Refining the Association Among Race, Education and Health

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Abstract

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Education holds a complex, multifaceted association with health. In efforts to flesh out this relationship's nuances, researchers have found that how these two factors relate is dependent upon different social characteristics. In efforts to explain the appearance of this cross-group variation, sociologists have begun to develop the theoretical framework of *resource substitution*. This paper seeks to add to the development of the resource substitution framework by first examining if the magnitude of health returns to additional education varies between non-Hispanic black Americans and non-Hispanic white Americans, after accounting for other measures of socioeconomic status, and then determining if said variation can adequately be described by resource substitution. Using the 2009 PSID, I find evidence to suggest that, conditioned on other socioeconomic factors, the magnitude of the health benefit from increased education does vary between blacks and whites, and that resource substitution does not hold in this scenario.

Across a variety of academic disciples, the particulars of how education relates to health have been given a fair deal of attention. In this mass, there is a subset of papers specifically focused on understanding how the nature of this education and health association is dependent on race. While the research of this subfield has been illuminating in many ways, the information it provides on how other socioeconomic forces factor into the focal narrative is limited. This paper is motivated by this feature of the literature; in more detail, this paper is designed to examine if the nature of the education and health association varies across black Americans and white Americans, net of some of the major socioeconomic factors which are both returns from education and for which we know black Americans face barriers in. In addition, on condition of finding evidence that measurable variation between racial groups exists, this paper seeks to describe the nature of the variation as it connects to an emerging theoretical framework in the health literature, *resource substitution*.

THEORETICAL FRAMEWORK

Education and health

Education is a well-researched example of a social condition operating as a fundamental cause of disease; through multiple mechanisms and on several outcomes, an additional year of education returns an individual a number of measurable health benefits (Eide and Showalter 2011; Phelan et. al. 2010).

There is no shortage of examples which illustrate education's relationship with health. For instance, educational attainment to a particular number of years typically returns an individual a specific credential (e.g., a bachelor's degree), which influences the type of job said individual can obtain, which in turn affects the level of his/her income and the amount and quality of health protective resources s/he can secure (Marmont 2002). Along the same lines, increased education decreases one's risk of unemployment at any given time (Mincer 1991). As being unemployed in itself is associated with a host of negative health outcomes, education is thought to effect health through it's relationship to employment status (Ross and Mirowsky 1995).

Even after accounting for material pathways like those mentioned above, a measurable amount of the the link between education and health has been shown to persist; this portion of the relationship is often referred to as *the direct effect of education* (Leigh, 1983).[1] Perhaps the most prominent hypotheses used to explain this component of the education-health link are that increased education develops health beneficial decision making patterns within those individuals who obtain it, and additional education equips an individual with more developed cognitive skills (e.g., how to learn, gather and analyze information efficiently) and non-cognitive abilities (e.g., how effectively one is able to maintain a feeling of control over their environment), both of which are associated with better health (Cutler and Lleras-Muney, 2006; Gallo and Matthews 2003; Mirowsky and Ross 2003). Other less cited hypotheses focused on explaining this component of the education-health association include the idea that increased education shapes individual's social networks in ways which promote health, makes people more risk adverse, and relieves some of the psychological burdens of relative inequality (Barsky et. al.1997; Cutler and Lleras-Muney 2006).

As illustrated above, education does appear to be tied to health through a number of different mechanisms. At a more abstract level, education appears to be related to health through a number of different *types* of resources. That is, education appears to offer those individuals who receive it greater access to various forms of capital. Pulling just from the small sample of mechanisms above, we can see that increased education returns individuals some amount of economic, social, and human capital.

In term's of it's association with health, education's ability to return this last type of capital makes it particularly unique among socioeconomic factors. The human capital benefits derived from education, like increased feelings of control and problem solving skills, are instilled *within* the individual. Because of their location relative to the individual, human capital resources are unlikely to be separated from their owner. Thus, even in a case where all material resources are depleted, an individual with some level of education will still likely have have a health protective resource available to them (Mirowsky and Ross 1998). For this, and the various other forms of

[1] Although I have reservations about referring to this part of the educational-health relationship with this term (the unaccounted for component could well be the product of some omitted socioeconomic variable), I do so at times in this paper because of it's common usage in the field.

capital education returns, some view education as one of the more promising means through which to address a population's health (Cutler and Lleras-Muney 2006).

The Intersection of Multiple Forces: Race, Education and Health

Given this interest in education as a tool to improve health, work is needed to more fully understand the complex ways this association works. Because education operates on health through a multitude of diverse pathways, for instance, it's association is likely impacted by other multifaceted, social determinants of health. In particular, looking at the intersection of different literatures motivates the idea that the strength of the association between education and health may vary across racial groups.

For example, audit studies have provided some evidence that, years of education being equal, black males are less likely to obtain jobs for which they are qualified for than white males (Pager 2007). Meshing this bit of evidence with the employment link to health presented above allows us to conceptualize how race and education may act jointly to produce different health outcomes for different individuals: If each additional year of education returns an individual a greater chance of obtaining a job with low risk of unemployment, and black men face greater obstacles in translating educational credentials to obtaining particular jobs, then perhaps the effect of education on health will be less for black males than it is for white males.

The literature has not been blind to the joint effect of education and race on health. Over the past few years, researchers have found evidence that nature of the association between education and health does in fact vary across members of different racial and ethnic groups (Kimbro et. al. 2008; Montez et al. 2012; Zajacova and Hummer 2009). While these pieces contribute useful information to our understanding of the the complex relationship among education, race and ethnicity, and health, certain features of their analyses leave some compelling questions unanswered.

In particular, none of the aforementioned studies accounted for measures of socioeconomic status (besides education) in their models. In these articles, the observed differences in health returns to education could be attributed to the difference in mean income levels for racial groups at different education levels (Walsemann et. al. 2013). Put differently, on condition of equal levels of education, whites tend to make more than their racial and ethnic minority counterparts. Since income itself is positively associated with a number of health outcomes, perhaps it is the case that these racial differences in income are driving a sizable portion of the differential returns from education to health. The same logic holds both for other socioeconomic variables for which we know racial minorities face disadvantage in (such as employment), or for any other group that faces disadvantage on some measure of socioeconomic status. Given the location of the literature, one of this paper's primary goals is to examine if the observed variation across racial groups, in terms of how education and health are associated, persists after accounting for socioeconomic measures both related to health and influenced by education.

Resource Substitution

On condition of finding evidence that the nature of the education-health relationship does still vary by race after controlling for socioeconomic measures, this paper's second goal is to describe the nature of this variation. In this endeavor, recent scholarly work provides a framework for exploring our results and thus, an opportunity for fleshing out said framework.

(Presumably) motivated by the potential role income and employment play in explaining the difference in returns to education across different subgroups, researchers have taken to modeling the health and education association across subgroups while accounting for these components of socioeconomic status. Through these studies, evidence was found to support the idea that there is variation in the effect of education on health across subgroups, even when accounting for related socioeconomic factors in which one group typically faces a disadvantage. For instance, for women and people of lower SES origins, the magnitude of the improvement to self-rated health via an additional year of education was greater than it was for men and people of higher SES beginnings, respectively. (Ross, Masters, and Hummer 2012; Ross and Mirowsky 2010; Ross and Mirowsky 2011).

Borrowing from economics, these researchers framed their findings in the framework of *re-*

source substitution. To summarize Mirowsky and Ross's (2010) explanation of the conceptual framework, resource substitution follows that:

1. Individuals have two interrelated resources, Resource A and Resource B, both of which can be used to achieve some outcome, Y.

2. As these resources are related, an individual with a limited amount of Resource A may use Resource B to effectively fulfill part of Resource A's role in realizing Y.

3. The importance of Resource B in determining Y thus relies on the amount of Resource A an individual has available; the strength of the relationship among Resource B and Y should be stronger for a person with less of Resource A, as said individual is relying more on Resource B to achieve end Y.

Changing a few terms around puts this abstraction in focus of the previously mentioned papers; education is one of many forms of socioeconomic status that shares a positive relationship with health. As explained above, at least part of this association is believed to stem directly from education (i.e, it is not a result of other SES factors tied to education). This component is thought to come through a form undeniable to an individual (i.e, cognitive abilities). Regardless of the presence of other physical resources then, an individual can always rely on some of the capital derived through education to achieve some level of good health. Under these assumptions, a member of a subgroup who faces disadvantage on some dimension of socioeconomic status should rely more on an additional year of education than an individual who does not to improve their health. That is, because material resources are relatively limited in supply to socioeconomically disadvantaged groups, and because the health benefits of education come in a form that cannot be lost, the economically disadvantaged member in this scenario should rely more on their education to protect their health than an individual who could rely on many different types of resources to achieve the same end.

Like I mentioned above, this pattern of resource substitution held for women and individuals of lower SES origins. This paper seeks to add to this strand of literature by examining how the health returns to education vary between members of different racial groups while accounting for related measures of SES, and if the nature of this variation could reasonably be described by resource substitution. Given what has been found for other groups whom face socioeconomic disadvantage, I expect to find variation between blacks and whites in terms of this education-health relationship, and for these patterns to conform to a form predicted by resource substitution.

Previous Research

Thus far, there has been one study which has examined the relationship among race, education and health in a fashion similar to what I propose here.[2] In a 2005 paper, Farmer and Ferraro used ordinary least squares (OLS) to estimate a linear model of a five category indicator of self-rated health as a function of education, race, the interaction of race and education, and a number of other covariates (including income and employment). Using this method, the authors found that *that as education level increased, self-rated health improved for white adults only*. While this piece is very important in that it allows a general look at the relationship among race, education and health, a few aspects of it's analysis prevent a deeper understanding of the relationship of interest.

In short, note that the response in Farmer and Ferraro's model was categorical in nature. Given this, in the worst case scenario, the author's standard errors and point estimates were biased due to unmet assumptions about heteroscedasticity, error distributions, and spacing between levels of the response. In the best case, where the aforementioned issues work themselves out to have little to no substantive effect, the estimates from Farmer and Ferraro's procedure only summed to an approximation of an approximation of the true data generating process they we are interested in. Put differently, even if the model avoided the statistical concerns that came with violating OLS assumptions, the expected value for any particular set of covariates necessarily gave a rough sense of only *the most typical* health status at said point in the covariate space.

This last point is most important to note because of it's substantive implications. To illustrate, imagine that we have a sample in which each element has both some reported health status

[2]Though not in the framework of the resource substitution theory.

{*Excellent*, *Good*, or *Poor*} [3] and a measured amount of education {1 year, 5 years, or 10 years}. Using an OLS fit model like Farmer and Ferraro's to analyze these data, say we find the following expected values:

Table 1: (Hypothetical) Expected Score of Health Status at Years of Education

	E(Health Status)		
Education	Group A	Group B	Group C
1	2.00	2.00	2.00
5	1.90	1.90	2.00
10	1.80	1.80	2.00

Now, suppose we analyzed the same data in a way that allowed us to recover information about the probability of reporting each health status at each level of education for each group. In doing so, we may find:

Table 2: (Hypothetical) Probability of Health Status at Years of Education

	P(Health Status)								
	Group A			Group B			Group C		
Education	Excellent	Good	Poor	Excellent	Good	Poor	Excellent	Good	Poor
1	0.25	0.50	0.25	0.25	0.50	0.25	0.10	0.80	0.10
5	0.35	0.40	0.25	0.25	0.60	0.15	0.30	0.40	0.30
10	0.45	0.30	0.25	0.25	0.70	0.05	0.50	0.00	0.50

Notice that our substantive conclusions change considerably depending on which of the methods we choose. From the first model, we may justifiably conclude that the way health and education are related is the same in Group A and as it is in Group B, and that education has no effect on health

[3] Scored 1,2, and 3, respectively.

for those in Group C. In contrast, the method which returned probabilities revealed that Group A and Group B differ in how education improves health, and that by some measure, education has the greatest effect in Group C.

As this example highlights, while the expected scores produced in the OLS model provide some look at the focal relationship, they miss out on detail that is within reach of other modeling strategies. In addressing *if* the association among health and education varies across racial groups, recovering this additional information is helpful; observing the expected probabilities of each health category allows us to comment specifically on the magnitude of change in health per year of education, though the direction of the expected OLS values does give us an approximate sense of if between-group variation exists at all. In describing *how* the relationship among education and health varies across groups however, recovering this additional information is necessary; the single-value scores produced through an OLS fit do not provide enough information on the nuanced ways in which health changes alongside education for us to determine if resource substitution is applicable. These features motivate this paper's existence, and (as will be discussed later) inform decisions about it's modeling strategy.

METHODS

Data

The data for this paper come from the Panel Study of Income Dynamics (PSID). The PSID is a nationally representative survey of families in the United States. The first wave of data from this survey was collected in 1968. Until 1997, data was collected on families annually. After this point, the survey began conducting surveys biannually (Institute for Social Research, University of Michigan 2013). This paper will make use of the 2009 wave of the PSID.

These data are particularly well suited for the questions at hand because of their attention to measures of income. Many large datasets which are strong in both health and social factors rely on self-reported measures of income to capture this component of socioeconomic status. As with many other self-reported survey instruments, self-reported measures of income are at risk of self-report bias; the income reported by an individual in the survey may be different from what their income actually is (Donaldson and Grant-Vallone 2002).

The degree of bias in self-reported measures like these are debated in literature. In a review of a number of self-reported income measures employed by large scale government surveys, Moore et. al. (2000) found that, for wage and salary measures (e.g, total income), the discrepancy between self-reported indicators and actual amounts was negligible. In contrast, Hurst et. al. (2010) found such error in self-reported measures that they were motivated to conclude, *...that it is naive for researcher to take it for granted that individuals will provide unbiased information to household surveys.*

Since accounting for income is of such import in addressing this paper's questions, ignoring the possibility of self-report bias in income is problematic. Fortunately, because of their special concern with income processes, PSID researchers have made several attempts to check the accuracy of the surveys income measures. In a recent paper, Gouskova et.al. (2010), compare PSID estimates of family income with what they feel is close to a gold-standard source for estimated income measures, the March Current Population Survey (CPS). While they find differences in the estimates from the two surveys, the researchers concluded that the close agreement of family income provided some evidence that PSID's income measures are not wildly biased. This special attention paid to the accuracy of income measures makes the PSID attractive for answering many a question where income plays a central role, like the one in this paper.

As an important last note on the survey, the PSID is of a complex survey design. That is, the data of the PSID is collected through a multistage probability sample, incorporating stratification and clustering, which leads to unequal probabilities of selection for different individuals in the survey. In particular, the data was composed by oversampling individuals from lower income families. To (try to) account for these complexities, the PSID includes sampling weights.

For regression analysis, like the one this paper will employ, there is no clear answer on whether one should use sampling weights to account for complexities of the data collection process (Gelman 2007; Thomas 2010). Following advice from Solen et. al. (2013), I preformed the analysis with and without weights and compared results. The difference between the weighted and unweighted models point estimates and standard errors were mostly negligible.[4] Because of the small discrepancy in results, and for the sake of parsimony, I chose to leave sampling weights out of the analysis.[5]

Dependent Variable: Self-Rated Health

Health is a multifaceted construct which cannot be fully described with a single indicator; sometimes the mechanisms which operate to influence a particular component of one's health operated differently or not at all on other indicators of health.

This point becomes a concern in addressing questions like those raised here. Recall that the section above that details the portion of the health and education relationship not explained away by controlling for material SES factors. Much of the work specifying the mechanisms underlying this component of the education-health link are theoretical or supported only by a small bit of empirical work. As such, it is difficult to justify choosing health outcomes whom are a function of very particular mechanisms for the questions presented in this paper. In face of this concern, I choose to use a very general measure, self-rated health, to represent health here. Though this measure is subjective, research has shown that self-rated health is highly correlated with several objective measures of health status (Idler and Benyamini 1997; Liang 1986; Moosey and Shapiro 1982). In the PSID, self-rated health is gathered by a instrument which asks respondents to asses their health as either *Excellent*, *Very Good*, *Good*, *Fair*, or *Poor*.[6]

Model: Multinomial Logit

[4] In all cases but one, the weighted and unweighted estimates were almost identical. The one instance where there was some difference was in the estimate of *Poor* health for black women; here the weighted model had the probability of reporting *Poor* health crossing *Excellent* health about two and a half years of education later then it did the unweighted model. This discrepancy did little to change my substantive interpretation of the results

[5] As Thomas (2010) points out, well-specified unweighted models, or models where the variables used to create unequal sampling probabilities for respondents are included as covariates, are unlikely to differ much form corresponding models with weights. I attribute the similarity of my weighted and weighted models to the fact that the PSID says it samples based on income and that I control for income.

[6] Note that the instrument is coded with integers from one to five, with one being equal to *Excellent* Health and five indicating that a respondent is in *Poor* health.

As motivated during the discussion of Farmer and Ferraro's (2005) analysis, selecting an appropriate model is of prime importance to this paper. To recap, analysis of this paper's research questions could benefit from a using a model that 1) appropriately recognizes that the categorical nature of the self-rated health response and 2) allows the examination of some notion of the probability of *every* possible choice of self-reported health status at any given point of education observed. There are a number of regression models which meet these two criteria. Two common choices for modeling this sort of data in the social sciences are the ordered probit/logit and the multinomial logit.

To choose which model was more well-suited for the analysis at hand, I checked the parallel slopes assumption of the ordered probit. In sum, this assumption states that the only one set of coefficients is needed to describe the relationship among any two levels of the outcome variable. If this assumption were to hold, we would have evidence that the ordered probit was a good model for the data. Use of the multinomial logit would be motivated in the case where a test of this assumption failed. Because of the tendency of statistical test to inappropriately reject the proportional odds assumption, I examined the parallel slopes using a graphical measure described by Harrell (2001). In doing so, I found some evidence that the assumption at hand did not hold for the analysis. For that reason, I choose to use the multinomial logit here.

In the multinomial logit framework, the health category an individual i could report, Y_i, is given by the combination of the stochastic competent:

$$Y_i \sim \text{Multinomial}(y_i|\pi_{ij}) \tag{1}$$

,where y_i is the level of health at a particular point, j indexes the categories of our self-rated health outcome, and $\pi_{ij} = \Pr(Y_i = j)$ for j = 1,...,J, and the systematic competent:

$$\pi_{ij} = \frac{\exp(x_i\beta_j)}{\sum_{k=1}^{J}\exp(x_i\beta_k)} \tag{2}$$

where x_i are the covariate values associated with individual i, and β_j are the coefficients for health category j. (Imai et. al. 2007).

In Eq. 2, we can see that the multinomial logit has both of the features on which we hoped to select a model. For one, while π_{ij} is dependent on the βs for other health categories, the multinomial logit makes no assumptions about the *spacing* between each level of our self-rated health; βs are determined separately for each health category. This feature respects the categorical nature of our outcome.

In addition, Eq.2 gives us a clear way to translate the the results of our modeling procedure into the probabilities of observing each health category at any point in the covariate space. After setting the first category, *Excellent*, to be the reference group (i.e, making its coefficients 0 to give us a way of identify all βs), and plugging in the estimated parameters ($\hat{\beta}$) and particular levels for all of the covariates used in the model ($\mathbf{x}_c$) into Eq. 2, we can find:

$$\hat{\pi}_{\text{Excellent}} = \frac{1}{1+\exp(\mathbf{x}_c\hat{\beta}_{\text{VeryGood}})+\exp(\mathbf{x}_c\hat{\beta}_{\text{Good}})+\exp(\mathbf{x}_c\hat{\beta}_{\text{Fair}})+\exp(\mathbf{x}_c\hat{\beta}_{\text{Poor}})} \tag{3}$$

$$\hat{\pi}_{\text{VeryGood}} = \frac{\exp(\mathbf{x}_c\hat{\beta}_{\text{VeryGood}})}{1+\exp(\mathbf{x}_c\hat{\beta}_{\text{VeryGood}})+\exp(\mathbf{x}_c\hat{\beta}_{\text{Good}})+\exp(\mathbf{x}_c\hat{\beta}_{\text{Fair}})+\exp(\mathbf{x}_c\hat{\beta}_{\text{Poor}})} \tag{4}$$

Through all levels of self rated health, up to:

$$\hat{\pi}_{\text{Poor}} = \frac{\exp(\mathbf{x}_c\hat{\beta}_{\text{Poor}})}{1+\exp(\mathbf{x}_c\hat{\beta}_{\text{VeryGood}})+\exp(\mathbf{x}_c\hat{\beta}_{\text{Good}})+\exp(\mathbf{x}_c\hat{\beta}_{\text{Fair}})+\exp(\mathbf{x}_c\hat{\beta}_{\text{Poor}})} \tag{5}$$

Having this ability to calculate specific expected probabilities for each level of health should allow us a more nuanced look at if and how health changes across the range of education differently across racial groups.

As with any other model, the multinomial logit comes with it's own set of assumptions. The *Independence of Irrelevant Alternatives* (IIA) assumption is of particular importance to our self-rated health outcome variable. In sum, the IIA assumption states that the odds of choosing health category A over health category B does not depend on the presence of some other health category

C. A proposed fix for cases where this assumption is violated is to model the response with a multinomial probit. The latent variable justification for this type of model allows the IIA assumption to be overcome. Some evidence has shown though that, regardless of if the IIA assumption is violated, the multinomial logit usually outperforms the multinomial probit (Kropko 2008). Because of this, I have confidence in the estimates produced by the multinomial logit here, even if the IIA assumption is violated.

Covariates

The covariates included in the models capture some notion of race, education, age, income, employment status, and marital status. In the following section, I will explain why said aspects are important to include in the analysis and through what variables they are realized.

Race is included in the model because it is part of the focal relationship being analyzed in this paper. This concept is represented with the variable *Black*, in which a score of 1 indicates a non-Hispanic black respondent, and a score of 0 indicates that a respondent is non-Hispanic white.

The decision to focus on only these two racial groups is largely a function of the nature of the data; the count of individuals that are neither black nor white in the data is, in sum, quite small. This concern over small counts is magnified by the fact that the multinomial model being used here produces separate estimates for each covariate at each level of health status, and that these counts would be spread over 12 categories of education. Instead of trying to produce reliable estimates on (somewhat) small categories of data, I choose to only focus on the two most sizable racial groups in the data.

Next, a measure of education is included in the model because of its position in the focal relationship. This concept is introduced into the model as the variable *Education*, which indicates the years of education completed by a respondent. Because of the very small number of people with scores less than six on this variable, only individuals with at least six years of education were included in the model. Of course, this exclusion limits the scope of the analysis in some ways. I believe, though, that the benefits of doing so (e.g., avoiding producing estimates on cells with very small counts) outweigh the limitations of doing so.

In the public-access file of the PSID, years of education is top-coded at 17 years; while a score of 0 to 16 on the education scale represent the actual number of years completed by a respondent, a score of 17 could refer to any actual number of years completed, 17 years and up. Because I did not want to lose the information association with respondents who had a score of 17 on this indicator, these individuals were kept in the analysis. Readers should be aware then, that estimates at this point of the education measure refer to some average conception of the average for all individuals who fall into that group.

Gender is also included in the analysis. As several researchers have pointed out, the relationship among health and education, and the nature of other measures of socioeconomic status vary by gender and gender-by-racial groups (Elo and Preston 1996; Montez et al. 2009, Montez et. al. 2012; Kaba 2008). Instead of introducing this measure as a covariate then, separate models are estimated for those respondents who identified as men and for those respondents who identified as women. Subsetting the analysis in this way allows a finer looker at the question at hand.

Age is an indicator of an individual's age at the time of the survey. Conceptually, age is related to both the amount of education an individual has completed, and the quality of one's health. To lessen the possibility of biasing the results by including respondents who are still in school, those individuals who less than 25 years old were excluded from the analysis.

After forming *Age* in the way described above, I examined how said variable was best entered into the model. To get a rough sense of this, I used a generalized additive model to fit the self-rated health variable to the covariates mentioned in this section while allowing health status to remain a smooth function of *Age*. The results of this exercise produced some evidence that *Age* deserved some sort of polynomial transformation. For that, Age^2 is included in the model.

Because squaring *Age* puts it on such a different scale than many of the other covariates in the model, and because obtaining Hessian matrices is an important step in the analysis (described in more detail below), I choose to scale this variable by converting it to age in centuries.

As described in detail in the sections preceding this one, accounting for income is essential to this analysis. *Family Income* was chosen as the indicator of this component because it provides a sense of all of the income related resources available to an individual. Choosing individual income would (somewhat) increase the risk of underestimating the resources available to a respondent who may not make much in terms of income themselves, but who would have access to more income through a member of the family unit.

The range of possible values for this income measures was quite large. Again, because later parts of the analysis rely on working with model's Hessian matrices, *Family Income* needed to be scaled. Since the PSID goes into such detail in measuring income, some respondents had negative values of this measure of family income. This meant that scaling through a log-transformation was not appropriate for these data. As an alternative, *Family Income* was transformed using what Zumel and Mount (2013) calls a *signed logarithm*. In the authors' own words, A signed logarithm takes the logarithm of the absolute value of the variable and multiplies by the appropriate sign. Values with absolute value less than one are mapped to zero. [7]

Like income, one's employment status is both a factor of an individual's level of education and race, and has an effect of said individual's health status. Because of its relationship to this analysis' focal variables, employment ought to be accounted for.

To capture this dimension of socioeconomic status, an indicator *Employment Status* was created. For this creation, individual's who were either fully employed at the time, or on temporary leave from a full time job where given a value of 1. Any individual that fell outside of these categories was given the value 0.

Finally, marital status is included in the model because it can be related to both race and health (Crowder and Tolnay 2000; Lillard and Panis 1996). This indicator is coded simply as 1 for married and 0 for anything else.

Analytical Strategy

The plan of action followed in this in this paper closely follows the strategies used in recent

[7] A potential drawback of this transformation is that all values between zero and one are considered the same. However, this is not problematic for this paper's analysis, as all values that fell in this range were zero to begin with.

papers focused on resource substitution and subgroup variation in the health returns to education. (Ross, Hummer, and Masters 2012; Ross and Mirowsky 2010; Ross and Mirowsky 2011). As a first step, I fit self-rated health as a function of the covariates listed above for each gender group using a multinomial logit. Next, I repeat the first step, only with the addition of an interaction term between *Black* and *Education*. Following this, the models with the interaction term between race and education and without said term are compared to see if the inclusion of the interaction term is justified, on the basis that it fits the data better.

To get a sense of how well the models fit the data, I calculated and compared each model's Akaike Information Criterion (AIC). In sum, the AIC is a measure of the likelihood of some model's parameters, given a set of data, penalized by the number of estimated parameters. In a little more detail, we can say that a model with a larger likelihood is more likely to be an accurate representation of the data generating process which produced the data. However, since it is often the case that adding any parameter (regardless of how much it helps improve our understanding of the process of interest) increases the likelihood of a model, we may want to adjust the sense of fit according to the number of parameters used in the model ; this facilitates comparison of models with different numbers of parameters. In the case of the AIC, this idea is achieved by: [8]

$$\text{AIC} = -2\log(L) + 2d \tag{6}$$

where L is the likelihood of the model, and d is the number of free parameters in the model. In comparing models, a lower AIC indicates a better model fit.

In addition, this analysis is pushed further in that it simulates expected values and some notion of confidence surrounding said simulated quantities for different points of interest. As mentioned above, understanding how the probabilities of reporting different health statuses vary as education

[8]While there are several different ways to penalize likelihood to achieve this goal, I choose the AIC here because of its underlying assumptions. In the derivation of the AIC, the "true model" that generated the data at hand is assumed to be unknown. As such, AIC assumes that the true model is not among the candidate models being compared, and that the model of best fit is the model that is a better approximation of the real data generating process. Given earlier comments of mine (e.g, how research on the exact processes linking education and health is developing), I believe that all of the models I am evaluating are just simple approximations of the true data generating process. For that, I believe the AIC works fairly well as a measure of goodness of fit here.

changes can offer important insights into the examination of this paper's questions. As such, taking care in calculating probabilities for focal spots in the covariate space, and giving readers an understanding of the uncertainty around those probabilities is of prime importance.

To simulate these probabilities and their confidence intervals, I make use of the simulation algorithm presented in King, Tomz, and Wittenberg (2000). In sum, this procedure involves:

1. Drawing a parameter value from a multivariate random normal distribution (with the vector of coefficients and variance-covariance matrix from an estimated model as the generated distribution's underlying parameters).

2. Using these parameters in combination with particular sets of covariate values and, in the case of this paper, all of the equations between the space of Eq. 3 and Eq. 5 to calculate an expected probability for each category of health for the chosen scenario.

3. Repeating Steps 1 and 2 many times over to get a set of information which can be used as a basis for deriving a notion of what the probabilities of health are at a particular combination of covariates and some sense of how much confidence one can have in the location of said estimate.

In this case, the scenarios are partially determined by the paper's questions. Because we are interested in examining if the relationship among education and health changes differently across individuals of the different races, we arguably should aim to calculate quantities for 48 different scenarios; an estimate of probability and level of confidence for black male respondents at all 12 levels of education, the same quantities for a white male respondent across the spectrum of educational attainment, the same quantities of interest for black women at the same levels of education, and finally, the same for white women across the entire range of education. In each of these scenarios, all other covariates in the model are held at their means.

In this analysis, I repeated Steps 1 and 2 10,000 times to obtain the information needed to comment on the probabilities of interest. To represent the estimate of probability of a health status, I took the average expected probability for each health category derived from 10,000 repetitions.

For the notion of confidence around these estimates, I calculated confidence intervals. For men, the confidence interval is calculated by finding the two points between which 90% of 10,000 expected probabilities fell. For women, the limit was raised to 95% because of the larger sample size associated with this group.

Following these calculations, I created plots of the expected values and confidence intervals surrounding them for each race-by-gender group. These plots act as a useful tool for examining if the association between education and health varies across racial groups. If how education and health relate is dependent on race after conditioning on income and occupation, I expect to see differences in the slopes and arrangement of the probabilities of health statuses across races.

To determine if the theory of resource substitution hold for these data, we can examine how the slopes for each health status compare across racial groups. If we see that the probabilities of the ”better” health statues (e.g., *Excellent*) increase more quickly for blacks than whites as education increases, the data would suggest that resource substitution does hold for these groups. While we can get a sense of how slopes compare across groups from the expected value plots, the additional (but important) information in these plots makes doing so with a reasonable amount of precision somewhat difficult. To get a more detailed view of how the slopes of the health statues vary relative to one another across the observed years of education, I estimated the relative risk for each counterfactual set of covariates:

$$\frac{\pi_{Bij}}{\pi_{Wij}} \tag{7}$$

where π_{Bij} is the simulated probability of health category i at j years of education for blacks, and π_{Wij} is the same for whites. The value of this measure indicates how many times the size of the probability for a black respondent at ij is of the probability for a white respondent at the same location.

Using Eq. 7 and a method similar to what I did to find the expected values above, I found the relative risk and associated confidence intervals for each health category at each year of education, for each gender group, and plot the results. As stated above, this exercise is useful in that it *only* provides information about about how the size of the probabilities change across racial groups relative to one another; no information on location of these probabilities is included in this graphic.

RESULTS

The parameter estimates and standard errors for both the male and female models are presented in the following two tables. A few interesting details can be gleamed from viewing the results of the modeling procedure in this way. For one, for both men and women, the addition of the interaction term initially changes the sign of the parameter estimate for *Black*. This suggest that, at least when viewed in relation to being in *Excellent* health, blacks have a higher chance of reporting a better health category than whites at the lowest levels of education. By considering all parts[9] of the interaction, one can see that this state of ”better” health quickly diminishes as education increases.

In addition, the tables include AIC scores for each model. For both men and women, the model that included the interaction term between race and education had a lower AIC. This fact supports the idea that the model with the interaction term better approximates the real process which produced the data than the model that left the interaction term out.

Based on the idea that solely examining the tables of coefficients from the multinomial models obscures information of interest to this analysis, the results of the simulation exercise described in detail above are presented below, after the tables. Because the models with the interaction terms were deemed to be better fits of data, I will only present the simulated probabilities from those models in this section. [10]

[9]As some combination of the parameter values in the *Black x Education*, *Education*, and *Black* all compose one, indivisible term, speaking of the interaction term in terms of *parts* is dubious. However, in this case, the use of such language quickly draws one’s attention to the point in the the table that supports the idea I am trying to communicate.

[10]For those curious, the expected values derived from the models with no race-education interaction term are just what you would expect: The shape/slope of the probability for any health category is almost identical across racial groups, though the starting point for any of said probabilities differs.

Table 3: Multinomial Logit Estimates of Self-Rated Health: Men

	Model 1				Model 2			
Covariate	Very Good	Good	Fair	Poor	Very Good	Good	Fair	Poor
(Intercept)	0.983	2.54	3.39	1.28	1.35	3.07	4.31	1.74
	(0.643)	(0.665)	(0.811)	(1.29)	(0.66)	(0.69)	(0.85)	(1.33)
Age	7.52	12.9	14.2	27.1	7.56	12.9	14.3	27.0
	(1.82)	(1.89)	(2.37)	(4.01)	(1.82)	(1.90)	(2.38)	(4.01)
Age^2	-5.95	-9.78	-10.3	-20.2	-5.98	-9.80	-10.4	-20.2
	(1.86)	(1.91)	(2.31)	(3.55)	(1.87)	(1.92)	(2.32)	(3.56)
[log] Family Income	-0.221	-0.675	-0.847	-1.02	-0.223	-0.681	-0.861	-1.02
	(0.140)	(0.141)	(0.154)	(0.174)	(0.140)	(0.141)	(0.153)	(0.174)
Black	-0.003	0.260	0.432	0.013	-1.60	-1.90	-2.86	-1.85
	(0.100)	(0.102)	(0.132)	(0.209)	(0.636)	(0.642)	(0.799)	(1.14)
Education	-0.094	-0.179	-0.254	-0.386	-0.119	-0.214	-0.319	-0.415
	(0.020)	(0.021)	(0.028)	(0.042)	(0.022)	(0.024)	(0.033)	(0.048)
Employed	-0.061	-0.264	-1.03	-2.42	-0.074	-0.280	-1.05	-2.44
	(0.118)	(0.120)	(0.144)	(0.255)	(0.118)	(0.120)	(0.145)	(0.254)
Married	-0.041	0.037	-0.291	-0.096	-0.033	0.049	-0.271	-0.089
	(0.113)	(0.119)	(0.148)	(0.227)	(0.113)	(0.119)	(0.149)	(0.228)
Black $\times$ Education	-	-	-	-	0.118	0.161	0.253	0.136
					(0.047)	(0.047)	(0.061)	(0.094)
AIC	12648				12638			
n	4836				4836			

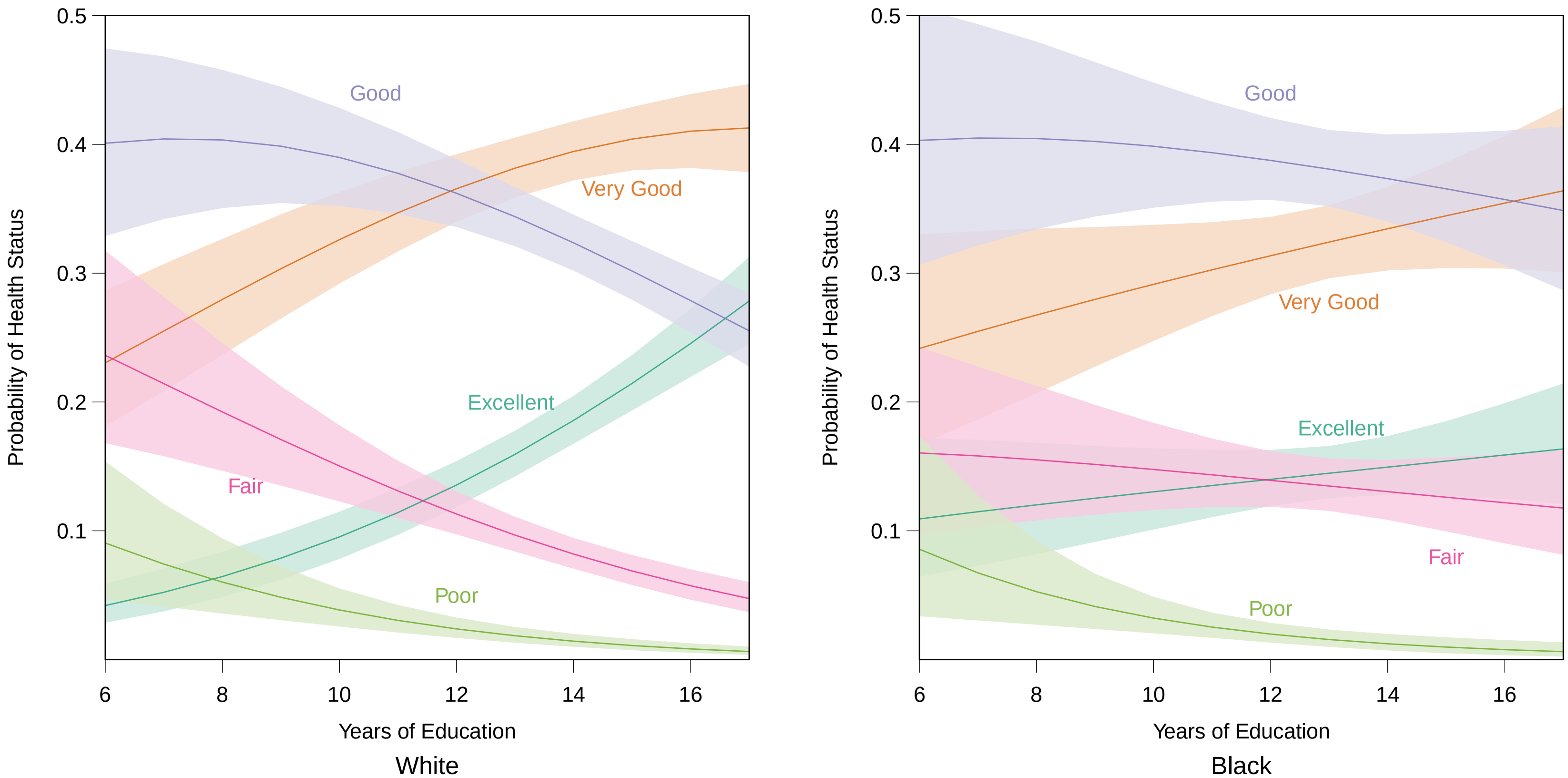
[1] Estimated βs and standard errors presented in table. βs are values not in parentheses, standard errors are in parentheses.
[2] *Excellent* used as baseline category in finding the above values.

Table 4: Multinomial Logit Estimates of Self-Rated Health: Women

	Model 1				Model 2			
Covariate	Very Good	Good	Fair	Poor	Very Good	Good	Fair	Poor
(Intercept)	1.59	3.74	3.38	2.49	2.45	4.92	4.75	3.44
	(0.629)	(0.633)	(0.742)	(1.04)	(0.660)	(0.669)	(0.790)	(1.08)
Age	2.40	4.80	10.5	13.9	2.72	5.22	10.9	14.2
	(1.75)	(1.76)	(2.09)	(2.96)	(1.75)	(1.77)	(2.10)	(2.97)
Age^2	-0.782	-2.29	-6.12	-7.87	-1.08	-2.75	-6.63	-8.19
	(1.80)	(1.80)	(2.05)	(2.67)	(1.81)	(1.81)	(2.06)	(2.68)
[log] Family Income	-0.202	-0.495	-0.832	-0.751	-0.215	-0.514	-0.851	-0.767
	(0.137)	(0.135)	(0.144)	(0.168)	(0.136)	(0.134)	(0.143)	(0.168)
Black	-0.009	0.357	0.497	0.288	-2.71	-3.14	-3.37	-2.58
	(0.095)	(0.095)	(0.117)	(0.171)	(0.596)	(0.586)	(0.689)	(0.897)
Education	-0.059	-0.176	-0.207	-0.322	-0.116	-0.256	0.303	-0.382
	(0.021)	(0.021)	(0.026)	(0.036)	(0.024)	(0.025)	(0.032)	(0.044)
Employed	0.082	-0.045	-0.632	-1.88	0.059	-0.076	-0.668	-1.91
	(0.095)	(0.097)	(0.118)	(0.205)	(0.101)	(0.103)	(0.124)	(0.176)
Married	0.072	0.071	-0.121	-0.150	0.059	0.054	-0.138	-0.166
	(0.101)	(0.102)	(0.123)	(0.176)	(0.101)	(0.103)	(0.124)	(0.176)
Black × Education	-	-	-	-	0.194	0.254	0.285	0.204
					(0.043)	(0.042)	(0.051)	(0.07)
AIC	16053				16019			
n	6014				6014			

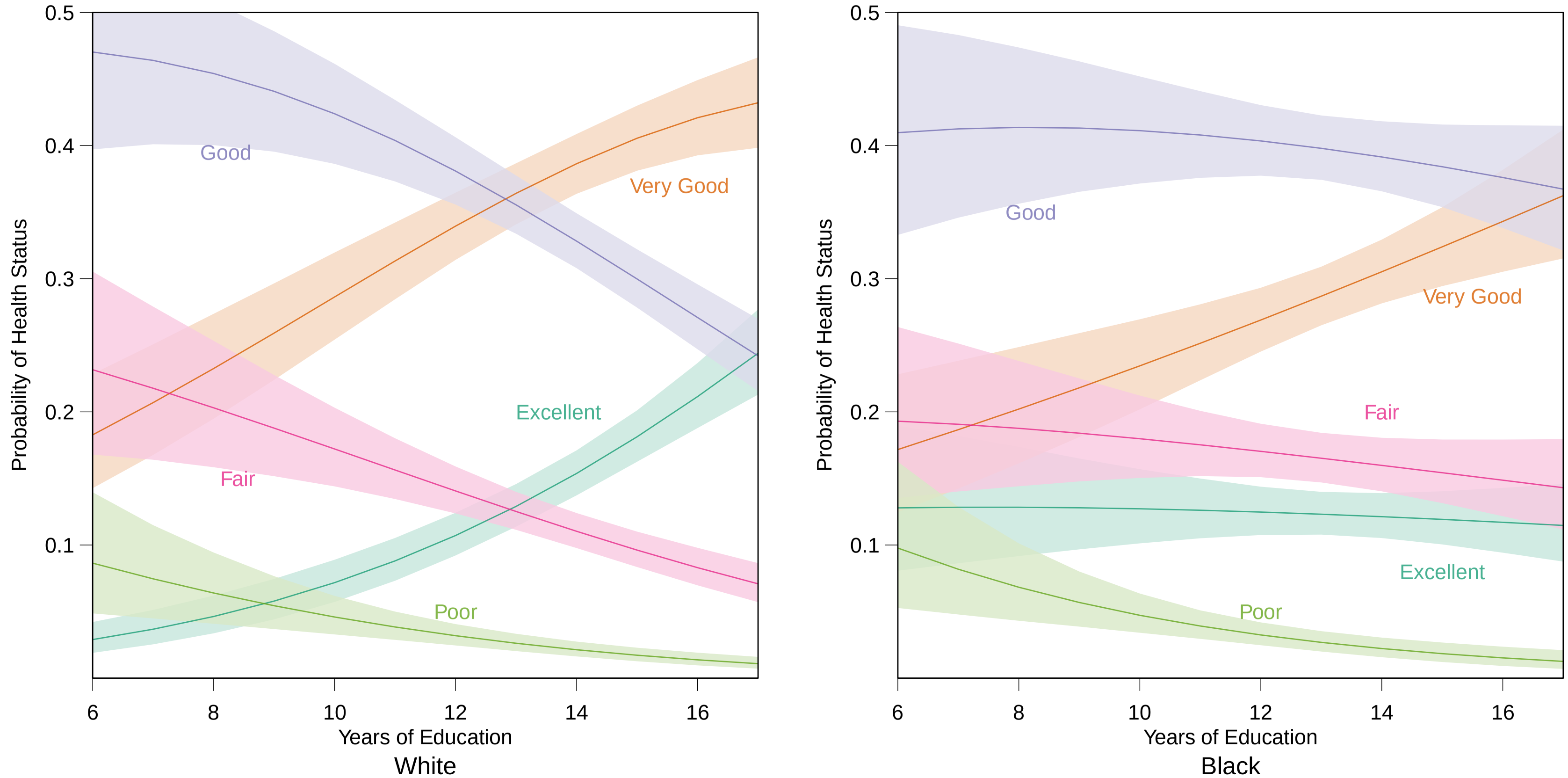
[1] Estimated βs and standard errors presented in table. βs are values not in parentheses, standard errors are in parentheses.
[2] *Excellent* used as baseline category in finding the above values.

Figure 1: Expected Probabilities of Self-Rated Health: Men with Race-Education Interaction



95% confidence intervals shaded

Figure 2: Expected Probabilities of Self-Rated Health: Women, with Race-Education Interaction



95% confidence intervals shaded

A careful study of these figures reveals a number of interesting differences between racial groups; let us take them step-by-step, starting with the figure for the male group.

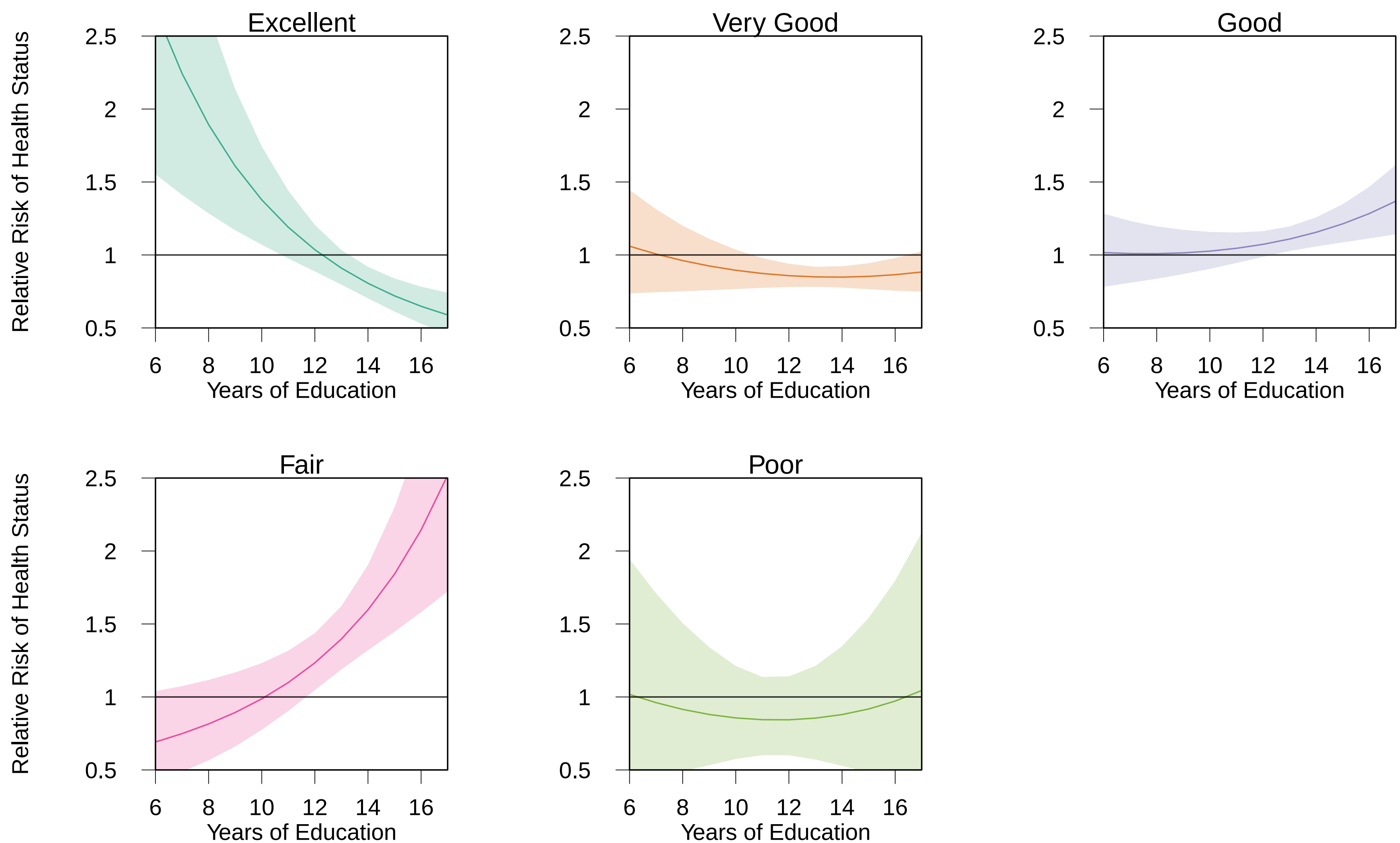
For the first health category, *Excellent*, the difference in expected probabilities between groups is noticeable. For white men, the probability or reporting excellent health steadily increases with years of education, to the point where it becomes tied for the second most probable reported category. For black men, this is not the case; in this group, reporting *Excellent* health increase slightly moving across the years of education. Notice that in this arrangement, the probability of *Excellent* is distinctly higher for blacks than it is for whites at the lower levels of education. The next health category down, *Very Good* is similar across both groups. For both black men and white men, the probability of being in very good health starts slightly above 20% and increase to become, at least, tied for the most probable health category towards the end of the observed education range.

Moving on, the probability of being in *Good* health differs between the two male groups. For blacks, *Good* health remains about as probable across each year of education, with a slight increase as education approaches 12 and a slight decrease afterwards. For whites, *Good* moves from the most probable category to the being tied for third at the end of the education spectrum.Finally, *Fair* and *Poor* behave similarly across groups. For whites though, the decrease in the probability of *Fair* is noticeably more severe for whites than it is for blacks.

In Figure 2, we can see that the many of the same patterns that existed for men exist for women. One area where there is a noticeable difference form the previous figure is in the behavior of *Excellent* health. For white women, the probability of *Excellent* health increases from the least probable category to the second most probable category as education increases. However, for black women, *Excellent* excellent health appears to stay consistent across all years of education. Further, *Excellent* hovers below *Fair* health for the entire range of education observed.

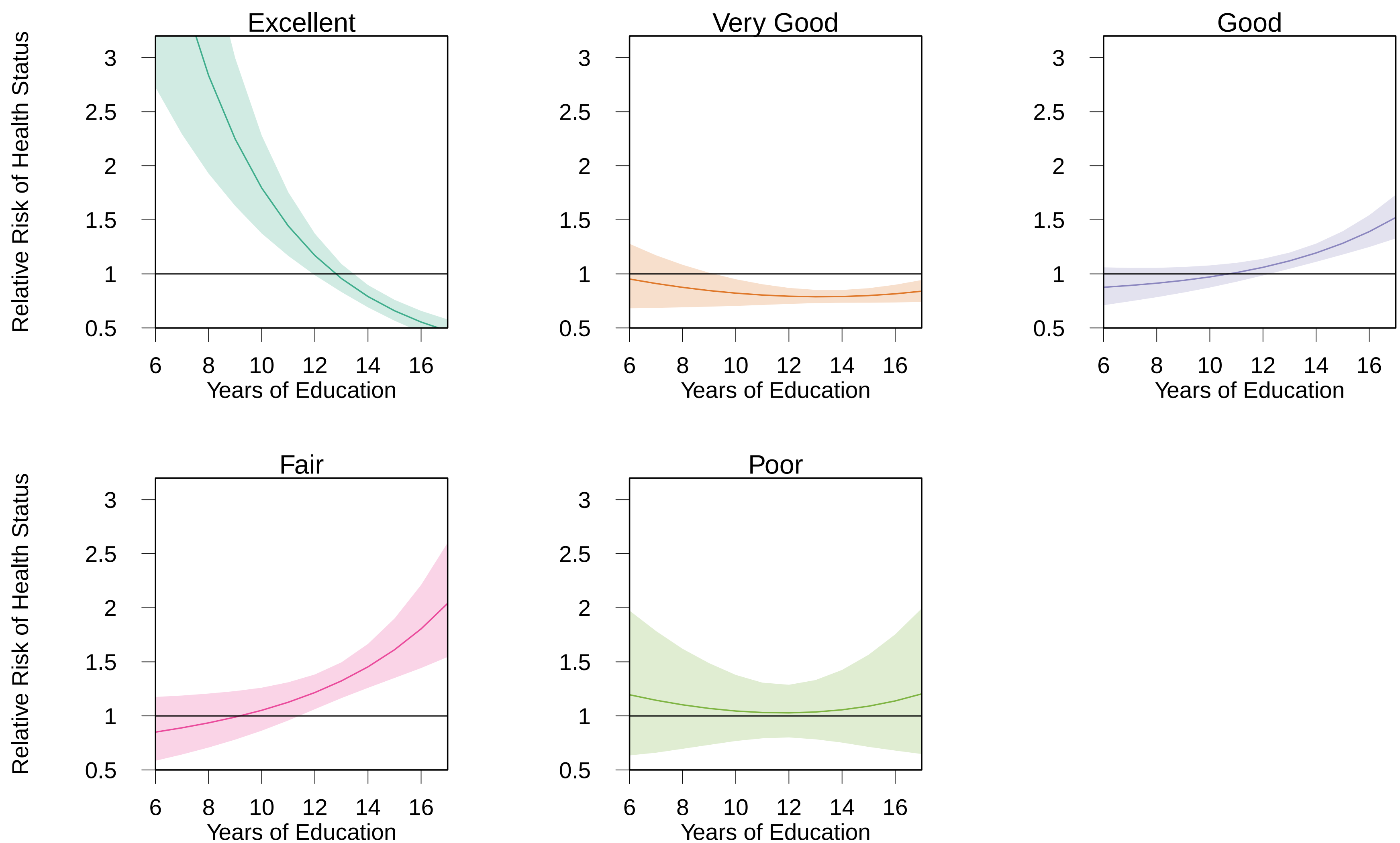
From the above plots, we see evidence that, when conditioned on income and employment status, measurable variation still exists between racial groups in terms of how education and health relate. To get a more refined look at how the slopes compare across groups, and thus an idea of if resource substitution adequately describes the process here, the plots of relative risk are below:

Figure 3: Relative Risks of Expected Health Statuses (Black/White) : Men



90% confidence intervals shaded

Figure 4: Relative Risks of Expected Health Statuses (Black/White): Women



95% confidence intervals shaded

Here too, taking each plot one by one sheds light onto how the relationship among education and health status varies across racial groups. For men, the probability of reporting *Excellent* health is initially about 2.5 times larger for blacks than it is for whites. The magnitude of this steadily decreases over the range of years of education until, at around 16 years of education, the probability of *Excellent* health is about half that of whites for blacks.

In contrast, the risk of *Very Good* remains about equal across the range of education. The risk of *Good* starts similarly, but towards the end of the education spectrum, blacks' probability for this health category increase to be about 1.5 times that of whites'. The relative risk of *Fair* health follows a similar pattern as the risk of *Good* health, with a more speedy slope.

Over the range of education, the probability of reporting *Fair* health for blacks moves from being just above .75 times that whites' probability of *Fair* health, to being above 2 times that same measure. Finally, the estimated risk for a black respondent reporting *Poor* health steadily approaches the risk of *Poor* health for whites as education increases, though the wide confidence interval around does suggest that we take this pattern with a grain of salt.

Like with the expected value plots, the relative risks plots for women are similar in shape to the corresponding plots for men. The biggest difference between the plots for men and the plots for women is in the size of the relative risk of *Excellent* health; in the plot for women, the estimated relative risk for this category starts nearly a half of a unit higher than the corresponding one for men.

DISCUSSION

With results in hand, we can now evaluate the questions posed earlier in this paper. To start, I will examine the first question, *Do the health returns to education appear to differ between black Americans and white Americans, even when accounting for potentially confounding dimensions of SES?*

According to the evidence produced here, it does appear that there are measurable differences between blacks and whites in how self-rated health changes across years of education; both the slopes and arrangement of the expected probabilities vary across racial groups.

This conclusion is not incompatible with what Farmer and Ferraro (2005) came to in their research on this question. If we were to just look at the predicted value of health at any level of education, we would (in most cases) come to Farmer and Ferraro's conclusion, that self-rated health did not increase with education for blacks, where it did appear to do so for whites.[11]

With that being said, looking a bit deeper into the expected values of self-rated health leads us to think differently about how this health-education relationship varies between blacks and whites. In both the male and female cases, the probability of being in *Very Good* health increases sharply as years of education increases. Also, this increase appears to come at the cost of some worse off health category: For black men, both *Fair* and *Poor* decrease as education increases. For black women, the same pattern holds, but the more positive category, *Excellent* arguably becomes less probable with greater education as well.

Given these patterns, I would qualify the association and argue that self-rated health does improve with increasing education for blacks. The evidence here points to the idea that health does increase with education for both whites and blacks, but the rate for which is does is measurably different for each group.

This last point moves into the discussion of this paper's second question, *If variation does exist between these two groups, can it accurately be described by the theory of resource substitution?* To evaluate the evidence for this, we can look back at the relative risk plots. For both men and women, the size of the probability of *Good* health appears to become bigger for blacks relative to whites as education increases. However, the opposite pattern is seen for *Excellent*; here, as education increases, the gap in probability between blacks and whites diminishes rapidly. To a lesser degree, the same pattern is seen for the *Very Good* category. In addition, the probability for blacks to report *Fair* health becomes measurably larger than the probability of whites doing the same as education increases. Because of these patterns, it appears that the rate at which health improves

[11] In our results, the predicted health value for a year of education is the health category with the highest probability at said point along education. For both black men and black women, *Good* never completely relinquishes it's control as the most probable category, meaning it stays the predicted value across the range of education. For white men and white women though, he predicted value clearly moves away from *Good* at higher levels of education.

with education is greater for whites than it is for blacks. This evidence leads me to conclude that resources substitution does not appropriately describe this scenario.

This conclusion can be viewed as unique in that it differs from the pattern seen in previous work on resource substitution in the context of the education-self-rated-health relationship. Ross, Masters, and Hummer (2012), Ross and Mirowsky (2010), and Ross and Mirowsky (2011), all found evidence to support the idea that resource substitution is occurring across different socioeconomically disadvantaged groups. Using methodology quite similar to those authors, these data suggest that a different pattern holds when examining black and white American's health returns to education.

LIMITATIONS

Of course, there are a number of limitations in this analysis. For one, the analysis is only able to observe individuals with at least six years of education. The portion of the population excluded because of this criterion likely have a unique relationship with both education and health. Excluding this group leaves out important details about the focal relationship of paper. Along similar lines, the top coding of education limits what can be made of the race and education and health relationship on the other side of the spectrum.

CONCLUSIONS

Given it's persistently positive (and potentially distal) [12] relationship with health, education (and it's related mechanisms) is often positioned as an incredibly effective means through which one can intervene to effect population health (Cutler and Lleras-Muney 2006). Based on the evidence produced in this paper, I would certainly not dispute this claim. By some measure, health appeared to improve as education increased for every group included in the analysis.

I would, however, argue that this paper's results suggest that such an idea needs to be dissected further. While every group did receive some benefit to their health as education increased,

[12] in terms of its relationship to other measures of socioeconomic status

the magnitude of said increase varied measurably across subgroups, even when conditioned on socioeconomic factors with positive associations with health, and for which we know black Americans face some level of disadvantage on relative to their white counterparts. As such, simply increasing education may serve to both increase overall health of the population and health disparities between certain groups. This conclusion is particularly surprising if looked at through the lenses of resource substitution. For other works concerned with this theoretical framework, education, conditioned on income and employment status measures, appeared to offer an opportunity to close gaps in health status.

This paper is only part of the initial step in understanding the way race and education interact to produce health outcome; much more research is needed to expand our understanding of the processes underlying the patterns observed above. In particular, future research might aim to specify, and test, mechanisms that explain why the probabilities of health statues vary the way they do in these models. Understanding why and how these patterns exist may allow us to more fully utilize education (or, at least it's associated mechanisms) as a tool for improving health for all.

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