How Education Affects Health Outcomes Across Genders

Jessica Li

University of California, Berkeley

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Abstract

This paper evaluates the differential impact of education on health in terms of C-Reactive Protein (CRP) level, self-reported health index, and the number of days with non ideal physical and mental health. I used two different OLS models to estimate the effects and the results are statistically significant to confirm the positive yet non-linear correlation between education and health, but I observe no statistically significant differential impact across genders.

Keywords

Education, Health Economics, Economics of Gender, C-Reactive Protein

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1 Introduction

According to National Longitudinal Mortality Study (NLMS), an additional year of education can increase life expectancy by 0.18 years with a 3% discount factor. There has been a persistent association established between education and health, however, in terms of the differential impact of education on females and males, there have been many relevant discussions but not established consensus. In the paper *Why Are the Returns to Schooling Higher for Women than for Men*, the authors analyzed the return to schooling for females and males in terms of their earnings. They found out that return to schooling tends to be higher for females than for males because the benefits of schooling for females can help reduce what has been causing the difference in their earnings such as discrimination. Their findings on the differential impact of education on gender inspired me to investigate the question of whether the increase in education impacts females' and males' health conditions differently.

Thus, this paper endeavors to empirically evaluate the impact of education on health for females and males by using the C-Reactive Protein (CRP) level as the indicator. C-Reactive Protein measures the level of inflammation in the human body caused by infections, chronic inflammatory disease, or cancer[1]. Generally, a high CRP level also indicates a high risk of heart attacks. Moreover, health condition is closely related to not only objective indicators such as the

[1] "C-Reactive Protein Test." *Mayo Clinic*, Mayo Foundation for Medical Education and Research, 21 Nov. 2017

level of C-reactive Protein that measures inflammation but also to subjective perception such as the number of days with non-ideal physical and mental health.

Since the return from education in terms of earnings for females are higher, and higher incomes are likely to lead to better health outcomes (Hyde, 2017), I hypothesize that individuals with a higher education level have better overall health conditions and lower expression of CRP. Thus, the result would be consistent with the Grossman model stating that more educated individuals can be more efficient producers of health and will have higher heath levels.

This paper follows the work of Cutler and Adriana Lleras-Muney (2006 & 2010) in examining the association between education and health. However, instead of using self-reported data, I examine the effect using CRP level data as the health indicator. This is important because the majority of previous literature were using different types of self-reported data for analysis of this issue. My results suggest that the effect of having an above college degree education is statistically the same for both female and male's health conditions, which is in alignment with the result found in Cutler and Adriana Lleras-Muney's paper.

The rest of this paper proceeds as follows: Section 2 reviews the previous literature on the association between education and health, Section 3 describes the data source and methodology used, Section 4 presents this paper's models, Section 5 reveals results, Section 6 discusses limitations, Section 7 concludes and Section 8 discusses possible policy implications.

2 Literature Review

There have been many research papers published in the field of health economics to discuss the association between education and health. However, many of the data set previous authors employed are self-reported health measurements, which are very subjective and could lead to very different and biased conclusions.

In the paper *Education and Health: Evaluating Theories and Evidence* published by David M. Cutler and Adriana Lleras-Muney, they analyzed the casual association between education and health using data from National Health Interview Survey (NHIS) in the United States, and they found out that the effect of education on health increases with increasing years of education (Cutler & Lleras-Muney, 2006). They also found that the return from education in terms of life expectancy seems to be higher for poorer countries. They have proposed several mechanisms to better understand this relationship. They discussed that education could lead to higher income and therefore greater access to health care. However, income and access to health care are not the sole factors contributing to the relationship between education and health. Because some behaviors such as smoking, exercising, or the use of seat belts are associated with an individual's health but are not affected by an individual's income. Moreover, another explanation they offered was the labor market. Besides potentially receiving higher income, more educated people's working environment could also be safer. In addition, more educated people are also more likely to invest in health since they are more aware and informed of the benefits of better health conditions. In a theory proposed by Murphy and Topel (2006), they found that as income increases, people's willingness to pay for their health also increases. In another theory proposed by Cutler, Deaton, and Lleras-Muney, they found that due to the universal demand for better health, more educated people are likely to use new knowledge and technologies more effectively to treat or prevent diseases (Cutler, Deaton, & Lleras-Muney, 2006). They also tend to have healthier behaviors and are more likely to exercise and obtain preventive care. Overall, they proposed several mechanisms but concluded that none of them can be the entire explanation of how education and health are related, and further research is needed in order to determine the magnitude of these explanations.

A few years later, David M. Cutler and Adriana Lleras-Muney published another paper to further analyze the association between education and health and provided a more detailed analysis on how much each factor accounts for the impact of education on health (Cutler & Lleras-Muney, 2010). They used data from NHIS, however, since the dataset doesn't provide any information on the health and family background of the individuals, they also used data from the Health and Retirement Study that contains family information. They estimated that material resources account for approximately 20 percent of the impact of education on health. This conclusion is very helpful to the understanding of my analysis since the dataset I used, NHANES, also doesn't include any information on wealth and family background. This is also one of the limitations of my regression model because not controlling for variables such as family income could lead to the problem of omitted variable bias, and I will further discuss it later in the paper. Furthermore, they provided a few additional explanations on factors affecting the impact of education on health including a very interesting factor - cognition. They used the Armed Services Vocational Aptitude Battery(ASVAB) scores, which is the basis for the Armed Forces Qualification Test (AFQT), to account for the effect of cognitive ability on the association between education and health. They concluded that overall knowledge and cognition account for about 5 – 30 percent of the association. In another paper, Hansen, Heckman and

Mullen (2004) suggested that an additional year of schooling can increase AFQT scores by 2-4 percentage points, meaning that cognitive ability is affected by education. Another study by Gottfredson and Deary also suggested that cognition is positively correlated with better health and health behaviors (Gottfredson and Deary, 2004). Therefore, they pointed out the causal effect of education on health through cognition. This was very interesting and provided another perspective analyzing the association between education and health.

Moreover, in another paper *The Links Between Education and Health*, the authors also demonstrated the positive association between education and health and provided other possible explanations. They argued that more educated people tend to have higher levels of social support and greater control over their lives. Furthermore, more educated people are more likely to work full-time with fulfilling and rewarding jobs, which could turn into better health conditions overall (Ross & Wu, 1995). With their explanations, I found it to be very interesting since education is not the sole factor that affects if individuals could get fulfilling jobs with high income, gender could also play a role. Based on the paper *Do Age, Gender and Sector Affect Job Satisfaction*, the authors discussed that female worker may have a higher level of perceived job satisfaction in terms of wage and working environments, and a possible explanation could be that they are comparing themselves to unemployed females instead of their male colleagues (Jung, Jae Moon, & Sung Deuk Hahm, 2007). Therefore, if we purely examine their self-reported health conditions, there could be biases caused by their perceptions.

Since self-reported health data could be biased, the paper *The Links Between Education and Health* also looked at physical functioning as an indicator (Ross & Wu, 1995). The authors asked questions about the level of difficulty the surveyed individuals experience when performing different physical activities such as "going up and down stairs". However, I still find that measurement to be potentially biased since it is also based on respondents answering questions with answers they perceive to be accurate. In order to eliminate the biases and examine the differential effect of education on health for different genders, I hope to use a more objective indicator, the C-Reactive Protein level.

In addition to all the discussion around the association of education and health using various indicators, previous literature has also examined if the impact of education on self-reported health is conditioned by gender. In the paper *Education and the Gender Gaps in Health and Mortality*, the authors used data from National Health Interview Survey-Linked Mortality Files (NHIS-LMF) and found out that education has a greater impact on females' self-reported health than on males', but males' mortality rate is higher (Ross, Masters, & Hummer, 2012). They discovered that females tend to have more nonfatal illnesses throughout their lives including nonfatal chronic and acute conditions, while males tend to have fatal health conditions in the later stage of life, which leads to the difference in mortality rate. However, overall, there are not enough research and consensus in academia on whether education has a significantly larger effect on females' health condition compared to males. In addition, the theory of resource substitution, which states that females are more dependent on education because they lack alternative resources such as power, authority, and earnings (Ross & Mirowsky, 2006). Thus, this paper hopes to further examine the impact of education on health for females and males by looking at their CRP level, instead of self-reported health data.

3 Data & Methodology

I used the dataset from 2009- 2010 wave of the National Health and Nutrition Examination Survey (NHANES), which contains statistics on blood samples that measure CRP from individuals aged 20+, and I excluded the individuals whose age are older than 50 years old to prevent the potential effect of health condition related to aging. The sample includes 2700 individuals of whom 1306 are male, and 1394 are female. This is cross-section data since it is the observation of many individuals at the same point of time in 2010. The sampled population is the civilian and noninstitutionalized U.S. population, and these individuals were interviewed in their homes and were asked to complete the health examination component of the survey.

First, I used an OLS model to estimate the effect of education on health conditions controlling for gender, age, and race. *Gender* is a dummy variable indicating the gender of the individual (1 = Female, 0 = Male), *Education* is a discrete variable indicating the level of education of the individual (1 = Less than 9th grade, 2 = 9-11th grade, 3 = HS grad/GED, 4 = Some college, 5 = College grad+). *Race* is a discrete variable indicating the race of the individual (1 = Mexican American, 2 = Other Hispanic, 3 = Non-Hispanic White, 4 = Non- Hispanic Black, 5 = Other Race). *Age* is another variable indicating the age of the individual at the time of the survey. In terms of the dependent variable, I picked *CPR*, which is C-Reactive Protein that measures the level of inflammation in human body caused by infections, chronic inflammatory disease, or cancer. I also used *HSQ (Physical)* and *HSQ (Mental)* which represent the number of days with non-deal physical health and number of days with non-ideal mental health respectively.

To further analyze the differential effect of education on health outcomes for females and males, I used another OLS model including an interaction term between gender and education. I created a new treatment variable using college education as the cut-off line. Specifically, the education level for a college degree and any degree above college will be counted as high education, represented by a binary variable 1 as treatment. Any education level below a college degree would be 0. The rest of the variables are the same as the previous model. I hypothesize that higher education will have a stronger effect on females' health conditions compared to males, controlling for race, ethnicity, and age.

In terms of the primary variables of interest, I am analyzing C-reactive protein level and current health status indicators, including the number of days with non-ideal physical and mental health, as the three dependent variables of interest. The Independent variable for model 1 is education, and control variables are gender, race, ethnicity, and age. Independent variables for model 2 are education and gender, and control variables are race, ethnicity, and age.

4 Model

4.1 Model 1:

$$CRP = \beta_0 + \beta_1 * Education + \beta_2 * Gender + \beta_3 * Age + \beta_4 * Other\ Hispanic + \beta_5 * Non\text{-}Hispanic\ White + \beta_6 * Non\text{-}Hispanic\ Black + \beta_7 * Other\ Race + epilison \quad (1)$$

$$HSQ(Physical) = \beta_0 + \beta_1 * Education + \beta_2 * Gender + \beta_3 * Age + \beta_4 * Other\ Hispanic + \beta_5 * Non\text{-}Hispanic\ White + \beta_6 * Non\text{-}Hispanic\ Black + \beta_7 * Other\ Race + epilison \quad (2)$$

$$HSQ(Mental) = \beta_0 + \beta_1 * Education + \beta_2 * Gender + \beta_3 * Age + \beta_4 * Other\ Hispanic + \beta_5 * Non\text{-}Hispanic\ White + \beta_6 * Non\text{-}Hispanic\ Black + \beta_7 * Other\ Race + epilison \quad (3)$$

4.2 Model 2:

$CRP = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} * Female + \boldsymbol{\beta_2} * Treatment + \boldsymbol{\beta_3} * (Female * Treatment) + \beta_4 * Age + \beta_5 * Other\ Hispanic + \beta_6 * Non\text{-}Hispanic\ White + \beta_7 * Non\text{-}Hispanic\ Black + \beta_8 * Other\ Race + epilison$ (4)

$HSQ(Physical) = \beta_0 + \beta_1 * Female + \beta_2 * Treatment + \beta_3 * (Female * Treatment) + \beta_4 * Age + \beta_5 * Other\ Hispanic + \beta_6 * Non\text{-}Hispanic\ White + \beta_7 * Non\text{-}Hispanic\ Black + \beta_8 * Other\ Race + epilison$ (5)

$HSQ(Mental) = \beta_0 + \beta_1 * Female + \beta_2 * Treatment + \beta_3 * (Female * Treatment) + \beta_4 * Age + \boldsymbol{\beta_5} * Other\ Hispanic + \boldsymbol{\beta_6} * Non\text{-}Hispanic\ White + \boldsymbol{\beta_7} * Non\text{-}Hispanic\ Black + \boldsymbol{\beta_8} * Other\ Race + epilison$ (6)

5 Results

5.1 Effect of Education on CRP Level, No. of Days with Bad Physical Health and Mental Health

Table 1: Effect of Education on CRP Level, No. of Days with Bad Physical Health and Mental Health

VARIABLES	(1) CRP	(2) Bad Physical Health	(3) Bad Mental Health
Education	-0.0415***	-0.463***	-0.556***
	(0.0103)	(0.124)	(0.147)
Gender	0.135***	0.973***	2.042***
	(0.0235)	(0.282)	(0.334)
Age	0.00258**	0.0949***	0.0125
	(0.00129)	(0.0155)	(0.0183)
Other Hispanic	0.00469	1.264**	1.028
	(0.0439)	(0.528)	(0.625)

Non-Hispanic White	0.0412	0.766*	2.076***
	(0.0335)	(0.403)	(0.477)
Non-Hispanic Black	0.175***	0.997**	2.368***
	(0.0398)	(0.478)	(0.566)
Other Race	-0.0554	0.274	2.237***
	(0.0556)	(0.668)	(0.791)
Constant	0.171**	-0.423	2.092**
	(0.0683)	(0.821)	(0.972)
Observations	2,700	2,700	2,700
R-squared	0.029	0.026	0.024

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1 displays the regression estimates for the impact of education on health conditions using the first model. Controlling for gender, race, and age, as education level increase by 1 index, CRP level drop by 0.0415 mg/dL on average. The coefficient is also statistically significant given that the p-value is less than 0.01, proving that education does have a positive effect on health conditions by reducing the CRP level. The coefficient for gender is 0.135, meaning that controlling for education, age, and race, females' CRP level is 0.135 mg/dL higher than males' CRP level on average. Alongside the coefficient for gender, the coefficients for age, Non-Hispanic Black and Mexican American are also statistically significant based on their p values, meaning that it's important to control for these variables in our regression.

Examining the other two dependent variables, the number of days with bad physical health and mental health, we can also conclude that as education level increase by 1 index, the number of days with bad physical health decrease by 0.463 days, and the number of days with bad mental health decrease by 0.556 days within the past 30 days' time frame at the time of the survey. These coefficients are also statistically significant, suggesting that an increase in education can also decrease the number of days with bad physical health and mental health.

However, it is important to note that these number of days are self-reported data, which could lead to potential bias in our conclusion.

Since our regression model only examines the average effect of changing the education index by 1, to further investigate the change of health condition across different education groups, I graphed the figure below.

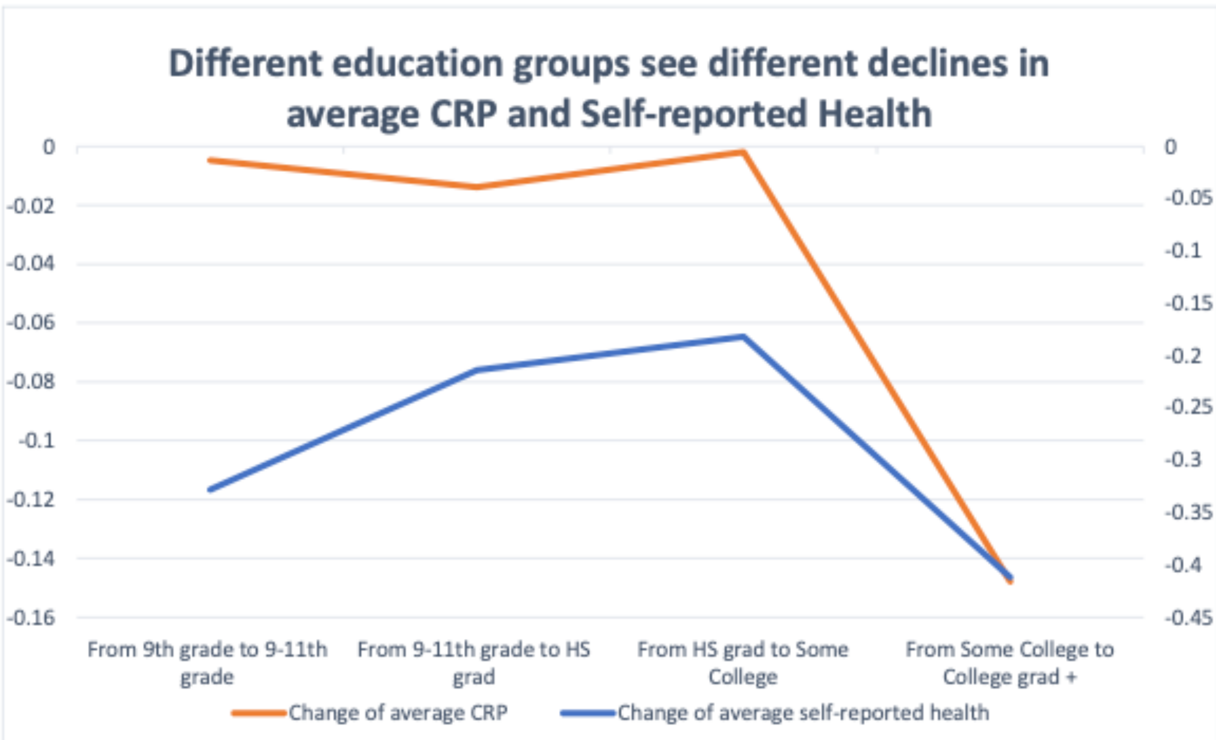

Figure 1: Different Education Groups See Different Declines in Average CRP and Self-Reported Health

Here, I used another variable, self-reported health condition, to examine the overall health condition of the surveyed individual. The variable is answering the general question of how the surveyed individual say about their health as 1 indicates excellent and 5 as poor. As we can observe from the graph, from 9th grade to some college education, the change in average

CRP and self-reported health level decrease gradually. This suggests that as people pursue higher education, the marginal benefit in terms of self-reported health conditions is getting lower and lower until college education. But once we look at the change in average from some college degree to college grad +, the average decreases significantly across the two groups. This indicates that health condition improves considerably when people have a college grad + education. Interestingly, this result shows that the benefits of education on health condition is not entirely linear across education level, suggesting that other factors associated with college grad+ education such as income, work-life balance that reduce stress, or having a better understanding of health as an investment could play into account. Therefore, we can conclude that people's health conditions improve significantly when they have a college grad + degree, measured by CRP level and self-reported health level, and the association between health and education is not entirely linear.

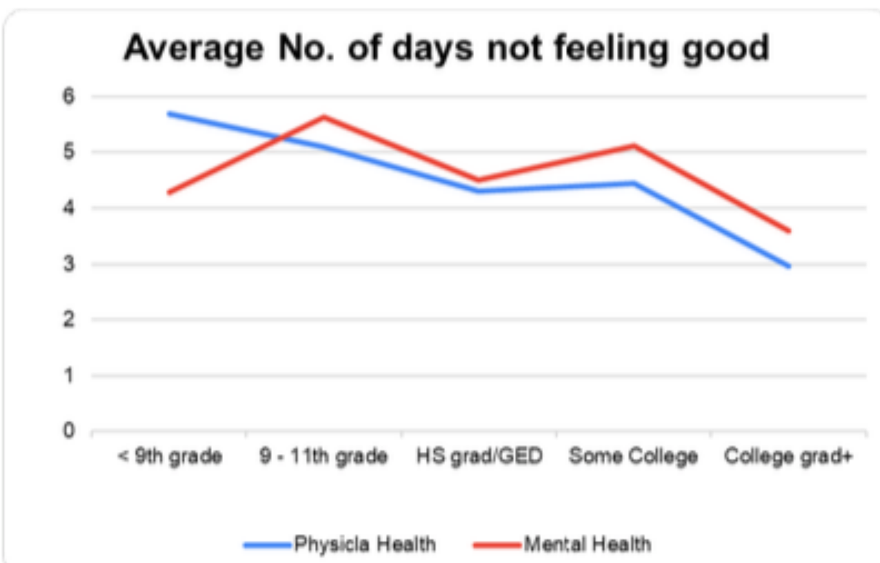

Figure 2: Average No. of Days with Non-ideal Physical and Mental Health

Additionally, to dive deeper into the change in health conditions across education groups, I calculate the average number of days with non-ideal physical and mental health for these groups. Based on Figure 4, as education level increases from 9th grade to college grad +, the average number of non-ideal physical health decreases almost by half. This result corresponds to the previous finding of the positive correlation between health conditions and education level. However, when we look at the average number of days with non-ideal mental health, we find that people with 9th-grade education have a similar number of days with non-ideal mental health as people with college grad + education. This result indicates that the level of societal pressure and anxiety are less for people on the two ends of the education level spectrum. However, depending on the geographical locations and communities, the way people view mental health might be different. For people in the less educated group, they might not feel as comfortable expressing mental health problems to others due to the potential lack of acceptance from their families and communities. But to consider the overall health condition, people with a college grad + education have the best overall physical and mental health in terms of having the lowest number of days not feeling good. For people with a medium education level from 9-11th grade to some college education, they have a relatively higher number of days feeling mental health are not good.

5.2 Differential Effect of Education on female and male in terms of their CRP Level, No. of Days with Bad Physical Health and Mental Health

Table 2: Differential Effect of Education on CRP level, No. of Days with Bad Physical Health and Mental Health

VARIABLES	(1) CRP	(2) Bad Physical Health	(3) Bad Mental Health
Gender	0.174***	1.155***	2.561***

	(0.0341)	(0.411)	(0.486)
Treatment	-0.0536	-0.397	-0.291
	(0.0345)	(0.415)	(0.491)
Interaction	-0.0712	-0.348	-0.980
	(0.0471)	(0.567)	(0.672)
Age	0.00262**	0.0961***	0.0133
	(0.00129)	(0.0155)	(0.0183)
Other Hispanic	-0.00170	1.087**	0.845
	(0.0437)	(0.527)	(0.623)
Non-Hispanic White	0.0213	0.408	1.669***
	(0.0323)	(0.389)	(0.460)
Non-Hispanic Black	0.159***	0.719	2.057***
	(0.0391)	(0.471)	(0.557)
Other Race	-0.0762	-0.146	1.778**
	(0.0546)	(0.657)	(0.778)
Constant	0.205***	-0.602	2.656***
	(0.0546)	(0.658)	(0.779)
Observations	2,700	2,700	2,700
R-squared	0.029	0.022	0.022

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2 displays the differential effect of having a higher education on females' health conditions. More specifically, the coefficient of -0.0712 for the interaction term represents that differential effect. However, since it is not statistically significant based on the p-value, we fail to reject the null hypothesis. The treatment effect of having an above college degree education is statistically the same for both females and males. Analyzing the rest of the coefficients, the coefficient of -0.0536 represents the average effect of having a higher education on a males' health condition. By subtracting the coefficient of interaction term from the treatment variable, -0.0536 - (-0.0712), we get the number of 0.0176, which represents the effect of having a higher education on females' health conditions. Even though the effects of having an above college education on females and males in terms of their health condition are different, these coefficients are not statistically significant. The coefficient of 0.174 represents the difference in average CRP level between females and males in the control group, which are individuals receiving below college degree education. This coefficient is statistically significant, meaning that females and males with below college education have different CRP levels naturally, and females' CRP level is 0.174 mg/dL higher than males on average controlling for age and race.

6 Discussion

6.1 Omitted Variable Bias (OVB)

Given the limitation of the number of variables the dataset provided, I am only controlling for individuals' gender, age, and ethnicity. However, there might be the problem of omitted variable bias in my OLS estimator. For OVB to occur, the omitted variable has to be correlated with X and should also be a determinant of the dependent variable Y. Variables such as parental income could lead to omitted variable bias since it could affect the health condition of the individual, measured by the CRP level, and could also affect the level of education the individual pursuit. In this case, we will be violating one of the OLS assumptions that $E(U_i|X_i) = 0$. This assumption means that all other factors that affect the dependent variable Y_i (contained in u_i) are unrelated to X_i in the sense that, given a value of X_i, the mean of these other factors equals zero. Variables such as parental income would certainly violate this assumption and lead to OVB.

In terms of the direction of the bias, since variable such as parental income is affecting education and health condition in the same direction, this would lead to an upward bias. However, when analyzing the result, the positive effect of education in decreasing the CRP level could be caused by OMV. The actual effect of education on health conditions could be 0 or more, but we cannot have a definitive conclusion given the problem of an upward bias caused by omitted variables.

6.2 Reverse Causality

Moreover, since I am examining the effects of education on health, there also exists the problem of reverse casualty. It is possible that one's health condition will affect his or her decision to get more educated. For example, if an individual has severe mental illness around the time they graduate from high school, they might choose to get therapy and take a break from school instead of going through the rigorous application process and going to college. One's health condition could also affect if they can successfully obtain the degree they are pursuing. Since worse health conditions could lead to lower education, and better health could lead to higher education, this will create an upward bias since both coefficients are in the same direction, the actual effect might be smaller.

6.3 Other Limitations

It's important to mention that all the conclusions are drawn from the 5000 samples in the N2009-2010 wave of the National Health and Nutrition Examination Survey (NHANES). The 5000 samples may not fully represent the condition of the general population across different locations, and the result will vary based on the influence of racial factors as well. Besides, all the findings rely on the average number across different education groups, which can be impacted by outliers. Another limitation of the NHANES data is the lack of statistics on the number of years of education across different categories. People with some college degree education may have very distinct years of college education which can potentially affect their income level. Further studies are needed to determine a statistically accurate relationship between education level, health condition, and CRP level.

6.4 Robustness Check

For robustness check, I break down the sample by race and run the same linear probability model as before with the same dependent and independent variables. The coefficients for education on CRP level for Non-Hispanic White is -0.071 and is statistically significant with a p-value < 0.01. This represents that with one level increase in education for Non-Hispanic White, their CRP level decrease by 0.071 mg/dL on average controlling for gender and age. However, the coefficients of education for Mexican Americans, Other Hispanic, and Non-Hispanic Black are not statistically significant.

Table 4: Preliminary Robustness Check – Effect of Education on CRP Level based on Race

VARIABLES	(1) CRP(Mexican American)	(2) CRP(Other Hispanic)	(3) CRP(Non-Hispanic White)	(4) CRP(Non-Hispanic Black)	(5) CRP(Other Race)
Education	-0.00188	-0.0253	-0.0710***	-0.0530	-0.0606**
	(0.0151)	(0.0247)	(0.0156)	(0.0422)	(0.0244)
Gender	0.208***	0.100	0.104***	0.174**	0.0624
	(0.0381)	(0.0652)	(0.0332)	(0.0846)	(0.0530)
Age	0.000814	-0.00225	0.00316*	0.00932**	-0.000259
	(0.00209)	(0.00360)	(0.00185)	(0.00452)	(0.00293)
Constant	0.0221	0.349*	0.349***	0.0929	0.399**
	(0.107)	(0.178)	(0.101)	(0.251)	(0.169)
Observations	554	307	1,222	448	169
R-squared	0.052	0.011	0.026	0.021	0.043

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7 Conclusions

There has been numerous research discussing the association between education and health, but most of them used self-reported data for their analysis and could lead to biased results. The CRP level indicator, however, is a more objective measurement of an individual's health condition through the measurement of the inflammation level. I approached the question by explaining the association between education and health using OLS model. Through my first OLS model, I confirmed the positive correlation between education and health. Then, I used another OLS model that included an interaction term between gender and education to evaluate the differential effect of education on health for females and males. I concluded that there is no statistically significant differential effect across genders, thus rejecting my null hypothesis that the impact of education on health is greater for females than for males. Moreover, I examined the change in CRP level and the number of days for non-ideal physical and mental health to further evaluate the intensity of impact across different education levels. I concluded that the impact of education on health conditions is the greatest when people receive college grad + degrees compared to high school or some college degrees.

8 Policy Implications

My results suggest the importance of having a college grad+ education for all genders and could serve as inspirations for possible policy implications. There is a large proportion of people uninsured and relying on Medicaid and government subsidies, meaning they need to overcome extra barriers to get appropriate health care. Besides, there are several correlation between health and education as education can create opportunities for better health, and poor health can affect ones education attainment. Given my result that people with higher education have better health conditions in terms of lower CRP level, and based on the research by Dynarski - an $1000 aid can lead to an increase in education of 0.16 years, translating to an increase in life expectancy of 0.03-0.10 years, if we can implement policies to further reduce the financial burden of obtaining a college grad + degree, and thus motivate more students to pursue higher education, we could ultimately improve social welfare and reduce medical expenditure.

Current policy such as the 529 plans, are supported by the federal government to make tax-free for college saving accounts to reduce the financial burden of education. However, based on a survey conducted by an investment firm Edward Jones, they found out that only a small proportion of families are aware of the 529 plans and its associated benefits, and a large proportion of families with 529 accounts are above the $150,000 income level. There has been debate going on about whether these educational policies have been favoring the wealthier families over low-income families. It is important to note that the implementation of the policy and its actual effect on the overall population might be different, and we need to consider the possible side effects when examining certain educational policies.

9 Referencess

Cutler, D. M., & Lleras-Muney, A. (2006, July 3). Education and Health: Evaluating Theories and Evidence. Retrieved from National Bureau of Economic Research Working Paper Series website: http://www.nber.org/papers/w12352

Cutler, D. M., & Lleras-Muney, A. (2010). Understanding differences in health behaviors by education. *Journal of Health Economics*, *29*(1), 1–28. https://doi.org/10.1016/j.jhealeco.2009.10.003

Cutler, D., Deaton, A., & Lleras-Muney, A. (2006). The Determinants of Mortality. *Journal of Economic Perspectives*, *20*(3), 97–120. https://doi.org/10.1257/jep.20.3.97

Dynarski, & Susan, M. (2003). Does Aid Matter? Measuring The Effect Of Student Aid On College Attendance And Completion. *American Economic Review*, *v93*(279-288).

Gottfredson, L. S., & Deary, I. J. (2004). Intelligence Predicts Health and Longevity, but Why? *Current Directions in Psychological Science*, *13*(1), 1–4. https://doi.org/10.1111/j.0963-7214.2004.01301001.x

Hansen, K. T., Heckman, J. J., & Mullen, K. J. (2004). The effect of schooling and ability on achievement test scores. *Journal of Econometrics*, *121*(1-2), 39–98. https://doi.org/10.1016/j.jeconom.2003.10.011

Hyde, S. (2017). *Income and health outcomes*. Retrieved from https://www.bls.gov/opub/mlr/2017/beyond-bls/pdf/income-and-health-outcomes.pdf

Jung, K., Jae Moon, M., & Sung Deuk Hahm. (2007). Do Age, Gender, and Sector Affect Job Satisfaction? Results From the Korean Labor and Income Panel Data. *Review of Public Personnel Administration*, *27*(2), 125–146. https://doi.org/10.1177/0734371x06289229

Murphy, Kevin M., & Topel, Robert H. (2006). The Value of Health and Longevity. *Journal of Political Economy*, *114*(5), 871–904. https://doi.org/10.1086/508033

Ross, C. E., Masters, R. K., & Hummer, R. A. (2012). Education and the Gender Gaps in Health and Mortality. *Demography*, *49*(4), 1157–1183. https://doi.org/10.1007/s13524-012-0130-z

Ross, C. E., & Mirowsky, J. (2006). Sex differences in the effect of education on depression: Resource multiplication or resource substitution? *Social Science & Medicine*, *63*(5), 1400–1413. https://doi.org/10.1016/j.socscimed.2006.03.013

Ross, C. E., & Wu, C. (1995). The Links Between Education and Health. *American Sociological Review*, *60*(5), 719. https://doi.org/10.2307/2096319

10 Appendix

Table 3: Descriptive Statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Self-Reported Health	2,700	2.763	0.952	1	5
Bad Physical Health	2,700	3.486	7.405	0	30
Bad Mental Health	2,700	5.318	8.762	0	30
Gender	2,700	1.516	0.500	1	2
Age	2,700	35.20	9.132	20	50
Race	2,700	2.767	1.139	1	5
Education	2,700	3.411	1.231	1	5
CRP	2,700	0.369	0.617	0.0100	9.140