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Work and the accommodation of chronic illness: A re-examination of the health-labour supply relationship

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This study uses a data set of over 14 000 households from the state of New Jersey in the USA to estimate the impact of specific chronic health conditions on the probability of employment and finds wide variation of employment impacts across chronic conditions. Additionally, the elasticity of the employment response is generally greater for women and lower-skilled workers. Most notable is the role of co-morbidity. Individuals with multiple conditions have markedly lower probability of employment, and chronic illness explains virtually all of the large gap in employment probability for those who have multiple conditions. This is shown using a summary index of disease status that correlates closely with employment rates across age groups. In the aggregate, chronic disease striking in adulthood explains about 10% of the total non-employment in the New Jersey among those aged 35–74. Finally, cross-sectional evidence gives little support for health as a primary determinant of the aggregate age-employment profile, though controlling for the age-specific severity of conditions may alter this finding.

I. INTRODUCTION

Many crucial policy issues of the twenty-first century spring from the relationship between health and labour supply.[1] And though this relationship has received considerable theoretical and empirical attention over recent decades, one is still able to say relatively little about how current trends in health will affect labour supply in the coming decades.[2] For instance, given the growth of social insurance programmes and the increased earning potential of female spouses over the 20th century, it is natural to posit that the labour supply response of males has become more elastic with respect to health status; an increasingly elastic response would be consistent with the somewhat puzzling fact that male labour force participation at older ages has fallen even as overall health has improved. However, Costa (1998) claims that the health elasticity of labour force participation for males has actually declined over the past century in the USA.[3] If Costa is right, and the trend continues, then improvements in health may lessen the demand for Medicare and disability compensation, but not necessarily the demands upon Social Security retirement funds.

The difficulty in analysing the health–labour supply relationship has come, in part, from the tendency in the economic literature to treat health as a latent, uni-dimensional and unobservable variable rather than as a complex, multi-dimensional and uncertain aspect of the human condition. A natural first step in correcting this problem is to focus attention on specific diseases rather than on unobservable latent variables. And when summary measures of health status are necessary, they can be constructed from data

[1] Here labour supply is used to encompass both supply on the extensive margin (participation) and the intensive margin (hours worked).
[2] See Sammartino (1987), Quinn and Burkhauser (1990) and Weaver (1994) for reviews.
[3] The health measure she uses is Body Mass Index (BMI). It is defined as BMI $= w/h^2$, where w is weight in kilograms, and h is height in metres.

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on specific conditions. Chronic diseases are observable, concrete, relatively objective (even if self-reported), and comparable across individuals (though the severity of the conditions may not be).

Perhaps the most persuasive argument in favour of investigating the disease-specific effects of health is relevance to public policy. As medical science advances, innovations will surely take the form of prevention of and treatments for specific conditions, and the behavioural changes of interest, such as the labour supply response, will depend fundamentally on how these innovations alter the physical and mental condition of the individual. Because the economic burden of poor health is best described in disease-specific terms, the more is learnt about the role played by specific conditions upon behaviour, the better prepared society will be to allocate public investment in the prevention and treatment of disease.

The remainder of this paper proceeds as follows. Section II discusses the theoretical context of the health capital approach and discusses the empirical implications of extending health capital to encompass a set of chronic disease variables. Section III discusses the data and specification issues and presents the essential estimates of disease impacts upon the probability of employment. Section IV discusses the importance of these estimates both for the individual and in aggregate, the impact of co-morbidity, and life-cycle implications of the results. Section V draws conclusions based on results presented in the preceding sections and points towards needed directions in future research.

II. THEORETICAL CONTEXT

Over the past three decades, health economics research has been grounded in the health capital model of Grossman (1972). The standard formulation treats health as a unidimensional capital stock that evolves over time according to the accounting identity:

$$H_{t+1} = H_t(1 - \delta_t) + I_t \tag{1}$$

where H_t is health in period t, δ_t is the period-specific rate of capital depreciation, and I_t is investment that is directly determined by expenditures on m_t, which includes medical care and other commodities that augment health. The dominant feature of this model is the ability of individuals to choose their health status (or expected status in the relatively few models that consider any kind of uncertainty). In this formulation, health capital can be augmented at will by purchasing m_t, and individuals determine their times of death simply by choosing the point at which health capital falls below the subsistence level.

The endogeneity of health status is the central contribution of the Grossman model, and the empirical specification in the next section of this paper explicitly addresses the issue of endogeneity. But other aspects of health and health-related behaviour not addressed in the Grossman framework are surely important. For example, for a large number of people, poor health strikes quite suddenly and, in some cases, little can be done to ease the physical effects of disease. Conditions such as diabetes, arthritis or spinal chord injury can often be treated, but they do not disappear. Indeed, the essence of chronic illness is its permanence, even in the face of modern medical techniques. Furthermore, poor health can strike through a wide variety of different diseases. Diseases differ not only in their severity but in the variety of ways that they can alter physical function and affect behaviour. They can alter mobility, strength, dexterity, endurance, vision, hearing, patience and mood. Diseases also differ in their effect on life expectancy, medical expenditure and overall pain and discomfort. Therefore, decisions such as labour supply depend on the specific diseases individuals contract and on how other variables, such as occupation and education, interact with the physical effects of disease.

Because the health capital model, as typically formulated, cannot capture these and other important aspects of health, the empirical legacy it has created largely ignores the multi-dimensional, uncertain, and permanent aspects of poor health mentioned above. Much of the literature focuses on investigating important relationships in the Grossman model, such as the intertemporal relationships between health and wages, earnings, education and wealth.[4] While many scholars have been concerned about the problems with common health measures, the majority of the debate has focused on the self-reported nature of the measures rather than on their practical relevance.[5] Almost all studies have used either a crude summary measure, 'Is your health excellent, good, fair or poor?'[6] or a work limitations measure, 'Does your health limit the amount or type of work you can do?'[7] Because these measures have had, almost universally, a statistically significant effect in regression models, discussion has been minimal on what

[4] Important studies include Grossman (1974), Chirkos and Nestel (1981, 1985), Lee (1984), Gustman and Steinmeier (1986), Wagstaff (1986), Kemna (1987), Butler *et al.* (1989), Berkovec and Stern (1991), and Haveman *et al.* (1994).

[5] Numerous studies both in economics and other disciplines have focused on the problems associated with self-reported measures of health. They include Maddox and Douglas (1973), LaRue *et al.* (1979), Ferraro (1980), Lambrinos (1981), Mossey and Shapiro (1982), Anderson and Burkhauser (1984, 1985), Butler *et al.* (1987), Bound (1991).

[6] Grossman (1974), Lee (1984), Chirkos and Nestel (1985), Sickles and Taubman (1986), Kenna (1987).

[7] Quinn (1977), Lambrinos (1981), Anderson and Burkhauser (1984, 1985), Lee (1984), Bazzoli (1985), Bound (1989, 1991), Berkovec and Stern (1991), Bound and Waidman (1992), Haveman *et al.* (1994), Bound *et al.* (1994), Loprest *et al.* (1995).

these measures actually mean or what their policy relevance might be. And although some work has focused on the importance of specific diseases,[8] very little work has been done examining simultaneously the variety of chronic conditions individuals may have.[9]

The accommodation of chronic illness and injury

The empirical section that follows addresses the question of endogeneity highlighted by Grossman, but the focus of this study is understanding the impact of chronic conditions after they strike. Rather than explicitly addressing the tradeoffs between current behaviour and expenditures with changes in the expected value of future health, this study concentrates on the tradeoffs individuals are faced with after the onset of a chronic condition.[10]

Chronic conditions are assumed to affect the set of physical abilities that individuals employ both within the labour market and in home production. These abilities include strength, endurance, dexterity, vision, hearing, emotional fitness and, in general, the ability to perform tasks at work and within the household. Each condition can affect a subset of the total ability set and, depending on factors such as education and occupation, diseases will have differential effects upon employment probability. Changes in the disease status and changes in ability can alter the labour-leisure tradeoff in important ways.

Disease accommodation affects labour supply through at least four different pathways. First, chronic illness can induce a change in wages if the productivity of workers is affected by disability. If market wages fall, holding all else constant, the probability of employment falls as well. This wage effect, of course, will be mitigated by the potential of disability insurance programmes. Second, a change in abilities can, depending on how abilities affect the marginal utilities of consumption and leisure, affect the work decision. If disease lowers the marginal utility of leisure sufficiently, individuals may actually work more. But the stronger is the effect of abilities on the marginal utility of consumption, the greater is the probability of working. The third pathway is a simple income effect induced by out-of-pocket medical expenses. Simply, individuals are induced to keep their jobs in order to pay medical costs. This is particularly true in the USA, where health insurance is often tied to employment. These costs may be incurred whether or not the chronic conditions result in any disability. The fourth pathway is a reduction in the total time available to the agent because of increased time in health maintenance. A reduction in time will induce a reallocation of labour and leisure that depends on the preferences and resources of the agent. In a life-cycle context, the reduction in time may also take the form of reduced life expectancy. Some conditions, with treatment, impose little current disability but can significantly affect life expectancy.

In sum, chronic conditions can affect the employment decision in a variety of ways. The empirical implication of the discussion above is that no summary variable can capture the multiple ways in which disease affects labour supply. Sometimes disease affects labour supply through disability (in either the market or the home); sometimes through medical costs; and sometimes through changing the amount and value of time, including changes in life expectancy. Furthermore, because there are both positive and negative effects of a particular disease, it is possible that some diseases, while 'serious' in some contexts, will actually increase the probability of employment. Summarizing health with a single variable such as a health capital stock is very useful in some contexts, but a clear understanding of labour market behaviour depends critically on expanding the conceptualization of health beyond single-measure methods.

III. ESTIMATION METHODS AND RESULTS

The probability of employment, P_E, depends on the disease state indirectly through abilities, health expenditures and available time. If these variables are grouped together into a vector Ω and X represents additional exogenous variables thought to affect the employment decision, then the employment probability relationship can be expressed as

$$P_E = F(\alpha_0 + \alpha_1 X + \alpha_2 \Omega) \tag{2}$$

where F is a cumulative density function whose argument is linear in X and Ω. This equation is complemented by an equation determining the elements of Ω

$$\Omega = \gamma_0 + \gamma_1 X + \gamma_2 \Delta \tag{3}$$

Here Δ represents the disease-state vector, which is the set of binary variables indicating the chronic conditions the agent has. Given richer data, Δ could potentially represent continuous or polychotomous measures of disease which capture the severity or progression of the disease. Data restrictions prohibit the direct estimation of Equations 2 and 3, but Equation 3 can be substituted into Equation 2 to obtain the reduced-form equation

$$P_E = F(\pi_0 + \pi_1 X + \pi_2 \Delta) \tag{4}$$

[8] For instance Mitchel and Butler consider arthritis (1986), and Inman (1987) looks at multiple sclerosis.
[9] Important exceptions are Bartel and Taubman (1979) and Stern (1989). Cooper and Rice (1976) estimate the costs of illness for broadly defined disease groups, but their analysis of labour supply is very rudimentary.
[10] A formal theoretical model has been developed and is available from the author upon request.

Assuming that F is standard normal, the reduced-form coefficients can be consistently estimated with probit regression using maximum likelihood. A variety of socio-economic and demographic variables described below comprise the elements of the X vector, and π_2 is the vector of parameters that represent the total effects of individual diseases on the probability of employment.[11]

One aspect of health-related behaviour not incorporated into the above equation is that some variables in X, such as education, will likely be correlated with the probability of having a disease, as implied by the health capital model. Suppose, for instance, that the disease-state vector is a function of X:

$$\Delta = G(\eta_0 + \eta_1 X) \tag{5}$$

This formulation represents a fully recursive system and Equations 4 and 5 can be consistently estimated separately. The recursivity in this system depends on X determining Δ and not the other way around. To this end, respondents who reported any condition prior to age 25 are excluded from the sample, and the assumption is made that Δ has no effect on the predetermined X vector. Thus the estimation of Equation 4 concerns only those health conditions that strike later in life. Diseases of childhood and adolescence (which may affect investment in education and other forms of human capital) are not considered here, even though they may have very severe effects on labour supply over the life cycle. Because of Equation 5, the disease-state vector is not strictly exogenous; diseases are a function of a random process, G, which depends on variables such as education that are assumed to be pre-determined. Thus investments in health over the life cycle as modelled by Grossman are allowed by this specification.

An alternative approach to estimating π_2 within the recursive structure outline above would be to allow X to depend on Δ and obtain estimates by the method of instrumental variables (IV). In spite of their popularity, IV estimation is not appropriate (and can even make matters much worse) when the instruments are weak.[12] In the case at hand, extensive investigation has revealed that none of the other variables are correlated with the disease variables by more than a trivial amount, certainly not enough to function as effective instruments for diseases status. Furthermore, identification of the system requires a strong correlate of disease-status that is uncorrelated with employment probability. Without relying on arbitrary and unjustified covariance restrictions, IV estimates are not identified. The results that follow strongly imply that disease-status is largely independent of other explanatory variables in the system (for instance, including or excluding the disease variables has virtually no effect on the coefficient estimates for the other regressors in the model), which justifies the recursive structure employed here.

Data

The data employed in this study come from a relatively unexploited recent data collection conducted by health economists at Rutgers University entitled the New Jersey Demographics of Disability Survey (NJDDS). New Jersey is a large and diverse (ethnically and economically) state. Data in the NJDDS were collected from a random sample of over 40 000 individuals in over 14 000 New Jersey households during the summer of 1991. Extensive demographic, health and labour market data were collected on household members of all ages during a telephone survey, in which the male or female head of household provided all information. For this study, the NJDDS was limited to non-students between the ages of 35 and 74. For reasons discussed above, those who reported illnesses occurring before age 25 were excluded. The sample, then, represents individuals who were free of chronic illness acquired during childhood and adolescence. There are 7600 women and 7059 men in the final sample.

An especially appealing feature of the NJDDS is the design of the survey. Individuals are asked to report first the chronic diseases household members had contracted (and when they were diagnosed) before they are asked any information about labour market behaviour. This fact and the objective nature of the questions certainly reduce the amount of 'rationalization' often thought to accompany many self-reported health measures. While it is true that individuals may falsely report the existence of specific diseases to rationalize their behaviour, less rationalization would surely result from a question such as 'Has a doctor ever told you that you have diabetes?', than from the question 'Does your health limit the amount of work you can do?', which is the survey question used in many studies by economists.

The NJDDS queried respondents about numerous commonly debilitating chronic illnesses and whether or not the disease had been diagnosed by a physician. Respondents could also report conditions not specifically mentioned in the survey. Because of very small counts for many of the diseases and because several of these diseases strike predominantly in childhood, the diseases were collapsed into 18 disease groups. Table 1 lists the diseases by physical system, their sample prevalence, and the specific diseases incorporated in each of the 18 disease groups. The label in capital letters refers to the variable name for each group

[11] Other potentially important determinants of employment probability are insurance coverage and occupational choice. Because these are clearly endogenous variables, they belong to Ω and represent other important relationships that could be uncovered with estimation of the full structural model.

[12] See, for instance, Bound *et al.* (1993) and Staiger and Stock (1994).

Table 1. *Chronic disease: classifications and sample prevalence rates*

System/disease	Variable name	Sample prevalence	
		Women	Men
Cardiovascular			
1. Heart disease	HEART	6.8%	38.9%
2. Hypertension	HYPERTENSION	14.8%	13.6%
Central Nervous System			
3. Traumatic injury Includes: head injury, spinal injury	CNS-TRAUMA	1.3%	0.8%
4. Other CNS disorder Includes: epilepsy, Parkinson's disease, stroke, multiple sclerosis	CNS-OTHER	1.8%	1.3%
Ear			
5. Hearing loss (otherwise unspecified)	HEARING	5.4%	2.3%
Endocrine			
6. Diabetes	DIABETES	4.3%	3.8%
Eye			
7. Eye disease Includes: cataracts, glaucoma, macular degeneration, other eye disease	EYE	4.3%	4.5%
Gastrointestinal			
8. Ulcer	ULCER	1.9%	1.9%
Genitourinary			
9. Kidney disease	KIDNEY	0.5%	0.4%
Musculoskeletal			
10. Arthritis	ARTHRITIS	7.2%	12.9%
11. Lower back trouble	BACK	9.0%	7.8%
12. Other musculoskeletal disorders Includes: orthopedic impairment, permanent stiffness, missing limbs, muscular dystrophy	MUSC-OTHER	2.0%	1.8%
Neoplasia			
13. Cancer of all types	CANCER	1.3%	2.1%
Psychological			
14. Mental and psychological disorders Includes: Alzheimers, schizophrenia, paranoid disorder, obsessive compulsive disease, drug and alcohol abuse, memory loss, other mental illness	MENTAL	1.8%	2.2%
Respiratory			
15. Asthma	ASTHMA	0.9%	1.7%
16. Emphysema	EMPHYSEMA	0.8%	0.7%
17. Other respiratory disease Includes: chronic bronchitis, tuberculosis, other respiratory disease	RESP-OTHER	1.4%	1.9%
Miscellaneous and other			
18. Other condition	OTHER	5.7%	7.2%

Notes: Data are from the 1991 New Jersey Demographic and Disability Survey (NJDDS) restricted to those aged 35–74, excluding those who reported any chronic disease prior to age 25.

that appears in subsequent tables. Based on comparisons not shown here, the NJDDS results show a remarkable agreement with estimates of prevalence from the National Health Interview Survey (NHIS) during the same year (1991).

Table 2 contains the other variables used in the regression analysis and their sample means and frequencies. The dependent variable used in the analysis is a binary employment variable, in which a value of one indicates that the individual is working (either full- or part-time). Age is controlled for with a set of dummy variables, and frequencies for the different age groups are provided. Education consists of years of schooling completed, and education squared is used to control for non-linearity. Race consists of a simple dummy variable indicating whether the individual is white or non-white. Family status and spousal income are incorporated into a set of dummy variables that capture marital status, the income of spouse, if present, and

Table 2. *Sample means and frequencies*

Variable	Women	Men
Age		
35–39	18.1%	18.9%
40–44	18.2%	18.4%
45–49	13.9%	14.3%
50–54	11.6%	12.1%
55–59	9.5%	9.6%
60–61	3.9%	3.9%
62–64	4.8%	5.5%
65–66	5.4%	4.8%
67–68	4.5%	3.8%
69–70	4.7%	3.5%
71–72	2.8%	3.0%
73–74	2.6%	2.2%
Education (years)	13.2	14.0
Race (% white)	82.4%	83.7%
Number of minor children	1.0	1.1
Family structure/income		
Married with		
1. No minor children; spousal income < median	24.7%	36.0%
2. No minor children; spousal income > median	16.4%	11.3%
3. Youngest child < age 6; spousal income < median	4.4%	9.1%
4. Youngest child < age 6; spousal income > median	2.5%	2.4%
5. Youngest child age 6–17; spousal income < median	10.2%	13.9%
6. Youngest child age 6–17; spousal income > median	6.0%	5.0%
Single with		
7. No children	20.2%	12.8%
8. Youngest child < 6	0.7%	0.3%
9. Children age 6–17	3.8%	0.6%
10. Adult living with parents	1.7%	2.2%
11. Family structure unknown	9.5%	6.4%
County economic variables[a]		
County average log wage	253.0%	285.6%
County unemployment rate	4.5%	5.3%
Sample size	7600	7059

Notes: Data are from the 1991 New Jersey Demographic and Disability Survey (NJDDS) restricted to those aged 35–74, excluding those who reported any chronic disease prior to age 25.

the age of the youngest child. Number of children is included as a separate control. Finally, regional economic variation is controlled by including the county unemployment rates and the average county wage rate calculated from within the sample.

Disease and employment probability

Estimating the effect of a chronic disease is conceptually a difficult problem. In addition to the different pathways discussed above through which disease can alter behaviour, the dynamic aspects of diseases vary considerably. Some result in a gradual decline in physical and mental functioning, others produce severe episodes of disability but later are brought under control. One approach to estimating the magnitude of these effects would be to calculate the 'incidence-based' effect of the disease on labour supply. This might be defined as the complete profile of period-by-period effects of the disease from time of onset until death. More simply, it might be the reduction of total lifetime hours of labour supply following the onset of disease. An incidence-based approach provides a natural step towards developing theoretically appealing willingness-to-pay measures of disease cost, which would have to incorporate not only losses in wage income, but the complete expected utility cost of disease over the life-cycle.

The approach undertaken here is a 'prevalence-based' approach. Magnitudes can be used to develop estimates of disease cost consistent with the widely-used Cost of Illness (COI) approach,[13] though no COI estimates will be made here. The estimates here are meant to capture changes in employment rates due to marginal changes in the prevalence of a disease. These estimates have obvious import for such policy applications as forecasting rates of participation in social insurance programmes, such as Social Security retirement and disability programmes in the USA. Critics of prevalence-based estimates correctly note that they do not accurately capture the complete response that individuals have to disease over the life cycle. However, without complete life-course data on individuals, incidence-based approaches also fail in this respect. Incidence-based estimates made on longitudinal data can only capture the effects of a disease that occur within the time frame of the panel. Some diseases can be present for decades and have little effect until their later stages. Prevalence-based estimates, on the other hand, include cases where the disease is both of recent onset and long-standing. Furthermore, while not giving a complete picture of responses to disease the relative magnitudes of prevalence-based effects hopefully approximate the importance of different diseases on the labour supply decision.

Columns 3 and 4 of Tables 3 and 4 contain regression estimates of Equation 4 for women and men respectively. Disease variables in each case are sorted by the absolute value of the regression coefficients. Columns 1 and 2 contain, for comparative purposes, regression estimates for a model without health variables. For both men and women the impact of disease varies widely across disease groups. Demographic variables in the model have the expected signs and are generally highly significant. The model is dominated, as expected, by the age variables, with employment decreasing rapidly for both men and women after age

[13] See Cooper and Rice (1976).

Table 3. *Employment estimates (probit)–women*

	Model 1		Model II	
Dependent variable: currently employed (1 = yes/0 = no)	Coefficient	St. error	Coefficient	St. error
Intercept	−0.0038	0.457	0.1450	0.462
Age = 35–39	0.0178	0.060	−0.0073	0.061
Age = 40–44	0.1738***	0.059	0.1678***	0.059
Age = 45–49		omitted group		
Age = 50–54	−0.1981***	0.063	−0.1679***	0.064
Age = 55–59	−0.3917***	0.066	−0.3565***	0.068
Age = 60–61	−0.6708***	0.087	−0.5917***	0.088
Age = 62–64	−0.9791***	0.082	−0.9302***	0.084
Age = 65–66	−1.4559***	0.083	−1.4016***	0.085
Age = 67–68	−1.6964***	0.093	−1.6355***	0.096
Age = 69–70	−1.9397***	0.098	−1.8849***	0.100
Age = 71–72	−2.0355***	0.125	−1.9781***	0.130
Age = 73–74	−2.4534***	0.152	−2.3286***	0.158
Education (years)	−0.0162	0.025	−0.0131	0.026
Education squared	0.0034***	0.001	0.0032***	0.001
Number of children	−0.0942***	0.017	−0.0918***	0.017
Race (white = 1; non-white = 0)	−0.1477***	0.044	−0.1622***	0.045
Family structure/income				
Married with				
1. No minor children; spousal income < median	−0.1343**	0.052	−0.1305**	0.053
2. No minor children; spousal income > median		omitted group		
3. Youngest child < age 6; spousal income < median	−0.5633***	0.108	−0.5761***	0.108
4. Youngest child < age 6; spousal income > median	−0.6651***	0.088	−0.6755***	0.088
5. Youngest child age 6–17; spousal income < median	−0.1818**	0.076	−0.1971**	0.077
6. Youngest child age 6–17; spousal income > median	−0.0718	0.067	−0.0769	0.067
Single with				
7. No children	0.3548***	0.057	0.4209***	0.058
8. Youngest child < 6	−0.1263	0.189	−0.1359	0.189
9. Children age 6–17	0.3003***	0.100	0.3818***	0.102
10. Adult living with parents	0.0570	0.131	0.0479	0.132
11. Family structure unknown	0.1120*	0.068	0.1147*	0.068
County economic variables[a]				
County average log wage	0.2331	0.161	−0.9329	0.163
County unemployment rate	−0.6989	1.566	0.1977	1.579
CNS-OTHER			−0.8692***	0.165
MUSC-OTHER			−0.4403***	0.130
CNS-TRAUMA			−0.3765**	0.179
HEART			−0.3619***	0.094
CANCER			−0.3032***	0.115
RESP-OTHER			−0.2149*	0.127
DIABETES			−0.2045**	0.089
ARTHRITIS			−0.1815***	0.054
ULCER			−0.1483	0.126
MENTAL			−0.1335	0.121
EMPHYSEMA			−0.1298	0.228
EYE			−0.1084	0.091
OTHER			−0.1078*	0.064
BACK			−0.0834	0.063
KIDNEY			−0.0060	0.299
HEARING			0.0148	0.118
HYPERTENSION			0.0964*	0.050
ASTHMA			0.1028	0.128
$N =$	7600		7600	
Likelihood ratio index	0.223		0.236	
2 Log L =	−8314.946		−8169.879	

Notes: $p < 0.1$; $p < 0.05$; $***p < 0.01$.
Data are from the 1991 New Jersey Demographic and Disability Survey (NJDDS) restricted to those aged 35–74, excluding those who reported any chronic disease prior to age 25.

Table 4. *Employment estimates (probit) – men*

	Model 1		Model II	
Dependent variable: employment (1 = yes/0 = no)	Coefficient	St. error	Coefficient	St. error
Intercept	1.7456**	0.704	2.2360***	0.722
Age = 35–39	0.0246	0.093	−0.0711	0.097
Age = 40–44	−0.1819**	0.088	−0.2461***	0.092
Age = 45–49		omitted group		
Age = 50–54	0.0192	0.098	0.0097	0.103
Age = 55–59	−0.64380***	0.091	−0.6555***	0.095
Age = 60–61	−0.9068***	0.109	−0.9619***	0.113
Age = 62–64	−1.3710***	0.097	−1.3876**	0.102
Age = 65–66	−1.8663***	0.101	−1.8560***	0.107
Age = 67–68	−2.2609***	0.113	−2.2677***	0.118
Age = 69–70	−2.2878***	0.118	−2.2564***	0.123
Age = 71–72	−2.3903***	0.126	−2.3165***	0.132
Age = 73–74	−2.3542***	0.140	−2.3128***	0.146
Education (years)	−0.0548*	0.032	−0.0600*	0.033
Education squared	0.0043***	0.001	0.0043***	0.043
Number of children	0.0790***	0.025	0.0702***	0.025
Race (white = 1; non-white = 0)	0.0234	0.058	0.0529	0.060
Family structure/income				
Married with				
1. No minor chidren; spousal income < median	−0.2690***	0.074	−0.2787***	0.076
2. No minor children; spousal income > median		omitted group		
3. Youngest child < age 6: spousal income < median	−0.0492	0.131	−0.0344	0.135
4. Youngest child < age 6; spousal income > median	−0.2130		−0.2683	0.196
5. Youngest child age 6–17: spousal income < median	−0.1803*	0.102	−0.1794*	0.105
6. Youngest child age 6–17; spousal income > median	−0.0140	0.147	−0.0298	0.150
Single with				
7. No children	−0.4382***	0.085	−0.3777***	0.088
8. Youngest child < 6	−0.1513	0.494	−0.1075	0.524
9. Children age 6–17	−0.1538	0.324	0.1098	0.370
10. Adult living with parents	−0.7477**	0.146	−0.8274***	0.148
11. Family structure unknown	−0.1305	0.103	−0.1840*	0.105
County economic variables[a]				
County average log wage	0.0636	0.218	−0.0188	0.223
County unemployment rate	−5.7324***	1.844	−6.2322***	1.887
CNS-TRAUMA			−1.2851***	0.164
MENTAL			−0.5877**	0.146
MUSC-OTHER			−0.4038***	0.133
EYE			−0.3079***	0.093
OTHER			−0.2925***	0.085
HEART			−0.2684***	0.076
BACK			−0.2444***	0.072
ULCER			−0.2192	0.139
EMPHYSEMA			−0.1807	0.201
CANCER			−0.1723	0.158
RESP-OTHER			−0.1473	0.160
ASTHMA			−0.1362	0.202
HYPERTENSION			−0.0877	0.056
ARTHRITIS			−0.0667	0.074
CNS-OTHER			−0.0245	0.144
KIDNEY			−0.0244	0.288
DIABETES			0.0890	0.091
HEARING			0.1509*	0.086
N =			7059	
Likelihood ratio index	0.383		0.412	
2 Log L = 10 699.064	−4661.955		−4445.034	

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Data are from the 1991 New Jersey Demographic and Disability Survey (NJDDS) restricted to those aged 35–74, excluding those who reported any chronic disease prior to age 25.

55. Education has strong positive effects on employment probability, and the increasing quadratic term is dominant.

The family structure dummy variables, which capture living arrangements, including marital status, children present in the home, and spousal income, differ substantially between men and women. The presence of a child under six strongly reduces a woman's probability of employment as does the number of children. Single women are, as would be expected, much more likely to be employed than married women. Conversely, the number of children increases the probability of men being employed, and the age of the youngest child has only modest effects for men. Furthermore, single men without children are markedly less likely to be employed than are married men, particularly those men who are still living in their parents' home. The effects of spousal income follow a similar pattern for both men and women, though neither has pronounced effects. Married persons without children under six have an employment probability that moves positively with spousal income, indicating the presence of positive assortative matching along income lines. However, for those with a young child, a negative relationship exists, possibly because the presence of a child causes couples to increase specialization between home and workplace along the lines predicted by Becker (1991), though the estimates are not precise enough to draw firm conclusions. Finally, the employment probability of men is highly sensitive to local economic activity, as indicated by the county unemployment rate. Women's response to local economic variables is largely non-existent (except possibly through spousal income).

The variables of most significance are the chronic disease variables, which are sorted by order of their importance at the bottom of Tables 3 and 4. These tables also contain, for comparative purposes, coefficients from a model that contains no disease variables. This comparison reveals three salient facts about the presence of chronic illness among individuals in this sample. First, the inclusion of the chronic disease variables has very small effects on the other coefficients in the model. Second, chronic disease explains very little of the overall variation in employment probability for this sample; the likelihood ratio index rises from 0.223 to only 0.236 for women and from 0.383 to only 0.412 for men. Third, the magnitude of the disease coefficients vary widely, with some variables having large and statistically significant effects.

In summary, the onset of chronic disease among the portion of the population who were free of disease at young adulthood explains very little of the overall variation in employment, but for those few individuals who have the most severe diseases, the effects of even a single condition can be profound. And though it is well beyond the scope of this paper to perform a disease-by-disease analysis, the results indicate a general conformation with expectations. Health conditions, which are typically thought of as highly disabling, such as central nervous system trauma (CNS-TRAUMA) or diseases of the musculoskeletal system (MUSC-OTHER) have strongly negative effects (an exception is the negligible impact of the CNS-OTHER category for men). On the other hand a disease such as hypertension, which is typically not debilitating, has little effect on employment. A few conditions even have positive effects, as allowed for in theory, though these effects are relatively small.

Tables 5 and 6 convert the regression coefficients into percentage changes in employment probability. The first column of the tables use the probit coefficients to calculate the percentage change in the probability of employment for sample individuals caused by a change in the specific disease variable from zero to one, holding all other variables constant at their mean values. The remaining columns in Tables 5 and 6 provide age-specific effects calculated in the same manner, where other variables were held constant at the mean values for the age group. To account for the possibility that disease effects differ across age groups, the model was re-estimated for the 35–54 and 55–74 year age groups and these regression coefficients (not shown) were used to calculate the employment effects (noted as the 'age-specific model,' as opposed to the 'Base model'). The 35–54 group was estimated together in both models because of the relative lack of chronic disease between the 35–44 and 45–54 year age groups and the similarity in employment rates between the ages. Individuals aged 55–74 were also estimated together in order to keep sufficient sample size.

One of the theoretical predictions of the disease accommodation model is that disease effects may vary by market wage levels. This variation occurs for two reasons. First, individuals facing higher wages are more likely to be on the portion of the labour supply schedule that is either backward bending or highly inelastic. Thus disease-induced changes in wage will have little effect on labour supply. Second, the abilities required by low-skilled jobs are more affected by disease than are the abilities of high-wage workers. Because wage and occupation data was observed only on those who are employed,[14] years of schooling is used as a proxy for market wage, and Equation 4 is estimated separately by education level.

Variations in disease effects across educational levels are shown in Table 7 for both women and men. While there are a few important exceptions, the effects of disease are much greater for those with only a high school education or less than they are for those who have at least some schooling beyond high school. And in many cases the differences between the disease effects is substantial across education levels. These effects are most pronounced for women,

[14] Furthermore, the wage data for employed individuals in the NJDDS has a high percentage of unreported values.

Table 5. *Magnitude of employment effects – women*

Age	Estimated percentage reduction in employment probability due to disease[a]						
	All	35–54		55–64		65–74	
Disease		Base model[b]	Age-specific model[c]	Base model[b]	Age-specific model[c]	Base model[b]	Age-specific model[c]
CNS-OTHER	−54.3%	−41.4%	−30.3%	−57.0%	−60.9%	−81.4%	−84.4%
MUSC-OTHER	−28.4%	−19.6%	−16.9%	−30.5%	−34.9%	−54.0%	−59.7%
CNS-TRAUMA	−24.4%	−16.5%	−24.2%	−26.3%	−10.7%	−48.1%	−22.4%
HEART	−23.2%	−15.8%	−15.7%	−25.1%	−26.3%	−46.1%	−47.9%
CANCER	−19.5%	−13.1%	−14.1%	−21.2%	−20.5%	−40.4%	−39.5%
RESP-OTHER	−13.8%	−9.0%	0.5%	15.0%	−28.3%	−30.2%	−50.9%
DIABETES	−13.1%	−8.5%	−14.5%	−14.3%	−4.0%	−28.8%	−8.8%
ARTHRITIS	−11.5%	−7.5%	−4.7%	−12.4%	−13.3%	−25.5%	−27.2%
ULCER	−9.5%	−6.1%	−2.1%	−10.4%	−24.3%	−21.7%	−45.2%
MENTAL	−8.5%	−5.5%	−9.1%	−9.3%	−3.2%	−19.7%	−7.2%
EMPHYSEMA	−8.3%	−5.3%	−8.9%	−9.1%	0.3%	−19.2%	0.7%
EYE	−6.9%	−4.4%	−21.8%	−7.6%	−0.7%	−16.1%	−1.6%
OTHER	−6.8%	−4.3%	0.5%	−7.5%	−21.4%	−16.1%	−41.0%
BACK	−5.3%	−3.3%	−2.6%	−5.8%	−4.4%	−12.6%	−9.7%
KIDNEY	−0.4%	−0.2%	−0.9%	−0.4%	−12.9%	−1.0%	−26.4%
HEARING	0.9%	0.6%	5.6%	1.0%	4.4%	2.4%	10.6%
HYPERTENSION	6.1%	3.7%	4.6%	6.8%	6.4%	16.4%	15.5%
ASTHMA	6.4%	3.9%	8.3%	7.1%	−8.5%	17.3%	−18.0%

Notes: [a] Percentage change in employment probability due to a change in disease variable from zero to one holding other variables constant at their mean values.
[b] Uses probit coefficient estimates from Model II in Table 3.
[c] Uses probit coefficient estimates analogous to those in Model II of Table 3, but the model is estimated separately for age groups 35–54 and 55–74.
Data are from the 1991 New Jersey Demographic and Disability Survey (NJDDS) restricted to those aged 35–74, excluding those who reported any chronic illness prior to age 25.

where it is clear that many of the diseases with large negative effects result primarily from the reduction in employment among those with low education. Further, the sign of the disease effect for those with low education is positive in only one case for both women (HYPERTENSION) and men (KIDNEY). Since those with lower education are also older and employed at a significantly lower rate (mean ages and employment rates are given towards the bottom of Table 7), some differences would be expected in the response to disease between the two groups; however, the probit regressions contain detailed controls for age, suggesting that the educational differences are related to variables such as occupation rather than age. In short, the estimates in Table 7 leave us with several puzzles, but they provide clear evidence of a non-uniform response to disease across levels of education, particularly for those conditions with the greatest disease effects in the overall population.

Since the method undertaken here is essentially an exercise in finding the economic effects of relatively rare events (most diseases have a sample prevalence of under 2%), it is not surprising that high standard errors exist, as revealed in Tables 3 and 4. However, it is reassuring that almost all diseases have negative effects upon employment and that the relative ranking of diseases appears reasonable. It should be noted as well that some of the effects are very large, particularly for older individuals. Any objective variable that can generate a 40–90% reduction in the probability of employment is surely worthy of attention.

IV. CO-MORBIDITY AND THE AGGREGATE EFFECTS OF DISEASE

A disease-status index

The preceding section focuses on the impacts of individual diseases, holding the probability of having other diseases constant. In the modern world, however, while relatively few working-age individuals have anything more than mild disability, some individuals are beset with high rates of co-morbidity, meaning the presence of two or more chronic conditions. Therefore, a summary index of health status based on underlying chronic conditions can be useful in

Table 6. *Magnitude of employment effects – men*

Age	Estimated percentage reduction in employment probability due to disease[a]						
	All	35–54		55–64		65–74	
Disease		Base model[b]	Age-specific model[c]	Base model[b]	Age-specific model[c]	Base model[b]	Age-specific model[c]
CNS-TRAUMA	−50.7%	−30.1%	−25.8%	−64.0%	−57.6%	−90.7%	−86.9%
MENTAL	−19.7%	−9.1%	−19.7%	−28.8%	−17.7%	−59.9%	−42.0%
MUSC-OTHER	−12.6%	−5.4%	−9.3%	−19.3%	−6.4%	−45.2%	−17.9%
EYE	−9.2%	−3.8%	−1.9%	−14.3%	−16.1%	−35.5%	−38.8%
OTHER	−8.6%	−3.5%	−5.1%	−13.5%	−5.3%	−34.3%	−15.0%
HEART	−7.8%	−3.2%	−5.2%	−12.2%	−12.1%	−31.4%	−30.8%
BACK	−7.0%	−2.8%	−3.6%	−11.1%	−8.3%	−29.2%	−22.6%
ULCER	−6.3%	−2.5%	−2.6%	−10.1%	−9.4%	−26.8%	−25.0%
EMPHYSEMA	−5.1%	−2.0%	§	−8.2%	−12.0%	−22.5%	−30.7%
CANCER	−4.9%	−1.9%	§	−7.8%	−11.8%	−21.5%	−30.3%
RESP-OTHER	−4.1%	−1.6%	−7.3%	−6.6%	−1.8%	−18.6%	−5.4%
ASTHMA	−3.8%	−1.5%	2.4%	−6.1%	−12.6%	−17.3%	−32.2%
HYPERTENSION	−2.3%	−0.9%	1.6%	−3.8%	−7.2%	−11.2%	−20.1%
ARTHRITIS	−1.8%	−0.7%	−4.0%	−2.9%	0.7%	−8.7%	2.2%
CNS-OTHER	−0.6%	−0.2%	−10.5%	−1.1%	5.5%	−3.3%	18.7%
KIDNEY	−0.6%	−0.2%	−3.8%	−1.1%	1.1%	−3.2%	3.4%
DIABETES	2.2%	0.8%	−7.4%	3.8%	8.1%	12.4%	28.2%
HEARING	3.6%	1.3%	−1.7%	6.3%	7.5%	21.7%	26.1%

Notes: [a] Percentage change in employment probability due to a change in disease variable from zero to one holding other variables constant at their mean values.
[b] Uses probit coefficient estimates from Model II in Table 4.
[c] Uses probit coefficient estimates analogous to those in Model II of Table 4, but the model is estimated separately for age groups 35–54 and 55–74.
Data are from the 1991 New Jersey Demographic and Disability Survey (NJDDS) restricted to those aged 35–74, excluding those who reported any chronic illness prior to age 25.

analysing the cumulative effect of having several chronic conditions upon employment probability.[15] This analysis can be accomplished by using the coefficients from the regression model to construct a 'disease status index', where D_i is the value of the index for the ith individual. If B_d is the coefficient vector corresponding to the disease variables and, as before, Δ_i represents the disease state vector, then $D_i = -\lambda B_d^{\prime}\Delta_i$ is simply a weighted sum of the individuals' diseases, where λ is a factor used to scale the index between zero and one.[16] As opposed to other summary measures of disease, this measure is not based on individuals' subjective assessments of their health, but on their reports of physician-diagnosed chronic illnesses. An important aspect of this index is that it can be compared much more readily across individuals than other summary measures of health discussed previously.

For analytical purposes, the disease status index can be used to define four severity levels:

No disease: $D_i = 0$

Mild: $0 < D_i \leqslant 0.85$

Moderate: $0.85 < D_i \leqslant 0.95$

Severe: $0.95 < D_i \leqslant 1$

Sorting individuals into these groups allows one to look at the effects of co-morbidity on employment and to see how the model of the preceding section performs in predicting

[15] Wilson and Nguyen (1998) find that even though veterans of the US Civil War in the early 1890s had much higher rates of disability than found in today's population, rates of chronic illness are generally much higher today than they were among Civil War veterans when restricting the population to those who are disabled. Their result implies that in modern times disability typically results from a combination of conditions, whereas in earlier times the presence of a single condition (often one that is trivial given modern medicine) could lead to substantial disability.
[16] In the construction of D_i, individual coefficients where $\beta > 0$ are set equal to 0, though results differ very little from the case where positive β coefficients are allowed.

Table 7. *Employment effects by educational level*

	Percentage change in employment rate due to disease[a]				
	Women			Men	
Educational level:[b]	High school or less	Beyond high school	Education Level:[b]	High school or less	Beyond high school
Disease			Disease		
CNS-OTHER	−50.1%***	−63.2%***	CNS-TRAUMA	−59.9%***	−41.3%***
MUSC-OTHER	−35.6%***	−18.7%*	MENTAL	−40.2%***	−11.5%**
CNS-TRAUMA	−43.7%**	−5.3%	MUSC-OTHER	−22.3%**	−8.4%**
HEART	−35.3%***	−8.8%	EYE	−18.8%***	−4.8%*
CANCER	−34.5%***	−7.7%	OTHER	−1.7%	−12.6%***
RESP-OTHER	−8.6%	−19.2%*	HEART	−6.5%	−7.4%***
DIABETES	−17.7%**	2.1%	BACK	−7.9%*	−4.4%**
ARTHRITIS	−10.8%**	−12.8%**	ULCER	−14.0%*	−3.1%
ULCER	−29.1%**	16.3%*	EMPHYSEMA	−2.5%	−9.0%
MENTAL	−0.1%	−18.6%*	CANCER	−4.3%	−6.2%
EMPHYSEMA	−49.7%**	25.6%**	RESP-OTHER	−21.5%**	7.4%**
EYE	−8.5%	−4.9%	ASTHMA	−9.4%	−2.9%
OTHER	−10.9%	−3.2%	HYPERTENSION	−0.7%	−3.9%**
BACK	−16.9%***	4.9%	ARTHRITIS	−9.7%**	1.9%
KIDNEY	−5.6%	12.5%	CNS-OTHER	−19.1%**	4.7%*
HEARING	−0.8%	0.6%	KIDNEY	8.1%	−3.4%
HYPERTENSION	8.6%*	4.3%	DIABETES	−5.5%	4.4%**
ASTHMA	−6.1%	10.7%	HEARING	−8.1%	6.2%***
$N=$	4337	3263	$N=$	3291	3768
Employment rate	0.511	0.723	Employment rate	0.703	0.840
Mean age	54.0	47.7	Mean age	53.2	48.9

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
[a] Percentage change in employment probability due to a change in disease variable from zero to one holding other variables constant at their mean values.
[b] 'Combined' values are estimated from the coefficients in Model II of Tables 3 and 4, the 'High school or less' and the 'Beyond high school' values are estimated separately by education level (regression coefficients not shown).
Data are from the 1991 New Jersey Demographic and Disability Survey (NJDDS) restricted to those aged 35–74, excluding those who reported any chronic illness prior to age 25.

the employment of these individuals.[17] This analysis is performed in Table 8 and represented graphically in Fig. 1, where three data series are represented for each age group. The first series is the actual employment rate, which generally declines for all age groups as D_i increases, especially for those in the severe group. The second series is the employment rate for each disease-status group predicted from Equation 4 (Model II in Tables 3 and 4). In all cases, except for men over age 65, the model accurately predicts the sharp decline in the employment rate for those with a severe disease status. Finally, the third series uses Model I, the reduced form equation that contains no disease variables, to capture how much of the variation in employment rates is captured by the other variables. This series is surprisingly constant across disease levels for each age group.

This analysis suggests that even though chronic disease does not explain much of the variation in employment probability in the sample, it is a dominant predictor for those who actually have high rates of chronic illness or who have a particularly severe condition, such as spinal chord injury (included in CNS-TRAUMA). Indeed, for most of the age groups, employment is halved for those in the severe group. Because individuals are sorted by diseases-status alone, the sharp differences across the severity categories in age-specific employment rates are clear evidence that chronic disease and co-morbidity affect the employment decision. The drop in employment at high levels of disease is predicted closely by the model, which includes disease variables but not by the model without the disease indicators. If health status were primarily a choice variable, as postulated by the Grossman model,

[17] Note that due to the arbitrary division of the index into severity categories, the different classifications of mild, moderate, severe have no direct physiological basis. The classification is used solely for illustrative purposes. The result, however, are robust to changes in the classification scheme.