The Effects of Current and Past Health Status on Wages

Rameh Rezazadeh Mehrjou

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By: Rameh Rezazadeh Mehrjou

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______________________________ Examiner
Professor Christian Sigouin

______________________________ Supervisor
Professor Damba Lkhagvasuren

Approved by ______________________________
Professor Christian Sigouin
Graduate Program Director

____
Professor Pascale Sicotte, Dean
Faculty of Arts and Science

Abstract

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In this paper, I analyze the impact of health status on the wages of men and women in National Longitudinal Survey (NLSY79) from 1979 to 2018. In doing so, I use self-assessed health status as the health measurement and address the potential endogeneity problem of health status in the wage equation by considering a fixed-effects model. The results of the fixed-effects model are compared to those of a random-effects model. The analysis involves not only the impact of the current health status but also the impact of the health status of the previous year on current wages. The findings in this paper suggest that poorer health status of time t means lower wages for both White and non-White workers. The lagged effect of health status on wages is higher for women than men. The results are robust across race and gender groups.

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1. Introduction

Health is an essential component of human capital and therefore is viewed as an input to produce different forms of human capital. In general, employees in better health are expected to be more productive. A study of a small group of workers at a commercial laundry plant in the U.S. Midwest shows that participating in employer-sponsored health programs increases the productivity of employees by approximately four percent in the subsequent year. The most remarkable increased productivity was observed among workers whose health significantly improved from one annual screening to the next. The productivity of this group of employees was increased on the order of eleven percent from the previous year (Gubler et al., 2018).

Poor health causes reoccurring sick leaves and/or long-term absences from work. At the societal level, there is a strong relationship between a poor health population and reduction in savings rates, return on capital, and domestic and foreign investment; consequently, all of these factors contribute to the reduction in economic growth (Ruger and Kim, 2006). Therefore, even from a purely economical point of view, health is one of the essential areas that governments need to pay attention to. Governments have to be aware of how health affects different sectors of the economy and interacts with different economic variables, such as wages.

Wages are among the most reliable measures of labor productivity. Therefore, the impact of health status on labor productivity can be measured by comparing the hourly wages of individuals with different health conditions. However, it should be noted that the wage is not an entirely flawless variable for the purpose of the analysis. For example, Forbes et al. (2010) argue that not taking into account the measurement issues and the wage-setting mechanisms in the labor markets could lead to serious downward or upward biases when estimating the effects of poor health on labor productivity.

The impact of health conditions on wages can be explained through different mechanisms. Some researches considered the relationship between improvements in health status and productivity. With this mechanism, health status influences the stock of human capital and the ability of workers to gain new skills (Bartel and Taubman, 1979). Consequently, the difference in skill sets that are driven by health status differences, can result in wage differences. Thus, employers can perceive health status as an unobserved characteristic associated with the productivity of workers, such as preference, risk aversion, and so on.

Health status can also impact wages due to discrimination. There is wage discrimination against individuals with poor health (Halima and Rococo, 2014). Therefore, people with poor health are more likely to have fewer job opportunities and thus lower wages.

There is a causal relationship between health status and wages in the real world. Not only can health status affect wages, but also wages impact health status. In general, people with higher wages have more access to decent health care and better nutrition. Conversely, people with low income levels are more likely to have problems accessing a good health care system and affording the necessary daily nutrition. Therefore, people with lower incomes are more vulnerable to suffering from chronic diseases (on Social Determinants of Health and Organization, 2008).

This study estimates the effects of past and current health status on wages using NLSY79 from 1979 to 2018. The paper is organized as follows. The literature review is presented in Section 2. The concept of health and its measurements are reviewed in Section 3. The unobserved heterogeneity is discussed in Section 4. The data and econometrics model are described in Section 5. Section 6 presents the estimated results. The conclusion of the study is drawn in Section 7.

2. Literature Review

The relationship between health status and labor market variables, including wages, has been the subject of several research works. Regardless of the utilized research methodology, all these studies have reached almost the same results, confirming that there is a direct relationship between health status and wages. In this section, some important studies on the subject of the relationship between health status and wages are briefly reviewed.

2-1. Impact of Health Status on Wages

Pelkowski and Berger (2004) studied the effects of poor health on employment, annual hours worked, and hourly wages. They used Health and Retirement Study data (HRS) to analyze jobs and health experience profiles over individuals' lifetimes. These profiles were used to estimate the effects of temporary and permanent illnesses on labor market indexes. The findings of this research showed that permanent health problems can result in a considerable decrease in the wages of female workers and the working hours of male employees.

Halima and Rococo (2014) estimated the level of unexplained parts of the wage gap in France that could be attributed to wage discrimination. Their findings showed that the observed discrimination had been rooted in health status. They used data from Health, Health care, and Insurance survey among 1594 individuals. They considered the endogeneity of health and some unobserved differences in productivity to measure the wage gap. Their results demonstrated wage discrimination for individuals with poor health regardless of the health measurement techniques.

Tompa (2002) suggested that, health improvements increase individuals' productivity. This study goes beyond the apparent impact of health on capacity and incentives to work and describes additional pathways through which health affects individuals' earnings during their lifetimes. As its central concept, this paper shows that if individuals are rewarded based on their productivity, an increase in productivity leads to an equivalent rise in wages.

Employing NLSY79 longitudinal data, Cawley (2004) examined the relationship between body weight and wages. Body weight itself can be an indicator of health condition. In this paper, different strategies were used to study the effect of body weight on wages. The results of this paper showed that being overweight lowers wages for White females. In addition, this paper showed that the adverse relationship between weight and wages, observed for other gender-ethnic groups, has resulted from unobserved endogeneity.

Gambin et al. (2005), using the European Community Household Panel (ECHP), and considering self-assessed health and chronic illness or disability as health status indicators, studied the relationship between health status and wages by gender. This study showed that health problems negatively affect the wages of both genders.

Jäckle and Himmler (2010) studied the relationship between hourly wage and self-reported health with data from Germany. Their findings suggested no statistically significant relationship between health status and wages in women. However, the study showed that healthy men have higher wages than those with health problems. This paper showed that there are different mechanisms through which health problems can create wage gaps: directly by reducing health capital and indirectly by affecting employment transitions. Transitions in employment lead to a reduction in human capital. Therefore, the onset of the disability and its effect on occupation change can cause a decline in hourly wages.

Gilleskie et al. (2017) quantified the contemporaneous and dynamic impact of human and health capital on the wage distribution in the sample of women of NLSY79. They measured the effect of body mass-as a measurement of health status-on wages. They found significant differences in the impact of body mass on wages depending on age, race, and the wage level.

Jones et al. (2020) studied the labor market reactions to an acute health shock. They used the post-crash-era data of Understanding Society. They utilized combining matching and entropy balancing techniques to pre-process data prior to performing the parametric regression analysis. The main finding of this paper implies a considerable decrease in earnings and reduction in working hours as a result of acute health shocks.

Kotschy (2021) empirically investigated the long-run effect of significant health improvements on income growth in the United States. This study used quasi-experimental variations in cardiovascular disease mortality across states. Using an econometrics model and data of the White population, this paper showed a causal link between health and individuals' income. In addition, the findings of the study showed that health dynamics shape life-cycle incomes.

Vaalavuo (2021) studied the effect of poor health (caused by breast cancer) on earnings and employment using data from Finland. Findings of this research work showed that the studied health problem lowers the annual earning. The results indicated that there are significant differences in the earning reductions between different earnings quintiles.

2-2. Impact of Wages on Health Status

Cottini and Lucifora (2013) examined the relationship between working conditions, health, and wages in Europe. Using self-assessed health indicators, they show that working conditions and levels of payment should be considered as critical factors of health status.

Assuming that poverty is associated with poor health, Landefeld et al. (2014) studied the relationship between income, self-reported health, and social status in the Dominican Republic. This paper shows that there is a direct relationship between higher wages and higher subjective social status. This paper also shows that the relationship is more significant among women than men.

Andreyeva and Ukert (2018) estimated the impact of wages on risky health behaviors, health care access, and self-reported health. Using data from the Behavioral Risk Factor Surveillance System, they argue that a wage reduction leads to a reduction in daily fruit and vegetable intake and consequently, results in obesity and poor health.

Kim and Koh (2021) estimate the effects of household income on self-reported health. This study uses random variations in the number of lottery award winners in Singapore. They find that an increase in household revenue leads to a rise in individuals' health status. This level of health improvement can be explained by the increased household consumption spending and overall life satisfaction improvements with no important changes in medical care spending and risky health behaviors.

Many studies have argued that self-reported health indicators are an appropriate health measurement. For example, the findings of several studies show that self-reported poor health can better predict mortality than some other objective measures of health status (Wuorela et al., 2020; Williams et al., 2017).

3. Health Measurements

The concept of health, like the idea of ability, is difficult to define and considerably challenging to measure. The World Health Organization (WHO) defines health as "a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity." One of the factors contributing to the heterogeneity in health is the health measurement methods. In practice, health measurements that are usually considered in the literature can be divided into eight categories as shown in Table 1.

Most of the studies that used data from developing countries utilized the measures of nutritional status or health problems that limit activities of daily living. On contrary, most researchers working on data from developed countries use other health measurement indicators, such as health care, self-assessed health, or health limitations (Currie and Madrian, 1999).

Table 1: Health Measurements

1	Self-reported health condition; in this method, individuals are asked to identify their health condition as excellent, good, fair, or poor.
2	Identifying any health limitations that may affect individuals' ability to work.
3	Identifying health problems that can limit activities of daily living (ADLs).
4	Identifying if an individual is exposed to a chronic or acute health problem.
5	Measuring the frequency of individual use of medical care.
6	Clinical appraisal of different physical and mental health indicators.
7	Assessment of the quality of diet nutrients.
8	Expected mortality

Note: Table 1 shows the descriptions of different health measurements.

However, self-reported health indicators are unlikely to be consistent between different types of individuals. In fact, individual preferences or incentives can affect the accuracy of health status reports. For instance, individuals who are no longer in the job market (or those who have reduced availability) tend to report more health problems and use health care to justify their reduced labor force participation. Sometimes abusing government social benefits persuades some people to report poor health conditions (Currie and Madrian, 1999).

Self-reported health may also be affected by the incentives for seeking treatment. This can be influenced by education, wage, employment, and health insurance status. Also, individuals who have higher incomes are more likely to use health care services than low wage individuals. Therefore, those with higher incomes may report more health problems.

Because of these reasons, studies that use self-reported health measurement, usually employ a certain econometrics technique to address the measurement issues.

Section 4 of this paper discusses the endogeneity problem and its consequences on the accuracy of the results. The methodology of this study to manage the endogeneity problem is discussed later, in Section 5.

4. Unobserved Heterogeneity

Unobserved heterogeneity refers to situations in which unobserved characteristics are related to both the dependent and independent variables. Unobserved heterogeneity causes endogeneity bias. Based on the results of previous studies (mentioned in Section 2), unobserved heterogeneity exists in the context of the relationship between health and wages. As an example, self-discipline can be considered as an unobserved factor that is expected to improve both health and wages (Currie and Madrian, 1999). In this case, estimated coefficients of the effects of health on wages might be biased. Therefore, they may not properly reflect the actual impact of health on wages. Therefore, when using self-reported health, the health measurement correlates with the error term in the wage equation, and thus it must be treated as an endogenous component. The endogeneity problem is expected to bias the relevant regression coefficients upward (Currie and Madrian, 1999). This means that the actual effects of health on wages may be overestimated by the model.

In this study, I use the fixed-effects model to correct the bias associated with unobserved heterogeneity. The fixed-effects model removes omitted variable bias by measuring changes within groups across time. In statistics, the omitted variable bias occurs when a statistical model overlooks one or more relevant variables. In particular, the omitted variable bias appears when the dependent variable is correlated with one or more independent variables omitted from the model. Under such circumstances, the results of the regression will be biased. This happens because omitting one or more variables violates the assumption that the error term is uncorrelated with the regressors.

Some models, such as fixed-effects, can be used to handle the problems of omitted variable bias. Accordingly, I use the fixed-effects model to deal with time-invariant unobserved variables.

5. Data and Econometrics Model

This section describes data and variables that are used to estimate the wage equation.

5-1. Data

Data extracted from National Longitudinal Survey of Youth (NLSY79) were used in this study. This database contains income details and the health status of individuals from 1979.

In this study, the wage equations for men and women were estimated separately. This approach makes it possible to account for gender-sensitive experiences in the labor market. For instance, previous studies have shown that, in general, women earn less than men, and they experience slower wage growth compared with men. Gender-sensitive differences in the labor market have roots in different factors, such as different human capital investment strategies for men and women (Preston (2000), Eastough and Miller (2004)).

This paper uses self-reported health status as a measure of health condition. In the self-reported part of NLSY79, respondents are asked whether their health conditions limit the type/amount of work they can do. The answer is either Yes or No. This means that the health status is a binary variable; 1 and 0 indicate poor health and good health condition, respectively.

In NLSY79, respondents are asked to report their race categorized into three groups: Black, Hispanic, and non-Black/non-Hispanic. Due to brevity, Black and Hispanic groups are referred to as non-White and the last group is referred to as White in this paper.

In terms of the level of education, the highest grade completed at the age of thirty is used in the model to consider differences in human capital.

Work experience was considered as one of the variables of the model. To obtain work experience, the number of weeks an individual worked in each year is divided by fifty. The accumulated work experience is then calculated by adding up this number for previous years. Thus, the work experience number for each year is a cumulative value. This value represents the work experience of individuals from the beginning of the study period (1979). CPI (Consumer Price Index) is used to calculate the real hourly wage. Wages less than 1 dollar and greater than 500 dollars are omitted from the model.

Table 2 shows the number of individuals in the sample. Table 3 represents the descriptive statistics of the variables in the four subsamples of White and non-White workers.

Table 2: Number of Individuals in the Sample

Sample	Number of individuals
Original sample	12,686
Individuals 30 years or older	9,362
Men	4,634
Women	4,728
White men	2,236
Non-White men	2,398
White women	2,279
Non-White women	2,449

Note: Table 2 shows the number of individuals in the sample.

Table 3: Descriptive Statistics

Variable	Mean	Std. Dev.
Men:		
White		
Hourly wage	14.00	16.58
Health status	0.062	0.24
Work experience	18.83	9.59
Education	13.91	2.71
Non-White		
Hourly wage	9.99	13.31
Health status	0.10	0.31
Work experience	13.19	9.59
Education	12.81	2.55
Women:		
White		
Hourly wage	9.85	14.41
Health status	0.09	0.29
Work experience	16.49	9.41
Education	14.18	2.64
Non-White		
Hourly wage	8.21	10.16
Health status	0.131	0.33
Work experience	12.42	9.02
Education	13.43	2.77

Note: Table 3 shows the means and the standard deviations of variables in the subsamples of White and non-White workers.

5-2. Model

I build on the well-known Mincer equation, which explains the wage as a function of two main variables: education and work experience. Specifically, the standard Mincer equation is given by

$$ln(w_{i,t}) = \beta_0 + \beta_1 s_i + \beta_2 x_{i,t} + \beta_3 x_{i,t}^2 + \epsilon_{i,t}, \tag{1}$$

where s_i is the education level of person i, $w_{i,t}$ and $x_{i,t}$ are his/her wage and work experience at time t, respectively, while $\epsilon_{i,t}$ is the error term. To study the effect of health status on wages, I consider the following equation:

$$\ln(w_{i,t}) = \beta_0 + \beta_1 s_i + \beta_2 x_{i,t} + \beta_3 x_{i,t}^2 + \delta h_{i,t} + \epsilon_{i,t}, \tag{2}$$

where $h_{i,t}$ represents the health status of individual i at time t.

As the first step of the regression analysis, the random-effects model is estimated. Then, to take the unobserved heterogeneity into account, the fixed-effects model is estimated.

6. Empirical Results

6-1 Impact of Current Health Status

This section presents the results of the two models. As discussed earlier, the models were estimated for the subsamples of men and women, separately. Results are presented in Tables 4 and 5. Tables 4 and 5 show that the coefficients of health status are negative and significant for all four subsamples in both random-effects and fixed-effects models, regardless of gender and race.

In all subsamples, using the fixed-effects technique resulted in lower health status coefficients compared to those obtained using the random-effects technique. In the subsample of White men the, estimated health coefficients are -0.077 and -0.065 using the random-effects and fixed-effects models, respectively. In the subsample of non-White men, the estimated health coefficients are -0.078 and -0.045 using the random-effects and fixed-effects models, respectively. In the subsample of White women, the estimated health coefficients are -0.076 and -0.061 using the random-effects and fixed-effects models, respectively. In the subsample of non-White women, the estimated health coefficients are -0.051 and -0.028 using the random-effects and fixed-effects models, respectively.

Table 4: Results for White Workers

Variable	Random-Effects	Fixed-Effects
	Coef. (Std. Err.)	Coef. (Std. Err.)
Men:		
Current health status, $h_{i,t}$	-0.077***	-0.065***
	(0.023)	(0.015)
Work experience, $x_{i,t}$	0.030***	0.030***
	(0.002)	(0.001)
Work experience^2, $x_{i,t}^2$	-3e-4***	-3e-4***
	(5e-5)	(2e-5)
Education, s_i	0.099***	
	(0.004)	
Constant	0.514***	1.963***
	(0.068)	(0.013)
Women:		
Current health status, $h_{i,t}$	-0.076***	-0.061***
	(0.017)	(0.013)
Work experience, x_{it}	0.030***	0.028***
	(0.023)	(0.001)
Work experience^2, $x_{i,t}^2$	-4e-4***	-4e-4***
	(5e-5)	(3e-5)
Education, s_i	0.083***	
	(0.003)	
Constant	0.427***	1.673***
	(0.059)	(0.013)

Note: Table 4 shows the coefficients and standard errors of random-effects and fixed-effects models in the subsamples of White workers. The significance level of 0.01 is denoted by ***.

Table 5: Results for non-White Workers

Variable	Random-Effects	Fixed-Effects
	Coef. (Std. Err.)	Coef. (Std. Err.)
Men:		
Current health status, $h_{i,t}$	-0.078*** (0.028)	-0.045** (0.010)
Work experience, $x_{i,t}$	0.020*** (0.002)	0.018*** (8e-4)
Work experience^2, $x_{i,t}^2$	-3e-4*** (6e-5)	-3e-4*** (2e-5)
Education, s_i	0.093*** (0.005)	
Constant	0.561*** (0.076)	1.869*** (0.012)
Women:		
Current health status, $h_{i,t}$	-0.051*** (0.016)	-0.028** (0.012)
Work experience, $x_{i,t}$	0.028*** (0.002)	0.027*** (0.001)
Work experience^2, $x_{i,t}^2$	-5e-4*** (5e-5)	-5e-4*** (3e-5)
Education, s_i	0.083*** (0.003)	
Constant	0.430*** (0.049)	1.649*** (0.008)

Note: Table 5 shows the coefficients and standard errors of random-effects and fixed-effects models in the subsamples of non-White workers. The significance level of 0.01 is denoted by ***. The significance level of 0.05 is denoted by **.

6-2 Impact of Past Health Status

In this section, the impact of health problems on the wages of the year following health incidents is discussed. In other words, this part of the study examines whether past health status affects the current wage. Specifically, I consider the following model:

$$ln(w_{i,t}) = \beta_0 + \beta_1 s_i + \beta_2 x_{i,t} + \beta_3 x_{i,t}^2 + \delta h_{i,t} + \gamma h_{i,t-1} + \epsilon_{i,t}, \qquad (3)$$

where $h_{i,t-1}$ denotes health status of person i in year *t-1*.

Tables 6 and 7 show the estimated coefficients of health status in the year following a reported health problem, that is time *t-1*, and in the year in which the health problem occurs, namely time *t*, in the subsamples of White workers and non-White workers respectively.

In the subsample of White men, the estimated health coefficients are -0.054 and -0.047 using the random-effects and fixed-effects models, respectively. In the subsample of non-White men, the estimated health coefficients are insignificant in both random-effects and fixed-effects models. In the subsample of White women, the estimated health coefficients are -0.078 and -0.070 in random-effects and fixed-effects models, respectively. In the subsample of non-White women, the estimated health coefficients are -0.085 and -0.074 in random-effects and fixed-effects models, respectively.

Comparing the results presented in Table 6 and Table 7, can be seen that, in the subsample of White men, the estimated coefficients of health status in both random-effects and fixed-effects models in the year following a health incident are smaller than the year in which the health problem is reported. On contrary, for the subsamples of White and non-White women, the estimated coefficients of health status in the year following the health problems are higher compared to those estimated for the year in which health problems occur, in both random-effects and fixed-effects models.

The summary of the results is reported in Table 8. Results presented in Table 8 show that, regardless of the gender and race of the studied subsamples, health problems have an adverse impact on wages in time *t*. Except for the subsample of non-White men, health problems of time *t-1* have a negative impact on wages of time *t* in the other subsamples.

Table 6: Results for White Workers

Variable	Random-Effects	Fixed-Effects
	Coef. (Std. Err.)	Coef. (Std. Err.)
Men:		
Past health status, $h_{i,t-1}$	-0.054**	-0.047**
	(0.024)	(0.017)
Current health status, $h_{i,t}$	-0.052**	-0.044**
	(0.022)	(0.017)
Work experience, $x_{i,t}$	0.028***	0.028***
	(0.002)	(0.001)
Work experience^2, $x_{i,t}^2$	-3e-4***	-3e-4***
	(5e-5)	(3e-5)
Education, s_i	0.102***	
	(0.004)	
Constant	0.496***	1.989***
	(0.071)	(0.015)
Women:		
Past health status, $h_{i,t-1}$	-0.078***	-0.070***
	(0.018)	(0.015)
Current health status, $h_{i,t}$	-0.036*	-0.026*
	(0.019)	(0.015)
Work experience, $x_{i,t}$	0.030***	0.029***
	(0.002)	(0.001)
Work experience^2, $x_{i,t}^2$	-4e-4***	-4e-4***
	(5e-5)	(3e-5)
Education, s_i	0.083***	
	(0.004)	
Constant	0.417***	1.673***
	(0.060)	(0.014)

Note: Table 6 shows the coefficients and standard errors of random-effects and fixed-effects models in the subsamples of White workers. The significance level of 0.01 is denoted by ***. The significance level of 0.05 is denoted by **. The significance level of 0.1 is denoted by *.

Table 7: Results for non-White Workers

Variable	Random-Effects	Fixed-Effects
	Coef. (Std. Err.)	Coef. (Std. Err.)
Men:		
Past health status, $h_{i,t-1}$	0.001 (0.030)	0.014 (0.020)
Current health status, $h_{i,t}$	-0.058* (0.030)	-0.038* (0.020)
Work experience, $x_{i,t}$	0.020*** (0.002)	0.019*** (0.001)
Work experience^2, $x_{i,t}^2$	-3e-4*** (6e-5)	-3e-4*** (3e-5)
Education, s_i	0.096*** (0.005)	
Constant	0.556*** (0.072)	1.904*** (0.011)
Women:		
Past health status, $h_{i,t-1}$	-0.085*** (0.017)	-0.074*** (0.015)
Current health status, $h_{i,t}$	-0.005 (0.019)	0.009 (0.015)
Work experience, $x_{i,t}$	0.028*** (0.002)	0.027*** (0.001)
Work experience^2, $x_{i,t}^2$	-5e-4*** (6e-5)	-5e-4*** (3e-5)
Education, s_i	0.083*** (0.003)	
Constant	0.433*** (0.051)	1.648*** (0.009)

Note: Table 7 shows the coefficients and standard errors of random-effects and fixed-effects models in the subsamples of non-White workers. The significance level of 0.01 is denoted by ***. The significance level of 0.1 is denoted by *.

Table 8: Summary of the Effects of Health Status on Wages

Variable	Random-Effects	Fixed-Effects
Men:		
White		
Health status of time *t*	-7.7%***	-6.5%***
Health status of time *t-1*	-5.4%**	-4.7%**
Non-White		
Health status of time *t*	-7.8%***	-4.5%**
Health status of time *t-1*	0.1%	1.4%
Women:		
White		
Health status of time *t*	-7.6%***	-6.1%***
Health status of time *t-1*	-7.8%***	-7.0%***
Non-White		
Health status of time *t*	-5.1%***	-2.8%**
Health status of time *t-1*	-8.5%***	-7.4%***

Note: Table 8 shows the effects of health status on wages in all subsamples. The significance level of 0.01 is denoted by ***. The significance level of 0.05 is denoted by **.

7. Conclusion

In this paper, the relationship between health status and the hourly rate of wages was studied using NLSY79. The fixed-effects estimation method was used to solve the possible endogeneity of the self-assessed health status in the wage equation.

The findings of this study showed that health problems of time t adversely affect wages in both White and non-White subsamples. In other words, individuals with poor health conditions are more likely to have lower wages compared with peers with normal health conditions.

The same results can be obtained using either the fixed-effects or random-effects models. However, when using the fixed-effects model, the estimated impact of health status on wages is lower than the impact levels estimated using the random-effects model.

In this study the impact of health problems on the wages of the year following health incidents was also examined. In the subsample of White men, the estimated coefficients of health status are smaller compared to the estimated coefficients for the year in which health problems occur. In the subsample of non-White men, based on the results of both random-effects and fixed-effects models, health problems of the last year have no impact on the hourly rate of wage of the current year. Conversely, for the subsamples of White and non-White women, the estimated coefficients of health status in the year following the health problems are higher compared to the estimated coefficients for the year in which health problems occur. In the subsamples of women, poor health can be related to the pregnancy duration or pregnancy-related complications. Thus, one year after these health-related issues, it is possible that these women decide to quit the labour force or reduce their working hours. Also, it is likely that they switch from a full-time job to a lower paying part-time job.

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A. Appendix

This section provides information about age categories and the health status of all subsamples.

Table 9: Age Categories

Age	Percent
Men:	
White	
30-40	40.00
41-50	36.04
51 and older	23.06
Non-White	
30-40	40.10
41-50	36.04
51 and older	23.06
Women:	
White	
30-40	39.80
41-50	36.20
51 and older	24.00
Non-White	
30-40	39.82
41-50	36.20
51 and older	23.98

Note: Table 9 shows the age distribution in each subsample.

Table 10: Health Status

Health status	Percent
Men:	
White	
Good health	93.70
Poor health	6.30
Non-White	
Good health	89.09
Poor health	10.91
Women:	
White	
Good health	90.24
Poor health	9.76
Non-White	
Good health	86.90
Poor health	13.10

Note: Table 10 shows the percentage of individuals with different health statuses in each subsample.