Existing studies on the association between unemployment and health indices suffer reciprocal causality bias. Existing studies do not demonstrate that unemployment results in poor health rather than vice versa. This study avoids the reciprocal causality bias by measuring disability as an incidence rate and using measures of unemployment prior to the onset of the disability. Evidence from a large national longitudinal data set is presented that suggests that an individual's unemployment is useful in predicting subsequent disability. Aggregate countywide measures of unemployment, on the other hand, do not help predict an individual's probability of becoming disabled.

The Effects of Unemployment on the Probability of Suffering a Disability

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Evidence is accumulating that contractions and expansions of economic activity are associated with community health statistics. Although some attention has been focused on inflation, stock prices, and incomes, most existing studies are concerned with the effects of unemployment. Such studies fall into two categories, macro and micro studies. The former use aggregate, time-series data, which are usually national, and attempt to relate Bureau of Labor Statistics data on unemployment to indices of community health such as mortality and morbidity rates. The typical finding is that worsening unemployment is associated with higher disease and death rates (see, for example, Brenner, 1971, 1973, 1976, 1979; Mark, 1979; Bunn, 1979). The usual

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explanation for the findings is that higher levels of unemployment result in greater financial hardship and are accompanied by rising levels of stress. The hardship may mean that health insurance coverage runs out and people are afraid to spend funds to see a doctor for preventive care or possible early diagnosis of disease. The stress simply means that people worry, which in turn may lead to disease. Employed people may fear a layoff and unemployed people may worry about whether or not they will be able to find a new job.

Aggregate studies suffer the so-called ecological fallacy: What is true for the group may not be true for the individual. The literature concerned with the effects of unemployment on individuals is very thin.[1] The most carefully conceived micro study was done by Catalano and Dooley (1983), who conducted extensive telephone surveys in the Los Angeles area from 1978 through 1980. Respondents were asked questions that measured psychological symptoms, health status, social support, employment experiences, and the incidence of economic and other stressful life events. The dependent variable was constructed from questions that asked respondents if they had been physically ill or injured in the past three months. The dependent variable was binary, for example, was or was not ill or injured. As Catalano and Dooley note, this variable suffers from respondents' subjectivity. What is a major illness for some may be only a minor complaint for others. Because the dependent variable is binary, Catalano and Dooley used logit analysis to avoid problems of heteroscedasticity and predicted values outside the 0-1 range.

Catalano and Dooley arrive at an important conclusion: A given individual's chances of experiencing an illness or injury are increased by personal, undesirable job events, such as unemployment, but are not affected by fluctuations in aggregate unemployment statistics. If this result is robust, it means that although aggregate unemployment can result in health problems for the unemployed (and perhaps their families), it has no apparent effect on those remaining employed.[2] What Catalano and Dooley have labeled the "contagion effect"—the effect of worsening aggregate unemployment on the health of employed workers, for which Brenner and others have argued—may be nonexistent.

But Catalano and Dooley's study has a number of drawbacks. First, their measure of aggregate unemployment, in the Los Angeles-Long Beach standard metropolitan statistical area for 12 quarterly time periods, varies from one quarter to the next only moderately in the years

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they considered. The cross-section data used herein for counties in the United States has much greater variation. Second, their data are geographically limited. Thus their findings may not be applicable to other parts of the country. Third, they were unable to distinguish between minor and major ailments. This study considers only major health disabilities that limit the amount of work a person can do. The fourth drawback is the most serious. Catalano and Dooley do not indicate if their observations on, for example, job loss, preceded or followed the illness or injury. If the job loss followed the health problem, it would, of course, be incorrect to argue that the data support their view that job loss *results in* stress, which *results in* health problems. This is a serious defect because frequently people become unemployed because they recently suffered a severe illness or injury. Unemployment must precede health problems if the Catalano and Dooley hypothesis is to be confirmed.

This study tests whether Catalano and Dooley's central conclusion can be supported with national longitudinal data while simultaneously controlling for a number of other variables known to influence an individual's health. The four problems mentioned above will be avoided. Three questions will be addressed:

(1) Are aggregate statistics on unemployment positively associated with health problems for individual members of the labor force?
(2) Does personal unemployment increase an individual's chances of suffering a disabling illness or injury?
(3) If yes is the answer to either question, does the effect increase at an increasing or decreasing rate as unemployment worsens?

The format of this article is simple. A short theoretical discussion appears in the first section. The second section introduces the data and variables to be used in the analyses. The third section presents the results in two parts: The first provides information on the many control variables entered into the estimating equation that have been mentioned in the literature as correlates of ill health, and the second provides the results for the unemployment variables. Conclusions are presented in the final section. An appendix explains how logit regression coefficients on linear *and quadratic* terms can be transformed into partial derivatives. The appendix results will be of interest to other researchers interested in attaching an intuitive interpretation to logit coefficients.

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A MODEL OF THE DETERMINANTS OF HEALTH

From a sociological point of view, the determinants of health are legion. Nevertheless, researchers have identified a number of variables that appear to be particularly strong predictors. The demographic variables, age, race, sex, education, marital and family status, have been widely discussed. For obvious reasons, biological aging has been found to be strongly associated with worsening health.

For much less obvious reasons there are radical disparities in health statistics. Age-adjusted total mortality for Blacks is higher than for Whites. Although some genetic differences may explain part of the result, for instance, sickle-cell anemia, many observers point to the disparity in economic and educational status between Blacks and Whites as a primary determinant of the difference in their mortality rates. The well-known divergence in Black and White unemployment rates, for example, may partly explain the difference.

Females tend to report more illnesses and to seek medical care more often than men, even after controlling for gynecological problems (see Sindelar, 1982; Verbrugge, 1980). Men, on the other hand, are outlived by women by some 8 years. The genetic reasons for such a difference are obscure. The behavioral reasons are straightforward once the medical causes are considered. Men have higher rates of death due to suicide, homicide, accidents, cirrhosis of the liver, lung cancer, and heart disease (McMillen, 1984). Men take more risks than women. They also drink, smoke, and use weapons for sports and threats more frequently than women. Attempts to live up to the prevailing view of masculinity and femininity, in other words, are partly responsible for the difference in health statistics for men and women.

Grossman (1975), Comstock and Tonascia (1977), and Leigh (1983) have argued and presented strong evidence for the beneficial effects of education on health. It is argued that education allows for wise use of medical care and encourages the practice of preventive medicine through selection of a nutritious diet and exercise. Education may also have an effect through unemployment. The more educated suffer lower unemployment rates than the less educated.

The average married person outlives the average unmarried person, whether widowed, divorced, or single, by roughly 4 years (McMillen, 1984). Moreover, Taubman and Rosen (1982) find that married individuals experience fewer health problems than unmarried individuals. These authors have attributed the difference to the lower levels of

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stress experienced by the married group and free nursing care provided by spouses.

Other variables have also been identified in the literature. House (1974), for example, points to occupational stress as a primary determinant. Chelius (1979) and Smith (1973) discuss hazardous jobs. Finally, economists such as Grossman (1975) mention earnings as a correlate of health.

The list from age through earnings is illustrative and not meant to be exhaustive. Other variables have been considered by other researchers. In the sociological and economic literature, however, the above variables have received more attention than any others. Moreover, in the empirical analysis that follows, additional control variables will be considered.

One of Brenner's contributions to the medical sociology literature has been to point to unemployment as an important but neglected determinant of ill health. He has argued for two effects: an own effect and a contagion effect. The own effect assumes that, on balance, the person does not like being unemployed for any great length of time. He or she is "involuntarily unemployed," as Keynes would put it. Under these conditions, the person experiences psychological stress, since he or she has hopes of becoming employed that are being thwarted. The stress is probably most severe for heads of households. If it becomes severe enough, for instance, if unemployment persists, it is argued that the outcome is adverse health. Disease could result from a deteriorating immune system or injury from negligence.

The contagion effect can apply to two groups: (1) workers who remain employed while aggregate unemployment worsens, and (2) family members of unemployed workers. For the first group, it is argued that workers who have jobs will begin to fear layoff, resulting in stress for them and the same prediction for adverse health outcomes. The contagion effect is probably greater for family members of the unemployed. Both child molestation and wife beating are commonly thought to increase with rising unemployment. Moreover, financial hardship undoubtedly creates stress for family members.

The contagion effect for family members is not examined in this study because of a lack of data. Respondents are asked only about their own work-limiting disability, not those of family members. Future researchers, with richer data, should assess the magnitude of the contagion effect for family members.

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Figure 1 summarizes the arguments in this section. The far left-hand box comprises control variables, that is, variables that are not the immediate concern of this study. The control variables can have direct or indirect effects on health, as the following examples illustrate: Aging can have a direct effect, as indicated by the bottom arrow, through physiological deterioration. Education can have indirect effects by altering employment prospects, which in turn can lower stress, which can ultimately enhance health. Occupation could directly effect stress, as House (1974) suggests, which, again, could result in a change in health. Earnings could allow access to medical care which, in turn, could influence health.

The individual's own unemployment and others' unemployment have only indirect effects. The individual's unemployment can cause stress and can affect preventive measures and medical care if health insurance is lost. The unemployment of others can have effects on stress if the individual worries he or she might be laid off.

Finally, luck, heredity, and toxic exposure can have obvious effects on health. Unfortunately, information on these variables is not available in the data examined in the empirical section, hence they are assumed here to be included in a random error term.

DATA AND VARIABLES

This section describes the data and then the variables selected for analysis. Because of its unique characteristics, some attention is focused on the construction of the dependent variable—the probability of suffering a disabling accident or illness.

The data are drawn from the Michigan Panel Study of Income Dynamics (PSID).[3] Beginning in 1968, researchers at the University of Michigan's Survey Research Center (SRC) began conducting interviews of household heads of 5,000 randomly selected American families. These data constitute the PSID. Questions pertained to work, disability, family life, income, upbringing, personality, and values. Follow-up interviews have been conducted every year since 1968.

For the interviewing years considered in the analysis, each respondent was asked the following questions: (1) "Do you (head) have a physical or nervous condition that limits the type of work or amount of work you can do?" Typically, 22% of the sample in any given year responded yes,

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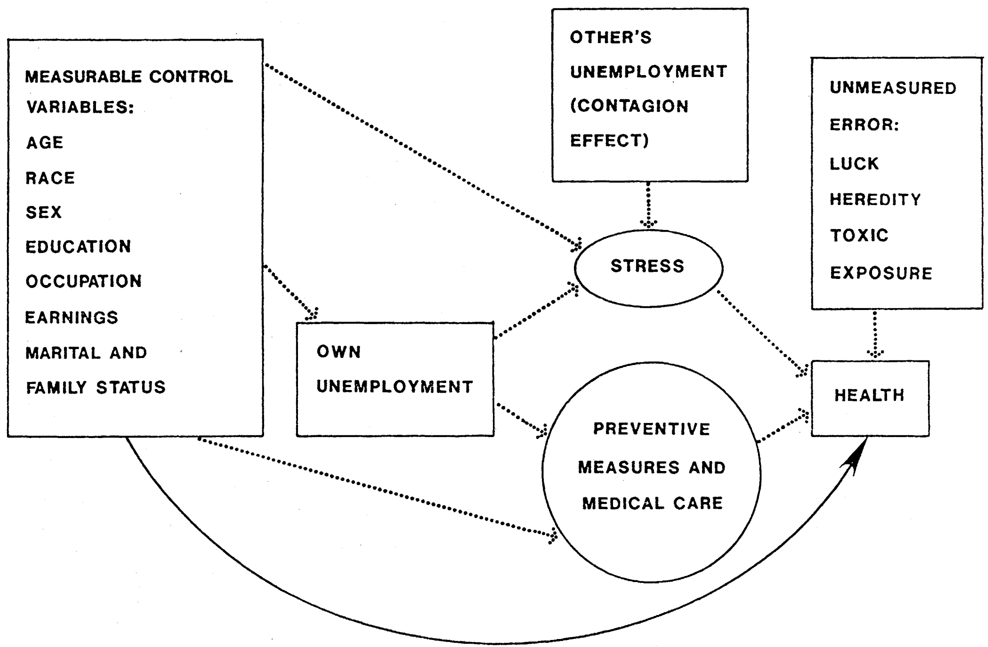

Figure 1: Determinants of An Individual's Health

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77% said no, and 1% were in the "don't know" or "not applicable" category. The very next question was (2) "Does it limit your work a lot, somewhat, or just a little?" Typically, 12% said a lot, 5% said somewhat, 4% said a little, and the remainder, who had answered no to the first question, were in the "inappropriate" category. The answers to the second question are used to construct the dependent variable used here. Because the data are longitudinal, an individual can be identified before and after he or she becomes disabled. The variable DISABLE is designed to identify people who have recently become disabled. People who answer no to the first question or a little or somewhat to the second question in a given year, and in the next year a lot to Question 2 are considered disabled (i.e., DISABLE = 1). All other persons are given a zero for DISABLE. Persons who are severely disabled in both years are excluded from the analysis. Thus the variable DISEASE can indicate which persons have experienced an accident or illness resulting in disability within the past 12 months. The longitudinal nature of the data allows the researcher to gather information on such characteristics as the individual's unemployment experiences, job, marital status, and income *before the accident or disease occurs.*

Because of the timing of the interviews, the year immediately preceding the accident or disease could not be accurately identified. The interviews take place in the spring. The disability questions, of course, pertain to the time the interview is actually conducted. The information on the job, earnings, unemployment, and car miles traveled, however, pertain to the previous year. If DISABLE = 1 for some person, it means that *sometime* between the spring of last year and the spring of this year, the person became severely disabled. If it happened, for example, in August of last year, then clearly the disability will affect the person's earnings, and hours of travel and unemployment. In other words, the reciprocal causality problem can occur. To avoid mutual causality bias, data are obtained from two years preceding the interview year in which it was first discovered that the person suffered from a disability on all variables. If, for example, DISABLE = 1 after comparing the respondent's answers in the spring of 1977 and 1978, then information is gathered from 1976 on all variables.

Unemployment enters the analysis in two ways. First, as a countywide average and, second, as the person's own unemployment hours.

In any given year only a small fraction of the sample experienced an accident or disease severe enough to cause a work-limiting disability. For the entire sample from 1978 to 1979, for example, only 1.12% of the respondents would have been in the DISABLE = 1 category. In an effort

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to increase the size of the DISABLE = 1 category, two years of data, one for 1978 to 1979 interviewing years (recovery years) and another 1975 to 1976 interviewing years (recession years), were combined in the first subsample.[4] These years were selected to allow for considerable variation in measurements of unemployment.

Not all individuals were included in the subsample. Attention was restricted to household heads (1) with no missing data; (2) between the ages of 20 and 65, inclusive; (3) not residing in foreign countries; (4) who worked 500 hours in the year preceding the accident or disease; (5) who did not report being moderately or severely disabled in both years. The first and third restrictions are required to guarantee reliable data. The age restriction excludes youths and the retired, for whom health problems are probably different than those of working-age adults. The hours restriction was imposed to assure that all respondents would have meaningful data on variables pertaining to the job.[5] The fifth restriction is included to omit individuals who did not develop a *new* disability. Notice, however, that individuals who state they have "a little" or "somewhat" the first year and "a lot" the second are included in the analysis and receive a DISABLE = 1. These restrictions cut the 1975-76 sample to 4,408 and the 1978-79 sample to 5,003.

A potential criticism applies to the sample restrictions implied in the definition of DISABLE. The sample is limited to only people who contemplate working in the labor force. Homemakers, students, children, and the retired are thus excluded. It may be that when breadwinners experience unemployment their families suffer health problems. Since no questions pertaining to the health of family members are asked by the PSID researchers, these issues cannot be addressed.

Table 1 presents the definitions and descriptive statistics on variables used herein. Observations pertain to the interviewing years 1976, 1977, 1978, and 1979. Variable selection was based on hypotheses found in the existing literature. The two most important variables for this study are UNPHRS, the annual hours the individual spends unemployed, and CUNEMP, the county unemployment rate. Variable definitions are straightforward and are included in Table 1.

RESULTS

Table 2 presents logit results from explaining the probability of recently becoming disabled either between spring 1978 and spring 1979

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TABLE 1
Variable Definition and Description Statistics

Variable	Definition	Mean (standard deviation[a])
DISABLE	equals 1 if last year had no disability, but now does	.0112
UNPHRS	annual hours of unemployment	77 (232)
SQRUNRS	UNPHRS x UNPHRS	5929 (68839)
CUNEMP	county unemployment rate	6.752 (3.844)
AGE	age in years	38.003 (13.157)
CITY	size of city in which respondent resides (thousands)	301 (240)
ANNWG	annual earnings from job	10365 (9117)
WRKHRS	annual work hours	1992 (704)
KIDS	number of kids under 18 in family	1.377 1.842
FEMALE	equals one for woman	.188
INDINJ	two digit industry injury and illness rate	9.763 (7.488)
BLUE	equals one for craftsman, operative or laborer	.477
INJBLU	INDINJ*BLUE	4.656 (4.052)
MARRIED	equals 1 for married, living with spouse	.685
SINGLE[b]	equals 1 for single, never married	.102
SPSSCH	spouse's years of schooling	10.597 (4.993)
SCH	years of schooling	11.959 (3.212)
FMLINC	annual total family income	17863 (15437)
OTHERIN	FMLINC - ANNWG	7498 (9323)
OVERTM	equals 1 if job frequently requires overtime	.282

(continued)

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TABLE 1 Continued

SQRSCH	SCH*SCH	143 (88)
NOEST	equals 1 if live in Northeast	.170
SOUTH	equals 1 if live in South	.433
NOCNT	equals 1 if live in Northcentral	.252
WEST	equals 1 if live in West	.149
WHITE	equals 1 if white	.643
JUSTD1	equals 1 if divorced within last year	.020
JUSTWD	equals 1 if widowed within last year	.002

a. Standard deviations for 0-1 and percent variables can be calculated from

$$S.D. = \sqrt{m - m^2}$$

where m is the sample mean and S.D. is sample standard deviation.
b. Omitted categories include divorced, widowed, separated.

or between spring 1975 and spring 1976. The two were selected to allow for considerable variation in measuring unemployment. In the first year, 1975, the economy was in recession; 1978 was a year of recovery. Logit was used to avoid heteroscedasticity and predicted values outside the 0-1 range that would have resulted from ordinary least squares (OLS). Data on independent variables correspond to the year before the disability would have occurred. For example, data on independent variables for individuals with DISABLE = 1 or 0 for 1978-1979 come from 1977. Values for independent variables *must* pertain to the time period preceding the disability, otherwise reciprocal causality could occur. For example, annual wages will be zero after the worker suffers a severe disability. If wage data are taken from the same year as the disability occurs, one could not conclude that it is the low wages that *result in* disability.

Two years of data from 1975 and 1977 are used to explain DISABLE. The data are combined roughly to double the sample size. Two years of data rather than one were used to increase the number of observations on DISABLE (see McMillen, 1984).[6]

Table 2 presents results for estimated coefficients and partial derivatives evaluated at the mean for DISABLE. Partial derivatives can be derived from coefficients, as the appendix indicates. Partial derivatives are more informative than estimated logit coefficients since the derivatives provide the estimated effect of, for example, a one unit or

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TABLE 2
Logit Results Explaining the Probability of Recently Becoming Disabled, 1975 and 1977[a]

Explanatory Variable	Estimated Partial Derivative at the mean[b] and (asymptotic t-Statistic)	Estimated Coefficient
UNPHRS	.000029* (2.9226)	.00266*
SQRUNRS	.00000001* (2.1508)	.00000080*
CUNEMP	.0003319 (.9778)	.02997
AGE	.000569* (2.017)	.05143*
CITY	.0000145 (1.1094)	.00131
ANNWG	-.0000002 (.955)	-.000022
WRKHRS	.000008 (.9627)	.00075
KIDS	-.00246 (1.449)	-.2099
MILES	.00000001 (.3152)	.000009
FEMALE	.009510 (1.420)	.8591
INJBLU	.0018329* (3.1517)	.16551*
MARRIED	.0017719 (.7584)	.1600
SINGLE[c]	.0001161 (.1120)	.1024
SPSSCH	.0000399 (.2570)	.00361
SCH	-.007458* (2.422)	-.6759*
SQRSCH	.000124 (.7617)	.0112

(continued)

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TABLE 2 Continued

OTHERIN	-.0000004 (1.186)	-.00004
OVERTM	.001376* (2.012)	.1243*
WHITE	.0014175 (.1899)	.1280
JUSTDI	.03728* (2.7729)	3.367*
JUSTWD	.08982* (2.9785)	8.1109*

-2Ln (likelihood ratio)	268.84
critical chi-square, α = .05	38.89
sample size	9411

a. The logit regression included a constant term and 3 dummies for the four regions identified in Table 1. The constant was significant, but none of the dummies was.
b. See the Appendix for derivation of partials from logit coefficients. In general the formula is

$$\frac{\partial P}{\partial X} = \hat{\beta}(\bar{P}[1 - \bar{P}]) \text{ where } \bar{P} \text{ is the probability}$$

DISABLE = 1 and $\hat{\beta}$ is the estimated Logit coefficient. For example,

$$\frac{\partial P}{\partial UNPHRS} = .00266\ (.0112\ [1 - .0112]) = .000029$$

*Significant at the .05 level in a one-tailed test.

one standard deviation change of the independent variable on the dependent variable. They thus have the same interpretation as OLS coefficients provided one does not consider changes far from the mean value of the dependent variable.

RESULTS FOR CONTROL VARIABLES

As mentioned above, an extraordinary number of control variables enter the equation. The intent of entering so many controls is to test for the robust nature of the findings between the unemployment variables and the probability of becoming disabled.

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Increasing age is positively and significantly associated with increased probability of becoming disabled, as common sense would suggest. At the mean for DISABLE, 10 more years adds roughly .0057 to the probability, which represents roughly a 50% increase over the mean probability of .0112.

The data do not suggest any particular advantage or disadvantage of city size. The person's annual wage, again, prior to the disability, might be viewed as the opportunity cost of becoming disabled and thus one would expect a negative relationship. ANNWG draws negative sign but is insignificant. No unambiguous prediction could be made for hours of work. Many argue that full-time work increases feelings of self-worth and optimism, which, in turn, should inhibit the deterioration of health. On the other hand, if work is undesirable in and of itself, hours at work ought to be correlated with stress, which should, in turn, lead to health deterioration. In any case, the data do not indicate any statistical association between work hours and the probability.

One might have thought that household heads with children would be healthier than those without since reproduction requires at least a minimal amount of good health. The data do not reveal any association between having children and experiencing a disability.

If a greater number of car accidents are experienced by those who travel more, one would expect a positive relation between MILES and DISABLE. Again the data do not support the hypothesis.

In only two previous studies explaining general measures of health status—namely, Leigh (1983) and Wolfe and Haveman (1984)—have controls been entered for a risky job. As their results and these indicate, such an omission is a serious oversight. The variable entering the equation with the largest t-statistic is INJBLU, the 2-digit industry injury and illness rate interacted with the blue-collar occupations, for example, craft workers, operatives and laborers. Work in blue-collar occupations in hazardous industries is dangerous.[7] Moreover, the estimated coefficient is large. A one standard deviation increase in INJBLU leads to a .0074 [(.00183)(4.052) = .0074] increase in the probability of experiencing a disability, which represents a roughly 70% increase over the mean of .0112.

Taubman and Rosen (1982) found a strong association between marriage and the lack of health deterioration, which they attributed to the sense of well-being, common purpose, and free nursing care provided by the spouse. The data here suggest that it is not marriage per se that enhances health but the recent dissolution of marriage either by

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choice or death that (greatly) worsens health. The recently divorced and recently widowed stand roughly 3 to 7 times, respectively, greater than average chance of becoming disabled. Moreover, the t-statistics on JUSTDI and JUSTWD are unusually large.[8] The results support the hypothesis that death of a spouse creates more stress and hardship than separation from a spouse through divorce.

Grossman (1975) finds years of schooling for the spouse adds significantly to health. No effect is found in these data. Years of own schooling do appear to inhibit the deterioration of health, however. One more year of schooling reduces the probability for disability by roughly .005. Two fewer years of schooling roughly double the chances of experiencing a disability at the mean for DISABLE. These strong effects of schooling are consistent with the results found in Comstock and Tongslia (1977), Grossman (1975), and Leigh (1983).

Frequent overtime at work should result in fatigue, which should, in turn, result in more work-related accidents. OVERTM has the predicted sign and is statistically significant. The effect, however, is modest. Persons reporting frequent overtime experience roughly a .001 increase in the probability of becoming disabled. These results are therefore not as strong as those found by Smith (1973), in which a "typical change in overtime had a greater impact on injuries than did any other variable" (p. 14). The difference in part may be due to the difference in the dependent variable. Smith's was the industry's accident rate. The dependent variable here is the probability of becoming disabled, whether due to an industrial *or home* accident or illness.

Finally, once other variables are controlled for, no difference is evident in the probability of experiencing a disability across racial or gender lines.

RESULTS FOR THE UNEMPLOYMENT VARIABLES

The preceding discussion concerned, from the standpoint of the major purposes of this study, control variables. It is obviously important to take account of influence of these variables in assessing the importance of unemployment variables. If no controls were accounted for, one could easily argue that any association between an unemployment variable and the probability of suffering a disability was spurious and merely reflected the influences of third variables. An extremely

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generous number of third variables was included in the analysis. While the inclusion of many control variables raises standard errors, thus making it harder to reject the null hypothesis for any given coefficient, entering many controls greatly minimizes the chances that any association found between unemployment and ill health is an illusion.

The results shown in the first three rows of Table 2 support Catalano and Dooley's findings. It appears that it is the individual's own experiences with unemployment, not countywide experiences, that influence his or her probability of becoming disabled. Both own hours spent unemployed are strongly significant (UNPHRS and SQRUNRS), while the county unemployment rate CUNEMP), although entering with the appropriate positive sign, is insignificant.

The results suggest that the effect of own unemployment hours on the probability is positive and increases with more hours. The estimated coefficients on UNPHRS and on hours squared, SQRUNRS, are positive. The results for SQRUNRS are interesting since they imply that as an individual continues to remain unemployed, his or her chances of suffering a disability increase *at an increasing rate*. The negative health effects apparently worsen rather than get better over time. At the mean unemployment hours and mean probability, the partial derivative of the probability with respect to hours is roughly .0000308.[9] This number is not as small as it looks, considering the typical values of the probability and hours unemployed. For example, a one standard deviation increase in hours unemployed (232) over its mean (77) results in an increase in the probability of .0071 (= .0000308 × 232), which is roughly a 70% increase over the probability's mean of .0112.

CONCLUSION

Catalano and Dooley (1983) have presented evidence suggesting that it is the individual's direct experiences rather than indirect experiences with unemployment that are important in predicting his or her probability of becoming ill or injured. But as indicated here, Catalano and Dooley's study suffers some methodological flaws, including measurement of unemployment, reciprocal causality between unemployment and ill health, and a geographically limited sample. This study attempts to overcome these flaws by using a large nationally based longitudinal sample with well-defined measures of unemployment and

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ill health. The results support Catalano and Dooley's conclusion: Personal experiences with unemployment are far more important than communitywide experiences in predicting whether an individual will fall ill or suffer an injury. In addition, evidence is found that the effect of own unemployment increases at an increasing rate as the span of unemployment lengthens. The results also suggest that the probability of becoming disabled is positively associated with employment in a risky job, being recently divorced or widowed, and frequent overtime. It appears to be negatively associated with years of schooling. Earnings, race, and sex have no apparent simple effect on the probability.

A major drawback of the study, which is the result of the data used, is that only people in or recently in the labor force are included in the sample. Students, children, homemakers, and retirees are excluded. It may be that if the major wage earner suffers unemployment, members of his or her family experience health problems. To the extent this is true that adverse health effects of unemployment reported here understate the effect of unemployment on all members of society.

APPENDIX: DERIVATION OF PARTIAL DERIVATIVES FROM LOGIT COEFFICIENTS

1. *General Approach.* Logit regression can be expressed as follows:

$$\mathrm{Ln}\left(\frac{P}{1-P}\right) = f(X) \qquad [1]$$

where P represents, say, the probability of suffering a disability and X, hours of unemployment in the year prior to the observations on P. The function f(X) is assumed linear in the parameters. Now equation 1 may be rewritten as:

$$\left(\frac{P}{1-P}\right) = e^{f(X)} \qquad [2]$$

or, implicitly,

$$\left(\frac{P}{1-P}\right) - e^{f(X)} = H(P, X) = 0 \qquad [3]$$

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By the implicit function theorem

$$\frac{\partial P}{\partial x} = - \frac{\partial H/\partial X}{\partial H/\partial P} \qquad [4]$$

2. Let $f(x) = \alpha.X$. If $f(x) = \alpha.x$, then

$$\frac{\partial H}{\partial X} = \frac{\partial(-e^{\alpha.x})}{\partial x} = -e^{\alpha.x}.(\alpha) = -\alpha e^{\alpha.x} \qquad [5]$$

and

$$\frac{\partial H}{\partial P} = \frac{\partial\left(\frac{P}{1-P}\right)}{\partial P} = \frac{1(1-P)-(-1)P}{(1-P)^2} = \frac{1}{(1-P)^2} \qquad [6]$$

so that

$$\frac{\partial P}{\partial X} = -\frac{(-\alpha.e^{\alpha.x})}{(1-P)^{-2}} = \alpha.e^{\alpha.x} \cdot (1-P)^2$$

$$= \alpha.\frac{P}{(1-P)} \cdot (1-P)^2 = \alpha[P(1-P)] \qquad [7]$$

Generally, this partial is evaluated at the sample mean for P.

3. Let $f(x) = \alpha x + \beta x^2$. If $f(x) = \alpha x + \beta x^2$, then

$$\frac{\partial H}{\partial X} = \frac{-\alpha[e^{\alpha x + \beta x}]}{\partial x} = -e^{\alpha x + \beta x^2} \cdot (\alpha + 2\beta x) \qquad [8]$$

and

$$\frac{\partial H}{\partial P} = (1-P)^{-2} \qquad [9]$$

since this partial is the same as appears in equation 6. These partials expressed as a ratio yield

$$\frac{\partial P}{\partial X} = \frac{(\alpha + 2\beta x)\,.e^{\alpha x + \beta x^2}}{(1-P)^{-2}} = (\alpha + 2\beta x)[P(1-P)] \qquad [10]$$

Again, this partial is generally evaluated at the sample means for X and P. The reader interested in pursuing the technical aspects of logistic analysis is referred to a useful discussion in Pindyck and Rubinfeld (1976: chap. 8).

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NOTES

1. Moser et al. (1984) offer evidence from England using a longitudinal file on men aged 15-64 that suggests that individual experiences of unemployment are associated with increased risk of illness and accidents. The analysis is extremely limited, however, as no model is even specified and no explicit account is taken for confounding factors strongly associated with unemployment and health such as income and education. Cobb and Kasl (1977) and Kasl (1984) find evidence that individuals on layoff and unemployed due to plant closures have higher blood pressures than similar individuals who were currently employed.

2. Leigh (1985) finds support for the second part of Catalano and Dooley's conclusion. Leigh finds that job absenteeism due to illness *decreases* when aggregate unemployment worsens.

3. Data tapes for the PSID were made available through the Inter-University Consortium for Political and Social Research.

4. Pooling the years allows for some dependence between observation; for instance, the error terms might be correlated across the years for the same individual. One way to handle this problem is to create dummy variables for each of the roughly 4,500 individuals. Such a procedure is extremely costly in terms of computer time. As an alternative, two separate regressions for the 2 years were run and are available from the author. The results concerning the unemployment variables are essentially the same.

5. Alternative hours restrictions were considered. One run was limited to people with at least 1,000 hours; another, of people with at least 250 hours. The major result of this study—that it is the individual's actual experiences with unemployment rather than countywide unemployment that matter—was not altered.

6. The question of pooling can be addressed purely on statistical grounds: Are all the parameters estimated in the pooled model significantly different from those that would be estimated in any one year? Under OLS, a Chow test is typically used to answer this question. Under maximum likelihood (ML), a likelihood ratio statistic performs the analogous test. An example will illustrate the procedure: Regress DISABLE on the vector of exogenous variables, X, for the full pooled sample. Next regress DISABLE on X for the sample in only, say, 1977, *forcing all the parameters* to be equal to the estimates obtained in the pooled model and obtain the value for the likelihood function, L_o. Finally, regress DISABLE on X for the sample in 1976, allowing the ML procedure to pick the "best" estimates and obtain a value for the likelihood function, L_{max}. Now define the likelihood ratio as:

$$\lambda = \frac{L_o}{L_{max}}$$

The appropriate test follows directly from the fact that:

$$-2\ln(\lambda) = -2(\ln(L_o) - \ln(L_{max})$$

follows the chi-square distribution with K degrees of freedom where K is the number of parameters in the restricted (L_o) equation.

Two likelihood ratios were calculated comparing the constrained pooled estimates with the unconstrained estimates from 1975 and 1977. The calculated chi-squares were

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well below the critical chi-squares with = .05, thus failing to reject the null hypothesis that the parameters were the same across the years. The empirical evidence thus supports pooling.

7. Work in white-collar jobs in hazardous industries is not nearly so dangerous. The BLS numbers on injuries and illnesses more appropriately apply to blue-collar workers. See Root and Sebastian (1981).

8. The construction of variables representing whether a respondent was recently divorced or widowed was made possible by a series of marital status changes questions asked in 1978 and 1979.

9. See appendix for the following formula:

$$[.00266 + 2(0.00000080) \times (77)] \times [.0112(1 - .0112)] = .0000308$$

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