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Job Absenteeism Costs of Obesity in the United States

National and State-Level Estimates

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Objective: To estimate the causal effect of obesity on job absenteeism and the associated lost productivity in the United States, both nationwide and by state. **Methods:** We conducted a retrospective pooled cross-sectional analysis using the 2001 to 2016 Medical Expenditure Panel Survey and estimated two-part models of instrumental variables. **Results:** Obesity, relative to normal weight, raises job absenteeism due to injury or illness by 3.0 days per year (128%). Annual productivity loss due to obesity ranges from $271 to $542 (lower/upper bound) per employee with obesity, with national productivity losses ranging from $13.4 to $26.8 billion in 2016. Trends in state-level estimates mirror those at the national level, varying across states. **Conclusions:** Obesity significantly raises job absenteeism. Reductions in job absenteeism should be included when calculating the cost-effectiveness of interventions to prevent or reduce obesity among employed adults.

Keywords: indirect costs, instrumental variables, job absenteeism, obesity, two-part negative binomial model, work productivity

The rising prevalence of obesity in the United States (U.S.)[1–3] imposes a substantial economic burden due to both direct medical care costs and indirect productivity-related costs. The latter includes increased job absenteeism, presenteeism, disability, and payments from workers' compensation insurance.[4–9]

Individual studies and systematic reviews of the literature have found consistent evidence of an association between obesity and loss of workdays or productivity at work[5,10–15]; however, these previous studies only estimate correlations and do not estimate the causal effect of obesity on job absenteeism. The two could be quite different due to reverse causality and omitted variables bias. For example, injuries or underlying health conditions could cause both weight gain and higher job absenteeism. One way to address these biases and estimate the causal effect of obesity is to estimate models of instrumental variables (IV), which have been used to estimate the causal effect of obesity on direct medical care costs.[16–18] This study estimates the causal effect of obesity (both overall and separately by class of obesity) on job absenteeism and the dollar value of the associated lost productivity. Models are estimated for the U.S. overall and by state.

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Clinical significance: This study provides the first-ever estimates of the causal impact of obesity on job absenteeism and associated productivity loss. These costs represent part of the economic burden of obesity, beyond direct medical costs. Avoidance of these costs should be included when calculating cost-effectiveness of treatments to prevent and reduce obesity.

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METHODS

Data

We estimate our models using data from the 2001 to 2016 Medical Expenditure Panel Survey (MEPS), a nationally representative survey of civilian, non-institutionalized adults in the U.S. which collects information regarding medical conditions, healthcare use, cost, and insurance coverage.[19] As part of the Household Component MEPS interview, respondents were asked to report the number of days of work they had missed in the past year for health-related reasons. Specifically, the question asks whether the person lost a half day or more due to illness or injury. The wording of this question does not allow one to determine the exact amount of the day that was lost—it may be as little as half a day or as much as a full day. The MEPS also collected self-reported or proxy-reported (for another household member) height and weight, which we used to calculate body mass index (BMI). Obesity is defined as BMI $\geq 30\,kg/m^2$ and divided into classes for adults: class 1 ($30 \leq$ BMI$<35\,kg/m^2$), class 2 ($35 \leq$ BMI $< 40\,kg/m^2$), and class 3 (BMI $\geq 40\,kg/m^2$).

Inclusion/Exclusion Criteria

In our models of IV, our instrument for respondent BMI is the BMI of their biological child. In order to estimate this IV model, we must limit our sample to adult respondents (aged 20–65) who have a biological child in their household (the MEPS contains information on both parents and children only if they live in the household). This age restriction reflects the relative lack of adults over age 65 with a biological child living in the household. We use the BMI of a biological child between 11 and 19 years of age. The lower age limit of 11 is due to high levels of non-response in height and weight for younger children. For households with multiple children, we used the oldest child with valid BMI data, mitigating concerns over joint environment effects on the child's BMI by ensuring that data from adolescent children were used to construct the instrument when possible.[20] We further subset the sample to respondents who worked at any time during the year since work loss days is our outcome of interest.

We dropped observations for which BMI was missing for either the parent or the biological child, because the IV model requires both. We excluded pregnant women to avoid conflating weight gain from pregnancy with obesity. We excluded underweight individuals (BMI $< 18.5\,kg/m^2$) so that the model could better predict the nonlinear changes in job absenteeism at high levels of BMI. We extend our analysis to the 14 most populous states with sufficient sample size to estimate the two-part IV model: CA, FL, GA, IL, KY, MI, MO, NJ, NY, NC, PA, TX, VA, and WI.

Two-Part Model

Job absenteeism, the dependent variable of interest, is defined as the number of days missed from work due to illness or injury. Respondents to the MEPS were asked to report the number of days in which they lost half or more of the day due to illness and injury. For the purposes of estimating the *number* of workdays lost, we treated each of these as equal to a single lost day, that is, ''affected workdays.''

We estimated a two-part model of job absenteeism because absenteeism is a highly positively skewed count variable: a nontrivial number of individuals have zero missed workdays and a small number of individuals miss many days of work. The two parts of the model are estimated separately. We specified the first part of the two-part model as the following logit model:

$$Prob(Y_{it} > 0) = \gamma_0 + \gamma_1 \cdot BMI_{it} + \gamma_2' \cdot X_{it} + \delta_t, \tag{1}$$

where Y_{it} is the number of missed workdays for individual i in year t, BMI_{it} is parent BMI, X_{it} is a vector of sociodemographic control variables, δ_t is a vector of year fixed effects, and γ_k are parameters to be estimated. We used the logistic distribution to measure probability, and estimated the model using the full sample of adults (ie, both those who missed no workdays and those who missed some).*

In the second part of the two-part model, we used a negative binomial distribution to model nonzero values of missed workdays because the number of missed workdays (Y_{it}) is a count, rather than continuous, variable.† Therefore, we specified the second part of the two-part model as

$$Prob(Y_{it}|Y_{it} > 0) = \frac{\Gamma(Y_{it} + \alpha^{-1})}{\Gamma(\alpha^{-1})\Gamma(Y_{it} + 1)} \left(\frac{1}{1 + \alpha\mu_{it}}\right)^{\alpha^{-1}} \left(\frac{\alpha\mu_{it}}{1 + \alpha\mu_{it}}\right)^{Y_{it}}, \tag{2}$$

$$\mu_{it} = \exp(\beta_0 + \beta_1 \cdot BMI_{it} + \beta_2' \cdot X_{it} + \delta_t), \tag{3}$$

where $\Gamma(\cdot)$ is the gamma function and α, β_k are parameters to be estimated. We estimated the second part of the model (the negative binomial model) separately from the first part of the model (the logit model), using the sample of adults who reported a positive number of missed workdays. We then constructed predictions and the marginal effect estimates by combining the appropriate estimating functions from both parts of the two-part model and evaluating them using the full sample.[21]

In both parts of the two-part model, we controlled for characteristics that are likely to be correlated with workdays missed due to injury or illness (the set of regressors is the same in both parts). These include: gender, race/ethnicity, respondent age, education level (because jobs held by better-educated individuals may be less strenuous and thus easier to perform when ill), U.S. census region, whether the respondent lives in an urban area (specifically, a Metropolitan Statistical Area or MSA), household composition (number and age of household members), health insurance plan enrollment, HMO or managed care plan enrollment, whether the respondent receives paid leave for doctor's visits and/or sick pay, employment status including work industry, employer size, if employed in a ''white-collar'' occupation, and whether the respondent works in a job that is unionized. We also control for gender of the oldest child and age of the oldest child in months, which has the effect of adjusting child BMI for the child's age and gender (and thus the instrument is the child's BMI relative to others of the same age and gender). Additionally, indicator variables for whether the data were self- or proxy-reported were included because individuals who self-report their height and weight may provide more biased estimates than a spouse or other relative. Indicator variables for year were also included as regressors.

Method of Instrumental Variables (IV)

In an IV model, the instrument should meet the following two conditions: 1) the instrument must be strongly correlated with the endogenous regressor of interest (in this case, respondent BMI) and 2) the instrument must be uncorrelated with the error term in the second stage of IV (in this case, unobserved factors that impact missed workdays).

The use of the BMI of a biological child as an instrument for the respondent's BMI is based on the heritability of weight. The genetics literature has demonstrated a strong heritable component of BMI and obesity, supporting that notion that a child's BMI is strongly correlated with that of their biological parents.[22–24] We confirmed the significant correlation between biological child BMI and parent BMI by computing the F-statistic of the instrument in the first stage regression of the IV model. The F-statistic was 1704 when we estimated the first stage using the full national sample (ie, the first part of the two-part model), and 788 when we estimated the first stage using the national sample of those with a nonzero number of missed workdays (ie, the second part of the two-part model). Analogous F-statistics in the state-specific samples ranged from 42 to 253. Each of these F statistics is well above the threshold of $F > 10$, which was suggested by Stock et al[25] as a threshold of adequate power in the case of a continuous instrument and endogenous variable.

We next discuss the validity of the instrument. Our identification strategy is based in part on findings from the behavioral genetics literature, which finds that the common household environment, which could affect missed workdays, has been shown to only affect child BMI at young ages.[20] Another possible threat to validity is that parent BMI may influence the household environment and thus indirectly affect the child's BMI (eg, a lack of emphasis on physical activity by the parent could lead to the child being less physically active and more susceptible to obesity). However, genetic studies establish that parental genes important in determining the parent's BMI that are *not* inherited by the child have no detectable impact on the child's BMI, which is consistent with the assumption that parent BMI does not affect child BMI through the household environment.[26–28] According to the genetics literature, genes affecting BMI are associated with BMI's components (weight and height) and obesity-related illnesses, but not characteristics unrelated to obesity,[27,29] which is also consistent with the validity of our instrument.

It is always impossible to prove instrument validity (one cannot prove that the instrument is uncorrelated with unobservables, because by definition unobserved variables are not available). However, one standard approach is to conduct an overidentification test, which provides suggestive evidence of whether the instrument is uncorrelated with unobserved factors that might affect missed workdays. We constructed an overidentified model by including the level and square of child BMI in the instrument set ($F = 933$ using the full sample). The Hansen J-statistic for the test was 1.96 ($P = 0.16$), indicating a failure to reject the null hypothesis that the instrument set is uncorrelated with the model error term. We also conducted a falsification test to investigate whether child BMI is determined by common household environment, which is an

* Some formulations of the two-part model use a normal distribution for $Prob(\cdot)$. The choice between normal and logistic distribution is innocuous in non-IV versions of the two-part model, but convergence is more reliable in the logit version of the IV estimator.

† We conducted a test of overdispersion to determine whether to use a Poisson or negative binomial distribution. The null hypothesis of equivalence between the mean and variance was rejected at the 1% level of significance, indicating that the negative binomial distribution is most appropriate.

assumption of our identification strategy. Using the sample of parents with stepchildren ($N = 2369$), we regressed the BMI of stepparents on the BMI of their stepchild and the control variables. The F-statistic measuring the correlation between the BMI of parents and their stepchildren ($F = 8$) was far lower than the F-statistic measuring the correlation between the BMI of parents with their biological children ($F = 1704$). The results of this test are consistent with findings from the behavioral genetics literature that living in the same household does not in itself result in a large correlation between parent and child BMI.

Model Estimates

We implemented the IV estimator by applying the procedure developed by Carroll et al[30] and Hardin et al[31] to the first and second parts of the two-part model specified in Eqs. (1) to (3). We estimated models for the U.S. as a whole as well as separately for each state that had enough observations to provide sufficient statistical power. The coefficient estimates from the first and second stages of our IV two-part model for the U.S. as a whole are reported in appendix tables A1, http://links.lww.com/JOM/A894 and A2, http://links.lww.com/JOM/A895, respectively.

We calculated the average marginal effect (AME) of obesity on job absenteeism in three steps: 1) predict the lost workdays for the mean BMI among normal weight individuals (BMI 18.5 to $<25\,\text{kg/m}^2$) using the two-part model, 2) predict the lost workdays for the mean BMI among individuals with obesity (BMI $\geq 30\,\text{kg/m}^2$) using the two-part model, and 3) subtract the predicted lost workdays for normal weight individuals from the predicted lost workdays for individuals with obesity. To account for the complex survey design of the MEPS, we computed all standard errors using balanced repeated replications and Fay's method.[32]

We converted estimates of lost workdays into the value (dollar cost) of lost productivity by multiplying the number of lost work hours by the person's wage, which is the best available proxy for productivity. Economic theory states that a perfectly competitive market with easily observed worker productivity results in wages paid to workers that equal to their marginal revenue product of labor (the increase in firm revenue generated by an additional hour of their work, all else equal).[33] Where wage was not available in the MEPS because the individual was self-employed, it was imputed using a two-part model in which wages were the dependent variable and the regressors included age, gender, race, education, household composition, region, family income, and spouse's wage (when available, otherwise denoted as "missing").[‡]

As mentioned earlier, the MEPS asked respondents to report the number of days on which they lost a half of a workday or more due to illness or injury. To account for the uncertainty over the exact amount of each workday affected, we estimated productivity impacts twice: 1) a lower bound that assumes that only half of each affected workday was lost; and 2) an upper bound that assumes that all of each affected workday was lost.

The results of our IV model allow us to estimate the aggregate (national) productivity loss attributable to obesity by 1) estimating the aggregate productivity loss due to obesity for our estimation sample and 2) using the sample weights of the MEPS to inflate the estimate from our sample to that of the entire civilian, non-institutionalized population of adults in the U.S. Throughout, results were considered statistically significant if the P-value < 0.1, and all monetary estimates are reported in 2017 USD.

RESULTS

Summary Statistics (Pooled Sample)

The study sample pools data from the 2001 to 2016 MEPS and includes 50,789 employed adults aged 20 to 65 years. Descriptive statistics for control variables for the pooled sample and the four most populous states are presented in Table 1. The mean BMI is $28.34\,\text{kg/m}^2$, and the prevalence of obesity was 32.5% in the sample. More than one-third (38%) of the sample missed at least one workday due to injury or illness during the year they were surveyed; the unconditional mean of annual number of workdays lost to injury or illness (including zeros for those who did not miss any workdays) was 3.58.

Although there were fourteen states with enough respondents in the MEPS to permit separate estimation of the two-part model, many of the estimated impacts on absenteeism were imprecise. In describing the results, we focus on the states with the most precise estimates.

Impact of BMI on Job Absenteeism

Table 2 presents the marginal effect of an additional unit of BMI on the number of affected workdays lost to injury or illness, as well as on the value of lost productivity per worker. Based on pooled national data, an additional unit of BMI raises the number of days that an individual missed work because of injury or illness by 0.24 days per year, or 6.3% of the predicted mean (3.77 days per year). The estimate of productivity loss per worker per year associated with an additional unit of BMI ranged from $21.32 (assuming only half of each day was affected) to $42.64 (assuming all of each day was affected).

At the state level, there were precisely estimated effects for California, Texas, Virginia, and Wisconsin. The estimates for number of workdays missed and productivity loss varied slightly for these four states but are well-aligned with the national estimates. An additional unit of BMI raises the number of workdays missed by 0.20 days per year in California, 0.21 days in Virginia, 0.22 days in Texas, and 0.24 days in Wisconsin. The lower and upper bounds (corresponding to half days affected and full days affected, respectively) of the dollar value of the estimated productivity loss per worker were $17.77 to $35.55 in California, $17.91 to $35.82 in Texas, $20.66 to $41.33 in Wisconsin, and $21.96 to $43.92 in Virginia.

Impact of Obesity on Job Absenteeism

We next describe the effect of moving from healthy weight to obese based on our AME calculation. Compared to individuals with normal weight, obesity raises job absenteeism by 3.00 workdays, from 2.34 to 5.34 days (128.2% increase), at the national level (Table 3). The impact of excess weight on absenteeism rises with class of obesity; national-level per-worker job absenteeism was higher by 2.07 days (88.5%) for those with class 1 obesity, 3.67 days (156.8%) for those with class 2 obesity, and 7.13 days (304.7%) for those with class 3 obesity, compared to workers with normal weight (results not shown).

The AME was precisely estimated using state-specific samples for California, Texas, Virginia, Wisconsin, and Michigan. Separate analyses at the state-level mirror those at the national level with obesity raising absenteeism by 2.45 workdays (109.9% increase) in California, 2.82 workdays (164.9%) in Texas, 2.73 days (133.1%) in Virginia, and 2.86 days (138.8%) in Wisconsin (Table 3). At 8.84 workdays (902.05%), the impact of obesity was particularly large for Michigan. The impact of excess weight on absenteeism rises with the class of obesity in the individual states, ranging from 83.4% to 231.4% in California (for class 1 to class 3 obesity, respectively), 111.1% to 369.6% in Texas, 92.7% to

[‡] Specifically, we used a probit in the first part of the two-part model and an OLS regression of log wages in the second part. In this context, a two-part model is preferred to a sample selection model when there is no exclusion restriction to separately identify the first part of the model.[34] In order to account for heteroscedasticity in the retransformation process, we computed separate smearing factors across age. In total, we imputed wages for 7426 out of 50,789 observations. The need to impute wages does lead to some measurement error in the monetized measures of lost workdays, but also increases the representativeness of the sample and the power of the models.

TABLE 1. Descriptive Statistics for Variable Used in the Job Absenteeism Models (National Level and Four Most Populous States)

	U.S.	California	Texas	Florida	New York
Variable			**Mean (S.D.)**		
Respondent					
Has positive work loss days	0.38 (0.47)	0.34 (0.55)	0.35 (0.53)	0.35 (0.47)	0.38 (0.44)
Work loss days	3.58 (14.54)	3.26 (17.34)	2.98 (13.4)	3.58 (14.01)	3.81 (13.58)
Hourly wage (imputed)	24.14 (15.40)	24.79 (19.63)	21.49 (15.86)	22.03 (13.69)	26.10 (15.43)
Daily hours (full day)	8.00 (2.18)	7.80 (2.56)	8.19 (2.31)	8.02 (2.03)	7.94 (1.97)
Daily hours (part day)	4.00 (1.09)	3.90 (1.28)	4.09 (1.15)	4.01 (1.02)	3.97 (0.99)
Paid leave to visit a doctor	0.52 (0.49)	0.48 (0.58)	0.54 (0.55)	0.55 (0.49)	0.57 (0.45)
Sick pay	0.58 (0.48)	0.53 (0.58)	0.58 (0.54)	0.59 (0.48)	0.62 (0.44)
BMI (kg/m^2)	28.34 (5.78)	27.69 (6.19)	29.14 (6.69)	28.22 (5.77)	27.70 (5.22)
Female	0.53 (0.49)	0.51 (0.58)	0.52 (0.55)	0.55 (0.49)	0.54 (0.46)
Race/ethnicity					
White	0.65 (0.46)	0.36 (0.55)	0.43 (0.54)	0.55 (0.49)	0.64 (0.44)
African American	0.11 (0.31)	0.05 (0.26)	0.10 (0.33)	0.15 ((0.35)	0.15 (0.32)
Hispanic	0.17 (0.36)	0.41 (0.57)	0.41 (0.54)	0.25 (0.43)	0.15 (0.32)
Other	0.07 (0.25)	0.18 (0.44)	0.06 (0.25)	0.05 (0.20)	0.07 (0.23)
Age (years)					
35–44	0.44 (0.48)	0.41 (0.57)	0.48 (0.55)	0.46 (0.49)	0.40 (0.45)
45–54	0.41 (0.48)	0.43 (0.57)	0.35 (0.52)	0.41 (0.48)	0.46 (0.46)
55 and older	0.07 (0.25)	0.08 (0.31)	0.06 (0.26)	0.07 (0.24)	0.09 (0.26)
Number of persons in the household					
Aged 0–5	0.15 (0.42)	0.19 (0.53)	0.18 (0.52)	0.12 (0.36)	0.11 (0.33)
Aged 6–17	1.53 (0.98)	1.56 (1.14)	1.54 (1.09)	1.37 (0.88)	1.49 (0.88)
Aged 18–64	2.37 (0.85)	2.55 (1.14)	2.38 (0.99)	2.30 (0.82)	2.41 (0.83)
Aged 65 and older	0.04 (0.21)	0.07 (0.34)	0.04 (0.28)	0.06 (0.26)	0.04 (0.19)
Married	0.79 (0.39)	0.79 (0.47)	0.81 (0.44)	0.75 (0.42)	0.79 (0.38)
Education level*					
Less than high school diploma	0.12 (0.32)	0.21 (0.47)	0.21 (0.45)	0.10 (0.30)	0.11 (0.28)
High school graduate	0.30 (0.45)	0.24 (0.49)	0.28 (0.50)	0.30 (0.45)	0.30 (0.42)
Some college	0.27 (0.43)	0.24 (0.49)	0.25 (0.48)	0.32 (0.46)	0.23 (0.39)
College graduate	0.31 (0.45)	0.30 (0.53)	0.26 (0.48)	0.28 (0.44)	0.36 (0.44)
Residence in MSA	0.82 (0.38)	0.96 (0.23)	0.91 (0.32)	0.97 (0.16)	0.87 (0.3)
Census region					
Northeast	0.16 (0.36)	Not applicable	Not applicable	Not applicable	Not applicable
Midwest	0.23 (0.41)				
South	0.38 (0.47)				
West	0.23 (0.41)				
Self-reporting survey information	0.56 (0.48)	0.53 (0.58)	0.55 (0.55)	0.58 (0.48)	0.55 (0.45)
Health insurance					
HMO or managed care	0.33 (0.46)	0.51 (0.58)	0.23 (0.46)	0.33 (0.46)	0.48 (0.46)
Private Insurance	0.81 (0.38)	0.74 (0.50)	0.75 (0.48)	0.78 (0.40)	0.81 (0.36)
Public	0.08 (0.26)	0.13 (0.39)	0.02 (0.17)	0.06 (0.23)	0.12 (0.30)
White collar job	0.65 (0.46)	0.66 (0.55)	0.64 (0.53)	0.68 (0.46)	0.66 (0.43)
Industry					
Construction or manufacturing	0.21 (0.40)	0.21 (0.47)	0.22 (0.46)	0.15 (0.35)	0.15 (0.35)
Trade or transportation	0.17 (0.37)	0.16 (0.43)	0.19 (0.43)	0.18 (0.38)	0.18 (0.38)
Services	0.49 (0.49)	0.48 (0.58)	0.46 (0.55)	0.52 (0.49)	0.52 (0.49)
Other industry	0.11 (0.30)	0.12 (0.38)	0.11 (0.34)	0.13 (0.33)	0.12 (0.30)
Company size					
<100	0.22 (0.40)	0.21 (0.47)	0.23 (0.46)	0.20 (0.39)	0.18 (0.35)
100–500	0.20 (0.39)	0.18 (0.44)	0.18 (0.42)	0.20 (0.39)	0.20 (0.36)
>500	0.16 (0.36)	0.14 (0.40)	0.14 (0.39)	0.15 (0.35)	0.17 (0.35)
Size missing	0.08 (0.26)	0.09 (0.33)	0.09 (0.32)	0.09 (0.28)	0.11 (0.28)
Size not applicable	0.11 (0.30)	0.12 (0.37)	0.12 (0.36)	0.12 (0.32)	0.09 (0.27)
Union membership	0.12 (0.32)	0.17 (0.43)	0.05 (0.24)	0.07 (0.25)	0.27 (0.41)
Eldest child in the household with valid BMI					
BMI (kg/m^2)	22.45 (4.88)	22.43 (5.67)	22.66 (5.61)	22.65 (4.91)	22.21 (4.55)
Female	0.48 (0.49)	0.48 (0.58)	0.47 (0.55)	0.47 (0.49)	0.49 (0.46)
Age (months)	191.08 (30.00)	192.77 (35.81)	189.42 (34.71)	191.95 (29.01)	192.24 (26.87)

Data from the 2001 to 2016 MEPS. Means and standards deviations are adjusted for the complex design of the MEPS.
BMI, body mass index; kg, kilogram; MEPS, Medical Expenditure Panel Surveys; SD, standard deviation; U.S., United States.
*Data for missing education not shown—this accounts for <1% for some states.

TABLE 2. Marginal Effect of an Additional Unit of BMI on Individual Work Loss Days and Productivity at National and State Level

	Work Loss Days	Productivity (Full Day Expenditure Estimates)	Productivity (Half Day Expenditure Estimates)
U.S., 2001–2016 (n = 50,789)	0.24 (0.15, 0.33)	42.64 (26.96, 58.31)	21.32 (13.38, 29.16)
2001–2005 (n = 17,064)	0.26 (0.16, 0.35)	44.99 (28.62, 61.36)	22.50 (14.31, 30.68)
2006–2010 (n = 15,380)	0.25 (0.15, 0.34)	43.29 (26.83, 59.75)	21.65 (13.42, 29.88)
2011–2016 (n = 18,345)	0.22 (0.14, 0.31)	40.05 (25.16, 54.94)	20.03 (12.58, 27.47)
California (n = 8554)	0.20 (0.04, 0.35)	35.55 (7.51, 63.59)	17.77 (3.75, 31.79)
Texas (n = 5732)	0.22 (0.06, 0.39)	35.82 (10.42, 61.22)	17.91 (5.21, 30.61)
Florida (n = 2708)	0.24 (−0.07, 0.54)	40.66 (−12.24, 93.56)	20.33 (−6.12, 46.78)
New York (n = 2619)	0.20 (−0.16, 0.56)	40.00 (−30.33, 110.34)	20.00 (−15.17, 55.17)
Illinois (n = 1961)	0.22 (−0.15, 0.59)	42.73 (−24.01, 109.46)	21.36 (−12.00, 54.73)
Michigan (n = 1691)	0.75 (−0.37, 1.87)	148.8 (−39.51, 337.12)	74.4 (−19.76, 168.56)
New Jersey (n = 1616)	0.37 (−0.23, 0.97)	87.47 (−47.97, 222.9)	43.73 (−23.99, 111.45)
Pennsylvania (n = 1551)	0.05 (−0.15, 0.25)	9.12 (−26.8, 45.05)	4.56 (−13.4, 22.52)
Georgia (n = 1546)	0.15 (−0.34, 0.64)	24.06 (−41.49, 89.60)	12.03 (−20.75, 44.80)
North Carolina (n = 1264)	0.40 (−1.23, 2.02)	66.16 (−170.33, 302.65)	33.08 (−85.16, 151.32)
Virginia (n = 1246)	0.21 (0.01, 0.40)	43.92 (4.10, 83.74)	21.96 (2.05, 41.87)
Wisconsin (n = 1038)	0.24 (0.01, 0.46)	41.33 (2.64, 80.01)	20.66 (1.32, 40.01)
Missouri (n = 897)	0.24 (−0.16, 0.65)	42.67 (−25.41, 110.75)	21.33 (−12.71, 55.37)
Kentucky (n = 831)	0.90 (−1.56, 3.37)	151.59 (−223.79, 526.96)	75.79 (−111.89, 263.48)

Data are from the 2001 to 2016 MEPS. Marginal effect estimates of BMI are from an IV two-part model and productivity loss is expressed in 2017 USD. The full day estimate for productivity loss is based on the assumption that the individual missed the full workday due to illness or injury. The half day estimate is based on the assumption that only half the day was missed. 90% confidence intervals in parenthesis are adjusted for the complex design of the MEPS.

BMI, body mass index; IV, instrumental variable; MEPS, Medical Expenditure Panel Surveys; U.S., United States; USD, United States Dollar.

280.5% in Virginia, and from 94.7% to 357.8% in Wisconsin. Michigan had the largest range—from 536.7% for class 1 obesity to 2742.9% for class 3. Caution should be used in interpreting the results for class 3 obesity as estimates were imprecise for all of the states.

Impact of Obesity on Value of Lost Productivity Per Worker due to Job Absenteeism

The average annual productivity loss per worker due to obesity had a lower bound of $270.79 (assuming a half day was lost) and an upper bound of $541.58 (assuming a full day was lost) in the national sample. Among the states, annual productivity loss per worker caused by obesity had the following lower and upper bounds: $221.83 to $443.67 in California, $228.38 to $456.75 in Texas, $293.27 to $586.53 in Virginia, and $255.18 to $510.36 in Wisconsin (Table 3). Michigan again differs from the other states in the analysis, with individual productivity loss ranging from $911.73 to $1823.45.

By class of obesity, the productivity loss in the national sample was $186.65 to $373.31 for those with class 1 obesity, $331.66 to $663.32 for those with class 2 obesity, and $643.27 to $1,286.54 for those with class 3 obesity (results not shown). The five states exhibit a similar pattern by class of obesity, with the greatest range again in Michigan.

Aggregate Work Productivity Loss due to Obesity

Table 4 contains the estimated aggregate productivity losses due to obesity at the national level. In 2016, across the U.S., obesity was responsible for productivity losses that ranged from $13.42 billion to $26.84 billion, for half and full day productively loss, respectively. Estimates indicate that the aggregate productivity losses rose from 2001 to 2016.

Productivity losses in 2016 varied by state, with costs in Texas ranging from $2.09 billion to $4.17 billion and those in Virginia ranging from $0.28 billion to $0.56 billion. As seen with the previous analyses, the greatest costs were for Michigan, where obesity was responsible for between $2.23 billion and $4.47 billion in productivity losses.

DISCUSSION

This study provides the first-ever estimates of the causal effect of obesity on job absenteeism in the U.S., at the national and state level, both in terms of lost workdays and the dollar value of the lost productivity. Two-part models of instrumental variables that exploit the heritable component of weight were estimated, using the BMI of a biological child as an instrument for the BMI of the parent, for MEPS data from 2001 to 2016.

Our national estimates indicate that obesity (relative to normal weight) raises the number of workdays lost to illness or injury by three days per worker per year (from 2.34 to 5.34), or by 128.2%. The impact of obesity on job absenteeism and productivity loss is more pronounced in some states compared to the others. The impact of excess weight on absenteeism rises with class of obesity, to an estimated seven workdays lost for an employee with class 3 obesity (relative to a worker of healthy weight). These lost workdays translate to a per-worker annual productivity loss caused by obesity ranging from $270.79 (assuming that only half of the affected workdays were lost) to $541.58 (assuming that the full workdays were lost). When class of obesity is considered, the lower (upper) bound of the per-worker productivity loss per year is $186.65 ($373.31) for individuals with class 1 obesity, $331.66 ($663.32) for those with class 2 obesity, and $643.27 ($1286.54) for those with class 3 obesity.

Aggregated at the U.S. national level, the total annual productivity loss due to obesity in 2016 ranges from a lower bound of $13.42 billion (assuming half-workdays lost) to an upper bound of $26.84 billion (assuming full workdays lost), both in 2017 dollars. The increase in productivity loss between 2001 and 2016 could be explained by a combination of factors including a growing adult population in the U.S., the rising prevalence of obesity, increases in hourly wages (above and beyond that of general inflation), and changes in clinical complications of people with obesity (eg, number and type of comorbidities).

Our study is novel in that it estimates the causal effect of obesity on lost workdays and the associated costs to employers rather

TABLE 3. Average Marginal Effect of Obesity on Individual Work Loss Days and Productivity at National and State Level

		Work Loss Days		Productivity (Full Day Expenditure Estimates)		Productivity (Half Day Expenditure Estimates)	
		Normal Weight	Obesity	Normal Weight	Obesity	Normal Weight	Obesity
U.S.	Predicted	2.34	5.34	424.41	965.99	212.20	483.00
(n = 50,789)	mean	(1.98, 2.71)	(4.62, 6.06)	(359.98, 488.84)	(832.26, 1099.73)	(179.99, 244.42)	(416.13, 549.86)
	Average marginal effect	–	3.00	–	541.58	–	270.79
			(1.95, 4.04)		(350.46, 732.71)		(175.23, 366.35)
California	Predicted	2.23	4.68	416.25	859.91	208.12	429.96
(n = 8554)	mean	(1.62, 2.84)	(3.24, 6.12)	(303.99, 528.50)	(587.72, 1132.11)	(152.00, 264.25)	(293.86, 566.05)
		–	2.45	–	443.67	–	221.83
	Average marginal effect		(0.51, 4.39)		(84.77, 802.57)		(42.38, 401.28)
Texas	Predicted	1.71	4.53	282.12	738.87	141.06	369.44
(n = 5732)	mean	(1.09, 2.33)	(3.27, 5.79)	(184.15, 380.09)	(526.95, 950.80)	(92.08, 190.05)	(263.47, 475.40)
		–	2.82	–	456.75	–	228.38
	Average marginal effect		(1.05, 4.59)		(164.25, 749.25)		(82.13, 374.62)
Florida	Predicted	2.45	5.50	417.03	938.51	208.51	469.26
(n = 2708)	mean	(1.19, 3.71)	(2.89, 8.12)	(196.78, 637.27)	(494.96, 1382.07)	(98.39, 318.64)	(247.48, 691.03)
		–	3.06	–	521.48	–	260.74
	Average marginal effect		(−0.50, 6.62)		(−82.63, 1125.59)		(−41.31, 562.80)
New York	Predicted	2.77	5.30	565.10	1083.12	282.55	541.56
(n = 2619)	mean	(1.57, 3.97)	(2.17, 8.43)	(336.92, 793.27)	(405.27, 1760.97)	(168.46, 396.63)	(202.63, 880.48)
		–	2.53	–	518.02	–	259.01
	Average marginal effect		(−1.70, 6.77)		(−362.46, 1398.50)		(−181.23, 699.25)
Illinois	Predicted	2.18	4.96	423.31	967.20	211.65	483.60
(n = 1,961)	mean	(1.03, 3.33)	(2.53, 7.38)	(199.35, 647.26)	(492.34, 1442.06)	(99.67, 323.63)	(246.17, 721.03)
		–	2.77	–	543.89	–	271.95
	Average marginal effect		(−0.59, 6.13)		(−110.60, 1198.39)		(−55.30, 599.19)
Michigan	Predicted	0.98	9.82	201.11	2,024.56	100.56	1012.28
(n = 1,691)	mean	(0.23, 1.73)	(3.53, 16.10)	(43.45, 358.77)	(681.92, 3367.21)	(21.72, 179.39)	(340.96, 1683.61)
	Average marginal effect	–	8.84	–	1,823.45	–	911.73
			(1.93, 15.75)		(362.50, 3284.41)		(181.25, 1642.20)
New Jersey	Predicted	2.50	6.95	599.51	1,681.90	299.75	840.95
(n = 1,616)	mean	(0.79, 4.21)	(2.07, 11.83)	(187.16, 1011.86)	(488.74, 2875.06)	(93.58, 505.93)	(244.37, 1437.53)
		–	4.45	–	1,082.39	–	541.20
	Average marginal effect		(−1.87, 10.78)		(−452.20, 2616.98)		(−226.10, 1308.49)
Pennsylvania	Predicted	4.22	4.87	754.82	872.83	377.41	436.42
(n = 1,551)	mean	(2.52, 5.91)	(3.46, 6.29)	(463.30, 1046.33)	(631.95, 1113.71)	(231.65, 523.16)	(315.98, 556.86)
		–	0.66	–	118.02	–	59.01
	Average marginal effect		(−1.97, 3.28)		(−352.78, 588.81)		(−176.39, 294.41)
Georgia	Predicted	2.07	3.92	351.45	661.33	175.72	330.66
(n = 1,546)	mean	(0.44, 3.71)	(1.14, 6.70)	(98.82, 604.07)	(151.53, 1171.12)	(49.41, 302.04)	(75.77, 585.56)
		–	1.84	–	309.88	–	154.94
	Average marginal effect		(−2.44, 6.13)		(−436.52, 1056.28)		(−218.26, 528.14)
North Carolina	Predicted	1.53	6.09	257.24	1,027.20	128.62	513.60
(n = 1,264)	mean	(−0.63, 3.70)	(−2.89, 15.07)	(−110.97, 625.46)	(−402.91, 2457.30)	(−55.49, 312.73)	(−201.45, 1228.65)
		–	4.56	–	769.96	–	384.98
	Average marginal effect		(−6.30, 15.42)		(−983.78, 2523.70)		(−491.89, 1261.85)
Virginia	Predicted	2.05	4.78	446.96	1,033.50	223.48	516.75
(n = 1,246)	mean	(0.92, 3.18)	(3.26, 6.30)	(208.22, 685.70)	(687.26, 1379.73)	(104.11, 342.85)	(343.63, 689.86)
		–	2.73	–	586.53	–	293.27
	Average marginal effect		(0.30, 5.16)		(55.95, 1117.11)		(27.98, 558.56)
Wisconsin	Predicted	2.06	4.92	373.21	883.56	186.60	441.78
(n = 1,038)	mean	(1.52, 2.60)	(2.74, 7.10)	(269.98, 476.43)	(491.59, 1275.54)	(134.99, 238.22)	(245.79, 637.77)
		–	2.86	–	510.36	–	255.18
	Average marginal effect		(0.45, 5.27)		(76.20, 944.51)		(38.10, 472.25)
Missouri	Predicted	2.36	5.48	434.30	1,004.27	217.15	502.13
(n = 897)	mean	(0.68, 4.04)	(2.57, 8.38)	(120.56, 748.05)	(496.88, 1511.65)	(60.28, 374.02)	(248.44, 755.82)
		–	3.11	–	569.96	–	284.98
	Average marginal effect		(−1.25, 7.48)		(−223.90, 1363.83)		(−111.95, 681.92)
Kentucky	Predicted	1.52	9.22	281.19	1,712.11	140.59	856.05
(n = 831)	mean	(0.15, 2.88)	(1.01, 17.42)	(19.46, 542.92)	(225.76, 3198.45)	(9.73, 271.46)	(112.88, 1599.23)
	Average marginal effect	–	7.70	–	1,430.92	–	715.46
			(−1.53, 16.93)		(−248.14, 3109.98)		(−124.07, 1554.99)

Data are from the 2001 to 2016 MEPS. Average marginal effect estimates of obesity are from an IV two-part model and productivity loss is expressed in 2017 USD. The full day estimate for productivity loss is based on the assumption that the individual missed the full workday due to illness or injury. The half day estimate is based on the assumption that only half the day was missed. Estimates of total productivity loss are inflated using MEPS sample weights to reflect productivity loss attributable to obesity for all employed adults aged 18 to 64. 90% confidence intervals in parenthesis are adjusted for the complex design of the MEPS.

IV, instrumental variable; MEPS, Medical Expenditure Panel Surveys; U.S., United States; USD, United States Dollar.

TABLE 4. Aggregate Full-Day and Half-Day Productivity Loss due to Obesity Among Employed Adults by Payment Type at National and State Level (Expressed in Billions of 2017 USD)

	Obesity		Class 1 obesity		Class 2 obesity		Class 3 obesity	
	Full-Day Productivity	Half-Day Productivity	Full-Day Productivity	Half-Day Productivity	Full-Day Productivity	Half-Day Productivity	Full-Day Productivity	Half-Day Productivity
U.S. (n = 50,789)								
2016	26.84	13.42	10.97	5.48	8.73	4.37	8.79	4.40
	(16.57, 37.12)	(8.28, 18.56)	(6.95, 14.98)	(3.47, 7.49)	(5.21, 12.26)	(2.60, 6.13)	(4.03, 13.56)	(2.01, 6.78)
2001–2016 Avg.	21.96	10.98	9.48	4.74	6.50	3.25	6.86	3.43
	(14.38, 29.54)	(7.19, 14.77)	(6.57, 12.38)	(3.28, 6.19)	(4.09, 8.91)	(2.05, 4.45)	(3.53, 10.20)	(1.76, 5.10)
Comparison of average trends								
2001–2005 Avg. (1)	21.41	10.70	9.36	4.68	6.09	3.04	6.74	3.37
	(13.81, 29.01)	(6.90, 14.51)	(6.43, 12.38)	(3.21, 6.15)	(3.70, 8.47)	(1.85, 4.24)	(3.33, 10.15)	(1.67, 5.07)
2006–2010 Avg. (2)	22.58	11.29	9.91	4.96	6.52	3.26	6.86	3.43
	(14.40, 30.77)	(7.20, 15.38)	(6.68, 13.15)	(3.34, 6.57)	(3.93, 9.11)	(1.96, 4.56)	(3.47, 10.25)	(1.73, 5.13)
2011–2016 Avg. (3)	21.89	10.95	9.21	4.60	6.83	3.42	6.97	3.48
	(14.45, 29.33)	(7.23, 14.66)	(6.35, 12.06)	(3.18, 6.03)	(4.39, 9.27)	(2.20, 4.63)	(3.57, 10.36)	(1.78, 5.18)
(3)-(1)	0.48	0.24	-0.16	-0.08	0.74	0.37	0.23	0.11
	(−2.23, 3.19)	(−1.11, 1.60)	(−1.52, 1.21)	(−0.76, 0.60)	(−0.24, 1.72)	(−0.12, 0.86)	(−1.00, 1.45)	(−0.50, 0.73)
(3)-(2)	−0.69	−0.35	−0.70	−0.35	0.31	0.16	0.11	0.05
	(−3.14, 1.75)	(−1.57, 0.88)	(−1.90, 0.49)	(−0.95, 0.24)	(−0.60, 1.22)	(−0.30, 0.61)	(−1.00, 1.21)	(−0.50, 0.60)
California (n = 8554)								
2016	1.64	0.82	0.76	0.38	0.51	0.26	0.46	0.23
	(0.26, 3.02)	(0.13, 1.51)	(0.17, 1.36)	(0.08, 0.68)	(0.02, 1.01)	(0.01, 0.50)	(−0.08, 1.00)	(−0.04, 0.50)
2001–2016 Avg.	2.27	1.14	1.10	0.55	0.65	0.33	0.62	0.31
	(0.52, 4.03)	(0.26, 2.01)	(0.33, 1.87)	(0.16, 0.94)	(0.10, 1.21)	(0.05, 0.61)	(−0.07, 1.31)	(−0.03, 0.65)
Texas (n = 5,732)								
2016	4.17	2.09	1.77	0.88	0.78	0.39	1.91	0.95
	(1.53, 6.82)	(0.76, 3.41)	(0.76, 2.78)	(0.38, 1.39)	(0.17, 1.39)	(0.09, 0.69)	(0.08, 3.74)	(0.04, 1.87)
2001–2016 Avg.	2.66	1.33	1.15	0.57	0.77	0.38	0.72	0.36
	(0.99, 4.33)	(0.50, 2.16)	(0.54, 1.75)	(0.27, 0.88)	(0.25, 1.28)	(0.13, 0.64)	(−0.03, 1.47)	(−0.01, 0.74)
Florida (n = 2708)								
2016	2.78	1.39	1.30	0.65	1.05	0.53	0.27	0.13
	(−0.34, 5.90)	(−0.17, 2.95)	(−0.05, 2.65)	(−0.02, 1.32)	(−0.34, 2.45)	(−0.17, 1.22)	(−0.22, 0.75)	(−0.11, 0.38)
2001–2016 Avg.	1.52	0.76	0.67	0.34	0.46	0.23	0.47	0.24
	(−0.24, 3.29)	(−0.12, 1.64)	(−0.01, 1.35)	(0.00, 0.67)	(−0.18, 1.10)	(−0.09, 0.55)	(−0.33, 1.27)	(−0.16, 0.64)
New York (n = 2,619)								
2016	2.01	1.00	0.90	0.45	0.71	0.36	0.38	0.19
	(−1.32, 5.34)	(−0.66, 2.67)	(−0.51, 2.31)	(−0.26, 1.15)	(−0.74, 2.18)	(−0.37, 1.08)	(−0.40, 1.16)	(−0.20, 0.58)
2001–2016 Avg.	1.20	0.60	0.53	0.26	0.37	0.19	0.40	0.20
	(−0.80, 3.20)	(−0.40, 1.60)	(−0.27, 1.33)	(−0.14, 0.66)	(−0.35, 1.10)	(−0.17, 0.55)	(−0.51, 1.32)	(−0.26, 0.66)
Illinois (n = 1,961)								
2016	0.80	0.37	0.27	0.13	0.45	0.16	0.17	0.09
	(−0.15, 1.74)	(−0.07, 0.81)	(−0.03, 0.57)	(−0.02, 0.28)	(−0.13, 1.02)	(−0.05, 0.37)	(−0.16, 0.51)	(−0.08, 0.27)
2001–2016 Avg.	1.10	0.51	0.43	0.21	0.38	0.14	0.35	0.19
	(−0.21, 2.40)	(−0.10, 1.11)	(0.00, 0.87)	(0.00, 0.43)	(−0.10, 0.86)	(−0.04, 0.31)	(−0.45, 1.16)	(−0.24, 0.61)
Michigan (n = 1691)								
2016	4.47	2.23	1.40	0.70	1.80	0.90	2.16	1.08
	(0.57, 8.37)	(0.28, 4.18)	(0.20, 2.61)	(0.10, 1.30)	(−0.34, 3.94)	(−0.17, 1.97)	(−1.44, 5.76)	(−0.72, 2.88)
2001–2016 Avg.	3.60	1.80	1.18	0.59	1.62	0.81	1.32	0.66
	(0.92, 6.28)	(0.46, 3.14)	(0.54, 1.82)	(0.27, 0.91)	(0.05, 3.19)	(0.03, 1.59)	(−0.78, 3.43)	(−0.39, 1.72)
New Jersey (n = 1616)								
2016	2.09	1.04	1.12	0.56	0.52	0.26	0.72	0.36
	(−1.03, 5.20)	(−0.51, 2.60)	(−0.35, 2.58)	(−0.18, 1.29)	(−0.46, 1.50)	(−0.23, 0.75)	(−1.82, 3.27)	(−0.91, 1.63)
2001–2016 Avg.	1.48	0.74	0.83	0.41	0.38	0.19	0.32	0.16
	(−0.66, 3.61)	(−0.33, 1.80)	(−0.25, 1.90)	(−0.12, 0.95)	(−0.26, 1.02)	(−0.13, 0.51)	(−0.52, 1.17)	(−0.26, 0.58)
Pennsylvania (n = 1551)								
2016	0.22	0.11	0.09	0.05	0.05	0.02	0.09	0.05
	(−0.70, 1.15)	(−0.35, 0.57)	(−0.27, 0.46)	(−0.14, 0.23)	(−0.15, 0.25)	(−0.08, 0.12)	(−0.44, 0.62)	(−0.22, 0.31)
2001–2016 Avg.	0.24	0.12	0.09	0.05	0.08	0.04	0.08	0.04
	(−0.74, 1.22)	(−0.37, 0.61)	(−0.27, 0.45)	(−0.13, 0.23)	(−0.26, 0.42)	(−0.13, 0.21)	(−0.29, 0.45)	(−0.14, 0.23)
Georgia (n = 1546)								
2016	0.59	0.30	0.31	0.15	0.13	0.06	0.10	0.05
	(−0.80, 1.99)	(−0.40, 0.99)	(−0.32, 0.48)	(−0.16, 0.45)	(−0.23, 0.48)	(−0.11, 0.24)	(−0.27, 0.47)	(−0.14, 0.23)
2001–2016 Avg.	0.51	0.26	0.22	0.11	0.14	0.07	0.19	0.10
	(−0.72, 1.74)	(−0.36, 0.87)	(−0.25, 0.52)	(−0.12, 0.34)	(−0.24, 0.52)	(−0.12, 0.26)	(−0.54, 0.93)	(−0.27, 0.26)

TABLE 4. (*Continued*)

	Obesity		Class 1 obesity		Class 2 obesity		Class 3 obesity	
	Full-Day Productivity	Half-Day Productivity	Full-Day Productivity	Half-Day Productivity	Full-Day Productivity	Half-Day Productivity	Full-Day Productivity	Half-Day Productivity
North Carolina (n = 1264)								
2016	2.21	1.11	1.13	0.56	0.33	0.17	0.80	0.40
	(−1.84, 6.27)	(−0.92, 3.13)	(−0.40, 2.65)	(−0.20, 1.33)	(−0.73, 1.39)	(−0.36, 0.69)	(−2.80, 4.40)	(−1.40, 2.20)
2001–2016 Avg.	1.46	0.73	0.67	0.34	0.45	0.22	0.39	0.20
	(−1.45, 4.37)	(−0.72, 2.19)	(−0.32, 1.67)	(−0.16, 0.83)	(−0.83, 1.72)	(−0.41, 0.86)	(−1.42, 2.21)	(−0.71, 1.10)
Virginia (n = 1246)								
2016	0.56	0.28	0.15	0.08	0.22	0.11	0.29	0.15
	(0.02, 1.09)	(0.01, 0.55)	(0.02, 0.29)	(0.01, 0.14)	(−0.06, 0.50)	(−0.03, 0.25)	(−0.11, 0.69)	(−0.06, 0.35)
2001–2016 Avg.	0.68	0.34	0.31	0.15	0.16	0.08	0.20	0.10
	(0.10, 1.26)	(0.05, 0.63)	(0.06, 0.55)	(0.03, 0.28)	(0.00, 0.33)	(0.00, 0.16)	(−0.02, 0.42)	(−0.01, 0.21)
Wisconsin (n = 1038)								
2016	1.05	0.49	0.47	0.23	0.25	0.09	0.35	0.18
	(−0.08, 2.18)	(−0.04, 1.01)	(−0.04, 1.99)	(−0.02, 0.48)	(−0.05, 0.56)	(−0.02, 0.21)	(−0.12, 0.82)	(−0.06, 0.43)
2001–2016 Avg.	0.55	0.26	0.22	0.11	0.21	0.08	0.17	0.09
	(0.09, 1.02)	(0.04, 0.47)	(0.02, 0.43)	(0.01, 0.21)	(0.04, 0.39)	(0.01, 0.14)	(0.00, 0.34)	(0.00, 0.18)
Missouri (n = 897)								
2016	0.84	0.42	0.24	0.12	0.47	0.24	0.12	0.06
	(−0.37, 2.04)	(−0.18, 1.02)	(−0.07, 0.55)	(−0.03, 0.27)	(−0.34, 1.28)	(−0.17, 0.64)	(−0.18, 0.42)	(−0.09, 0.21)
2001–2016 Avg.	0.70	0.35	0.25	0.12	0.22	0.11	0.28	0.14
	(−0.25, 1.64)	(−0.12, 0.82)	(−0.05, 0.54)	(−0.02, 0.27)	(−0.10, 0.54)	(−0.05, 0.27)	(−0.27, 0.83)	(−0.13, 0.42)
Kentucky (n = 831)								
2016	0.51	0.25	0.12	0.06	0.17	0.08	0.47	0.24
	(0.05, 0.96)	(0.03, 0.48)	(0.01, 0.22)	(0.01, 0.11)	(0.03, 0.31)	(0.02, 0.15)	(−0.62, 1.56)	(−0.31, 0.78)
2001–2016 Avg.	1.02	0.51	0.29	0.14	0.36	0.18	0.57	0.28
	(−0.21, 2.25)	(−0.10, 1.13)	(0.09, 0.49)	(0.05, 0.24)	(−0.27, 0.98)	(−0.13, 0.49)	(−0.67, 1.80)	(−0.34, 0.90)

Data are from the 2001 to 2016 MEPS. Average marginal effect estimates of obesity are from an IV two-part model and productivity loss is expressed in 2017 USD. The full day estimate for productivity loss is based on the assumption that the individual missed the full workday due to illness or injury. The half day estimate is based on the assumption that only half the day was missed. Estimates of total productivity loss are inflated using MEPS sample weights to reflect productivity loss attributable to obesity for all employed adults aged 18 to 64. 90% confidence intervals in parenthesis are adjusted for the complex design of the MEPS. Classes of obesity are defined as follows, class 1—30 $kg/m^2 \leq$ BMI $<$ 35 kg/m^2; class 2—35 $kg/m^2 \leq$ BMI $<$ 40 kg/m^2; class 3—BMI $\geq$ 40 kg/m^2.

Avg., average; BMI, body mass index; IV, instrumental variable; kg, kilogram; MEPS, Medical Expenditure Panel Surveys; U.S., United States; USD, United States Dollar.

than simply estimating the correlation between those variables. Our estimates of the causal effects are generally larger than the correlations estimated in previous studies.[12–15] For example, a previous estimate of the correlation of obesity with job absenteeism that was also based on the MEPS estimated that the annual per employee cost of the additional job absenteeism associated with obesity was $142 per year for women and $70 per year for men (both estimates in 2004 dollars). In contrast, our estimates from IV models indicate that the per employee job absenteeism cost of obesity for men and women pooled ranges from a lower bound of $271 to an upper bound of $542 (both in 2017 USD, which converted to 2004 USD are a lower bound of $207 and an upper bound of $413). This indicates that the causal effect of obesity on job absenteeism is considerably larger than its correlation, which implies that the indirect costs of obesity have traditionally been underestimated, and to the extent that studies of the cost-effectiveness of effective methods of obesity treatment and prevention have used those correlations, they may have underestimated the cost-effectiveness of such interventions.

The finding that obesity among employees increases missed workdays is relevant for employers. One margin by which employers can potentially promote healthy weight among their employees is by their choice of health insurance plan, in particular the extent to which it covers effective treatments for obesity. Another margin is that employers can take advantage of the increased flexibility for workplace wellness programs provided by the Affordable Care Act (ACA), for example, by offering incentives for healthy weight. However, evidence on the effectiveness of workplace wellness programs is mixed.[35] To some extent lost productivity may also represent a negative externality, which represents an economic rationale for government intervention. Numerous methods of obesity prevention and treatment have been found to be effective and cost-effective.[36]

This study has several limitations. Instrument validity must be carefully considered in all IV models. It is impossible to prove the validity of an instrument, but the findings in other studies that non-transmitted parental alleles for BMI have no detectable impact on child BMI,[26,28] and the lack of evidence for a household effect on BMI for adolescents[20,26–28] supports our identification strategy.

We use genetic variation in weight to identify the effect of obesity on job absenteeism, and our estimates may not generalize to variation in weight due to other factors. Our IV model can be estimated only for those individuals with a biological child residing in the household, affecting the age range of the adult sample. This may potentially limit the generalizability of the results to adults without children and adults whose children do not live in the same household. Additionally, we are only able to estimate the impact of obesity on job absenteeism for employed individuals and not reductions in home production among those not in the labor force. Nor do our data allow us to estimate another type of indirect cost of obesity, which is presenteeism (ie, lower productivity while at work).

BMI, though a widely used measure of adiposity, does not directly measure fat or body composition. However, it is the only measurement available in the MEPS data. Moreover, the MEPS panels span two calendar years, which is insufficient for observing how job absenteeism varies in response to within-person changes in BMI over time. Our measure of BMI is calculated using self-reports or proxy-reports rather than measurements. The IV method does, however, to some extent address the problem of measurement error in the regressor of interest.

We measure productivity losses due to worker absenteeism, but a fuller accounting of the productivity loss from obesity would include effects on presenteeism (lower productivity at work), disability (short- and long-term) and workers' compensation payments. In addition, the measure of missed workdays in the MEPS does not allow us to disentangle whether absenteeism was due to an injury as opposed to a chronic condition, or if due to a chronic condition, which specific one (eg, diabetes). Having this information could help to elucidate the mechanisms through which obesity reduces productivity.

Lastly, sample sizes in the MEPS limited the ability to generate precise estimations for some states; thus, caution should be used in the interpretation of estimates for states with smaller sample sizes.

CONCLUSIONS

The findings from this study make an important contribution to the literature on the indirect costs of obesity. Specifically, it provides the first estimates of the causal impact of obesity on job absenteeism and the associated productivity loss per worker at national and state levels, which are substantial.

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