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Professor Diamond

CS112 Fall Semester 2018

Decision Memo: Final Project

TO: Amanda De Cadenet, CEO of Girl Gaze

FROM: Kira Fines-Kested & Isabella Buchanan, Seoul, South Korea

SUBJECT: Business recommendation for advocating for obese women

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Executive Summary

Girl Gaze's platform connects females with partner organizations to empower and employ women (De Cadenet, 2018). Girl Gaze not only aims to create meaningful jobs for women but also to advocates for them and fights against discrimination. This decision memo seeks to answer the question: Should Girl Gaze use their new extended budget to create a system to advocate for obese women? Girl Gaze prides itself in finding women secure jobs with benefits including employer-provided health insurance. It is for this reason that our findings regarding the effects of obesity on hourly wages for insured individuals are directly applicable to Girl Gaze. It was found that employer insured obese women of color are paid $0.93 less than their non-obese counterparts, whereas white, obese women are paid $1.54 less. We hope that these findings allow Girl Gaze to most strategically target this discrimination. It is recommended that Girl Gaze address this problem by firstly, allocating extra time to contract negotiations for obese women, and secondly, by putting in a place a health program to empower obese women to lose weight and that their extended budget should be used for this pressing issue.

Context for Research

Previous research has been conducted into the effects of obesity on hourly wages. Bhattacharya and Bundorf (2014) used the National Longitudinal Survey of Youth (NSLY) and Medical Expenditure Panel survey data to conclude that obese individuals, who generally face higher healthcare costs, ‘pay’ for these increased costs through lower hourly wages from their employers who sponsor their health insurance.

They claim that their most robust finding is that obese individuals with an employer covered insurance face a penalty of $1.48 lower wages than their non-obese counterparts. They further argue that obese women face harsher penalties of $2.64 compared to obese men who see $0.68 less. These results were found using ordinary least squares (OLS) regression. This finding sparked the idea to further look into the effects on women.

However, we argue, that these results could be largely model dependent, meaning the results they compute could vary primarily based on the variables used in the model (Ho et al., 2007). Although fascinating, further research is required to have confidence in findings related to obesity and wages. A primary problem with the OLS regression technique is that there is a lack of balance between the obese and non-obese groups. To have confidence that the difference in wages is due to obesity, we require the “distribution of observed covariates” of the individuals in the obese and non-obese groups to be very similar (Diamond & Sekhon, 2012). It is for this reason that we conduct an investigation using genetic matching which will be described further in the following section.

Methods

Genetic matching is a revolutionary technique which allows users to make stronger inferences about a causal effect. It “ uses a search algorithm to iteratively check and improve covariate balance” which ensures that the treatment and control groups have near identical distributions so that we can infer more strongly, that the difference in the outcome variable of the groups is indeed due to the treatment (Diamond & Sekhon, 2012). Achieving covariate balance means that the observed characteristics, besides the treatment and the outcome, have similar distributions between treatment and control groups. In our case, we wish to infer the causal effect of being obese versus not being obese on hourly wages.

We run Genetic Matching using a total of 34 of the 82 covariates (Appendix A). The covariates used were the same covariates used in Bhattacharya and Bundorf's (2014) paper for two reasons. The first being that it allowed us to make a meaningful comparison with the original paper. The second being, that restrictions in resources did not allow for more covariates to be matched on. However, we also replicated Bhattacharya and Bundorf's (2014) results using linear regression to compare with our Genetic Matching results. We run Genetic Matching on a random subset of 2000 women. We use a random subset of the population because computationally the dataset was too large to process in entirety, and random selection should eliminate selection bias (IWS, 2014).

To provide meaningful insight to Girl Gaze, we stratify our data into two groups that Girl Gaze works mainly with: insured, young women of color, and insured, young, white women. We run Genetic Matching on these two groups. We can compute estimates for the effect of being obese versus not being obese on hourly wages for these groups. We calculate the balance on the matched treatment and control groups, standard errors, and significance values.

Data

We were able to replicate Bhattacharya and Bundorf's (2014) results using linear regression. The regression results were statistically significant at 0.0004 which means that there in only a 0.04% chance that these results happen by chance, which is unlikely. But, they had a very low balance in observed covariates indicating the difference in wages could be caused by some other difference, other than obesity, between the groups. With Genetic Matching, the P-Value of 0.025 still yielded a statistically significant result, unlikely to occur just due to chance, but with far greater balance. This suggests that the linear regression results were dependent on the model used and would vary if other covariates were used. Therefore, the estimated treatment effect of $1.33 less per hour for insured women is more reliable because our obese and non-obese groups are similar with regards to observed characteristics and hence there is less bias.

Table 1: Table comparing linear regression results to matching results for the treatment effect of obesity on hourly wages on insured women

	Treatment effect	P value	Leximin P value	Standard Error
Regression	-2.64	0.000416	$2.2e^{-16}$	0.747152
Matching	-1.33	0.01899	0.15576	0.85749

Our secondary findings apply to Girl Gaze. We were able to achieve balance women of color and white women, which will mean the difference in wages is more likely to be due to obesity and not some other difference between the groups.

We found that insured women of color are paid $0.93 dollars less than non-obese women of color. Our p-value of 3% demonstrates that there is a 3% chance that these results were due to chance, which is very unlikely.[1] Moreover, our standard error of $0.44 shows we are 95% certain that obese women of color will earn between $1.81 to $0.05 less than non-obese women of color (Minitab, 2014). This shows that even when on the upper end of the pay distribution, obese women are still likely to earn less than non-obese women.[2] This finding is critical which demonstrates why Girl Gaze should allocate budget to change this problem.

[1] **#significance:** Calculates and interprets significance in the context of obese women's wages.
[2] **#confidenceintervals:** Calculates confidence interval using standard error. Interprets the significance of having a confidence interval with negative ranges for obese women.

Moreover, white obese women are paid $1.54 less than non-obese white women. These results are less certain than those for women of color, since the significance value is higher (5.5%) and there is a higher standard error (0.96 versus 0.45). This uncertainty is largely due to limited resources in computational power, and therefore it is recommended further research be done, but in the meantime, it is still evident that white, obese women face a wage gap which should also be addressed by Girl Gaze's new budget.

Table 2: Table showing the results from computing the effects of obesity on hourly wages for insured women of color and insured white women using matching

	Treatment effect	P value	Leximin P value	Standard Error
Women of Color	-0.93	0.03922	0.00450	0.44924
White women	-1.54	0.05532	0.15584	0.96

Discussion

Based on our findings we strongly recommend that Girl Gaze use their new extended budget to address the issue of obese women receiving lower hourly wages due to their insurance premiums. Initially, it was unclear as to how the specific demographic was affected by being obese. This finding was due to possible model dependency, and big generalizations being made for the entire population. After stratifying the population into insured, young women of color, and insured, young, white women it is clear that both group's hourly wage is affected by obesity. Seeing as women already face a gender wage gap (Miller, 2017), a wage gap between obese and non-obese is unacceptable and should be addressed. A solution to this could involve assigning additional time to negotiate obese women's contracts to check for this discrimination. This would involve critically assessing a women's skills and evaluating the market worth of these skills, so not as to settle for less money than she deserves. We recommend further research into a system for computing this.

Additionally, another solution could be helping obese women to lose weight. Girl Gaze already has a secure network of women who inspire each other through photography, marketing and creative work (De Cadenet, 2018). Extending this network to empower women to lose weight would allow these same women not to be discriminated against and paid more. Although this is not addressing the problem of size discrimination in the workplace, we feel it is worthwhile as it will also improve the health of Girl Gaze members. We strongly feel that these simple solutions, which will not require much budget, will ensure that all women get the pay they deserve, regardless of size.

Conclusion

It is important to take into consideration that women already face a gender pay gap when considering extending Girl Gaze's budget to protect obese women from further pay discrimination. It was found that both white women and women of color face this pay discrimination. Through Genetic Matching, we were able to determine statistically significant results with balance, whereas the original paper found statistically significant results but low balance suggesting model dependence. Further research is suggested to better estimate these exact effects with higher computational power. However, finding statistically significant results with balance gives us confidence that this is how Girlgaze should utilize and expand their budget on fighting this discrimination.

Appendix

Appendix A

The covariates we used are

Female, Any children in household, Female with children in household, Age, Urban Residence, Survey Year, Armed Forces Qualification Test, Education, Tenure, Employer Size, Race Black, Race Other, , Never Married, Formerly Married, Agriculture Industry, Foresty Industry, Mining Industry, Construction Industry, Manufacturing Industry, Transportation Industry, Wholesale Trade Industry, Retail Trade Industry, Finance Industry, Business Services Industry, Personal Services Industry, Entertainment Industry, Professional Services, Management Occupation, Technical Occupation, Administration Occupation, Service Occupation, Farming Occupation, Production Occupation, Operators Occupation.

Appendix B

Code for assignment:

https://gist.github.com/kirafk/de8d4739e78a89d6920fa9755b69ad56

Appendix C:

Table 3: Table comparing linear regression results to matching results for the treatment effect of obesity on hourly wages on insured people

	Treatment effect	P value	Leximin P value	Standard Error
Regression	-1.44	0.0567	$2.2e^{-16}$	0.52357
Matching	-1.38	0.0254	0.10179	0.79645

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