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EMPIRICAL RESULTS: THE NORC SAMPLE

This chapter presents empirical estimates of demand curves for health and medical care and gross investment production functions. The first part of the chapter contains the analysis performed with whites in the labor force who reported positive sick time in 1963. This analysis is emphasized because of the 1,770 persons in the labor force, 558 had some sick days in 1963 and 1,212 had no sick days. Since the characteristics of these two groups are very similar, it is difficult to explain the behavior of the latter. Put differently, the two groups essentially represent "two different samples," and problems arise when the data are pooled. The second part discusses these difficulties and also shows how the results are affected by excluding females from the regressions.

1. WHITES WITH POSITIVE SICK TIME

Demand Curves for Health and Medical Care

Tables 1, 2, and 3 present alternative estimates of health stock, health flow, and medical care demand curves. Five demand curves appear for

TABLE 1

Stock Demand for Health by Whites with Positive Sick Time

(N = 558)

Income Measure	ln Y	ln W	E	i	Sex	ln FS	$\bar{R}^2$
$Y1$	.004	.127	.025	−.009	−.092	−.018	.171
	(.09)	(2.41)	(4.05)	(−6.23)	(−1.90)	(−.45)	
$Y2$	.049	.098	.025	−.009	−.108	−.027	.172
	(.99)	(2.01)	(4.12)	(−6.32)	(−2.15)	(−.69)	
$Y4$	.063	.090	.025	−.009	−.112	−.033	.174
	(1.41)	(1.95)	(4.11)	(−6.36)	(−2.26)	(−.82)	
$Y4$[a]	.117		.029	−.009	−.159	−.049	.170
	(3.36)		(5.09)	(−6.25)	(−3.64)	(−1.26)	
Y omitted		.130	.025	−.009	−.091	−.017	.172
		(3.63)	(4.06)	(−6.26)	(−1.93)	(−.45)	

NOTE: N indicates the sample size, t ratios are in parentheses, and intercepts are not shown. For definitions of the three income variables, see Chapter IV, Section 2.

[a] In this regression, the wage rate is excluded.

TABLE 2
Flow Demand for Health by Whites with Positive Sick Time

Income Measure	ln Y	ln W	E	i	Sex	ln FS	$\bar{R}^2$
			$TL = WLD1$				
$Y1$	−.280	.554	.046	−.006	.010	.251	.087
	(−2.03)	(4.01)	(2.87)	(−1.67)	(.08)	(2.46)	
$Y2$	−.221	.497	.044	−.007	.033	.261	.085
	(−1.72)	(3.88)	(2.74)	(−1.75)	(.25)	(2.51)	
$Y4$	−.031	.367	.046	−.007	−.032	.222	.080
	(−.26)	(3.04)	(2.86)	(−1.86)	(−.25)	(2.12)	
$Y4$[a]	.193		.063	−.007	−.223	.155	.067
	(2.08)		(4.14)	(−1.68)	(−1.93)	(1.51)	
Y omitted		.349	.046	−.007	−.043	.214	.082
		(3.69)	(2.87)	(−1.89)	(−.34)	(2.13)	
			$TL = RAD$				
$Y1$	−.282	.392	.046	−.009	−.072	.226	.063
	(−1.97)	(2.74)	(2.77)	(−2.17)	(−.54)	(2.15)	
$Y2$	−.248	.352	.044	−.009	−.040	.242	.062
	(−1.85)	(2.65)	(2.64)	(−2.23)	(−.30)	(2.25)	
$Y4$	−.147	.280	.046	−.009	−.076	.226	.058
	(−1.21)	(2.33)	(2.73)	(−2.28)	(−.56)	(2.09)	
$Y4$[a]	.023		.058	−.009	−.222	.176	.052
	(.24)		(3.73)	(−2.15)	(−1.86)	(1.65)	
Y omitted		.186	.046	−.010	−.125	.190	.058
		(1.89)	(2.77)	(−2.38)	(−.97)	(1.82)	

NOTE: See the notes to Table 1.

each of the four dependent variables—ln H, −ln $WLD1$, −ln RAD, and ln M.[1] In the first three regressions, family income equals $Y1$, $Y2$, or $Y4$. The fourth regression shows how the coefficients are affected if income is measured by $Y4$ and the wage rate is excluded. The last regression includes the wage but leaves out income.

As a guide to interpreting these regressions, Table 4 shows the means and coefficients of variation of the four endogenous variables. Since individuals are the units of observation, the coefficients of variation are

[1] Since 2.4 percent of the sample reported no medical outlays, M, and not its natural logarithm, is the dependent variable in Table 3. All regression coefficients were converted to elasticities or percentage changes at the mean by multiplying by $1/\bar{M}$. These elasticities or percentage changes are presented in Table 3.

TABLE 3
Demand for Medical Care by Whites with Positive Sick Time

Income Measure	ln *Y*	ln *W*	*E*	*i*	Sex	ln *FS*	$\bar{R}^2$
*Y*1	.701	−.170	.009	.016	.597	−.122	.063
	(3.36)	(−.81)	(.35)	(2.66)	(3.10)	(−.79)	
*Y*2	.754	−.162	.015	.016	.473	−.190	.069
	(3.87)	(−.84)	(.62)	(2.71)	(2.37)	(−1.21)	
*Y*4	.695	−.105	.012	.016	.499	−.204	.070
	(3.92)	(−.57)	(.47)	(2.72)	(2.54)	(−1.29)	
*Y*4[a]	.632		.007	.016	.554	−.185	.071
	(4.57)		(.29)	(2.70)	(3.21)	(−1.20)	
Y omitted		.343	.008	.018	.730	−.031	.046
		(2.38)	(.33)	(3.00)	(3.83)	(−.20)	

NOTE: See the notes to Table 1.

TABLE 4
Means and Coefficients of Variation,
Endogenous Variables

Variable	Mean	Coefficient of Variation (percent)
H[a]	3.1	47.0
*WLD*1[b]	16.6 days	194.1
RAD	16.3 days	211.4
M	$208.2	179.7

[a] The frequency distribution of health status is as follows: excellent, 35.7 percent of sample; good, 41.8 percent; fair, 17.9 percent; poor, 4.7 percent.

[b] The mean of *WLD*1 exceeds the mean of *RAD* because reported work-loss was multiplied by 52/*WW*—a number that is equal to or greater than unity.

extremely large. This explains why the coefficients of multiple determination ($\bar{R}^2$) are relatively low.[2] The correlation coefficient between *WLD*1 and *RAD* is .835, which indicates the close relation between these two measures of sick days.

[2] J. S. Cramer has shown that in the absence of errors of measurement, grouping the data by the independent variables would *raise* the R^2, *reduce* the *t* ratios associated with regression coefficients, and *have no effect* on the expected value of the estimate of the residual variance. See "Efficient Grouping, Regression and Correlation in Engel Curve Analysis," *Journal of the American Statistical Association*, 59, No. 5 (March 1964).

Since the coefficients of the investment model depend on the elasticity of the MEC schedule, it is helpful to estimate ε. This parameter can be computed from the production function of healthy days given by

$$h = 365 - BH^{-C},$$

or

$$-\ln TL = -\ln B + C \ln H,$$

since it has been shown that $\varepsilon = 1/(1 + C)$. Using $-\ln WLD1$ and $-\ln RAD$ as alternative proxies for $-\ln TL$, I obtained the following two regressions:

$$-\ln WLD1 = .854 \ln H \quad (8.58) \qquad \varepsilon = .54$$

$$-\ln RAD = .955 \ln H \quad (9.49) \qquad \varepsilon = .51$$

In neither case is the regression coefficient significantly different from one at the .05 level of confidence on a two tail test. Therefore, it is concluded that the best estimate of ε is .5.

Table 5 shows the effects of selecting alternative sets of scales for health status on the stock demand curve. Series A is the one stressed in

TABLE 5
Stock Demand Curves, Alternative Health Capital Series

$\ln Y4$	$\ln W$	E	i	Sex	$\ln FS$	$\bar{R}^2$
			Series A[a]			
.171	.252	.067	−.028	−.360	−.096	.153
(1.25)	(1.78)	(3.59)	(−6.09)	(−2.37)	(−.79)	
			Series B[a]			
.094	.177	.049	−.017	−.166	−.034	.189
(1.20)	(2.21)	(4.59)	(−6.54)	(−1.92)	(−.49)	
			Series C[a]			
14.927	19.466	5.789	−1.927	−20.321	−7.253	.181
(1.60)	(2.02)	(4.52)	(−6.23)	(−1.96)	(−.87)	

[a] See the text for definition.

Chapter IV and used in Table 1: 1 = poor, 1.7 = fair, 2.3 = good, 5.0 = excellent. In Series B, the four values of health status are 1 = poor, 2 = fair, 3 = good, 4 = excellent; and in Series C, these four values are 0 = poor, 206 = fair, 290 = good, 411 = excellent.[3] Since health capital can equal zero in the last series, H, and not $\ln H$, is the dependent variable in all three regressions. Although the magnitudes of the regression coefficients vary with the series employed, their signs do not vary, and their t ratios are fairly insensitive.[4] These findings should strengthen our confidence in the results obtained with Series A. This series, like the theoretical index, is free of units. Therefore, there is some justification for the magnitudes of its regression coefficients.

A comparison of the results in Tables 1 and 3 reveals that although medical outlays were used to scale health capital, the estimated regression coefficients in the health stock demand curve are not linear transformations of the regression coefficients in the medical care demand curve. For example, the coefficient of education in the health stock demand curve is .025 with a t ratio of approximately 4. The corresponding coefficient in the medical care demand curve is approximately .010 with a t ratio of approximately .5.

The estimated demand parameters of age, education, the wage rate, family income, sex, and family size are now discussed in detail. The regression coefficients of age are negative in the health stock and health flow demand curves, while the regression coefficient is positive in the medical care demand curve. These signs are exactly what would be expected if depreciation rates rose with age and if the elasticity of the MEC schedule were less than unity. All regression coefficients are significant at the .05 level of confidence on a one-tail test, and their magnitudes are independent of the family income variable employed. The results indicate that health capital falls over the life cycle at a continuously compounded rate of .9 percent per year. The rates of increase in restricted-activity days, work-loss days, and medical outlays are .9, .7, and 1.6 percent per year, respectively.

The estimates of ε and $\tilde{H}$ can be used to compute $\tilde{\delta}$, the continuously compounded rate of increase in the depreciation rate over the life cycle. The age parameter in the stock demand curve is $-s_i\tilde{\delta}\varepsilon = .009$. Since $\varepsilon = .5$, one can solve for $\tilde{\delta}$ by assigning arbitrary values to s_i, the share

[3] See Chapter IV, Section 2, for a discussion of these three series.

[4] These conclusions hold when $Y1$ or $Y2$ replaces $Y4$ as the measure of family income.

of depreciation in the cost of health capital. For values of s_i that range from .25 to 1, the estimates of $\tilde{\delta}$ are:[5]

s_i	$\tilde{\delta}$
.25	7.2%
.50	3.6
.75	2.4
1.00	1.8

Since s_i rises with age, $\tilde{\delta}$ is unlikely to be as large as 7.2 percent. Perhaps the best estimate is an average of the last two rates or 2.1 percent.

Suppose none of the reduction in health capital associated with a given increase in the rate of depreciation were offset by an increase in gross investment. Then the number of periods it would take for a certain percentage of a person's initial stock of health to depreciate could be calculated.[6] With $\tilde{\delta} = 2.1$ percent, 70 percent of the initial stock would depreciate by age 58, 80 percent by age 77, and 90 percent by age 96. In fact, medical outlays rise over the life cycle so that these ages understate the time that must elapse before the stock of health falls to specified levels. If, for example, the ratio of the death stock to the initial stock were .3, individuals would not die at age 58. Instead, because the demand for health is relatively inelastic, they would have an incentive to postpone death by investing more at later than at earlier ages.

Whether health is measured by H, $-WLD1$, or $-RAD$, the regression coefficient of education is positive and statistically significant at conventional levels. It is seen that the continuously compounded rate of growth in health capital for a one year increase in the level of formal schooling is 2.5 percent. The rates of decrease in the number of work-loss days and the number of restricted-activity days are both equal to 4.6 percent. These results imply that an increase in education raises the marginal products of the direct inputs in the gross investment production function, lowers marginal cost, and shifts the MEC schedule to the right. Therefore, the demand for health increases. Since there is reason to believe the elasticity of the MEC schedule is less than unity, education should be

[5] Since $\tilde{H}$ equals $\widetilde{RAD}$ and is only slightly greater than $\widetilde{WLD}1$, the calculations of $\tilde{\delta}$ would not be affected if the flow parameters were utilized. Note that the age-health profile is concave to the origin for $s_i < 1$, which suggests that the square of age should be added to the set of independent variables. Attempts to do this were not successful because age and age squared are extremely highly correlated.

[6] If none of the increase in $\tilde{\delta}$ were offset, then $H_i = H_1 \exp(-\tilde{\delta}i)$. Given $\tilde{\delta}$, one can find the age at which H_i/H_1 equals, for example, .1.

negatively correlated with medical expenditures. In fact, the regression coefficient is positive but not significant.

The education parameter in the health demand curve is given by $r_H \varepsilon$, where r_H is the percentage improvement in health productivity per unit increase in E or the percentage reduction in marginal cost. Since $\varepsilon = .5$, the stock coefficient suggests r_H equals 5.0 percent, and the flow coefficient suggests it equals 9.2 percent.[7] An average of these two estimates indicates that the marginal cost of producing gross additions to health capital is roughly 7.1 percent lower for consumers with, say, eleven years of formal schooling compared to those with ten years.

In accordance with the a priori notion that an increase in the wage rate raises the monetary return and hence the rate of return on an investment in health, the wage is positively related to the stock of health and the number of healthy days. All wage elasticities of health are statistically significant but tend to vary with the measure of family income employed. Therefore, the first column of Table 6 shows the average of, for instance, the stock elasticities obtained with the three family income variables. Mean wage elasticities of H, $-WLD1$, and $-RAD$ are .105, .471, and .341, respectively. The large magnitudes of the flow elasticities are more consistent with the investment model than with the consumption model.[8]

TABLE 6
Average Wage, Income, and Family Size Elasticities

Dependent Variable	Average Wage Elasticity	Average Income Elasticity	Average Family Size Elasticity
$\ln H$	.105	.039	.013
$-\ln WLD1$	.471	−.177	.067
$-\ln RAD$	.341	−.226	.006
$\ln M$	−.146	.717	.545

[7] Since the best estimate of C is unity, stock and flow regression coefficients of a given variable should be equal. Although the age coefficients are very similar, the flow coefficient of education is almost twice as large as the stock coefficient. This accounts for the variation in the estimate of r_H.

[8] To the extent that people must be paid higher than average wages to enter occupations or industries that are detrimental to health, wage elasticity estimates are biased *downward.* In addition, it should be realized that the analysis is limited to members of the labor force. Thus, any statements about the superiority of the investment model relative to the consumption model pertain to this group alone.

An upward shift in the wage rate should not only increase health but also medical care. Unfortunately, the wage elasticity of medical care is negative but not significant.

The wage elasticity of health equals $(1 - K)\varepsilon$, where K is the fiaction of the total cost of gross investment accounted for by time. According to the stock elasticity estimate, K equals .79, and according to the flow elasticity, it equals .19.[9] The mean of these two time shares is .49. If the average time intensity of nonmarket production equaled .5, gross investment in health would be neither a goods-intensive activity nor a time-intensive activity. Of course, this is merely a tentative conclusion because the average time intensity is unknown and because the estimate of K has a large variance.

It should be noted that the effects of measurement errors may explain why education and the wage rate have the "wrong signs" in the demand curve for medical care.[10] Appendix D, Section 2, indicates that regression coefficients are influenced by measurement error for two reasons. First, the wage rate is likely to contain random errors of observation. Second, with education held constant, the wage rate is probably positively correlated with other determinants of nonmarket efficiency, such as innate ability. Under certain conditions, it can be shown that these two forces bias the estimated wage elasticity of health in *opposite* directions; measurement error biases it downward, ability biases it upward, and the net effect is not clear. Similarly, the education coefficient in the health demand curve is biased in opposite directions. On the other hand, the two sources of bias operate in the *same* direction on any given coefficient in the demand curve for medical care. In particular, they bias the wage elasticity downward and the education coefficient upward.[11]

[9] The calculation of K from the flow parameters uses an average of the wage elasticities of $-WLD1$ and $-RAD$.

[10] Jacob Mincer points out that the observed effects of the wage rate and education on medical outlays can also be explained by assuming that the stock of health is one determinant of the wage rate. Mincer postulates that w'th the wage fixed, an increase in education may be accompanied by a decrease in health and other forms of human capital. Since a reduction in health is likely to increase medical outlays, the education coefficient would be biased upward. The difficulty with this explanation is that it tends to be contradicted by the health demand curve estimates. With the wage constant, healthy time and the index of health capital are positively related to education.

[11] Suppose the two biases exactly offset each other in the health demand curve. Then the expected value of any regression coefficient would be an unbiased estimate of the corresponding population parameter. In this situation, one can, for example, use the wage elasticity of health to solve for the wage elasticity of medical care. He can then force the

Before the effects of family income are summarized, recall that $Y1$ and $Y2$ are partially adjusted for variations in weeks worked, while $Y4$ is not adjusted. The relationship between each of these three income variables and the stock of health is positive but not significant at conventional levels. On the other hand, income effects are *negative* in the flow demand curves. When $Y1$ or $Y2$ enters the regressions, flow income elasticities are statistically significant. The elasticities are not significant when $Y4$ enters and are much smaller in absolute value. In contrast to the negative or weak positive health income elasticities, the income elasticities of medical care are all positive and very significant.

To check the validity of the income elasticity estimates, these coefficients were recomputed after excluding members of "atypical families" —those with three or more wage earners—from the sample. In the regressions run with persons from families with one or two wage earners, family income fully adjusted for variations in weeks worked by all members ($Y3$) was added to the set of income proxies. Income elasticities for this group are as follows:[12]

Income Measure	$\ln H$	$-\ln WLD1$	$-\ln RAD$	$\ln M$
$Y1$	−.005	−.285	−.288	.722
$Y2$	.041	−.238	−.251	.752
$Y3$	.032	−.240	−.213	.611
$Y4$	.057	−.040	−.149	.693
Average elasticity	.031	−.201	−.225	.695

The average income elasticities are almost identical to those for all whites with positive sick time, which are given by column 2 of Table 6. Moreover, $Y3$ elasticities are in most cases very similar to $Y2$ elasticities.

It should be noted that income has a negative effect on the number of healthy days and a positive but weak effect on the amount of health capital only if the wage rate is held constant. When the wage is left out of the regressions, health income elasticities are positive and, with the exception of the RAD elasticity, statistically significant. The simple

wage coefficient to assume its proper value in the demand curve for medical care and see how the estimates of the other coefficients in this function are affected. For some a priori estimates along these lines, see Appendix E, Section 1.

[12] The sample size is 542. The coefficients of the other exogenous variables are quite similar to those in Tables 1, 2, and 3.

correlation coefficients between ln W and ln $Y1$, ln $Y2$, and ln $Y4$ are .754, .645, and .606, respectively. Hence, health income elasticities are seriously biased by the omission of the wage rate.[13]

The consumption model predicts a positive correlation between health and income, while the investment model predicts a zero correlation. This raises the question: How should one interpret the negative income elasticity of healthy days? Some readers may say that this finding is artificial, for if the wage rate is one of the independent variables, it is not meaningful to include income as an additional explanatory variable. For the benefit of these readers, Tables 1, 2, and 3 reveal that gross wage elasticities of health—elasticities obtained when family income is omitted from the regressions—always exceed gross income elasticities. Furthermore, the gross wage elasticity of medical care is positive and significant, as the investment model would predict. I would argue, however, that it is meaningful to include both family income and the wage in the regressions. These variables are not so highly correlated that the results are dominated by multicollinearity. In addition, the gross wage elasticity of medical care is much smaller than the gross income elasticity (.343 compared with .632). This suggests that income has an effect in the model that is at least partly independent of the wage effect.

Given that my procedure is valid, does the negative income elasticity of healthy days imply health is an inferior commodity? If the consumption aspects of health were at all relevant, then a literal interpretation of the income coefficient would suggest that this is in fact the case. It is possible, however, to account for the negative income elasticity of health without assuming it is an inferior commodity. The explanation offered in the next chapter stresses that medical care is not the only market input in the gross investment production function. Instead, inputs such as diet, exercise, recreation goods, alcohol, cigarettes, and rich food are also relevant. The last three inputs have *negative* marginal products, and if their income elasticities exceeded the income elasticities of the beneficial inputs, the shadow price of health would be positively correlated with

[13] For a similar conclusion, see Morris Silver, "An Economic Analysis of Variations in Medical Expenses and Work-Loss Rates," in Herbert E. Klarman (ed.), *Empirical Studies in Health Economics*, Baltimore, 1970, and reprinted as Chapter 6 in Victor R. Fuchs (ed.), *Essays in the Economics of Health and Medical Care*, New York, NBER, 1972. Although Silver's interpretation of the negative health elasticity differs from the one I present in Chapter VI, he should be credited for stressing the importance of holding the wage constant. It should also be indicated that the partial correlation between ln Y and ln W is relevant in an examination of "omitted variable bias." But in the NORC sample, this correlation coefficient is approximately equal to the simple correlation.

income. This appears to be a promising explanation because it can also account for the positive correlation between medical care and income. That is, it can show the conditions under which persons with higher incomes would simultaneously reduce their demand for health and increase their demand for medical care.

The role of the sex dummy variable (1 = female) in the health demand curves is somewhat ambiguous. Females have significantly smaller stocks of health than males, more restricted-activity days, but fewer work-loss days except when income is measured by $Y4$. In the demand curve for medical care, the coefficient of the sex dummy indicates that outlays by women are approximately 50 percent higher than outlays by men. Although these results are generally consistent with the hypothesis that males are more efficient producers of health than females, they are also undoubtedly related to childbearing.

Column 3 of Table 6 gives average family size elasticities of health and medical care. These elasticities are computed by summing the actual coefficients of $\ln Y$ and $\ln FS$ and are the coefficients that would be obtained if command over resources were measured by per capita income. Family size is positively correlated with each of the three indexes of health and also with medical care. One interpretation of these correlations is that the number of children in a family and the health levels of its adult members are complements.

The Gross Investment Production Function

Table 7 presents ordinary least squares and two-stage least squares estimates of gross investment production functions. In the ordinary least squares regressions, the elasticities of the three measures of health with respect to medical services are all *negative*, which reflects the strong positive relation between medical care and the depreciation rate. The two-stage regressions employ values of M predicted from its demand curve.[14] It is seen that when income is excluded from the second stage, the elasticities of H and $-WLD1$ with respect to M are both positive and approximately equal to .2, while the elasticity of $-RAD$ is negative. If income is included as a proxy for other market inputs in the production function, the elasticity of H is reduced to .1. On the other hand, the elasticities of $-WLD1$ and $-RAD$ rise to .5 and .3. Income itself is negatively related to $-WLD1$ and $-RAD$ but positively related to H.

[14] The prediction equation uses per capita income and sets the family size coefficient equal to .491. Per capita income is measured by $Y4/FS$ because this variable gives the medical care demand curve with the highest $\bar{R}^2$.

TABLE 7
Gross Investment Production Functions of Whites with Positive Sick Time

Dependent Variable	ln *M*	*E*	*i*	Sex	ln *Y4/FS*	$\bar{R}^2$
			Two-Stage Least Squares			
ln *H*	.170	.029	−.012	−.248		.168
	(3.13)	(4.93)	(−6.52)	(−4.78)		
ln *H*	.098	.029	−.011	−.219	.044	.168
	(.97)	(4.93)	(−5.21)	(−3.48)	(.84)	
−ln *WLD*1	.224	.060	−.012	−.418		.059
	(1.55)	(3.87)	(−2.41)	(−3.02)		
−ln *WLD*1	.545	.060	−.015	−.550	−.198	.060
	(2.01)	(3.88)	(−2.79)	(−3.29)	(−1.40)	
−ln *RAD*	−.024	.057	−.010	−.269		.048
	(−.16)	(3.58)	(−1.95)	(−1.89)		
−ln *RAD*	.275	.057	−.013	−.391	−.184	.049
	(.99)	(3.59)	(−2.32)	(−2.28)	(−1.27)	
			Ordinary Least Squares			
ln *H*	−.060	.036	−.007	−.117		.203
	(−5.84)	(6.73)	(−5.02)	(−2.83)		
ln *H*	−.068	.030	−.008	−.143	.117	.226
	(−6.54)	(5.47)	(−5.91)	(−3.49)	(4.33)	
−ln *WLD*1	−.294	.007	−.001	−.124		.241
	(−11.66)	(5.85)	(−.33)	(−1.23)		
−ln *WLDI*	−.304	.068	−.003	−.163	.175	.249
	(−11.98)	(4.99)	(−.89)	(−1.61)	(2.56)	
−ln *RAD*	−.334	.067	−.003	−.093		.277
	(−13.24)	(5.11)	(−.98)	(−.93)		
−ln *RAD*	−.339	.063	−.004	−.112	.085	.278
	(−13.28)	(4.60)	(−1.23)	(−1.11)	(1.24)	

Although it is encouraging that the utilization of two-stage least squares generates positive medical care elasticities of health, these results should be interpreted with *extreme* caution. This follows because they are very sensitive to the particular set of variables excluded from the second stage (*FS* and *W* or *FS*, *W*, and *Y4/FS*). Moreover, the production function coefficients of education and age should be similar to the estimates of r_H and $\tilde{\delta}$ previously computed. Instead, they are almost identical to the actual demand curve coefficients. For these reasons, it is better to emphasize the demand curves that were fitted to the data than to emphasize the production function.

The Role of Disability Insurance

Table 8 introduces two disability insurance dummy variables into the demand curves for health and medical care. The members of the NORC sample who reported positive sick time were not asked whether they were potentially eligible for disability insurance benefits. Instead, only those who had positive gross earnings lost due to work-loss were asked if they received disability benefits. Of the 558 persons who had positive sick time, 285 had no gross earnings lost, 203 had positive gross earnings lost but did not receive disability payments, and 70 received such payments. To compare these three classes, two dummy variables, *Gross* and *Dis*, are used. They are coded as follows:

Class	*Gross*	*Dis*
No gross earning lost	0	1
Disability insurance	1	1
No disability insurance	1	0

In this form, the regression coefficient of *Gross* compares those with no gross earnings lost to those with disability benefits, the coefficient of *Dis* compares those who received benefits to those who did not, and the difference between the two coefficients compares those with no earnings lost to those with no insurance benefits.

The regressions in Table 8 reveal that persons who receive disability benefits had smaller stocks of health, more sick days, and higher medical outlays relative to persons with no benefits and relative to persons with no earnings lost.[15] The regressions also reveal that individuals with no gross earnings lost had larger quantities of health capital, fewer sick days, and smaller medical outlays compared to individuals with gross earnings lost but no disability benefits. Moreover, the coefficients of education in the health demand curves are the ones that are most affected by the introduction of the two dummies. Tables 1 and 2 show these coefficients are very significant when *Dis* and *Gross* are excluded from the regressions. If the dummies are held constant, the stock coefficient of education falls from .025 to .018, and the flow coefficients become insignificant. The coefficients of the other independent variables do not depart radically from those previously obtained.

As shown by the *t* ratio of *Dis* or *Gross*, the partial correlation between either of these two variables and sick time is larger than the partial

[15] The income variable in these regressions is *Y*4. The conclusions reached in the text are not altered when the other income variables are employed

TABLE 8

Demand Curves with Dummies Included for Disability Insurance and Gross Earnings Lost

Dependent Variable	ln *Y4*	ln *W*	*E*	*i*	Sex	ln *FS*	*Dis*	*Gross*	$\bar{R}^2$
ln *H*	.053	.086	.018	−.010	−.104	−.037	−.032	−.170	.192
	(1.29)	(1.90)	(2.85)	(−6.83)	(−2.11)	(−.94)	(−.54)	(−2.87)	
−ln *WLD*1	−.047	.349	.005	−.011	.008	.173	−1.009	−1.561	.245
	(−.44)	(3.18)	(.34)	(−3.18)	(.07)	(1.82)	(−6.96)	(−10.90)	
−ln *RAD*	−.160	.261	.005	−.013	−.036	.176	−1.058	−1.596	.221
	(−1.44)	(2.28)	(.30)	(−3.60)	(−.29)	(1.78)	(−7.02)	(−10.72)	
ln *M*	.698	−.086	.051	.021	.462	−.149	1.205	1.675	.151
	(4.11)	(−.49)	(2.11)	(3.54)	(2.45)	(−.99)	(5.23)	(7.37)	

correlation between sick time and any one of the basic exogenous variables in the model. Does this mean that *Dis* and *Gross* are the major determinants of sick time and that the education effects previously observed are spurious? In my judgment, this is not the case, for I would question the usefulness of holding *Dis* and *Gross* constant. Two factors suggest that the causal relationship runs not from these two variables to sick days but vice versa. In the first place, most informal sick leave arrangements allow employees a certain number of sick days before they begin to lose wages. In the second place, disability insurance plans typically begin to pay benefits only after the recipient has experienced a certain minimum number of sick days. For both these reasons, one would expect that the more sick days a respondent reported, the greater the likelihood that he lost earnings and received disability insurance benefits. This implies that the proper way to assess the impact of sick leave and disability plans on sick days would be to ask all individuals whether they are *potentially* eligible for the benefits provided by these plans. Since the NORC sample was not structured in this manner, the two dummies are, at least in part, proxy variables for sick time.

Additional considerations indicate that the education effects estimated in Tables 1 and 2 are the relevant ones. If an increase in education shifts the MEC schedule to the right, it would simultaneously increase the demand for healthy days and reduce observed gross earnings lost. In fact, *Gross* and E are strongly negatively correlated ($r = -.328$).[16] Since *Gross* is negatively correlated with $-\ln WLD1$, the regression coefficient of E is greatly increased when *Gross* is omitted. The simultaneous determination of earnings lost and sick days by education implies that one should not hold *Gross* constant in estimating the relationship between $-\ln WLD1$ and E.

Even if it is assumed that individuals are partially or fully compensated for their loss in market earnings due to illness, the general properties of my model are still valid. Persons would still have an incentive to demand health capital in order to reduce the time they lose from nonmarket activities and the disutility of illness. In addition, what may be termed "the inconvenience costs of illness" are positively correlated with the wage rate. That is, the complexity of a particular job and the amount of responsibility it entails certainly are positively related to the wage. Thus, when an individual with a high wage rate becomes ill, tasks that only he can perform accumulate. These increase the intensity of his work load

[16] The absolute value of this correlation coefficient is larger than that between *Gross* and any of the other independent variables

and give him an incentive to avoid illness by demanding more health capital.

Once disability insurance and sick leave arrangements are introduced, the value of the marginal product of health capital might not equal WG, but it would surely not equal zero. In the NORC sample, net earnings lost per work-loss day are positively correlated with the number of work-loss days ($r = .102$). Suppose the total loss in earnings due to work-loss is given by WTL, where W equals net earnings lost per day instead of the wage rate. Then the value of the marginal product of health capital would be $W(1 + 1/e_{TL})G$, where e_{TL} is the elasticity of the average loss with respect to sick days. Since this elasticity is positive, the marginal loss $W(1 + 1/e_{TL})$, exceeds the average loss. Therefore, the marginal rate of return on an investment in health might be substantial even if the average daily loss is small.[17]

The behavior of the average loss might explain why many educated persons report no gross earnings lost due to work-loss. Chapter II indicated that if health capital is viewed as a form of self-protection against uncertainty, the rate of return might equal zero in relatively desirable states of the world. Since the more educated have higher rates of return on a given stock of health than the less educated, they would have the greatest incentive to drive the rate of return to zero in relatively desirable states. Suppose individuals suffered no loss in earnings unless their sick time exceeded some maximum quantity TL^*. Then consumers with high levels of formal schooling could drive their rates of return to zero by holding enough health capital to make the number of sick days they experience less than TL^*.

2. SUPPLEMENTARY RESULTS

All Whites in the Labor Force

Table 9 presents health and medical care demand curves for all whites in the labor force. The income variable in these regressions is $Y4$.[18] Since persons with no sick days are included in these regressions, the

[17] If the average daily loss replaces the wage variable in the regressions, a simultaneous equations problem arises because the daily loss depends on sick time. By employing the wage as an index of the potential benefits from reducing sick time, this problem is avoided. Earlier it was shown that the weekly wage variable is positively correlated with net earnings lost per day. Therefore, it does take some account of the effect of informal sick leave arrangements and disability insurance on the value of the marginal product of health capital.

[18] For results obtained with the other income measures, see Appendix E, Tables E-2, E-3, and E-4.

TABLE 9
Demand Curves for All Whites in the Labor Force
(N = 1,770)

Dependent Variable	ln $Y4$	ln W	E	i	Sex	ln FS	$\bar{R}^2$
ln H[a]	.019	.060	.022	−.007	−.041	−.032	.106
	(.84)	(2.96)	(6.76)	(−8.58)	(−1.58)	(−1.37)	
−ln $WLD1$	−.092	.277	.066	−.009	.150	.216	.008
	(−.52)	(1.75)	(2.65)	(−1.18)	(.75)	(1.20)	
−ln RAD	−.294	.144	.060	−.006	−.156	.348	.005
	(−1.56)	(.85)	(2.15)	(−.87)	(−.75)	(1.87)	
ln M	.521	.014	.025	.012	.507	−.280	.043
	(4.66)	(.14)	(1.53)	(3.03)	(4.01)	(−2.48)	

[a] The health stock series is 1 = poor, 2 = fair, 3 = good, 6 = excellent. It is based on average medical outlays of all whites in each of the four health status categories.

dependent variables in the flow demand curves are $-WLD1$ and $-RAD$. All regression coefficients have been converted into elasticities or percentage changes by multiplying by $1/\overline{WLD1}$ or by $1/\overline{RAD1}$. These elasticities or percentage changes, and not the actual regression coefficients, appear in the table.[19]

When the model is estimated for the entire white labor force, the $\bar{R}^2$ in the flow demand curves fall dramatically. In Table 2, the work-loss days regression that employs $Y4$ as the income measure has an $\bar{R}^2$ of .080, and the restricted-activity days regression has an $\bar{R}^2$ of .058. In Table 9, these $\bar{R}^2$ equal .008 and .005, respectively.[20] Despite the differences in explanatory power, the regression coefficients of the four main independent variables—age, education, the wage rate, and family income—are generally consistent with those previously obtained. The two sets of coefficients tend to have the same signs and magnitudes and also tend to be statistically significant at similar levels of confidence. There are,

[19] When many of the observations on a dependent variable equal zero, probit analysis should, in principle, be applied. This technique was not employed because it was felt the costs would greatly outweigh the benefits. For a description of probit analysis, see James Tobin, "Estimation of Relationships for Limited Dependent Variables," *Econometrica*, 26, No. 1 (January 1958).

[20] Strictly speaking, the $\bar{R}^2$ in the two tables are not comparable because different forms of the dependent variable are utilized. When the arithmetic value of sick time replaces the natural logarithm as the dependent variable in the regression in Table 2, the $\bar{R}^2$ falls slightly. It is still, however, much larger than the one in Table 9.

TABLE 10
Demand Curves for Males with Positive Sick Time
(N = 406)

Dependent Variable	ln $Y4$	ln W	E	i	ln FS	$\bar{R}^2$
ln H[a]	.041	.111	.028	−.010	.018	.193
	(.76)	(2.13)	(4.01)	(−5.89)	(.41)	
−ln $WLD1$	−.040	.434	.052	−.012	.314	.118
	(−.27)	(3.06)	(2.77)	(−2.69)	(2.63)	
−ln RAD	−.138	.339	.047	−.014	.257	.082
	(−.91)	(2.32)	(2.40)	(−3.06)	(2.09)	
ln M	.869	−.369	.027	.025	−.314	.082
	(3.92)	(−1.73)	(.94)	(3.76)	(−1.75)	

[a] The health stock series is 1 = poor, 1.6 = fair, 2.9 = good, 4.9 = excellent. It is based on average medical outlays of males in each of the four health status categories.

however, three exceptions. The wage elasticity of medical care is positive in Table 9, the wage elasticity of $-RAD$ is not significant at conventional levels, and the age coefficients in the flow demand curves are not significant.

Since persons with no sick time have similar characteristics compared to those with positive sick time—the same mean level of education, the same average wage, etc.—the model cannot explain the behavior of the former group. Even though the model cannot explain their behavior, the relationships computed when this group was excluded from the analysis are not destroyed when they are included. This finding should strengthen our confidence in the conclusions reached in Section 1.

Males

Table 10 shows demand curves for white males with positive sick time. The income variable in these demand functions is $Y4$.[21] Demand curves were also fitted for females, but the results were generally unsatisfactory and are not included in the text.[22] The regressions reveal that the effects of the exogenous variables on the demand for health and medical care are not altered by restricting the sample to males. Two points are worth noting about the magnitudes of these effects. First, the negative

[21] Results obtained with the other income measures appear in Appendix E, Tables E-5, E-6, and E-7.

[22] For the female demand curves, see Appendix E, Tables E-8, E-9, and E-10.

relation between age and health and the positive relation between age and medical care are strengthened when females are excluded. Second, the male wage elasticities of health are larger than the elasticities for males and females combined.

A tentative explanation of the first result is that the percentage rate of increase in the rate of depreciation over the life cycle is larger for men than for women. A tentative explanation of the second is that with education held constant, the correlation between the wage rate and nonmarket ability rises when females are removed from the sample. Since women are typically secondary members of the labor force, their wage might be less closely correlated with their nonmarket ability. In addition, it might not adequately reflect the monetary value they attach to an increase in their total time.