

The Impact of Obesity on Medical Care Costs and Labor Market Outcomes in the US

Adam Biener,¹ John Cawley,^{2*} and Chad Meyerhoefer³

BACKGROUND: The prevalence of obesity has risen dramatically in most countries of the world, and the economic consequences of obesity are not well understood.

METHODS: We analyzed data from the Medical Expenditure Panel Survey (MEPS) for 2001–2015 and estimated the percentage of healthcare costs that were associated with adult obesity, both for the US as a whole and for the most populous states. We also reviewed the literature on the impact of obesity on economic outcomes such as medical care costs, employment, and wages.

RESULTS: The percent of US national medical expenditures devoted to treating obesity-related illness in adults rose from 6.13% in 2001 to 7.91% in 2015, an increase of 29%. Substantial differences existed across states; in 2015, some states (AZ, CA, FL, NY) devoted 5%–6% of medical expenditures to obesity, whereas others (NC, OH, WI) spent >12% of all healthcare dollars on obesity. A review of previous literature that exploited natural experiments to estimate causal effects found that obesity raises medical care costs and lowers wages and the probability of employment.

CONCLUSIONS: A substantial and rising percentage of healthcare costs are associated with obesity. This is true for the US, for individual states, for each category of expenditure, and for each type of payer. Previous literature generally found that obesity worsens economic outcomes, such as medical care costs, wages, and employment, and imposes negative external costs that may justify government intervention.

© 2017 American Association for Clinical Chemistry

The prevalence of obesity, which is defined as a body mass index (BMI)⁴ of 30 or higher, where BMI is calculated as weight in kilograms divided by height in meters squared, has risen dramatically in many countries of the world in recent decades (1, 2, 3). This has led to considerable interest in the economic consequences of obesity.

The purpose of this article is two fold. First, it provides new and up-to-date estimates on the percent of healthcare expenditures in the US that are associated with obesity, both at the national level and for individual states. An important contribution is that the estimates for individual states are the first to be based on state-specific microdata as opposed to being based on national data and then attributed to individual states based on assumptions.

Second, this review summarizes what is known from the research literature about the causal effect of obesity on economic outcomes, including medical care costs, earnings, and employment. This information is useful for better understanding the economic consequences of obesity. More specifically, it is useful for estimating the cost effectiveness of interventions that prevent or reduce obesity. This information also helps payers of medical services (such as health insurance companies and government programs such as Medicare and Medicaid) better forecast future expenses in light of obesity trends.

Materials and Methods

We discuss the methods of this paper in 2 parts that correspond to the contributions of the paper. First, we discuss the methods of estimating the medical expenditures associated with obesity; second, we discuss the literature review.

ORIGINAL ANALYSIS OF MEDICAL EXPENDITURES ON OBESITY

We estimated models of medical care costs using data from the 2001–2015 Medical Expenditure Panel Survey (MEPS), which is a comprehensive, nationally representative survey of the US civilian noninstitutionalized

¹ Agency for Healthcare Research and Quality (AHRQ), Rockville, MD; ² Department of Policy Analysis & Management, Cornell University, Ithaca, NY; ³ Department of Economics, Lehigh University, Bethlehem, PA.

* Address correspondence to this author at: Department of Policy Analysis & Management, Cornell University, 2312 MVR Hall, Cornell University, Ithaca NY 14853. E-mail johncawley@cornell.edu.

Disclaimer: The views expressed in this article are those of the authors, and do not necessarily reflect those of the Agency for Healthcare Research and Quality or the US Department of Health and Human Services.

Received June 22, 2017; accepted October 12, 2017.

Previously published online at DOI: 10.1373/clinchem.2017.272450

© 2017 American Association for Clinical Chemistry

⁴ Nonstandard abbreviations: BMI, body mass index; MEPS, Medical Expenditure Panel Survey; BRR, balanced repeated replications; 2PM, 2-part model; GLM, Gamma generalized linear model; IV, instrumental variables; NLSY, National Longitudinal Survey of Youth.

Table 1. National and state sample sizes.

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
US	21 644	24 822	21 241	21 473	21 155	21 542	19 608	20 704	23 330	21 131	22 904	25 441	23 864	22 305	23 115
AZ	453	695	571	580	589	661	509	387	423	365	376	396	357	313	318
CA	3122	3594	3031	2891	2888	3068	2847	3324	3824	3347	3678	4419	4281	4002	4077
FL	1196	1333	1123	1130	1109	1162	1078	1350	1539	1290	1515	1659	1476	1432	1559
GA	594	687	616	688	611	575	550	630	760	688	718	757	665	703	716
IL	845	935	823	869	875	872	741	713	846	810	771	879	875	781	787
KY	437	471	410	423	398	422	403	445	461	426	447	458	395	377	376
MA	353	363	277	284	263	254	260	304	333	320	359	456	454	447	470
MD	465	478	412	445	432	369	290	331	381	342	384	448	449	459	436
MI	864	870	762	719	701	719	646	655	711	680	783	790	668	635	709
NC	664	827	738	713	684	693	626	651	694	576	637	691	600	591	631
NJ	538	615	527	528	539	550	525	623	740	698	759	746	675	648	621
NY	1245	1468	1214	1230	1237	1223	1174	1245	1410	1241	1365	1606	1481	1227	1188
OH	764	874	708	728	715	719	665	635	752	741	746	718	620	595	657
PA	782	803	613	687	689	683	659	629	658	659	704	796	892	805	877
TX	1965	2452	2330	2499	2365	2251	1979	1990	2164	1822	2051	2379	2208	2073	2231
VA	495	483	387	423	423	429	488	618	695	644	672	772	725	624	696
WA	375	604	485	461	525	563	486	479	559	547	531	564	578	550	518
WI	448	505	427	399	402	440	431	399	409	401	427	420	380	380	346

Data Source: Medical Expenditure Panel Survey data for 2001–2015.

population that has been conducted annually since 1996 using an overlapping panel design. Respondents are surveyed about their medical care use and expenditures in 5 interview rounds that take place over the course of 2 years. In addition, utilization and expenditure data are collected directly from participants' medical service providers and pharmacies through the Medical Provider Component.

For the purposes of this article, we focused on adults and thus limited the sample to individuals aged 18 or older. Within each household, the weight and height of each family member are typically reported by a single respondent, most often the wife/mother. We excluded from the sample all adults with missing values of height or weight. We also excluded from the sample (a) 47 individuals with implausibly high BMI, i.e., above 80; (b) 8913 women who were pregnant; and (c) 15 individuals with extreme values of annual medical expenditures, i.e., above \$500 000. The remaining sample consisted of 334 297 adults, 99 377 (30%) of whom are obese. See Table 1 for sample sizes by year and geographic unit (the US as a whole and individual states).

To ensure comparability over time, medical expenditures in each year were converted to year 2015 dollars using the Consumer Price Index of the US Bureau of Labor Statistics (4). Total medical expenditures included

inpatient care, ambulatory care (which includes emergency department visits, outpatient visits, and other office-based care), prescription drugs, and other care, which includes dental, vision, home healthcare services, and medical equipment but excludes spending on over-the-counter medications. In addition to presenting results for total medical expenditures, we also present results for the major categories of expenditures: ambulatory, inpatient, and prescription drugs. Medical expenditures were examined overall as well as separately by payer: private health insurance companies, Medicare, Medicaid, all third-party payers combined, and patient out-of-pocket expenditures.

MEPS data were collected through a stratified multistage probability design, which was accounted for in the calculation of the standard errors of the estimates. Specifically, the method of balanced repeated replications (BRR) was used to estimate standard errors, accounting for clustering at the primary sampling unit level, stratification, and weighting (5).

To estimate the impact of obesity on medical spending, we estimated a 2-part model (2PM) of medical expenditures. The first part of the model estimated the probability of having positive medical expenditures; this was estimated as a logit model using the entire sample. The second part of the model estimated

the amount of medical expenditures conditional on having any; this was estimated as a Gamma generalized linear model (GLM) with log link and was estimated using only the sample that had positive medical expenditures. Put another way, the first part of the model was concerned with the extensive margin of medical expenditures (whether there are any) and the second part of the model was concerned with the intensive margin of medical expenditures (how much conditional on having some nonzero amount).

We computed the share of medical expenditures associated with obesity by first estimating the association of individual annual medical expenditures with obesity and then summing the average effect over the entire sample using the MEPS sample weights. We then used the estimates of the 2PM to predict the average total individual medical care expenditures, which was also aggregated across the entire sample using the MEPS sample weights to estimate total national medical expenditures. We subsequently divided the national expenditures associated with obesity by the national total medical care expenditures to compute the share of all medical care expenditures that are associated with obesity. This was performed for the nation as a whole using models estimated using the entire MEPS sample, as well as for the most populous individual states using only the MEPS respondents who live in those states. Due to sample-size limitations, MEPS estimates for this paper could only be produced for the following states: AZ, CA, FL, GA, IL, KY, MA, MD, MI, NC, NJ, NY, OH, PA, TX, VA, WA, and WI. We used state-specific weights in our BRR procedure to ensure that the state-level estimates were representative of state populations (6).

To clarify, the numerator in this percentage was the amount by which obese individuals have higher medical expenditures than nonobese individuals with otherwise identical observed characteristics. In other words, it was not the total amount of medical expenditures of the obese but rather the amount by which the medical expenditures of the obese exceed those of otherwise identical nonobese individuals.

Our approach for estimating state-level expenditures on obesity is an improvement over the methods used by previous studies because those earlier studies did not estimate models separately for respondents from each state. Instead, they estimated a national model of obesity-attributable medical expenditures using the MEPS and then imputed state-level expenditures using the characteristics of respondents in another survey, the Behavioral Risk Factor Surveillance System (7, 8). This method did not allow for differences across states in the correlations between medical expenditures and obesity, such as differences in access to medical care by the obese, the amount and type of medical care provided to obese individuals, and the prices of such treatments.

All of the medical expenditure models controlled for the following individual characteristics: gender, race/ethnicity, age, education, urban residence, marital status, household composition, whether the survey information was self-reported as opposed to proxy-reported, source of health insurance, whether the respondent's health insurance was administered by an HMO or managed care plan, and indicator variables for year. The regression using national data also controlled for census region. We did not control for additional comorbidities (such as diabetes or high blood pressure) because these may be in part affected by obesity (9) and thus should be omitted to allow for the coefficient on obesity to reflect the total association of healthcare costs with that condition.

REVIEW OF PREVIOUS LITERATURE ON THE ECONOMIC IMPACT OF OBESITY

A selective review was conducted in the spring of 2017 on the economic impact of obesity using the database EconLit and databases of unpublished research such as the working papers series of the National Bureau of Economic Research. The research focused on the impact of obesity on medical care costs, earnings and wages, and employment. The research literature was assessed based on factors such as the strength of research design, data quality, sample size, generalizability, and other factors.

Results

ORIGINAL ANALYSIS OF MEDICAL EXPENDITURES ON OBESITY

Table 2 presents the percentage of total medical expenditures that are associated with obesity, both for the US and for the most populous states, from 2001–2015. Percentages in bold are statistically significant at the 5% level.

The results in Table 2 indicate that although there was some fluctuation from year to year, in general there was an upward trend in the share of national expenditures associated with obesity over the period 2001–2015. For the US as a whole, the percentage of medical expenditures associated with obesity rose from 6.13% in 2001 to 7.91% in 2015; this increase of 29% is statistically significant at the 5% level.

States varied in the share of medical expenditures associated with obesity; medical expenditure was relatively low (between 3% and 6%) in CA, FL, and NY, but it was much higher (between 8% and 14%) in IL, NC, OH, VA, and WI. Variation across states in the percent of expenditures associated with obesity is due to many factors, including differences in the prevalence of obesity, differences in healthcare utilization among the obese, differences in how physicians treat

Table 2. Trends in share of national and state all-payer expenditures associated with obesity.^a

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
US	6.13	6.22	6.36	6.67	6.83	7.01	7.08	7.38	7.55	7.67	7.63	7.73	7.90	7.85	7.91
AZ	4.71	5.23	5.35	5.15	4.78	5.61	5.27	6.19	6.73	5.17	6.80	6.67	4.44	5.42	5.67
CA	3.83	3.55	3.60	3.88	3.79	3.81	3.86	4.05	4.52	4.78	4.78	4.45	4.51	4.20	4.18
FL	4.26	5.38	5.46	4.79	5.13	5.52	5.51	5.61	5.78	6.04	5.71	5.41	5.84	5.86	5.80
GA	7.76	8.03	7.77	9.24	9.20	9.27	9.78	9.56	11.03	9.68	11.15	11.90	11.34	9.68	10.62
IL	9.01	9.15	9.60	10.39	11.24	11.59	11.00	10.20	10.65	10.86	8.96	9.91	11.38	10.73	11.21
KY	5.73	6.54	6.17	6.15	7.25	7.30	7.22	8.55	8.19	7.38	8.13	9.30	9.15	8.09	8.71
MA	7.42	5.45	6.01	6.18	6.49	6.50	6.58	10.21	10.11	7.00	9.01	8.11	9.18	9.28	7.59
MD	3.57	4.12	4.66	4.74	5.48	5.04	4.73	5.34	5.97	6.44	6.09	6.06	6.54	5.80	6.54
MI	7.90	8.12	8.72	9.34	9.27	8.96	9.68	8.83	8.80	9.91	9.84	11.28	10.40	9.53	9.52
NC	10.37	9.71	10.43	10.94	11.77	13.14	12.07	11.92	11.82	13.49	14.55	12.32	14.27	12.58	13.65
NJ	7.08	8.24	5.71	7.74	9.03	9.63	9.14	8.15	7.95	9.10	9.50	8.60	9.63	9.16	9.44
NY	4.53	4.35	4.69	5.53	5.10	5.35	5.54	5.93	5.49	5.74	5.90	5.58	6.16	5.99	5.55
OH	8.72	8.94	8.60	9.26	11.14	9.88	10.90	11.87	12.87	11.63	13.05	12.59	11.34	12.47	12.98
PA	4.72	4.05	4.84	5.53	5.65	5.40	5.26	4.93	5.08	5.54	6.14	6.87	6.47	6.51	6.16
TX	6.68	6.62	7.15	7.34	7.26	7.58	7.62	7.66	7.65	7.96	7.24	7.55	8.81	9.16	9.18
VA	8.52	9.61	9.49	8.16	7.13	9.57	9.56	10.07	9.89	9.57	9.19	10.47	10.82	11.52	10.33
WA	7.32	7.86	6.97	7.57	6.78	8.53	8.96	9.98	9.12	8.52	8.51	8.05	7.96	9.22	10.44
WI	10.74	9.12	10.02	10.17	10.91	10.83	10.22	9.68	10.43	11.08	10.15	11.15	11.84	11.81	12.71

^a All values are given as percent (%). Percentages significantly different from 0 at the 5% level are indicated in bold.
Data Source: Medical Expenditure Panel Survey data for 2001–2015.

obesity, and differences in the cost of services (or payment levels under Medicaid or private insurers in the state). Given the smaller samples (and thus greater standard errors), we cannot reject that there was no upward trend in the percentage of medical spending devoted to obesity for individual states.

Table 3 presents the percentage of total medical expenditures that are associated with obesity, separately by payer: all payers, private payers such as commercial health insurance, Medicare, Medicaid, all third-party payers (which includes private payers, Medicare, and Medicaid), and out-of-pocket spending by the patient. Results are again presented for the US and for the most populous states. For the sake of conciseness, results are not presented separately by year but are the average for the overall period 2001–2015 and the average for the more recent period 2010–2015.

The results in Table 3 indicate that a substantial percentage of expenditures by each payer was associated with obesity. For the US as a whole, the average percentage of expenditures devoted to obesity between 2010 and 2015 was 9.21% for private payers such as commercial health insurance, 6.86% for Medicare, 8.48% for Med-

icaid, and 4.74% for out-of-pocket payments by patients. The estimates for Medicare and Medicaid are of particular interest because they provide information about the magnitude of potential external costs: additional medical care costs associated with obesity that are paid by society as a whole.

The point estimates in subsequent rows of Table 3 indicate that, over 2010–2015, several states (KY, VA, and WI) devoted >20% of their Medicaid spending to obesity-related illness. Over the same period, there were several states (AZ, IL, PA, and VA) in which over 10% of Medicare spending was devoted to obesity-related illness.

Table 4 presents the percentage of total medical expenditures that are associated with obesity, separately by category of expenditure. The results in Table 4 indicate that the share of spending devoted to obesity-related illness in the US from 2010 to 2015 was higher for prescription drugs (13.00%) than for ambulatory care (6.97%) or inpatient care (7.38%). This is true for every type of payer; e.g., private health insurance companies, Medicare, Medicaid, and out-of-pocket spending by patients.

Table 3. Average share of national and state expenditures associated with obesity by source of payment.^a

	All Payers		Private		Medicare		Medicaid		TPP		OPP	
	AVG 01-15	AVG 10-15	AVG 01-15	AVG 10-15	AVG 01-15	AVG 10-15	AVG 01-15	AVG 10-15	AVG 01-15	AVG 10-15	AVG 01-15	AVG 10-15
US	7.27	7.78	8.61	9.21	6.42	6.86	8.23	8.48	7.92	8.41	4.33	4.74
AZ	5.61	5.64	4.42	4.58	13.90	14.14	6.19	5.18	6.04	6.02	5.65	6.03
CA	4.16	4.45	6.22	6.72	4.36	4.56	4.06	4.70	5.21	5.54	0.95	1.07
FL	5.54	5.77	5.39	5.59	5.87	6.01	4.95	5.51	5.82	6.03	2.45	2.69
GA	9.91	10.79	11.36	12.30	5.98	6.36	4.11	4.62	9.91	10.66	8.45	9.30
IL	10.44	10.57	10.78	10.76	11.32	11.29	16.30	16.12	10.42	10.49	9.23	9.46
KY	7.81	8.55	7.44	8.62	2.61	2.68	21.08	20.69	7.81	8.49	6.82	7.79
MA	7.94	8.40	8.32	9.27	3.24	3.30	16.95	16.86	9.30	9.78	2.21	2.48
MD	5.55	6.23	7.29	8.08	7.75	8.36	8.24	10.10	6.13	6.84	2.59	3.00
MI	9.42	10.00	10.70	11.63	9.82	9.89	1.69	1.70	9.77	10.35	6.40	6.88
NC	12.45	13.45	12.60	13.72	7.90	8.45	2.27	2.90	12.32	13.25	10.44	11.24
NJ	8.74	9.25	9.05	9.75	5.93	6.09	9.44	10.25	9.13	9.58	4.93	5.50
NY	5.50	5.81	5.43	5.90	0.91	0.98	10.88	10.55	5.73	5.97	2.70	3.01
OH	11.29	12.35	13.78	14.93	8.00	8.77	16.20	17.79	12.54	13.64	5.87	6.58
PA	5.74	6.33	4.37	4.80	12.49	13.65	8.32	8.85	5.89	6.44	4.70	5.41
TX	7.86	8.42	9.94	10.56	8.77	9.72	7.89	8.32	8.96	9.49	4.93	5.32
VA	9.84	10.48	11.74	12.64	10.34	10.70	19.66	20.63	11.06	11.65	5.60	6.32
WA	8.57	8.85	9.03	9.09	3.89	4.05	15.30	14.88	8.75	8.97	5.75	6.17
WI	10.86	11.58	13.91	15.64	6.07	6.01	27.94	25.06	12.53	13.29	2.17	2.36

^a All values are given as percent (%). Percentages significantly different from 0 at the 5% level are indicated in bold.
 TPP: third-party payers (private, Medicare, and Medicaid).
 OPP: out-of-pocket payments by patients.
 Data Source: Medical Expenditure Panel Survey data for 2001–2015.

REVIEW OF PREVIOUS LITERATURE ON THE ECONOMIC IMPACT OF OBESITY

The costs of obesity are sometimes divided into direct medical care costs and indirect costs such as labor market outcomes. In the following sections, we review (a) the literature that has estimated the causal effect of obesity on medical care costs and (b) the literature that has estimated the causal effect of obesity on labor market outcomes such as earnings/wages, employment, and job absenteeism. We focus on studies that have sought to estimate causal effects by exploiting natural experiments. In most of these studies, researchers estimated models of instrumental variables (IV) in which the respondent's weight was instrumented using the weight of a biological relative. This relies on 2 important assumptions. The first is that a biological relative's weight is highly correlated with the respondent's weight. Given that there is a substantial heritable component of weight, these instruments tend to far exceed the minimum standards of instrument power. The second assumption is validity, i.e., that the instrument (the weight of a biological relative) is uncorrelated

with the outcome except through respondent weight. This is ultimately untestable, and one concern is pleiotropy, i.e., the concept the genes that affect obesity may affect other individual characteristics as well as outcomes. However, studies of the genes that are associated with high BMI have tended to find that they are associated with obesity-related conditions such as diabetes but not with characteristics unrelated to obesity that could directly affect medical care costs or labor market outcomes (10, 11). More information on the general method of instrumental variables is available elsewhere (12, 13).

Review of the effect of obesity on medical care costs

Four published studies estimated the causal effect of obesity on medical care utilization or costs. Three studies examined adult obesity in the US (14, 15, 16), and 1 study examined childhood obesity in Ireland (17).

The 3 papers studying the effect of adult obesity on medical care costs in the US estimated the same models

Table 4. Share of national expenditures associated with obesity by type of expenditure.^a

	Ambulatory	Inpatient	Prescription Drugs
All-Payer			
Avg 01-15	6.55	6.84	12.19
Avg 10-15	6.97	7.38	13.00
Private			
Avg 01-15	7.77	9.07	13.73
Avg 10-15	8.23	9.72	15.16
Medicare			
Avg 01-15	4.33	5.19	11.96
Avg 10-15	4.70	5.76	11.92
Medicaid			
Avg 01-15	8.81	4.75	14.35
Avg 10-15	9.06	4.97	15.42
Third-Party			
Avg 01-15	7.34	6.86	13.01
Avg 10-15	7.78	7.41	13.68
Out-of-Pocket			
Avg 01-15	7.20	6.64	11.29
Avg 10-15	7.71	7.10	12.19

^a All values are given as percent (%). Percentages significantly different from 0 at the 5% level are indicated in bold.
Data Source: Medical Expenditure Panel Survey data for 2001-2015.
Avg: average.

using different years of the same data (14, 15, 16). The models were 2PMs of IVs, in which the 2 parts were the extensive and intensive margins of healthcare costs and the instrument for the BMI of the adult respondent was the BMI of their biological child. The data were from the MEPS for adults with a biological child in the household; the first study examined data for 2000–2005 (14), the second for 2000–2010 (15), and the third for 2006–2013 (16).

Each of these studies found that obesity significantly raised medical care costs. The estimates based on the most recent data indicated that obesity raised individual medical care costs by \$3429 per year in 2013 dollars (16). Importantly, the estimate of the causal effect was considerably larger than the correlation, which could have been due to the method of IV correcting for downward bias due to measurement error in weight or to that of correcting for omitted variable bias from factors correlated with obesity that also are associated with lower medical care costs (for example, if obese individuals tended to have worse access to medical care).

Under the assumption that the effect of obesity in the study subpopulation (which is adult respondents to

the MEPS who have biological children in the household) generalizes to the full noninstitutionalized population of adults, the total medical care costs of obesity for noninstitutionalized adults totaled \$342.2 billion in 2013, which implies that 28.2% of all healthcare costs in this population were attributable to obesity (16). A comparison to earlier studies indicates that the share of medical care spending of noninstitutionalized adults that is devoted to treating obesity-related illness rose from 20.6% in 2005 to 27.5% in 2010 to 28.2% in 2013; it rose both because the number of obese individuals in the US was rising and because prices for medical care were rising. These percentages are higher than those reported in Table 2 because the method of IV, by correcting for reporting error in weight and the endogeneity of weight, resulted in larger estimates of the medical care costs of obesity than non-IV models such as the one whose results are reported in Table 2.

Additional models indicated that obesity raises medical care costs for both men and women and for both whites and nonwhites (16), as well as for all major categories of expenditure such as inpatient care, outpatient visits, and prescription drugs (14). Importantly, all 3 studies indicated that obesity raises medical care expenditures by third-party payers, such as commercial health insurance companies, Medicare, and Medicaid, which indicates that there are significant external costs of obesity, which can be used as an argument to justify government intervention to prevent and reduce the condition.

Models that allow medical care costs to vary in a more nonlinear way with BMI indicate that medical expenditures have a J-shape over BMI; medical expenditures fall with BMI in the ranges of underweight (BMI < 18.5) and healthy weight (18.5 ≤ BMI < 25). They are relatively constant in the overweight range (25 ≤ BMI < 30), rise slowly with BMI through the range of obese class I (30 ≤ BMI < 35), and then rise rapidly with BMI in the range of obese class II (35 ≤ BMI < 40) and especially in that of obese class III (40 ≤ BMI); see Fig. 1 in (16). This indicates that the high healthcare costs of obesity are due to extremely high medical care costs among a small percentage of the population that are morbidly obese. This is useful information for targeting weight-loss programs, as it suggests that weight loss may be accompanied by substantial reductions in medical care costs only for those who are morbidly obese; individuals who are overweight or even class I obese simply do not have much higher medical care costs than those who are healthy weight.

There exists 1 published study on the causal effect of childhood obesity on healthcare utilization (17). It estimates IV models of medical care costs in which the BMI of a child aged 9 or 13 is instrumented using the BMI of the biological mother using data from the Growing Up in Ireland survey. The authors found no evidence that obe-

sity raises the probability of either visiting a general practitioner (GP) or having an inpatient stay at age 9, but when youth are age 13, obesity raises the probability of a GP visit by 2.5 percentage points and the probability of an inpatient stay by 2.1 percentage points. Consistent with the earlier studies, it was found that the causal effects of obesity are considerably greater than the correlations with these outcomes.

Review of the effect of obesity on earnings and wages

Numerous studies have used the method of IV to estimate the causal impact of obesity on labor market outcomes such as wages, earnings, or employment (18, 19). An early study in this area (20) estimated IV models of the impact of BMI on wages, using the adult BMI of a biological sibling as an instrument for the adult BMI of the respondent and US data from 1981 to 2000 from the National Longitudinal Survey of Youth (NLSY), 1979 Cohort. The results suggested that the effect of BMI on wages varies by race and gender. The effect tends to be significant and negative for women but small and not statistically significant for men. Among women, the greatest impact is among white females, for whom an additional 10 pounds lowers wages by 2.8%. A subsequent study applied similar methods (it instrumented for respondent BMI using the BMI of a sibling or the mother's obesity status) but examined a different US data set—the National Longitudinal Survey of Adolescent Health (21). The results of these IV models were consistent with those of the earlier study that used NLSY data (20): a higher BMI reduces wages among white females; it also lowers wages among black and Hispanic females to a lesser extent, but it does not lower wages for men.

Similar IV models, with some variations, have been used to analyze data from numerous European countries. One study examined data for 9 countries in the European Community Household Panel; their IV models (which used the BMI of a biological parent, child, or sibling as an instrument for the BMI of the respondent) indicated that a 10% increase in BMI reduced the earnings of females by 1.86% and of males by 3.27% (22). Other work estimated a nonparametric IV model of the impact of BMI on wages that used the BMI of a biological parent as an instrument for the BMI of the respondent (23). Using data from the 1970 British Cohort Study, the authors found that a higher BMI lowered the wages of both men and women and that for women that reduction in wages began at a relatively low level of BMI, which suggests that the mechanism is discrimination based on appearance instead of poor health reducing productivity.

A recent study that tests for an impact of BMI on labor market outcomes in Finland used a different IV approach (24). Instead of using the BMI of a biological

relative as an instrument, it used a genetic risk score for high BMI that was based on individual DNA samples. Another advantage of these data (from the Young Finns Study) is that the key variables were relatively free of reporting error; BMI was calculated from measurements, and labor market outcomes were taken from administrative employment records. The results of the IV models indicated that an additional unit of BMI lowered wages of men and women pooled by 6.6%.

Not all studies found evidence that obesity lowers wages. A study that estimated IV models that used parental weight as an instrument for respondent weight using Germany's Socio-Economic Panel (SOEP) found no detectable effect of BMI on earnings (25). Likewise, a study that estimated IV models for Australia using the Household, Income, and Labour Dynamics in Australia (HILDA) data, instrumenting for respondent BMI using the average BMI of the biological relatives in the sample, found no significant impact on wages (26). In both cases, the null result may have been due in part to a relatively small sample size.

Researchers have also studied the impact of obesity on employment. IV models of employment that used parental obesity status as an instrument for respondent weight, estimated with data from the British National Child Development Study, indicated that BMI had no detectable impact on employment at ages 33 or 42 years (27). The IV models estimated using the genetic risk score in Finnish data indicated that an additional unit of BMI reduced the share of years employed by 1.7% (24).

In a novel approach to estimating the causal impact of BMI on employment, a recent study (28) exploited the results of a randomized experiment involving 700 Germans, in which obese individuals were assigned to either a control group that received usual care or to treatment groups that were offered financial rewards for weight loss. Although the rewards were effective in incentivizing weight loss, the initial random assignment turned out not to be a particularly powerful instrument for BMI. The IV models indicated that a 1 percentage point decrease in BMI was associated with a 2.1 percentage point (2.8%) increase in the probability of remaining employed for women, with no significant impact on employment for men. An important detail is that all subjects began the study obese and the great majority remained obese even afterward; thus, the estimated effect was specific to marginal weight loss among obese individuals.

As mentioned earlier, one possible explanation for the obesity wage penalty is discrimination. In economic models of discrimination, employers might discriminate for 2 reasons: (a) they dislike certain types of workers and thus offer them less pay for the same productivity; and (b) statistical discrimination—employers may not know the productivity of each worker, so they may infer productivity based on observable characteristics (29). In the

present context, employers may dislike having obese employees, and/or they may believe that obese individuals are less productive.

Research has concluded that there is employment discrimination on the basis of weight (18, 19, 30). In one novel field experiment (30), the researcher submitted fictitious job applications to actual job openings in Sweden. The applications each contained a photo of the applicant, which is typical in Sweden; some of the pictures were altered using photo editing software to make the applicant appear heavier. Applications were submitted in pairs, with the resumes designed to be as identical as possible and the applicant photos chosen to be as visually similar as possible except for the appearance of heaviness. The study estimated that the relatively obese applicant was significantly less likely to be contacted for an initial job interview: 8% less for women and 6% less for men.

It is not well known whether obese workers are in fact less productive than nonobese workers, all else remaining equal. Lower productivity could take the form of either job absenteeism (missing work more because of obesity-related illness) or job presenteeism (lower productivity while at work because of obesity-related illnesses). Several studies have estimated correlations and found that obese individuals tend to have higher job absenteeism (12), but to our knowledge there is no study that estimates the causal effect of obesity on either job absenteeism or job presenteeism; this remains an important direction for future research.

In summary, there is substantial evidence that obesity has a significant impact on economic outcomes. Numerous studies find that obesity raises medical care costs, reduces earnings or wages, and lowers the probability of employment, and this has been found for the US as well as numerous European countries. There is evidence of discrimination against obese individuals in the labor market.

Discussion

This paper presents new estimates of the correlation of obesity with medical care costs and reviews the literature that estimates the causal effects of obesity on medical care costs. Both correlations and causal effects are of use, and each has its strengths and weaknesses. Estimates of the correlation are useful because they indicate the amount spent treating obese individuals, above and beyond what is spent treating otherwise identical individuals. Thus, it gives a sense of the amount of healthcare resources devoted to people with obesity. A limitation, however, is that it is not informative about the causal effect—even if obese individuals have higher medical care costs, that does not mean that obesity caused the higher costs.

A strength of estimates of the causal effect of obesity on healthcare costs (such as those produced using the

method of IVs) is that they are informative about the amount by which healthcare costs would rise if an individual was to become obese. As a result, they are useful for cost-effectiveness analyses of interventions that can prevent or reduce obesity.

Causal estimates have their limitations as well, however (12, 13). If the assumptions behind the model of instrumental variables are violated, then the estimates may be biased. In addition, models of instrumental variables measure the causal effect for a certain subgroup; this “local” average treatment effect may differ from the average treatment effect for the entire population that we wish to measure. This may be less of an issue when the instrument concerns genetics than when it concerns a treatment that affects only a small unrepresentative sample of the population. However, even in the cases above the samples often had to be limited to individuals with a biological relative in the sample, which may be a select sample. Finally, the method of IV increases standard errors.

The new results presented in this paper indicate that the percent of US national medical expenditures devoted to treating obesity-related illness rose from 6.13% in 2001 to 7.91% in 2015, an increase of 29% that is statistically significant. Large differences exist across states; in 2015, some states (CA, FL, NY) spent only 5%–6% of medical expenditures on obesity whereas others (NC, OH, WI) spent more than twice of that—>12% of all healthcare dollars in these states were used to treat obesity-related illness. These estimates of obesity-attributable costs that are specific to each state are an important addition to the literature because they are the first state-level estimates based on state-specific microdata, as opposed to being based on national data with state-level fractions imputed based on assumptions.

Estimates separately by payer indicate that the share of expenditures devoted to treating obesity is almost twice as large for third-party payers than for patients’ out-of-pocket payments. This is a reflection of the fact that obesity results in very high levels of medical spending that are in excess of common insurance deductibles (14). On average during 2010–2015, 6.86% of Medicare spending and 8.48% of Medicaid spending nationwide was devoted to treating obesity-related illness. This is consistent with obesity imposing negative external costs, which is an economic rationale for government intervention to prevent and reduce obesity (31).

We also found large differences across states in the proportion of Medicaid spending that is devoted to treating obesity-related illness. Whereas some states (e.g., CA, FL, PA, TX) devoted <10% of their Medicaid spending to treating obesity-related illness from 2010 to 2015, other states (KY, VA, WI) spent >20% of their Medicaid dollars treating obesity.

Obesity was associated with a higher percentage of total spending on prescription drugs (13.00%) than on

ambulatory care (6.97%) or inpatient hospital care (7.38%) during 2010–2015. This may be unsurprising given that, in 2012, metabolic agents, which include drugs used to treat conditions related to obesity such as hyperlipidemia and diabetes, had the highest total expenditures (\$54 billion) among all therapeutic classes of outpatient prescription drugs used to treat adults aged ≥ 18 years. They also had the second highest level of expenditures per prescription: \$104 (32).

The review of the literature on the causal effects of obesity on economic outcomes indicates that obesity raises medical care costs, reduces the probability of employment, and lowers earnings and wages. These are relatively robust findings from the US and numerous European countries.

Limitations of our original analysis include the fact that state-level estimates were not possible for all states. Because the MEPS sample is optimized for national estimates, sample sizes in less populous states are insufficient to produce reliable state estimates. In addition, we caution that these estimates reflect correlations of obesity with medical care expenditures and should not be interpreted as causal. Previous research (14, 15, 16) has consistently found that correlations between obesity and medical care expenditures underestimate the causal relationship.

There are several important directions for future research in this area. One is to estimate models of instrumental variables to generate estimates of the causal impact of obesity on medical care costs at the level of individual state. This has been done for national data in the US (14, 15, 16) and Ireland (17) but has not been done in the US for individual states because of a lack of

data within each individual state to provide sufficient statistical power. In general, it would be useful to have estimates of causal effects of obesity on economic outcomes that are based on different identification strategies to check the robustness of the IV models described earlier. Another important direction is to investigate the reasons that the percent of medical care spending devoted to obesity varies so much by state. Potential factors include differences in the prevalence of obesity, differences in healthcare utilization among the obese, differences in costs of services, and sampling variation.

Author Contributions: All authors confirmed they have contributed to the intellectual content of this paper and have met the following 3 requirements: (a) significant contributions to the conception and design, acquisition of data, or analysis and interpretation of data; (b) drafting or revising the article for intellectual content; and (c) final approval of the published article.

Authors' Disclosures or Potential Conflicts of Interest: Upon manuscript submission, all authors completed the author disclosure form. Disclosures and/or potential conflicts of interest:

Employment or Leadership: None declared.

Consultant or Advisory Role: None declared.

Stock Ownership: None declared.

Honoraria: None declared.

Research Funding: J. Cawley, Investigator Award from the Robert Wood Johnson Foundation.

Expert Testimony: None declared.

Patents: None declared.

Acknowledgment: The authors thank Barton Willage for research assistance. Dr. Cawley gratefully acknowledges financial support from an Investigator Award from the Robert Wood Johnson Foundation.

References

1. OECD. Obesity Update. <http://www.oecd.org/els/health-systems/Obesity-Update-2014.pdf> (Accessed June 2017).
2. NCD Risk Factor Collaboration. Trends in adult body-mass index in 200 countries from 1975 to 2014: a pooled analysis of 1698 population-based measurement studies with 19 · 2 million participants. *Lancet* 2016;387:1377–96.
3. GBD 2015 Obesity Collaborators. Health effects of overweight and obesity in 195 countries over 25 years. *N Engl J Med* 2017;377:13–27.
4. U.S. Bureau of Labor Statistics. The consumer price index. In: BLS handbook of methods. Washington (DC): Bureau of Labor Statistics; 2017. <http://www.bls.gov/opub/hom/> (Accessed June 2017).
5. Krewski D, Rao JNK. Inference from stratified samples: Properties of the linearization, jackknife and balanced repeated replication methods. *Ann Statistics* 1981;9: 1010–9.
6. Sommers JP. Producing state estimates with the medical expenditure panel survey, household component. Methodology Report #16. Rockville (MD); Agency for Healthcare Research and Quality; 2005. https://meps.ahrq.gov/data_files/publications/mr16/mr16.pdf (Accessed October 2017).
7. Finkelstein EA, Fiebelkorn IC, Wang G. State-level estimates of annual medical expenditures attributable to obesity. *Obes Res* 2004;12:18–24.
8. Trogon JG, Finkelstein EA, Feagan CW, Cohen JW. State- and payer-specific estimates of annual medical expenditures attributable to obesity. *Obesity* 2012;20: 214–20.
9. Hu F. Obesity epidemiology. New York (NY): Oxford University Press; 2008.
10. Locke AE, Kahali B, Berndt SI, Justice AE, Pers TH, Day FR, et al. Genetic studies of body mass index yield new insights for obesity biology. *Nature* 2015;518: 197–206.
11. Speliotes EK, Willer CJ, Berndt SI, Monda KL, Thorleifsson G, Jackson AU, et al. Association analyses of 249 796 individuals reveal 18 new loci associated with body mass index. *Nat Genet* 2010;42:937–48.
12. Cawley J. A selective review of the first twenty years of instrumental variables models in health services research and medicine. *J Med Econ* 2015;18:721–34.
13. Craig P, Katikireddi SV, Leyland A, Popham F. Natural experiments: an overview of methods, approaches, and contributions to public health intervention research. *Annu Rev Public Health* 2017;38:39–56.
14. Cawley J, Meyerhoefer C. The medical care costs of obesity: an instrumental variables approach. *J Health Econ* 2012;31:219–30.
15. Cawley J, Meyerhoefer C, Biener A, Hammer M, Winfield M. Savings in medical expenditures associated with reductions in body mass index among US adults with obesity, by diabetes status. *Pharmacoeconomics* 2015;33:707–22.
16. Biener A, Cawley J, Meyerhoefer C. The high and rising costs of obesity to the U.S. health care system. *J Gen Intern Med* 2017;32:56–8.
17. Doherty E, Queally M, Cullinan J, Gillespie P. The impact of childhood overweight and obesity on healthcare utilization. *Econ Hum Biol* 2017;27:84–92.
18. Meyerhoefer CD, Yang M. Poverty and obesity in developed countries. In: Komlos J, Kelly IR, editors. *Oxford Handbook of Economics and Human Biology*. Oxford University Press, 2016. DOI: 10.1093/oxfordhob/9780199389292.013.41.
19. Greve J. Why do people with higher body weight earn lower wages? In: Komlos J, Kelly IR, editors. *Oxford Handbook of Economics and Human Biology*. Oxford University Press, 2016.
20. Cawley J. The impact of obesity on wages. *J Human Res* 2004;39:451–74.
21. Sabia JJ, Rees DI. Body weight and wages: evidence from Add Health. *Econ Hum Biol* 2012;10:14–9.
22. Brunello G, D'Hombres B. Does body weight affect wages? Evidence from Europe. *Econ Hum Biol* 2007;5: 1–19.

-
23. Kline B, Tobias JL. The wages of BMI: Bayesian analysis of a skewed treatment-response model with nonparametric endogeneity. *J Appl Econ* 2008;23:767-93.
24. Böckerman P, Cawley J, Viinikainen J, Lehtimäki T, Rovio S, Seppälä I, Pehkonen J, Raitakari O. The effect of weight on labor market outcomes: an application of genetic instrumental variables. NBER Working Paper 2016;22200.
25. Cawley JH, Grabka MM, Lillard DR. A comparison of the relationship between obesity and earnings in the US and Germany. *Schmollers Jahrbuch* 125:119129, 2005.
26. Kortt M, Leigh A. Does size matter in Australia? *Economic Record* 2010;86:71-83.
27. Lindeboom M, Lundborg P, van der Klaauw B. Assessing the impact of obesity on labor market outcomes. *Econ Hum Biol* 2010;8:309-19.
28. Reichert AR. Obesity, weight loss, and employment prospects: evidence from a randomized trial. *Journal of Human Resources* 2015;50:759-810.
29. Becker G. 1957. *The Economics of Discrimination*. Chicago, IL: University of Chicago Press.
30. Rooth, DO. Obesity, attractiveness, and differential treatment in hiring a field experiment. *J Human Res* 2009;44:710-35.
31. Cawley J. An economy of scales: A selective review of obesity's economic causes, consequences, and solutions. *J Health Econ* 2015;43:244-68.
32. Roemer M. Expenditures for the top five therapeutic classes of outpatient prescription drugs, adults age 18 and older, U.S. civilian noninstitutionalized population, 2012. *Statistical Brief #468*. Rockville (MD); Agency for Healthcare Research and Quality; 2015. http://www.meps.ahrq.gov/mepsweb/data_files/publications/st468/stat468.pdf (Accessed October 2017).

Copyright of Clinical Chemistry is the property of American Association for Clinical Chemistry and its content may not be copied or emailed to multiple sites or posted to a listserv without the copyright holder's express written permission. However, users may print, download, or email articles for individual use.