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HEALTH, INCOME, AND RISK AVERSION: ASSESSING SOME WELFARE COSTS OF ALCOHOLISM AND POOR HEALTH

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ABSTRACT

The economic costs of adverse health outcomes have typically been evaluated in a cootext of risk oeutrality, an approach that ignores the potential welfare importance of individuals' risk preferences. This paper presents a framework that unifies the research in health capital and earnings with that on risk preferences in the presence of stochastic outcomes. The model is implemented to obtain estimates of the economic damages due both to general health problems as well as to one specific health problem that is of considerable interest from society's perspective: alcoholism. Our empirical findings, based on data from the Epidemiologic Catchmeot Area survey, indicate that failure to recognize the possibility of risk averse preferences leads to a potentially serious underestimation of the magnitudes of the "costs" of alcoholism and poor health. In particular, it is shown that while alcoholism problems have negative impacts on the conditional mean of income (consistent with most of the existing literature), they also have positive impacts on the conditional variance of income. Our conclusions are to some degree provisional because our estimates of conditional variances are necessarily biased to the extent that unobserved heterogeneity is an important determinant of the moment structure of income in our sample.

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I. Introduction

That poor health is costly to society is a proposition few would debate. Apart from the very real costs associated with pain and suffering themselves, poor health — when characterized as a depressed stock of one kind of productive human capital — has repeatedly and in many contexts been shown to result in reduced earnings and income, in disruptions to normal family life, and in a variety of other undesirable social consequences.¹

Nonetheless, despite the rigorous theory and econometrics that have been devoted to analyzing such relationships, the economic damages attributed to adverse health outcomes have typically been evaluated in contexts that do not account for *ex ante* uncertainty surrounding valued outcomes, thereby ignoring the vast literature on the importance of risk preferences towards stochastic outcomes.² Thus, for instance, if a specific health problem is found to reduce wages or earnings by \$500 on average, then \$500 is typically considered to be the per capita "cost" -- or at least the part manifested in the labor market -- attributable to the health problem. Even if implemented in a reasonable manner, such strategies are inherently "*ex post* productivity-based" rather than "*ex ante* welfare-based" approaches for measuring "social costs"; in particular, no allowance is made for risk aversion or the *ex ante* stochastic nature of earnings.

This paper presents an framework that unifies to some degree the research in health capital and earnings and in individual attitudes towards and decisionmaking in the presence of *ex ante* stochastic outcomes.³ The fundamental objective is to obtain a more comprehensive picture of

^{1.} See, e.g., Bartel and Taubman (1979, 1986) and Rice et al. (1990).

^{2.} Some parallel issues arise in the analysis of uncertain medical expenditures, but for that issue the importance of *ex ante* risk aversion has long been recognized as the driving force underlying the market for health insurance.

^{3.} A good analogy is the agricultural economics literature on estimation of the welfare costs of output variations; see Antle (1988) for an overview of the key issues.

the "costs" of general health problems as well as one specific health problem that is of considerable interest from society's perspective: alcoholism.⁴ A prevalent health problem,⁵ especially among males,⁶ alcoholism has been estimated to result in sizeable costs to society.⁷

The basic idea underlying the analysis can be summarized as follows. Suppose individuals have indirect utilities, $V(.;\gamma)$, defined over some measure of income, Y_t , and that each individual confronts *ex ante* a probability distribution of *ex post* income outcomes, $\Phi(.|Q_t;\lambda)$ which is conditioned on a vector of the individual's characteristics, $Q_t = (Z_t, \Theta_t)$. Only some elements of Q_t , i.e. Z_t , are observed by the econometrician; Θ_t is "unobserved heterogeneity" in the usual sense.

Conditional on Q_t , income is stochastic *ex ante* from the individual's perspective, as one property of the conditional distribution $\Phi(Y_t|Q_t;\lambda)$ is assumed to be $var(Y_t|Q_t)>0$. In this setting, an individual who, due to some policy change or other exogenous shock, experiences a shift in Q_t will be confronted with a new *ex ante* income distribution and will accordingly experience an *ex ante* welfare change whose direction and magnitude depend both on properties of V(.) and on how the shift in Q_t affects $\Phi(.)$. In general, even if the shift is "mean-preserving," there will be welfare consequences so long as there are variance effects and

^{4.} See Cook (1990) and Mullahy (1993) for surveys of the key issues, and NIAAA (1990) for details. NIAAA's estimate of the "economic cost" of alcohol abuse and alcohol dependence is \$136.3 billion for 1990 (NIAAA (1990), p. 174).

^{5.} See American Psychiatric Association (1980, 1987) for the medical/psychiatric perspective of alcoholism as a health disorder.

^{6.} Over 10% of males aged 18 to 65 are at any point in time estimated to manifest alcoholism symptoms, and more than twice this number are estimated to have exhibited symptoms of alcoholism at some point over the course of their lifetimes. Conversely, only about 3% of females are estimated to suffer from alcoholism symptoms.

^{7.} See, for instance, Chapters II and VII of NIAAA (1990) and Rice et al. (1990).

individuals are not risk neutral.

The paper has two main objectives. The first is to document empirically how the probability distribution of income outcomes – in particular, its mean and variance – depends on observables Z_t , especially those of interest from a policy perspective.⁴ Our particular focus is on how medically-defined alcoholism as well as general health status affect the moment structure of incomes. It might be noted that this study was motivated initially by the concern that econometric studies of how general health status and, in particular, alcoholism⁹ affect labor market performance may miss an important part of the evaluative picture to the extent that they focus only on mean effects, as is typically the case in regression analysis of such phenomena.¹⁰

This observation motivates our second objective, which is to consider in a mean-variance utility framework how such information might be utilized to gain some understanding of the welfare implications associated with policies designed to change various elements of the observables Z_t . To the extent that moments of Y_t of higher order than the mean depend on Z_t , then welfare computations based solely on how shifts in Z_t affect the mean of Y_t will misstate the true welfare effects of the shift in Z_t if individuals are not risk neutral. The empirical

^{8.} There are some commonalities of this paper with that of Low and Ormiston (1991), who specify and estimate using NLS data a stochastic specification akin to that described below. Their framework did not account for the role of health problems as determinants of the moment structure of income.

^{9.} See Mullahy (1993) for a survey on the relationships between alcohol use and labor market performance.

^{10.} Much of the pertinent literature – economics and otherwise – is concerned with the "costs" of illness. By explicitly or implicitly invoking a "wage equals value of marginal product" assumption, many such studies conclude in essence that the point estimate of the health status parameter in wage/earnings/income regressions is a measure of the productivity loss associated with the health problem. However, the relationships between such productivity losses and welfare in the way economists usually think of welfare are not obvious unless stringent assumptions (e.g. risk-neutrality) on preferences are invoked.

complication is that the econometrician, whose data permit conditioning only on Z_t but not on all elements of Q_t , will tend to measure greater conditional variance from the data *ex post* than the individual confronts *ex ante* so long as the role of Θ_t in conditioning $\Phi(Y_t|Z_t,\Theta_t;\lambda)$ is nontrivial.¹¹

The plan is as follows. Section II presents an expected utility framework in which both first and second moment welfare consequences of poor health can be assessed. Section III discusses the econometric strategy and data. Section IV presents the estimation results. Section V presents a set of estimates of some of the costs of alcoholism and poor health that are manifested in the labor market. Section VI concludes.

II. Health and Welfare

As above, consider an individual whose preferences can be described by an indirect utility function defined on income, $V = V(Y;\gamma)$, where Y > 0 denotes income, V' > 0, and γ is a vector of parameters that characterize preferences. From an *ex ante* perspective, an individual with characteristics Q has *ex ante* welfare determined by his or her expected utility (EU)

^{11.} The unobserved heterogeneity θ may, for example, have the character of an individual's knowledge of the quality of his/her job attachment or match or the knowledge of certain contractual or legal requirements that mitigate the uncertainty of labor market outcomes. With a reference to Becker (1975), Eden and Pakes (1981) state succinctly the empirical implications of such unobserved heterogeneity in a context similar to that considered here:

The problem with using the large unexplained portion of the cross-sectional dispersion of earnings to construct measures of the uncertainty in different earnings profiles is that individuals possess information on their probable future positions in the earnings distribution, that we, in our role as researchers, do not. Thus Becker concludes his discussion of the variance in the returns to college education with the question: "How much of this large variation in the gain from a college education can be anticipated due to known differences in ability, environment, etc., and, therefore, should not be considered part of the *ex ante* risk?"

$$EU(Q;\gamma,\lambda) = \int_{(0,\infty)} V(Y;\gamma) d\Phi(Y|Q;\lambda),$$

where the parameters γ describe preferences towards risk. The explicit dependence of expected utility on the parameters of the indirect utility function and the distribution function is written to emphasize that expected utility depends on the parametric structure of both preferences and the data generating process, as well as on any covariates that might condition preferences and probability distributions.¹²

To focus ideas, the familiar Grossman-Becker-Mincer¹³ human capital framework provides a convenient structure within which such dependencies might be analyzed. Dropping observation subscripts, suppose y = ln(Y) is determined as

$$y = f(\mu(Z;\alpha), \sigma(Z;\beta), \Theta, e), \qquad (1)$$

where $\mu(.)$ and $\sigma(.)$ denote (in a sense to be made clearer below) conditional mean and variance conditional functions, respectively, and where *e* represents the component of log-income that is *ex ante* stochastic to the individual. Z=(K,H,X) summarizes all observable covariates, with K a vector of human capital measures other than health (e.g. schooling, experience), H a vector

^{12.} We ignore here the interesting complication that arises when the utility function V(.) is itself health-state-dependent (e.g. different γ values depending on whether or not one is in the poor health state, or explicitly conditioning V(.) on Z), and instead allows Z to condition only the distribution function. Ignoring state-dependence of this nature may result in an underestimate of the expected utility losses due to poor health, as the approach proposed here accounts only for health-related income differentials, not for welfare losses due to "pain and suffering." For interesting discussions of this and related issues, see Cook and Graham (1977), Smith and Desvousges (1987), and Viscusi and Evans (1990).

^{13.} Grossman (1972a, 1972b), Becker (1975), Mincer (1974).

of health status measures, and X a vector of other covariates that affect the distribution of y.

If larger values of H indicate better health, then much empirical research¹⁴ suggests that $\partial E(Y|Q)/\partial H > 0$, i.e good health is a productive component of human capital. Any reasonable specification of preferences would have¹⁵

$$EU(H_{G}, X, \theta; \gamma, \lambda) > EU(H_{P}, X, \theta; \gamma, \lambda),$$
(2)

i.e. expected utility is greater, ceteris paribus, in the good (G) health state than in the poor (P) health state. Of course, even in the absence of risk and variance considerations, one would be led to this conclusion simply as a consequence of the $\partial E(Y|Q)/\partial H > 0$ result. However, once risk aversion and health-dependent conditional income variances are admitted, then as suggested above the standard "differences in mean income" approach to assessing the costs associated with adverse health outcomes is seen to provide only a partial picture of the welfare losses that attend poor health.

Were it found empirically, for instance, that $\partial E(y|Q)/\partial H > 0$ and $\partial var(y|Q)/\partial H < 0$, i.e. good health increases conditional mean income and reduces income's conditional variance, then in the presence of risk aversion there are two channels – a mean effect and a variance effect – through which poor health diminishes welfare. In such circumstances, welfare analysis must recognize that in addition to the lower mean incomes they would wish to avoid, risk-averse individuals would also be willing *ex ante* to incur positive risk premia to avoid adverse health outcomes.

^{14.} See, for instance, Bartel and Taubman (1979, 1986), Benham and Benham (1982) and Luft (1975).

^{15.} K is henceforth absorbed as part of X.

The model (1)-(2) provides a convenient analytical framework for assessing the key policy issue at hand, i.e. whether interventions designed to mitigate, forestall, or prevent adverse health outcomes may have payoffs in terms of increased expected utility that could well exceed simply the health-related differences in mean incomes. To the extent that the differences between EU in the good and poor health states can be described in terms of monetary equivalents (e.g. compensating or equivalent variations), it is then possible to meaningfully identify one component of the true economic costs of poor health.

To this end, if γ (the preference parameters) and λ (the probability distribution parameters) are known or estimable, then measurement of such costs would be feasible. The empirical analysis of such a structure would be relatively straightforward were it not for Θ , whose presence introduces a fundamental identification problem: the *ex ante* (and, therefore, welfare-relevant) variance confronted by the individual and the *ex post* variance the econometrician can measure will in general not be the same.

The empirical and evaluative implications of unobserved heterogeneity depend on precisely how Θ enters the model. While several reasonable possibilities can be entertained, the leading case of additive heterogeneity is illustrative to consider. Suppose the specific form of f(.) in (1) is

$$y = \mu(Z;\alpha) + s(Z;\beta)\varepsilon + \Theta$$
(3)
= $\mu(Z;\alpha) + u_{\star}$

where $s(.) = \sqrt{\sigma(.)}$, and suppose that the unobservables (e, Θ) and covariates satisfy the following mean-, variance-, and covariance-independence conditions:¹⁶

^{16.} See Manski (1988) for a discussion of the implications of these statistical restrictions.

$$E(\varepsilon | Z) = E(\Theta | Z) = cov(\varepsilon, \Theta | Z) = 0,$$

$$\tau_{\varepsilon} = var(\varepsilon | Z) = var(\varepsilon), \text{ and } \tau_{\Theta} = var(\Theta | Z) = var(\Theta).$$

That is, the observable conditioning covariates Z are assumed to be exogenous in a particular sense.¹⁷ It follows from (.) that

$$E(y|Z) = \mu(Z;\alpha), \tag{3a}$$

and, since $var(y|Z) = E(y^2|Z) - E^2(y|z)$,

$$\operatorname{var}(\mathbf{y}|\mathbf{Z}) = \sigma(\mathbf{Z};\boldsymbol{\beta})\boldsymbol{\tau}_{\boldsymbol{\mathcal{E}}} + \boldsymbol{\tau}_{\boldsymbol{\Theta}}.$$
 (3b)

Note that $\sigma(Z;\beta)\tau_{\mathcal{E}}$ is the true ex ante log-income variance confronting the individual whereas $\sigma(Z;\beta)\tau_{\mathcal{E}}+\tau_{\Theta}$ is what the econometrician can measure ex post.

The particular manner in which Θ enters the model in conjunction with the true functional

^{17.} While the discussion of "overdispersion" is cast here in terms of unobserved heterogeneity, there may be other reasons why the econometrician measures variance that is not relevant *ex ante* to the individual decisionmaker. For example, if any element of Z is measured inaccurately by the econometrician, then there is an extra source of "error" and, therefore, error variance, the econometrician confronts that is irrelevant to the individual's *ex ante* welfare.

Regardless of the interpretation of Θ (measurement error, unobserved covariates, etc.), it should be stressed that the assumption that the observed covariates Z are exogenous – i.e. Z serves as its own instruments – amounts to a best-case scenario for identifying the parameters of interest. Yet, even instrumenting strategies that are suitable for estimating linear conditional mean functions in the presence of unobserved beterogeneity, errors-in-variables, etc., will not in general suffice to identify all parameters of interest in a conditional variance function, as will be seen below.

Finally, while the exogeneity of some elements of the Z vector used here might be questioned, there are no obvious instrumental variables that would be manifestly preferred to using the elements of Z as their own instruments; this issue is taken up again in section III.b.

form of $\sigma(.)$ will determine which parameters of the variance function are estimable. The simplest case is where $\tau_{\Theta}=0$ and where the econometrician assumes the correct form for $\sigma(.)$, in which case all elements of β can in principle be estimated. A more relevant case to consider is where (3b) is the true variance function and the econometrician assumes a linear variance function $\sigma(Z;\beta)=Z\beta=\beta_0+Z_1\beta_1$. In this instance, the constant term parameter, β_0 , will capture the effects of unobserved heterogeneity, absorbing τ_{Θ} as well as τ_{ε} . As such, β_0 , τ_{Θ} , and τ_{ε} are not separately identified but the slope parameters β_1 are, at least in principle, estimable. If instead the true variance function was $\sigma(Z;\beta)\tau_{\varepsilon}\tau_{\Theta}$ and if $\sigma(Z;\beta)$ was assumed to be exponential ($\sigma(Z;\beta)=\exp(Z\beta)$), the constant term parameter β_0 would again absorb τ_{Θ} and τ_{ε} . For other specifications nonzero τ_{Θ} may have less straightforward implications for estimating the variance function parameters.

The econometric analysis conducted below estimates linear and exponential variance function models. We stress, however, that so long as τ_{Θ} is nonzero, the econometrician's estimates of the variance function will be biased; the bias may or may not be confined to the intercept parameter. For the welfare evaluations undertaken in section V, a key implication of such bias is that it will tend to result in overestimates of the *ex ante* variance confronted by the individual. That analysis proceeds as if $\tau_{\Theta}=0$, but in actuality the magnitudes presented in that section should be viewed as upper bounds on the true magnitudes.

III. Econometric Methodology and Sample Construction

III.a. Econometric Strategy

An econometric model is suggested by (.) and (.). Assume the data are T independent observations on (y_t, Z_t) . Assume $\mu(.)$ is linear, $\mu(Z_t; \alpha) = Z_t \alpha$, so that for all t,

$$y_t = Z_t \alpha + u_t, \tag{4}$$

with

$$E(u_t | Z_t) = 0 \tag{5a}$$

and

$$\operatorname{var}(\mathbf{y}_{t}|\mathbf{Z}_{t}) = \sigma(\mathbf{Z}_{t};\boldsymbol{\beta}), \tag{5b}$$

where Z_t , α' , and β' are $1 \times k$ vectors and where $\sigma(Z_t;\beta) = Z_t\beta$ or $\sigma(Z_t;\beta) = \exp(Z_t\beta)$.

Estimation of and inference concerning $\lambda = [\alpha', \beta']'$ is carried out via a generalized method of moments (GMM) approach (Hansen (1982); Newey (1985); Crowder (1987); Davidson and MacKinnon (1993), chapter 17). Consider the following cross-products of instruments Z_t and residuals $y'_t = E(y'_t | Z_t)$ for $\nu \in \{1, 2\}$:

 $m_{1t}(\lambda) = Z_t'[y_t - Z_t\alpha] = Z_t'\rho_{t1}$

and

$$m_{2t}(\lambda) = Z_t'[y_t^2 - (Z_t\alpha)^2 - \sigma(Z_t\beta)] = Z_t'\rho_{t2},$$

with

$$\mathbf{m}_{t}(\lambda) = [\mathbf{m}_{1t}(\lambda)^{\prime}, \mathbf{m}_{2t}(\lambda)^{\prime}]^{\prime}.$$

 $E[m_t(\lambda)] = 0$ follows as a consequence of (4)-(5a,b), and it is this vector of moment restrictions that provides the basis for the GMM estimator $\hat{\lambda}$, which is given by the minimizer of a quadratic form in the moment functions or estimating equations $m(\lambda)$,¹⁹

$$\min_{\lambda} \Gamma(\lambda) = m(\lambda)' \Omega^{-1} m(\lambda),$$

^{18.} In this formulation, Π is a consistent estimator of var($\sqrt{\text{Tm}}(\lambda)$) obtained using first stage residuals from least squares estimates $\overline{\lambda}$ of λ . The asymptotic covariance matrix of $\sqrt{\text{T}}\lambda$ is estimated as $[G(\lambda)'\Pi^{-1}G(\lambda)]^{-1}$, where $G(\lambda) = T^{-1}\Sigma_{t=1}^{T} \partial m_{t}(\lambda)/\partial \lambda|_{\lambda=\lambda}$ estimates $G(\lambda) = \text{plim}[T^{-1}\Sigma_{t=1}^{T} \partial m_{t}(\lambda)/\partial \lambda]$.

where

$$m(\lambda) = T^{-1} \Sigma_{t=1}^{T} m_{t}(\lambda)$$

and

$$\mathbf{G}_{ij} = \mathbf{T}^{-1} \Sigma_{t=1}^{T} \mathbf{m}_{it}(\mathcal{K}) \mathbf{m}_{jt}(\mathcal{K})' \quad i,j \in \{1,2\}.$$

In this instance, the GMM estimate of α is seen to be identical to OLS and its asymptotic covariance matrix identical to a White-type heteroskedasticity consistent covariance estimator. The GMM approach is taken so that inferences concerning β can be made in a straightforward and distribution-robust manner and, as will be seen below, so that several useful tests of misspecification can easily be conducted. Maximum likelihood under a normality assumption (the Low and Ormiston (1991) approach) in conjunction with a family of score tests is an alternative strategy that was considered. Although asymptotically less efficient than ML, the GMM approach is preferable for the purposes at hand since – unlike ML – it is robust against a variety of departures from normality.¹⁹

III.b. Data and Sampling Considerations

The empirical analysis utilizes data from Wave I of the New Haven, Connecticut site of the Epidemiological Catchment Area (ECA) 1980 survey of non-institutionalized individuals conducted under the auspices of the U.S. National Institute of Mental Health (NIMH). The survey is designed primarily to assess the prevalence of mental disorders – including alcoholism – in a community setting. The ECA data set is quite well-suited for study of the labor market consequences of alcoholism as it combines medically sophisticated diagnoses of alcoholism with information on income and labor force participation and demographic characteristics.

^{19.} Indeed, on the basis of some normality tests that we conduct and report below, there is some suggestion that a log-normality assumption may be tenuous for our data.

The ECA surveys were conducted by five major university teams in five areas of the country: New Haven, CT (Yale University); Baltimore, MD (Johns Hopkins University); Durham, NC (Duke University); St. Louis, MO (Washington University); and Los Angeles, CA (UCLA). Individuals aged 18 years old and older were surveyed the New Haven SMSA, comprising 13 towns that at the time of the survey had an adult population of 420,000. Wave I of the survey was completed between 1980 and 1981, yielding 5,034 observations for the New Haven site, a 78% completion rate. At the New Haven site, the elderly were substantially oversampled; thus explaining the relatively small sample size ultimately used, as described below.²⁰

From the 5,034 observations in Wave I of the survey, attention is restricted to males²¹ aged 30 to 59, with this age truncation rationalized by results discussed in Mullahy and Sindelar (1993a) where the importance of accounting for peculiarities in the relationships between alcoholism and labor market success at both the beginning and end of the working life cycle is demonstrated. Given the substantial oversampling of the elderly at the New Haven site, this age restriction reduces the sample size to 555 usable observations.²² The extent to which our results generalize is thus an important consideration.

Assessment of disorders in the ECA is via a professionally designed survey instrument, the

- 1. Restriction to age 30-59: 1,420 observations remain;
- 2. Restriction to males: 604 observations remain;
- 3. Miscellaneous missing data: 555 observations remain.

^{20.} See Eaton and Kessler (1985) for details on the ECA Surveys.

^{21.} We focus on males both because of their far greater propensity to suffer from alcoholism vis-avis females and because of the considerable body of accumulated research regarding the specification of earnings models for males; see Willis (1986).

^{22.} To be precise, the reduction from the original 5,034 observations to the sample of 555 used in this analysis is due to the following restrictions:

Diagnostic Interview Schedule (DIS), which corresponds to the American Psychiatric Association's DSM-III disorder diagnoses. This avoids the self-selection problem in which only individuals who seek treatment can be determined to be alcoholics, and avoids to a large degree the potential for self-reporting biases with regard to alcoholism. Although the issue of the accuracy and quality of the diagnoses based on the DIS is, of course, an open one, the ECA's DIS-based diagnosis of alcoholism has been found to have reasonably good correspondence with alternative diagnostic approaches (see Anthony et al. (1985)).²¹

For this analysis we consider two alternative characterizations of alcoholism. In the first, we define the variable ALCOHOLISM as a binary indicator of whether or not the individual ever satisfied DSM criteria for alcoholism. In the second, which we implement to determine whether the timing of the onset of alcoholism symptoms may be important, we define two variables, EARLY ONSET and LATE ONSET ALCOHOLISM, which subclassify ALCOHOLISM by whether the initial onset of an individual's alcoholism symptoms were up to age 18 years or after age 18, respectively.

If one wished to treat alcoholism as an endogenous consumption behavior, it is not at all apparent what identifying instruments would (a) be conceptually appropriate and (b) be practically available.²⁴ Even if some conceptually appropriate instruments could be identified (e.g. in general, one might consider using lagged alcoholic beverage prices, although such a strategy is not available to us since there is no geographic variation in our data), the recent econometric literature has stressed the dangers associated with using instruments that are weakly correlated with included endogenous variables.²⁵ Measures like family background variables

25. See Staiger and Stock (1993) for a very interesting discussion.

^{23.} See Mullahy and Sindelar (1993a) for discussion.

^{24.} See Strauss (1986) for a general discussion of such issues.

are another possibility, but the circumstances under which their use would be appropriate are also limited.²⁶ The empirical analysis, therefore, follows the mainstream tradition in the health capital literature (e.g. Bartel and Taubman (1979, 1986)) and maintains that the health capital measures (here, those pertaining to alcoholism and physical health status) are econometrically exogenous.²⁷

Table 1 defines the variables used in this analysis while the sample descriptive statistics are displayed in table 2. It should be noted that INCOME and SCHOOLING are created as pseudo-continuous variables using interval midpoints. For SCHOOLING, "17" was used to fill in the open-ended upper interval "grad school," while for INCOME "120" was used to fill in the open-ended upper interval "grad school," while for INCOME "120" was used to fill in the open-ended upper interval "grad school," while for INCOME "120" was used to fill in the open-ended upper interval "greater than \$100,000."²³ Income is income from all sources; more precisely, it is how much income the individual "brought into" the household in the

^{26.} See Kenkel and Ribar (1993) and Mullahy and Sindelar (1994) for discussion.

^{27.} The American Psychiatric Association as well as the World Health Organization provide some quasi-official standing for the disorder view of alcoholism in defining alcohol dependence and abuse as psychological disorders (see NIAAA (1990), Chapter VIII). However, it should be noted that there are many alternative views on the issue of whether alcoholism is simply a health problem or instead is a complex, heterogeneous phenomenon involving individual choice, genetic and metabolic heterogeneity, etc. (see Vaillant (1983), Sournia (1990), Fingarette (1988), NIAAA (1990), and, in a more general context, Becker and Murphy (1988)), so that the issue of the econometric exogeneity of ALCOHOLISM is admittedly unsettled. If exogeneity fails, then the estimates of the ALCOHOLISM coefficients will be inconsistent, with the bias not signable a priori.

^{28.} While the upper censoring of the INCOME variable might appear problematic, only 9 of the 555 observations in the sample report personal income in the \$100,000+ category. Moreover, Mullahy and Sindelar (1993a) show that estimates of the conditional mean of LOG-INCOME are not sensitive to how the upper interval is treated, both by using alternative "fill in" values than the one used here and, more explicitly, by accounting for the censoring via an upper-censored semiparametric Tobit model due to Powell (1986). In light of these results, and since the pseudo-continuous approach greatly simplifies the econometrics, the strategy pursued here would seem a reasonable one.

previous year, which presumably includes transfer payments.²⁹ EXPERIENCE is generated in the standard manner as age minus education minus 6. The two health status variables are measures of overall physical health and a diagnosis of lifetime alcoholism problems.

IV. Estimation Results

The estimates are presented in table 3.³⁰ Columns 1-3 report the results when the lifetime alcoholism variable (ALCOHOLISM) is used; columns 4-6 report the results when alcoholism is subcategorized by the timing of its onset (EARLY and LATE ONSET ALCOHOLISM). The results in column 1 suggest that both health outcomes of interest have statistically and quantitatively important effects on mean log-income, with the point estimate associated with ALCOHOLISM approximately one-half that associated with not being PHYSICALLY HEALTHY. Using $\exp(\hat{\alpha}_j)$ -1 to estimate the percentage change in $E(y_t|Z_t)$ due to turning on the j-th dummy variable, the results in column 1 translate into a *ceteris paribus*³¹ 22% increase in income for individuals not having ALCOHOLISM and a 48% increase in income for individuals who are PHYSICALLY HEALTHY.

The results for the X variables are seen to be consistent with the standard results found in the human capital and earnings literature: a concave EXPERIENCE profile; strong SCHOOLING effects; and statistically significant estimates for MARRIED and WHITE. It

^{29.} A reader has noted that one implication of the income measure including transfers is that the welfare losses from *ex ante* income variance may be overstated.

^{30.} Estimation is performed using GAUSS on a personal computer. The GAUSS estimation code is available on request.

^{31.} The ceteris paribus is an important consideration here since alcoholism may have important indirect effects on other human capital components over the course of the life cycle, e.g. presence of alcoholism symptoms may correspond to reduced educational attainment. See Cook and Moore (1990) and Mullahy and Sindelar (1989, 1990, 1993a,b) for further discussion.

might be noted that the EXPERIENCE effects are smaller and statistically somewhat weaker than might generally be anticipated. By and large, this appears to be attributable not so much to sampling quirks or data problems, but rather to the fact that the ages of the individuals in the sample are restricted to 30 to 59. By truncating off the lower end of the age distribution (i.e. 18 to 29), the portion of the profile that is likely to be most steeply sloping in experience is not observed in the estimation sample.³²

Columns 2 and 3 of table 3 display the estimates of the conditional variance functions under the exponential and linear assumptions, respectively. The results are qualitatively and quantitatively similar for both specifications of $\sigma(.)$, and support nicely the hypothesis that health problems may have important implications for not simply the mean, but also for the variance, of LOG-INCOME. Having ALCOHOLISM and not being PHYSICALLY HEALTHY both imply large ceteris paribus increases in the conditional variance of LOG-INCOME, with the magnitude of the ALCOHOLISM effect again approximately one-half that of the effect due to not being PHYSICALLY HEALTHY.³³ Moreover, it is interesting to see that being MARRIED is – like good health -- a factor that stabilizes income outcomes in the sense of reducing their conditional variance around a given conditional mean.³⁴

^{32.} See Murphy and Welch (1990) for further discussion.

^{33.} We compared the distributions of the OLS residuals for separate subsamples of alcoholics and nonalcoholics. The key difference in the distributions (after adjusting for mean differences) appears as a greater "spread" in the low end of the distribution for alcoholics as compared with nonalcoholics.

^{34.} The parameter estimates in table 3 suggest that the partial effects of ALCOHOLISM on the conditional mean and the conditional variance of LOG-INCOME are negative and positive, respectively. To determine the partial effects on the conditional mean and variance of INCOME itself, additional computations are required. From the moment properties of the lognormal distribution, and dropping observation subscripts to reduce clutter, then $E(Y|Z) = \exp(\mu + \sigma/2)$ and $var(Y|Z) = \exp(2\mu + \sigma)(\exp(\sigma) - 1)$ (recall, σ denotes variance, not standard deviation). For (continued...)

Because estimation of β is of primary focus here, tests for misspecification of the conditional variance functions are of some interest. Since misspecification of $\mu(Z_t\alpha)$ will in turn cause problems for consistent estimation of $\sigma(Z_t\beta)$, testing for misspecification of either is of concern. Following the methodology developed by Tauchen (1985), Newey (1985), and Pagan and Vella (1989), the tests involve examining cross-products of the estimated residuals $\hat{\rho}_{t1}$ and $\hat{\rho}_{t2}$ with a vector of functions of Z_t other than the vector used to form the moment functions $m_{jt}(\lambda)$ (i.e. Z_t itself). Under correct specification of the conditional mean or variance functions, such cross-products should tend in the limit to a zero vector. For the null hypotheses that the linear form of $\mu(Z_t\alpha)$ and the exponential and linear forms of $\sigma(Z_t\beta)$ are correct, the test statistics (each $\chi^2_{(7)}$ under the null) are 12.22 (p=.09), 10.39 (p=.17), and 11.10 (p=.13), respectively. Accordingly, there is no significant indication of misspecification of the kind tested here.³⁵

34. (...continued)

 $E(Y|ALCOHOLISM=1,X) / E(Y|ALCOHOLISM=0,X) = exp(\alpha_A + \beta_A/2)$ (*)

and

$$\operatorname{var}(Y | \operatorname{ALCOHOLISM} = 1, X) / \operatorname{var}(Y | \operatorname{ALCOHOLISM} = 0, X) = (**)$$
$$\operatorname{exp}(2\alpha_A + \beta_A) \times \{ [\operatorname{exp}(\beta_A + X\beta_X) - 1] / [\operatorname{exp}(X\beta_Y) - 1] \},$$

where $\alpha = (\alpha_A, \alpha_X')'$ and $\beta = (\beta_A, \beta_X')'$ are conformed to correspond to Z = (ALCOHOLISM, X')'. Using the point estimates from table 3, the ratio (*) is seen to be less than one, so ALCOHOLISM indeed is estimated to have a negative partial effect on E(Y|Z) for any X. To determine the partial effect on var(Y|Z), particular values of X must be considered since the first term on the rhs of (**) is less than one while the second (bracketed) term exceeds one when evaluated at the estimates of table 3. It turns out, that (**) is substantially greater than one at every X vector in the sample, with a range of 1.47 to 1.62. It thus seems fair to conclude, as is the case for LOG-INCOME, that ALCOHOLISM reduces INCOME's mean but increases its variance.

35. For conducting the tests, the functions of Z_t are specified to be the 7×1 vectors containing the cross-products: ALCOHOLISM*PHYSICALLY HEALTHY; (continued...)

a given X-vector of covariates, and using the linear specification of $\sigma(Z_{\beta})$ to simplify computations, the signs of the partial effects of ALCOHOLISM are determined by whether the following ratios are greater or less than one:

Columns 4-6 of table 3 report the results obtained when the EARLY and LATE ONSET ALCOHOLISM variables are used in place of the single alcoholism indicator. In the conditional mean function, it is seen that alcoholism's largest and most significant deleterious impacts are when its initial onset occurs after age 18. Conversely, it is when alcoholism's initial onset is at or before age 18 that the variance of income is most affected. Although both EARLY and LATE ONSET ALCOHOLISM have positive associations with income variance, the effects of EARLY ONSET are more than twice as large as those of LATE ONSET (with the estimated effects somewhat stronger for the exponential variance function specification).

V. An Evaluation of Welfare Losses Due to Alcoholism and Poor Health

To assess the magnitudes of the welfare losses attributable to alcoholism and to poor health, the expected utility framework sketched in Section II is adopted. That is, differences – specifically, as shown below, reductions – in expected utility owe to the shifts in the probability distribution of INCOME associated with either ALCOHOLISM or not being PHYSICALLY HEALTHY.

Such welfare measures can be rationalized in terms of the value individuals attach to certainty equivalences³⁶ in the presence of *ex anue* stochastic outcomes.³⁷ We consider the

^{35. (...}continued)

ALCOHOLISM*EXPERIENCE; PHYSICALLY HEALTHY*EXPERIENCE; ALCOHOLISM*SCHOOLING; PHYSICALLY HEALTHY*SCHOOLING; ALCOHOLISM*MARRIED; and PHYSICALLY HEALTHY*MARRIED. It should be pointed out that tests of this kind are renowned for having low power against a wide variety of alternatives; see Bierens (1990).

^{36.} The certainty equivalence of an income lottery is mean income minus the risk premium.

^{37.} For expositional simplicity the following discussion is cast in terms of a scalar "poor health" measure although the analysis that follows will be conducted for both poor health measures, ALCOHOLISM and not being PHYSICALLY HEALTHY.

certain monetary values corresponding to expected utility in the two states, i.e.

$$ce(EU(H_{i},X;\gamma,\lambda)) = ce_{i}, j \in \{G,P\}$$

denotes the certainty equivalence (in dollars) of the expected utility received under the income lottery the individual confronts if *ex ante* in health status j.

For the reasons spelled out earlier, we feel that our estimates of the ce_j should be viewed as upper bounds on the true measures. Since our estimation procedure is likely to overstate the *ex ante* variance faced by individuals, and since risk-averse individuals will demand positive risk premia to accept higher variances, then our estimated risk premia will tend to be too high. Given this caveat, we nonetheless feel it is useful and interesting to obtain a sense of how such risk premia affect computations of the costs of poor health.

For illustrative purposes and for ease of computation, $V(Y;\gamma)$ is specified to have a constant relative risk version (CRRA) form that depends on the single parameter γ , i.e. $V(Y;\gamma)=(Y^{\gamma}-1)/\gamma$, which has as a limiting case $V(Y;\gamma)=\ln(Y)$ as $\gamma \rightarrow 0$, and has the property that it characterizes risk-averse (-neutral; -loving) preferences for $\gamma < 1$ (=1; >1).³⁴ Focusing here on non-risk-loving preferences, only values of $\gamma \le 1$ are considered. The work of Hansen and Singleton (1983) and Constantinides (1990), among others, suggests that values in the range (-2, 1) might be reasonable to consider. Accordingly, the sensitivity of the welfare cost estimates to the assumed degree of risk aversion is assessed by considering values of $\gamma \in \{-2, -1, 0, 1\}$, with $\gamma=0$ understood to imply $V(Y;\gamma)=\ln(Y)$.

The computations are greatly simplified by assuming that the probability distributions of $Y_t|Z_t$ (INCOME) are lognormal. To gauge the reasonableness of such a lognormality

^{38.} See Hey (1979) for a good general discussion.

assumption, a test is undertaken to determine whether conditional normality of LOG-INCOME is empirically tenable for this sample. The conditional moment restrictions to be tested jointly are

$$E[(y_t - Z_t \alpha)^3 | Z_t] = 0$$

and

$$E[(y_{t} - Z_{t}\alpha)^{4} - 3\sigma(Z_{t}\beta)^{2} | Z_{t}] = 0,$$

corresponding, respectively, to conditional symmetry and conditional mesokurtosis. Using only the lifetime alcoholism variable (ALCOHOLISM) for this exercise, we find that the $\chi^2_{(2)}$ test statistics for the linear and exponential variance function specifications are 4.45 (p=.11) and 7.42 (p=.02), respectively. Despite the mixed evidence on lognormality provided by these tests, maintaining conditional lognormality does not seem terribly far-fetched for these data.³⁹

The probability distributions of $Y_t | Z_t$ are thus assumed lognormal. Focus is primarily on the outcomes for two distinct subpopulations (good health and poor health).⁴⁰ Given the assumptions on CRRA indirect utility⁴¹ and conditionally lognormal income, it follows that the

^{39.} See Pagan and Vella (1989) for additional discussion of this genre of misspecification test, and Kopp and Mullahy (1990) for some recent applications. It should be noted that the properties of standard normality tests based on third and fourth sample moments of OLS residuals (see, e.g., Greene (1990), p. 329) are uncertain in this application given the presence of conditional heteroskedasticity established above. The test proposed here, conversely, should have proper asymptotic size regardless of the presence of conditional heteroskedasticity. However, since high order moments of the estimated residuals are used in computing the test statistics, some caution should be exercised in interpreting them given our relatively small sample size.

^{40.} Henceforth, when examining effects due to ALCOHOLISM, PHYSICALLY HEALTHY will be absorbed as part of X_t , and vice versa.

^{41.} Representations of $V(Y;\gamma)$ "less risk averse" than ln(Y) (here $\gamma \in (0,1)$) actually suggest positive willingness to pay for increased σ (i.e. downward-sloping indifference curves in (μ,σ) (continued...)

expected utility associated with health status j, EU_j , is given⁴² by

$$EU_{j} = \gamma^{-1} \int_{(0,\infty)} Y^{\gamma} d\Phi(Y | H_{j}, X; \lambda)$$
$$= \gamma^{-1} exp(\gamma \mu_{j} + .5\gamma^{2} \sigma_{j}), \quad j \in \{G, P\}$$

recalling that σ denotes variance, not standard deviation. The ce_j are defined by placing unit probability mass on some Y in the domain of V(Y; γ) such that

$$\gamma^{-1} c e_j^{\gamma} = \gamma^{-1} e x p (\gamma \mu_j + .5 \gamma^2 \sigma_j),$$

giving

$$ce_{j} = exp(\mu_{j} + .5\gamma\sigma_{j}), \quad j \in \{G,P\}.$$

The ce_j computed here can be thought of as *ceteris paribus* estimates: holding other factors constant only the health state variable changes, so this set of estimates conceptually addresses the question of the worth of recovering from the poor health state while still otherwise being like a typical person in the poor health state. For ALCOHOLISM, these estimates are computed in two different ways: first, by turning on the ALCOHOLISM dummy for observations in the non-ALCOHOLISM subsample ("the healthy become sick"); second, by turning off the

^{41. (...}continued)

space) despite the fact that $V(Y;\gamma)$ is still concave in Y for $\gamma \in (0,1)$. Apparently counterintuitive results like this have been discussed extensively and resolved by Meyer (1987) and owe basically to the lognormality assumption. Heuristically, while increases in σ_j correspond to an increased risk premium in health state j, they also serve to increase mean income as a consequence of the parameterization of the lognormal's mean function.

^{42.} Given, that is, up to an additive constant $(-\gamma^{-1})$ that doesn't depend on j. See Aitchison and Brown (1969) on the moment properties of powers of lognormal variates.

ALCOHOLISM dummy for observations in the ALCOHOLISM subsample ("the sick become healthy"). Thus, using the "healthy become sick" case to illustrate, for $j \in \{G, P\}$

$$\hat{c}_{j} = \Sigma_{t \in S_{G}} \exp(X_{t} \hat{\alpha}_{X} + \delta_{jP} \hat{\alpha}_{A} + .5\gamma \exp(X_{t} \hat{\beta}_{X} + \delta_{jP} \hat{\beta}_{A})) / \#S_{G},$$

where δ_{ik} is the Kronecker delta. Again, analogous computations are made to estimate the PHYSICALLY HEALTHY equivalences.

The results are presented in table 4.⁴³ In an important sense, the key comparisons are between $\gamma \in \{-2, -1, 0\}$, the risk averse cases, and $\gamma = 1$, the risk neutral case that might be thought of as the standard approach. Panels I and II display the ce_j estimates based on the *ceteris paribus* assumption. Focusing first on ALCOHOLISM, it is particularly striking how the "cost" of becoming an alcoholic (panel I) or the "value" of recovering from alcoholism (panel II) depends on the degree of risk aversion. The welfare differences are trivial if risk neutrality ($\gamma = 1$) is assumed, whereas the differences in the monetary values of the good and poor health states are considerable at higher degrees of risk aversion. This pattern is similar for PHYSICALLY HEALTHY.

We conclude – admittedly provisionally – that failure to recognize the possibility of risk averse preferences leads to a potentially serious underestimation of the magnitudes of the "costs" of alcoholism and poor health. Our conclusions are provisional, as we have noted several times in the course of this discussion, because our estimates of conditional variances are necessarily biased to the extent that unobserved heterogeneity Θ is an important determinant of the moment

^{43.} The magnitudes are converted to 1991 dollars via the BLS all items consumer price index. It should be stressed that all these figures are annual and as such do not represent the present value of lifetime costs. Such computations, while possible, will depend among other things on the age of the individual as well as the rate of discount used.

structure of income in our sample.

VI. Summary

This paper has expanded the standard approach to the welfare analysis of health-related economic costs by accounting for risk aversion and variance in income that depends on health status. The results presented here suggest that such amendments may be both qualitatively and - at least in this application - quantitatively important. Again we stress, however, that the generalizability of the results beyond the population of "prime age" males must be approached with caution.

The present study has provided some empirical insight into the role of alcoholism as a costly health problem, suggesting that an evaluation of its welfare costs in terms of productivity differentials alone may significantly understate such costs. In addition, the framework presented here is a general one that might be applied to a variety of specific and/or general health problems of concern. The obstacles posed by unobserved heterogeneity are unlikely to be trivial, but by use of longitudinal data it may be possible to circumvent some of these obstacles to assessing the cost of poor health. This is the next item on the research agenda.

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Table 1

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Variable Definitions

Income Measures	
INCOME (Y)	Of household's total income before taxes for past year, including salaries, wages, social security, welfare, and any other income, how much was earned or brought in by individual (+1000)
Log-Income (y)	Natural log of INCOME
Independent Variables	
ALCOHOLISM	= 1 if symptoms of alcoholism ever present, = 0 else
EARLY ONSET Alcoholism	= 1 if first alcoholism symptoms were present at or before age 18, = 0 else
LATE ONSET Alcoholism	= 1 if first alcoholism symptoms were present after age 18, $=$ 0 else
PHYSICALLY HEALTHY	= 1 if individual reports physical health is excellent or good, = 0 if reports fair or poor
SCHOOLING	Years of completed schooling
EXPERIENCE	Age in years minus SCHOOLING minus 6
EXPERIENCE SQUARED	EXPERIENCE squared
WHITE	= 1 if race is white, = 0 if race is nonwhite
MARRIED	= 1 if currently married, = 0 else

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Table 2

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Sample Descriptive Statistics (N. Obs. = 555)

Variable	Mean	Std. Dev.	Minimum	Maximum
INCOME	23.42	17.68	0.500	120.0
LOG-INCOME	2.91	0.785	-0.693	4.79
ALCOHOLISM	0.204	0.403	o	1
EARLY ONSET ALCOHOLISM	0.059	0.237	O	1
LATE ONSET ALCOHOLISM	0.144	0.352	0	1
PHYSICALLY HEALTHY	0.899	0.301	0	1
EXPERIENCE	22.4	10.15	7.0	49.0
EXPERIENCE SQUARED	605.2	506.0	49.0	2401
SCHOOLING	13.44	3.04	2.0	17.0
MARRIED	0.723	0.448	0	1
WHITE	0.858	0.350	0	1

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GMM Estimates of Conditional Mean and Conditional Variance of LOG-INCOME (Asymptotic t-statistics in parentheses)

Variable $R(\gamma_{t} t_{t}) = t_{t}a$ ex ALCOHOLISH -0.202 EARLY ONSET ALCOHOLISH -0.202 EARLY ONSET ALCOHOLISH -0.390 HEALTHY (2.35) RYPERIENCE 0.0390 HEALTHY (2.55) EXPERIENCE 0.052 RYPERIENCE 0.052 EXPERIENCE 0.077 SCHOOLING (6.18) MARIED 0.312 MARIED 0.312 MHITE 0.290 WHITE 0.290				
Variable $R(y_t t_t) = t_a$ ALCOHOLISH -0.202 ALCOHOLISH -0.202 ENRLY ONSET (2.33) ALCOHOLISH (2.39) ALCOHOLISH 0.390 HTTE ONSET -10.001 ALCOHOLISH 0.390 PHYSICALLY (2.55) RYPERIENCE 0.052 RYPERIENCE (3.26) SCHOOLING (6.18) MARIED 0.312 WHITE 0.290 WHITE 0.290	var(etizt)=0(ztb)		var (e _t I _t	_E)=σ(Σ _E β)
ALCOHOLISH -0.202 ENELY ONSET - ALCOHOLISH - ALCOHOLISH - ALCOHOLISH - ALCOHOLISH - ALCOHOLISH - ALCOHOLISH - ALCOHOLISH - ALCOHOLISH - 12.55) EXPERIENCE 0.390 EXPERIENCE 0.052 EXPERIENCE 0.052 EXPERIENCE 0.077 SCHOOLING (1.19) MARTED 0.312 WHITE 0.290 WHITE 0.290	exp(zt) zth	$E(y_{t} z_{t}) = z_{t}\alpha$	axp(Σ _ε β)	Z F B
ALCOHOLISH ALCOHOLISH LATE CWSET ALCOHOLISH PHYSICALLY HEALTHY (2.55) EXPERIENCE 0.052 (3.26) EXPERIENCE 0.052 (3.26) SCHOOLING (3.26) SCHOOLING (1.19) MARIED 0.312 WHITE 0.290 WHITE 0.290	0.679 0.38 (2.36) (1.89		1	1
LATE ONSET ALCOHOLISH PHYSICALLY 0.390 HEALTHY (2.55) EXPERIENCE 0.052 (3.26) SQUARED (3.26) SCHOOLING (6.18) MARRED 0.312 (4.19) WHITE 0.290 WHITE 0.290	1	-0.153 (0.88)	1.102 (2.19)	0.669 (1.40)
PHYSICALLY 0.390 HEALTHY (2.55) HEALTHY (2.55) RXPERIENCE 0.052 SQUANED 0.001 SQUANED (3.26) SCHOOLING (2.69) SCHOOLING (6.18) MARRIED 0.312 WHITE 0.290	1	-0.222 (2.26)	0.500 (1.56)	0.271 (1.22)
EXPERIENCE 0.052 (3.26) EXPERIENCE 0.001 SQUARED (2.69) SCHOOLING (2.69) (6.18) MARRIED 0.312 (4.19) WHITE 0.290 WHITE (2.69)	-1.107 -0.85 (3.06) (2.41	(2.45) (2.45)	-1.187 (3.03)	-0.886 (2.41)
EXPERIENCE -0.001 SQUARED (2.69) SCHOOLING (6.18) MARRIED (.119) (4.19) WHITE (.290	0.01 (0.32) (0.32)	(4 0.052 () (3.25)	0.029 (0.29)	0.014 (0.32)
SCHOOLING 0.077 (6.18) MARRIED 0.312 (4.19) WHITE 0.290 (2.69)	-0.001 (0.36) (0.37	(2.68)	-0,001 (0,32)	-0.0003 (0.35)
MARRIED 0.312 (4.19) WHITE 0.290 (2.69)	0.046 0.02 (0.96) (1.03	24 0.078 3) (6.20)	0.053 (1.13)	0.026 (1.14)
WHITE 0.290 (2.69)	-0.666 -0.36 (2.56) (2.34	64 0.213 (4.21)	-0.655 (2.51)	-0.359 (2.30)
	-0.514 -0.35 (1.39) (1.36	57 0.288 6) (2.71)	-0.555 {1.58}	-0.369 (1.44)
CONSTANT 0.446 (1.48)	-0.085 1.28 (0.07) (1.94	39 0.447 8) (1.49)	-0.092 (0.07)	1.291 (1.98)
Wald test 118.20 for H ₀ : slopes=0*	38.98 17.(03 118.61	37.96	16.92

* Under H₀ the Wald test statistics are distributed χ^2 , and χ^2 for columns 1-3 and 4-6, respectively. The .05 (.01) * Under H₀ the Wald test statistics are 14.07 (18.48) and 15.31 (20.059), respectively. "slopes" refers to all parameters except CONSTANT.

Table 3

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	ALCOHOLISM		PHYSICALLY HEALTHY	
Computation	Ce _G	ce _p	¢e _G	ce _p
I. "Well Become Sick"				
γ ≠ −2	27.6	17.7	26.7	10.8
-1	31.5	22.6	30.7	15.7
0	36.1	29.5	35.7	24.2
• 1	41.8	40.1	41.7	40.2
II. "Sick Bacome Well"				
γ = -2	22.5	14.1	19.8	8.0
-1	26.2	18.6	22.8	11.6
0	30.9	25.1	26.7	18.1
1	36.7	36.5	31.7	32.3

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Certainty Equivalence Estimates for ALCOHOLISM and PHYSICALLY HEALTHY (Figures are 1991 dollars, in thousands)

Table 4

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