a binary variable for obesity, 1 meaning obese and 0 meaning not obese, and the diseases are the dependent variable in their respective iteration of the equation. Like the previous tables, a logit equation is used here to estimate probability.

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