Replication for “The Incidence of the Healthcare Costs of Obesity”

Soumik Ghosh Moulic

Minerva Schools at KGI

Abstract

Earlier this year, I was intrigued by reading your paper about how the insurance costs given to workers by their employers affect their wages, particularly the point that higher costs of insurance for obese workers borne by their employers get passed down to the workers themselves in the form of reduced payments — the findings of your paper, which back your point, were interesting to read. It inspired me to replicate your results using the tools that I have learned in my decision-making class. I used a random sample of 10,000 observations to create a subset of your dataset of 31,176 observations and ran genetic matching with simple linear regression. The results I obtained showed no such causation as your paper described. The factor of being obese and being insured was not statistically significant on any level and when compared to the results of your article, proved to be countering it. I would like it if you could check my results and let me know your thoughts on it. Maybe using my method on the full dataset could bring better results for your paper.

Background

Obesity is a significant contributor to increasing healthcare costs in the United States. Obese individuals incur annual medical expenditures estimated to be more than $732 greater than those faced by normal weight individuals (Finkelstein, Fiebelkorn, & Wang, 2003). It is challenging to understand who ultimately pays for this increased expenditure because judging the effects of medical costs accurately is incredibly difficult due to the intertwining of the various complex and sometimes unobserved factors (like motivation, stress, anxiety). If these factors affect obesity and other parts of human development, then the effect of obesity on other things (in our case, wages) has a greater chance to be biased and overestimated. Also, at this point where obesity is rising in the population worldwide (and mainly in the US) due to the emergence of numerous fast-food chains, knowing who ultimately pays for this increase in expenditure is crucial for health planning purposes and some employer policy purposes as well. The medical costs of obesity may be borne primarily by insurers; particularly employer‐sponsored insurance plans which account for the majority of health insurance coverage for adults under 65. Such policies tend not to risk‐adjust individual premiums (i.e., they do not charge obese enrollees more), and thus may transfer the bulk of obesity‐related healthcare costs to employers and insurers in the form of higher group plan premiums. This, in turn, may drive an adverse selection of obese individuals into such plans and create moral hazard in personal governance of 'obesogenic' behavior. (Turabi A., Saynisch P., 2014).

In your paper Miss Bundorf, you and Mr. Bhattacharya have used data from the National Longitudinal Survey of Youth (NLSY) to estimate the prevalence of the healthcare costs of obesity. You use the NLSY data from 1988 to 2002 and omit the year 1991 due to lack of information status for that year and also use only post-1988 data because earlier years of the survey did not include questions on health insurance status or other types of fringe benefits offered by employers. (Bhattacharya, J., & Bundorf, M. K., 2009). Then you further restrict the sample by eliminating pregnant women and individuals who did not work 7 or more hours a day in a private or non-profit firm in a given year. Finally, you prune your dataset to discard workers who indicated that they either had employer-sponsored health insurance in their name from their current employer or were uninsured (Bhattacharya, J., & Bundorf, M. K., 2009). A difference-in-differences framework is employed to analyze the outcomes, but rather than comparing treated and untreated groups before and after an intervention (like in a conventional tdifference-in-differences approach) the estimates are adjusted by hourly wages of obese and non-obese workers and then compared to the differences among active workers with and without employer-sponsored health insurance. The analysis concludes that medical costs of obesity are transferred to obese employees through a wage penalty of $1.45 per hour, after controlling for employee characteristics (Turabi A., Saynisch P., 2014).

My analyses built upon the pre-processed data and ran genetic matching to check if better estimates of the obesity-insurance wage penalty could be obtained.

Data and Method

I used the pre-processed NLSY sample that the analyses were based on to be able to replicate the findings as closely as possible and also because the dataset was quite robust. I chose Genetic matching because it reduces model dependency and bias and can achieve much better balance. However, I found it incredibly time taking to run meaningful genetic matching on all the 31,176 observations as genetic matching is very resource intensive and time-consuming. Ex - I tried running genetic matching on those 31,176 observations for a while with 250 population size and a hard max generation limit of 25 on an eight-core 64 bit CPU running at 3.4 GHz, but in 9 hours, it only got to generation 14. Now, to properly utilize the power of genetic matching and get a significantly optimized solution to the problem, I could not have reduced the number of generations or the population size of the algorithm, so I decided to stratify the dataset and use a random sample of 10,000 observations to get a result.

Matching was done to better balance observed covariates between obese and non-obese respondents, matching on a number of respondent characteristics: age, race, presence of children in household, being female with children at home, marital status, education, AFQT (Armed Forces Qualification Test) score, residing in an urban area, job tenure, occupation, industry, employer size, and survey year. The population size was reduced to 100, and the hard maximum generation limit was set to 25 with a wait generation for 3. The optimal solution was found at 25th generation. The result of the algorithm is in the Appendix.

Results

A balance table and a match improved table summarizing the results appear in Appendix. Genetic matching resulted in an analytic sample of 3664 observations (2051 obese, 1613 non-obese), compared with a pre-match sample of 10,000 observations (2051 obese, 7949 non-obese). Covariate matching improved notably with 26 variables becoming balanced after matching, seven variables remaining unbalanced after matching, one variable becoming unbalanced after matching, and 25 variables remaining balanced after matching. Matching also helped me conclude the two important results.

First, the balance between the mean hourly wage difference of obese and non-obese individuals, which happens to be the principal outcome measure of your studies, did not improve with matching. When taken with the same sample size of 10,000, the post-match results instead increased the difference between the wages than the pre-matched sample [$15.05 for non-obese vs. $14.27 for obese in pre-match (p-value = 0.024) and $15.33 for non-obese and $14.27 for obese post-match (p-value = 0.018). This means there was no statistical significance observed for the wage difference both pre and post-matching. Your original findings with the 31,176 observations found this wage gap to be statistically significant with $15.18 for non-obese and $14.13 for obese (p-value < 0.001).

Secondly, the Obese and Insured population for my sample did not show any statistically significant wage difference on any level than their non-obese counterparts, as shown in Table 1 in the appendix. For comparison, I use Table 1 to show your original results with my matched results. Your findings demonstrate a statistically significant difference of $1.448 for the obese and insured population, meaning that on an average they earn $1.448 less than their non-obese and insured counterparts. My results don't show that difference.

Now I do realize that dropping ⅔ of the observations for this study and doing the genetic matching for the remaining ⅓ might not be very fair as a lot of data that influenced your results is left out. But as I stated above, running a well optimized genetic matching for all the 31,176 observations was not possible for me due to the lack of computational resources available to me. So to compensate, what I did instead was to adjust your findings to my 10,000 observations and then compare my matched results to it. Table 2 in the appendix shows the results, and as you can observe, the pre-matched results for obese and insured does show a statistically significant difference at the 10% level, stating that those people earn $1.224 less than their non-obese and insured counterparts. But those findings remain no longer significant for the post-matched results.

Conclusion and Recommendation

What I can conclude from my above findings using a sample subset of your data is that there does not exist a statistically significant difference in wages of those who are obese and insured and those who are non-obese and insured. From my first, There also doesn't exist a statistically significant wage gap between obese and non-obese people. These findings oppose the findings of your original paper.

I, however, do realize that my sample size is ⅓ of the original and a lot of data is dropped, but if it is randomly taken, then I can safely say that it does represent all of your population. Also, the fact that when your original results are adjusted for my sample, they show statistical significance at the 10% level but do not show the same after genetic matching tells me that the pre-matched dataset might have a bias towards over-estimating the wage-penalty associated with obesity and obesity with insurance. An added fact is that my genetic matching algorithm found the optimal solution at the 25th generation and stopped because of the hard limit. So with increasing the number of generations and the population size, better-optimized results can be obtained.

I want to recommend you to reevaluate your complete dataset with genetic matching, setting an appropriate population size and generations to get the best results and then check if your updated results still stay the same as your original findings. I hope to see the updated paper sometime soon.

References

Bhattacharya, J., & Bundorf, M. K. (2009). The incidence of the healthcare costs of obesity. Journal of Health Economics, 28(3), 649–58. Retrieved from https://www-sciencedirect-com.ccl.idm.oclc.org/science/article/pii/S0167629609000113

Finkelstein, E. A., Fiebelkorn, I. C., & Wang, G. (2003). National Medical Spending Attributable To Overweight And Obesity: How Much, And Who's Paying? Retrieved from https://www.ncbi.nlm.nih.gov/pubmed/14527256

Turabi, A. E., & Saynisch, P. (2014). Overweight and Overburdened: Race and Gender Disparities in the Incidence of the Healthcare Costs of Obesity. Retrieved from https://dataverse.harvard.edu/file.xhtml?persistentId=doi:10.7910/DVN/25680/3GJZC4&version=2.0

Appendix

Link to my code - https://gist.github.com/Soumik0833/25165b2d1929a82074aeabcc4638a208

Genetic Matching Ouput

```
#genmatch output

NOTE: HARD MAXIMUM GENERATION LIMIT HIT

Solution Lexical Fitness Value:
0.000000e+00  1.268498e-06  2.095827e-06  2.095827e-06  3.608674e-06
3.608674e-06  2.570082e-05  2.570082e-05  2.912801e-05  8.991836e-05
6.018550e-04  2.240167e-03  2.240167e-03  1.424662e-02  1.424662e-02
1.424662e-02  1.424662e-02  2.400000e-02  3.091702e-02  3.136872e-02
3.136872e-02  3.729570e-02  3.729570e-02  6.800000e-02  7.800000e-02
9.459862e-02  9.459862e-02  1.796701e-01  1.796701e-01  2.513309e-01
2.513309e-01  2.580000e-01  2.640000e-01  3.000000e-01  3.173106e-01
3.173106e-01  3.173106e-01  3.173106e-01  3.173106e-01  3.173106e-01
3.173106e-01  3.173106e-01  3.457852e-01  3.457852e-01  3.650408e-01
3.650408e-01  5.127202e-01  5.127202e-01  5.398699e-01  5.840000e-01
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00

Parameters at the Solution:

 X[ 1] :   9.088441e+02
 X[ 2] :   4.141232e+02
 X[ 3] :   5.307889e+02
 X[ 4] :   5.055697e+01
 X[ 5] :   6.022365e+02
 X[ 6] :   6.672560e+02
 X[ 7] :   5.354206e+02
 X[ 8] :   7.866402e+02
```

```
 X[ 9] :   2.821236e+01
 X[10] :   6.919897e+01
 X[11] :   4.891194e+01
 X[12] :   1.326077e+02
 X[13] :   8.213863e+02
 X[14] :   5.633170e+02
 X[15] :   3.987195e+02
 X[16] :   5.313649e+02
 X[17] :   8.846210e+02
 X[18] :   5.301348e+02
 X[19] :   5.703647e+02
 X[20] :   9.850266e+02
 X[21] :   6.499526e+02
 X[22] :   6.822988e+02
 X[23] :   4.744775e+01
 X[24] :   9.162633e+00
 X[25] :   4.980530e+02
 X[26] :   1.211878e+02
 X[27] :   5.272579e+02
 X[28] :   7.274917e+02
 X[29] :   1.804035e+02
 X[30] :   3.909940e+02
 X[31] :   7.472372e+02
 X[32] :   1.923706e+02
 X[33] :   6.702722e+01
 X[34] :   9.138133e+02
 X[35] :   3.199009e+02

Solution Found Generation 25
Number of Generations Run 25

Thu Dec 20 19:37:35 2018
Total run time : 1 hours 2 minutes and 47 seconds
```

Table 1: Estimates of the obesity wage offset for health insurance, comparing the Original paper estimates with our GenMatched Samples

	Dependent variable:	
	Original	Matched
	(1)	(2)
Obese	-0.203	-0.546
	(0.491)	(0.586)
Insured	2.368***	2.034***
	(0.261)	(0.581)
Obese x Insured	-1.448**	-0.435
	(0.567)	(0.796)
Constant	24.435***	30.882*
	(7.342)	(16.141)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 2: Estimates of the obesity wage offset for health insurance, how the Original would look with the taken subset of dataset and comparing it to our GenMatched Samples

	Dependent variable:	
	Original	Matched
	(1)	(2)
Obese	-0.363	-0.546
	(0.511)	(0.586)
Insured	2.446***	2.034***
	(0.332)	(0.581)
Obese x Insured	-1.224*	-0.435
	(0.693)	(0.796)
Constant	43.491***	30.882*
	(13.007)	(16.141)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Variable Name	Pre-match non-obese	Pre-match obese	Pre-match p-value	Post-match non-obese	Post-match obese	Matched p-value	Improved balance with matching
Hourly wage*	15.05	14.27	0.024	15.33	14.27	0.018	No
Employer coverage in own name	0.81	0.84	0.006	0.81	0.84	0.054	Yes
Uninsured	0.19	0.16	0.006	0.19	0.16	0.054	Yes
Obese (BMI>30)	0	1	NaN	0	1	NaN	NA
Mildly obese (BMI>30 and BMI<35)	0	0.71	0	0	0.71	0	No
Morbidly obese (BMI>35)	0	0.29	0	0	0.29	0	No
Overweight	0.45	0	0	0.48	0	0	No
Obese * employer coverage (own)	0	0.84	0	0	0.84	0	No
Female	0.37	0.38	0.221	0.37	0.38	0.281	No
Any children in household	0.53	0.59	0	0.61	0.59	0.242	Yes
Female with children in household	0.21	0.24	0.022	0.24	0.24	0.397	Yes
Race - Black	0.12	0.17	0	0.14	0.17	0.003	No
Race - Other	0.02	0.03	0.301	0.02	0.03	0.319	No
Never married	0.25	0.25	0.398	0.22	0.25	0.07	No
Formerly married	0.21	0.19	0.013	0.19	0.19	0.383	Yes
Age	33.89	35.77	0	35.47	35.77	0.059	Yes
Education: 9-12	0.52	0.57	0	0.55	0.57	0.143	Yes
Education: 13 and over	0.46	0.4	0	0.43	0.4	0.083	Yes
AFQT: 0-25	0.13	0.18	0	0.14	0.18	0.012	No
AFQT: 25-50	0.22	0.23	0.205	0.28	0.23	0.003	No
AFQT: 50-75	0.29	0.29	0.34	0.29	0.29	0.346	No
AFQT: 75-100	0.36	0.3	0	0.29	0.3	0.38	Yes
Urban residence	0.75	0.69	0	0.72	0.69	0.05	No
Job tenure: 0-1 years	0.2	0.15	0	0.18	0.15	0.051	Yes
Job tenure: 1-3 years	0.23	0.22	0.341	0.22	0.22	0.394	No
Job tenure: 3-6 years	0.22	0.19	0.009	0.21	0.19	0.137	Yes
Job tenure: 6+ years	0.36	0.44	0	0.4	0.44	0.014	No
Employer size: 0-9	0.18	0.17	0.219	0.18	0.17	0.176	No
Employer size: 10-24	0.14	0.15	0.283	0.13	0.15	0.203	No
Employer size: 25-49	0.11	0.11	0.394	0.13	0.11	0.107	No
Employer size: 50-999	0.43	0.47	0.004	0.44	0.47	0.098	Yes
Employer size: 1000+	0.15	0.11	0	0.12	0.11	0.313	Yes
Survey year: 1989	0.13	0.06	0	0.08	0.06	0.028	No
Survey year: 1990	0.12	0.07	0	0.06	0.07	0.202	Yes

Variable Name	Pre-match non-obese	Pre-match obese	Pre-match p-value	Post-match non-obese	Post-match obese	Matched p-value	Improved balance with matching
Survey year: 1992	0.11	0.07	0	0.08	0.07	0.287	Yes
Survey year: 1993	0.11	0.09	0.005	0.09	0.09	0.398	Yes
Survey year: 1994	0.11	0.11	0.399	0.1	0.11	0.378	No
Survey year: 1996	0.11	0.13	0.039	0.13	0.13	0.392	Yes
Survey year: 1998	0.11	0.14	0	0.15	0.14	0.355	Yes
Survey year: 2000	0.1	0.16	0	0.15	0.16	0.198	Yes
Survey year: 2002	0.09	0.16	0	0.16	0.16	0.344	Yes
Industry: Agriculture	0.02	0.02	0.381	0.02	0.02	0.399	No
Industry: Forestry	0	0	0.134	0	0	NaN	No
Industry: Mining	0.01	0.01	0.398	0.01	0.01	0.374	No
Industry: Construction	0.08	0.05	0	0.06	0.05	0.15	Yes
Industry: Manufacturing	0.28	0.29	0.354	0.28	0.29	0.383	No
Industry: Transport	0.08	0.09	0.268	0.09	0.09	0.399	No
Industry: Wholesale trade	0.04	0.04	0.345	0.04	0.04	0.394	No
Industry: Retail trade	0.13	0.16	0.021	0.16	0.16	0.373	Yes
Industry: Finance	0.08	0.06	0.028	0.07	0.06	0.322	Yes
Industry: Business services	0.08	0.07	0.249	0.08	0.07	0.392	No
Industry: Personal services	0.02	0.03	0.124	0.03	0.03	0.369	No
Industry: Entertainment	0.01	0.01	0.225	0.01	0.01	0.375	No
Industry: Professional services	0.16	0.16	0.318	0.15	0.16	0.124	No
Industry: Public administration	0.01	0.01	0.166	0.02	0.01	0.27	No
Occupation: Management	0.28	0.22	0	0.24	0.22	0.092	Yes
Occupation: Technical	0.13	0.11	0.03	0.11	0.11	0.391	Yes
Occupation: Administrative	0.13	0.15	0.106	0.15	0.15	0.393	No
Occupation: Service	0.08	0.12	0	0.11	0.12	0.098	Yes
Occupation: Farming	0.02	0.02	0.29	0.02	0.02	0.389	No
Occupation: Production	0.15	0.16	0.124	0.15	0.16	0.3	No
Occupation: Operators	0.19	0.21	0.094	0.21	0.21	0.398	No
Occupation: Military	0.01	0.01	0.294	0.01	0.01	0.28	No
BMI	24.45	34.21	0	24.69	34.21	0	No

Variable Name	Balanced before matching	Balanced after matching	Balance improved by matching
Hourly wage*	No	No	No
Employer coverage in own name	No	Yes	Yes
Uninsured	No	Yes	Yes
Female	Yes	Yes	No
Any children in household	No	Yes	Yes
Female with children in household	No	Yes	Yes
Race - Black	No	No	No
Race - Other	Yes	Yes	No
Never married	Yes	Yes	No
Formerly married	No	Yes	Yes
Age	No	Yes	Yes
Education: 9-12	No	Yes	Yes
Education: 13 and over	No	Yes	Yes
AFQT: 0-25	No	No	No
AFQT: 25-50	Yes	No	No
AFQT: 50-75	Yes	Yes	No
AFQT: 75-100	No	Yes	Yes
Urban residence	No	No	No
Job tenure: 0-1 years	No	Yes	Yes
Job tenure: 1-3 years	Yes	Yes	No
Job tenure: 3-6 years	No	Yes	Yes
Job tenure: 6+ years	No	No	No
Employer size: 0-9	Yes	Yes	No
Employer size: 10-24	Yes	Yes	No
Employer size: 25-49	Yes	Yes	No
Employer size: 50-999	No	Yes	Yes
Employer size: 1000+	No	Yes	Yes
Survey year: 1989	No	No	No
Survey year: 1990	No	Yes	Yes
Survey year: 1992	No	Yes	Yes
Survey year: 1993	No	Yes	Yes
Survey year: 1994	Yes	Yes	No
Survey year: 1996	No	Yes	Yes
Survey year: 1998	No	Yes	Yes
Survey year: 2000	No	Yes	Yes

Variable Name	Balanced before matching	Balanced after matching	Balance improved by matching
Survey year: 2002	No	Yes	Yes
Industry: Agriculture	Yes	Yes	No
Industry: Forestry	Yes	Yes	No
Industry: Mining	Yes	Yes	No
Industry: Construction	No	Yes	Yes
Industry: Manufacturing	Yes	Yes	No
Industry: Transport	Yes	Yes	No
Industry: Wholesale trade	Yes	Yes	No
Industry: Retail trade	No	Yes	Yes
Industry: Finance	No	Yes	Yes
Industry: Business services	Yes	Yes	No
Industry: Personal services	Yes	Yes	No
Industry: Entertainment	Yes	Yes	No
Industry: Professional services	Yes	Yes	No
Industry: Public administration	Yes	Yes	No
Occupation: Management	No	Yes	Yes
Occupation: Technical	No	Yes	Yes
Occupation: Administrative	Yes	Yes	No
Occupation: Service	No	Yes	Yes
Occupation: Farming	Yes	Yes	No
Occupation: Production	Yes	Yes	No
Occupation: Operators	Yes	Yes	No
Occupation: Military	Yes	Yes	No