EFFECTS OF DRUG PLAN ELIGIBILITY ON PRESCRIPTION DRUG UTILIZATION AMONG ONTARIO AND BRITISH COLUMBIA SENIORS

By

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Abstract

All provincial Ministries of Health in Canada subsidize the prescription drug expenditures of individuals aged 65 and older. This exogenous change in insurance coverage is used to investigate several aspects of the prescription drug utilization of seniors in the provinces of Ontario and British Columbia. First, what is the magnitude of the increase in utilization and insurance program costs once drugs are provided free of charge? The second issue of interest is the incidence of the subsidy. Are any increases in utilization observed concentrated among those with the greatest medical need? Finally, what are the specific effects of the subsidy on physician and patient behavior?

The following conclusions were made. First, the effect of provision of insurance at age 65 is heterogeneous across individuals. Eligibility for insurance was found to increase the number of different drugs taken by Ontario females. In BC, pharmaceuticals use by low income single males in British Columbia was observed to increase. Also, the extension of insurance has made only a minor contribution to growth in seniors' drug utilization, relative to secular trends in utilization by seniors over time. Second, increases in utilization observed among Ontario seniors were concentrated primarily among lower health status individuals. Finally, most of the increases in utilization were among individuals probably already under physician care. The change in drug insurance status did not appear to lead to more physician consultations. The provision of insurance therefore appeared to affect the prescribing patterns of physicians. Given that physicians typically have better knowledge of appropriate drug therapy than patients, this increases the probability that the increased utilization is appropriately prescribed.

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1. Introduction

An important characteristic of health status is that the incidence of illness is uncertain (Arrow 1963). Because the incidence of illness is uncertain, it follows that one's need for health care is also uncertain. For many, uncertainty in the incidence of illness and associated health care costs is a source of disutility, creating a market for insurance contracts. The welfare of risk averse individuals is increased if they can purchase insurance contracts which reimburse the cost of the unpredictable health care services in exchange for a premium equal to its mathematical expectation.

Insurance against contingencies in health and other sectors is associated with a phenomenon frequently referred to as "moral hazard". Insurance coverage, it is conjectured, increases either the probability of a loss or the amount. The expected losses of individuals who are insured therefore tend to exceed the expected losses of those who are not insured. In the case of health insurance, this is due to the informational asymmetry between insurers and the insured. As Evans (1983, page 75) notes, "The reimbursement of health care expenditures is based on the assumption that such expenditures are a signal for the occurrence of exogenous illness events. But the linkage between illness and its associated necessary

expenditures is far from perfect; and the existence of insurance may create incentives to additional health care use for any given illness event. The loss resulting from the illness event, whether measured in terms of care expenditures or in terms of utility losses for the insured, would then be increased."

The social desirability of this additional health care consumption and appropriate policy responses depend on one's views concerning the market for health care and the definition of how the value of health care should be measured. On one hand, some analysts (e.g., Feldman and Dowd 1991, 1993; Manning *et al.* 1987; Feldstein 1973; Pauly 1969) argue that this utilization is socially undesirable because society's valuation of these services is less than its resource cost. Inherent in this viewpoint is the assumption that the contribution to social welfare of health care consumption is given by the summation of individuals' willingness to pay for given units of health care. Willingness to pay is, in turn, the result of a process of utility maximization by fully-informed consumers subject to prices and income. Further, the resource cost of health care is adequately measured by the health care "supply function", the amount of output firms wish to produce at each price. Finally, market prices for health care are set as to clear markets, i.e., where the quantity firms wish to supply is equal to the quantity consumers wish to purchase. The effect of insurance in this market is to lower the price consumers face below its resource cost, encouraging consumer/patients to increase their level of health care consumption. This additional consumption is deemed socially undesirable due

to the fact that the social value placed on this utilization (as measured by consumers' willingness to pay) is lower than its resource cost.

On the other hand, some analysts (e.g., Rice 1992, 1993; Stoddart *et al.* 1993; Evans 1983) argue that one cannot measure the contribution to social welfare of increased utilization on the basis of individuals' willingness to pay, even if external effects were absent. The basis of this assessment begins with the fact that health care is not valued for its own sake; the only reason it is consumed is for its expected positive impact on health status, which is the final consumption good. Indeed, the direct effects of health care interventions on patient utility are often negative. If the consumer/patient were able to choose levels of health status directly, then the postulate that consumer's willingness to pay corresponds to an assessment of relative value is restored. The relation between health care and other inputs on patient health status is, however, governed by a sufficiently complex production technology so as to render invalid the assertion that the health care utilization decisions made by consumer/patients in unregulated markets are rational and fully informed.

An institutional response to patient/consumer ignorance is professionalization of physicians and other health care suppliers who deal directly with patients and are therefore in a position to exploit this information asymmetry. Direct regulation serves to not only ensure the technical competence of physicians, but also to encourage behaviours which serve the patient interest over pecuniary

and other competing objectives. One such behaviour instilled in the medical training and socialization process is to direct utilization so as to meet patient "needs", defined technically as the capacity for the patient to derive improvements in health from the application of health care. It follows, then, that the resulting allocation of health does not reflect primarily patient decision making. Although the patient is responsible for initiating an episode of treatment (and even this decision may be affected by prior interactions with the health care system), subsequent health care utilization decisions are heavily influenced by the physician (Stoddart and Barer 1981). Indeed, it is estimated that patients have direct access to services representing only 7% of total health care expenditures in Canada (Stoddart *et al.* 1993).

Importantly, the resulting allocation of health care resources will not in general correspond to the patient's preferred allocation in the event that patients were endowed with the same information set as the physician. There are several reasons for this. First, the physician seeking to meet all health needs will in general over-provide care relative to the optimum because providing health care to the point where its marginal productivity is zero will also reduce its marginal utility to zero or less. At a utility maximizing allocation, on the other hand, goods have positive marginal utilities provided prices are positive. Second, physicians have difficulty knowing the precise nature of patient preferences such as willingness to accept risk, rate of time preference, and tradeoffs between quality and length of

life. Finally, physician preferences might be defined over a broad set of objectives including satisfying patient needs, practice style, net income and leisure. While regulatory incentives attempt to promote patient interests, there is sufficient uncertainty in the health production process so as to accommodate this wider range of provider objectives (Evans 1984). Using patient demand for health care interventions as a guide for resource allocation decisions is therefore criticized for simultaneously failing to recognize that patient willingness to pay for health care does not necessarily measure the valuation to patients of these services and second, that the predominant influence of supply on utilization may not reveal patient preferences either.

Policy prescriptions for the moral hazard problem which follow from these separate viewpoints could hardly be more different. According to proponents of the former view, the solution reduces to finding an optimal set of patient charges (including deductibles and co-payment rates) which maximize the *net* benefit of health insurance. The benefits of insurance are measured by the valuation placed on reductions in financial risk associated with uncertain health outcomes; these benefits are reduced by the deadweight or social losses due to the utilization induced by insurance. At the optimum, the patient pays some positive fraction of the cost.

Proponents of the latter viewpoint argue that even if the social welfare function is defined over the aggregation of individual's willingness to pay, patient

charges will not result in an improved allocation. The primary effect of such charges will be to deter patient initiation of treatment primarily among lower income individuals (Enterline *et al.* 1973, Badgley and Smith 1979; Wolfson and Tuohy 1980, Stoddart and Woodward 1980); there is no evidence to suggest, however, that charges will selectively deter the use of services with low value. Again, the results hinge on patients' inability to assess the marginal productivity of health care in improving health status.

The principal objective of a publicly financed health insurance system, such as Canada's, is to improve the match between utilization of effective health care services and need. Allocations of health care resources directed by physicians (on patients' behalf) are deemed to be closer to this ideal than allocations based on willingness and ability to pay of relatively uninformed consumer/patients. As Evans (1983, page 81) argues, this can be interpreted as moving to a closer approximation to the service patterns which hypothetical fully informed consumers, fully compensated for welfare losses due to illness would choose. That is not to say that the observed allocations are close to the ideal. As Birch *et al.* (1993, page 88) note: "Although in principle, providers are paid for providing services only where such services are needed, there is no mechanism to ensure or promote the sharing of services between competing needs on the basis of levels of need ..."

Allocation of health care on the basis of price was explicitly removed with Federal legislation outlined in the Medical Care Act of 1965. This legislation stipulated that all provinces in Canada were to publicly administer 100% insurance coverage for all "medically necessary" medical services in or out of hospitals. Somewhat surprisingly, there was no such legislation for coverage of out-of-hospital prescription drugs, even though pharmacological agents are often important in the diagnosis, treatment, cure, palliation and prevention of a range of human diseases and conditions and therefore would appear to be medically necessary. Since 1971, each provincial government has, however, established some form of categorical publicly-funded drug insurance for groups such as seniors (65 and older), individuals with low income, individuals with specific diseases (e.g., AIDS, diabetes), individuals taking specific medicines, or individuals with particularly large drug expenses.

The importance of pharmacotherapy in medical practice is evidenced by its widespread use and acceptance. For example, Canadian general practitioners provide prescriptions in 21% to 86% of all patient consultations (Lexchin 1990). Issues surrounding the utilization of prescription medicines among the elderly are of particular interest due to the fact that they are the fastest growing segment of the North American population and also have the highest rates of prescription drug utilization. In Ontario, for example, prescription drug expenses for seniors -- paid for by the Ontario Ministry of Health Drug Benefit program -- rose from $212.2

million in the 1985-86 fiscal year to $645.6 million in 1992-93 (Institute for Clinical Evaluative Sciences 1994).

Each provincial government in Canada has established some form of publicly-funded drug insurance for seniors, although the terms of the insurance differ among the provinces. Currently Ontario, through its Ontario Drug Benefit (ODB) plan, is the only province in Canada that provides universal first-dollar coverage for prescription drugs taken by seniors. All other provinces have some form of deductibles or co-payments. Despite the interest in prescription drug coverage for the elderly and the development of a range of universal coverage plans in Canada, there is very little empirical evidence regarding the effects of prescription drug insurance on prescription drug use in this group. The RAND Health Insurance Experiment examined the use of prescription drugs (Leibowitz, Manning and Newhouse 1985) but prescription drug insurance was part of a larger medical care insurance plan and the study excluded the elderly. Other studies based on natural experiments have used claims data from the UK National Health Service (Ryan and Birch 1991; O'Brien 1989; Lavers 1989), US Medicaid programs (Soumerai *et al.* 1987, 1994; Nelson, Reeder and Dickson 1984) and US managed care settings (Smith 1993; Harris, Stergachis and Ried 1990). A characteristic of these studies is that the population under study has been non-elderly. The degree to which this evidence can be generalized to the elderly, who are the heaviest users of medicines, is unclear.

The general aim of this study is to assess whether eligibility (by turning 65) for subsidized medicines under the provincial Ministry of Health drug plans operating in the provinces of British Columbia and Ontario is associated with an upward shift in individuals' probability and/or volume of use of medicines. Three specific issues are of interest. First, to what extent has the removal of (some or all of) the financial barriers to out-patient prescription drugs for seniors increased drug utilization? Information on the magnitude of moral hazard is useful for informing the debate on the "optimal" level of coinsurance and deductibles.

Second, and related to the first objective, what is the effect of prescription drug insurance coverage for seniors on real prescription drug *expenditures* reimbursed by Government? This information is useful to quantify the impact of moral hazard due to enhanced insurance coverage on public expenditures for seniors' prescription drugs.

Third, to what extent has the removal of financial barriers to out-patient prescription drugs for seniors improved the match between health care needs and drug utilization? This will be accomplished by examining the effects of co-payments on the prescription drug utilization among individuals with varying levels of health status, which is a useful first step in addressing the question of whether those in need of care are those who are deterred from using services at the margin. The analyses also attempt to shed light on the mechanisms by which utilization changes following a decrease in user charges. The physician acts as the patient's agent in selecting appropriate therapy. Therefore if evidence suggests that co-

payment related differences in utilization result primarily from consumer rather than physician decisions (due to non-compliance with physician prescriptions or a lower propensity to initiate treatment), it increases the probability that the appropriateness of therapy is not improved (Hurley and Johnson 1991). This issue is explored by decomposing expected changes in utilization between individuals into probability of any use and volume of use. The prior assumption is that the probability of using any medicines is more likely to be a patient-centered decision, while the volume of medicines used by individuals (given that they use any) is more likely to be a physician-centered decision. In addition, the probability of any physician consultations, which is likely to be patient-initiated, is modeled as a function of eligibility for senior's drug benefits. Information from this model will help determine whether patients' propensity to initiate treatment is affected by changes in insurance eligibility.

Different sources of data are used to address these behavioural responses to enhanced insurance coverage in the respective provinces. Data from the 1990 Ontario Health Survey (OHS) on self-reported use of medicines in the past 4 weeks are used to estimate the relationship between the expected number of medicines used per respondent and eligibility (age 65 or older) for the Ontario Drug Benefit program, while controlling for other covariates such as health status, age and income. These data are useful in addressing questions one and three, but are less informative in addressing the fiscal consequences on provincial drug plans of expanding prescription drug insurance for the elderly. To address this latter

issue, longitudinal administrative claims data from the British Columbia Ministry of Health Pharmacare and Medical Services Plan programs are used to estimate the relationship between the expected real ingredient cost per plan enrollee and eligibility for B.C. Pharmacare senior's benefits, while controlling for other covariates such as health status, age and gender. These administrative data are not, however, informative enough to fully identify this relationship. To overcome this, data from the 1990 Ontario Health Survey are used.

An additional contribution of this analysis is to consider alternative estimation strategies for each data set. Administrative claims data are designed to economize on informational content and therefore pose special challenges for the identification and estimation of parameters of the prescription drug utilization models. In particular, the data assembled from the B.C. Pharmacare program are hampered by both censoring of the prescription drug claims (drug expenditures under deductible limits cannot be claimed and are therefore not recorded) and limited information on confounding factors such as health status and demographics. The contribution to expenditures due to the onset of insurance was identified by treating health status and other demographic characteristics as being a individual-specific constant effect on prescription drug use over the 8 year period individuals were observed. When the dependent variable is censored, however, estimation of models incorporating these constant or fixed effects is problematic using standard statistical techniques. A new estimator which provides consistent

estimates in the presence of censoring and fixed effects (Honoré 1992) is therefore used instead.

On the face of it, the OHS data do not pose any unusual estimation problems. The prescription drug utilization measure collected was the number of different drugs taken in the 4 week period prior to the survey. Estimation methods designed to deal with count data such as the Poisson model have been developed. More sophisticated estimation techniques are required, however, when there is heterogeneity in drug use among individuals not accounted for by the covariates. The negative binomial model is appropriate if this individual heterogeneity can be modeled using the gamma distribution. But the negative binomial model is not adequate to model heterogeneity among individuals reporting zero values of drug utilization. It seems plausible, however, that differences among non-users exist on the basis of their capacity to benefit from prescription medicines. Otherwise healthy individuals would never use medicines. Individuals with a need for health care, but who face barriers to access, on the other hand, are potential drug users. The "zero altered" negative binomial and Poisson models proposed by Greene (1994) appear to be appropriate in this case. The expected number of drugs taken is a mixture of two distributions: the probability that an individual is a potential drug user times the expected number of medicines taken by potential drug users. These statistical models were dominated, however, on the basis of two model selection tests by an alternative estimation technique - the two part model -

advocated by Duan (1983, 1984) for modeling individual level health care utilization data.

The outline of the thesis is as follows. Chapter 2 reviews the existing evidence on the effects of insurance on prescription drug utilization. Data from the 1990 Ontario Health Survey are then used to estimate the effects of public insurance on the prescription drug utilization of Ontario seniors, the details of which are found in Chapter 3. Our analysis moves westward in Chapter 4 where the effects of public insurance on the prescription drug utilization of British Columbia seniors are estimated. Finally, Chapter 5 discusses the implications of the empirical results for the questions set out in this introduction.

2. Review of Existing Evidence

2.1 Estimates of Price Elasticities of Drug Utilization

The majority of previous work on the effects of user charges on the utilization of prescription medicines have used data from the United Kingdom and United States. The first group of studies (Ryan and Birch 1991; O'Brien 1989; and Lavers 1989), have examined the effects on drug utilization of the 600 percent increase in the real per-prescription charge in the U.K. National Health Service that took place between 1969 and 1986. The second group of papers have studied the effects of prescription drug co-payments in the context of insurance coverage provided by the U.S. Medicaid program (Soumerai *et al.* 1987; Nelson *et al. 1*984) and various managed health care organizations (Smith 1993; Harris *et al. 1*990). The remaining published study has explored data from the Rand Health Insurance Experiment (Leibowitz *et al.* 1985). There are no published estimates of the effects of user charges on the utilization of prescription medicines using Canadian data.

The studies investigating the administrative data from the U.K. National Health Service (NHS) have all used aggregated monthly data over the period 1969

to 1986. Regression models were estimated relating the monthly number of prescriptions dispensed to the per-prescription charge and a variety of control variables such as per capita disposable income, an index of the prices of substitute drugs, and the level of morbidity in the population.

Most of the investigations on U.S. populations have employed longitudinal data, although none have fully exploited the panel nature of the data. Typically, these studies have associated the average per capita monthly number of prescriptions dispensed to some change in the Medicaid insurance reimbursement criteria. In several of these studies, no controls (besides time trends) were included in the regression. Rather, the drug utilization of Medicaid populations in states unaffected by the insurance change formed the benchmark by which the utilization response of the study population was evaluated. The studies typically go to some length to establish that the Medicare populations in the two states are sufficiently homogenous so as to identify the price effect from confounding influences.[1]

As is true of much economic data, much of what is available has been gathered from non-experimental settings. Analysis of price effects has therefore been forced to deal with a variety of statistical issues such as the identification of

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[1] If there are important differences between the populations in the two jurisdictions which are not explicitly controlled for, then a simple comparison of the mean level of utilization in each area is not valid. Formally, the analysts run the risk of omitted variables bias which renders the estimate of the difference in utilization between the two jurisdictions inconsistent.

the price effects from confounding influences and self-selection bias. The one notable exception was the information produced by the Rand Health Insurance Experiment. To identify the effects of price changes on prescription drug utilization (and the utilization of other health services), a large scale randomized controlled trial was conducted.

A characteristic shared by most of these studies is that the populations under investigation tend to be non-elderly. This is regrettable because seniors consume disproportionately more prescription drugs than do other age groups. Moreover, indirect evidence suggests that seniors have a somewhat higher price sensitivity of prescription drug utilization than do other groups (Marcantonio 1989). For these reasons, it may be difficult to generalize the findings of the published studies to older populations.

2.1.1 Data from the U.K. National Health Service

The three U.K. studies (Ryan and Birch 1991; O'Brien 1989; and Lavers 1989) report price elasticities of drug utilization to be in the range of -0.10 to -0.64. These elasticity estimates appear to depend on the estimating specification (e.g., sample period, functional form, choice of explanatory variables, estimation technique and assumptions regarding the distribution of the disturbance term). The finding that utilization of prescription drugs is price inelastic is also consistent

with the elasticity estimates obtained for other health care services (Phelps and Newhouse 1974; Manning *et al.* 1987).

All of the studies used monthly data over a variety of sample periods. Lavers (1989) analyzed utilization over the period January 1971 to December 1982; O'Brien (1989) used data over the period 1969-86 (he also presented parameter estimates for the sub-periods 1969-77 and 1978-86); Ryan and Birch (1991), (hereafter RB) provide estimates from the period January 1979 to December 1985.

All three studies used a common set of explanatory variables. These included the own price per prescription, the price of substitutes (proxied by the monthly price index for medicines, surgical goods and toiletries), the personal disposable income of the population, morbidity index (proxied by the monthly new claims for sickness and invalidity benefits in Great Britain), monthly seasonal dummies, a time trend, and several dummy variables designed to capture the effects on utilization of changes in the program benefits and eligibility criteria.[2] O'Brien expanded the set of regressors to control for some demographic effects on utilization: the population aged less than 16; the population aged 60 and over (women) and 65 and over (men); and, finally, the population of working age: 16-

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[2] In O'Brien, the following structural changes were explicitly incorporated: contraceptives were dispensed free of charge after June 1975, the number of exempt beneficiaries was extended after April 1974 and the number of drugs eligible for reimbursement was restricted after April 1985.

65 (males) 16-60 (females). RB included a control for the supply influences on utilization (the number of general practitioners per 100,000 population).

The nature of the insurance coverage offered by the NHS precluded an analysis of the effect of user charges on the entire population. Under the NHS, patients are charged a fixed price per prescription, unless they qualify for exemption from charges. Before April 1974, groups exempt from charges were children under 15 years, and men and women over 65. After this date, the exempt groups were extended to children under 16 years, and women over 60 years. Over the entire period, pregnant women, mothers of infants, those in receipt of social security benefits and those with low income were exempt from prescription charges. Lavers confined attention solely to prescriptions for which payment was actually made by the consumer, while O'Brien and RB performed specified separate regression models for both chargeable and exempt prescriptions.

O'Brien's estimating methodology accounted for the possibility that the contemporaneous disturbances between the equations describing exempt and non-exempt prescriptions were correlated. Estimation proceeded with the use of Zellner's iterative seemingly unrelated regression. RB on the other hand, do not estimate the equations simultaneously. The authors, however, used the maximum likelihood estimation of the Box-Cox power transformation of all the variables in the estimating equation.[3] All three studies report tests indicating the presence of

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[3] All variables were raised to the power 0.15.

serially correlated (AR-1) errors and, based on this finding, make corrections for AR-1 errors. None of the studies report tests of the common factor restrictions implicit in adopting this type of error process.

RB (page 685) claim that estimating the price elasticity of utilization among exempt prescriptions facilitates the identification of the price effect in the non-exempt population. A finding that price elasticity in the former equation is not statistically significant indicates that, "... the observed association between price and utilisation in the nonexempt group is not the result of an underlying or unobserved third variable correlated with both price and utilisation." Clearly this reasoning is predicated on the assumption that any latent variables affecting utilization are operational in both the exempt and non-exempt groups. To the extent that behavior of non-poor individuals aged 16 to 65 is dissimilar to those eligible for subsidy (low income, aged and young individuals), this argument is weakened. RB report that the price variable was indeed insignificant in the equation explaining utilization among exempt groups and go on to support their interpretation of the price variable in the non-exempt utilization equation. These findings contrast with those reported by O'Brien. O'Brien indicates that the price variable was *positive* and significant in the equation explaining the volume of exempt prescriptions over the full sample period 1969-1986.

O'Brien and RB both report that the price index of over the counter (OTC) medications is positively related to the utilization of chargeable prescriptions. This

suggests that OTC medications are substitutes for prescription drugs. The cross-price elasticity for the full period data in O'Brien was 0.22; RB estimate a somewhat larger elasticity: 0.675. The cross price elasticity reported in Lavers was positive (0.13), but insignificant at conventional levels.

Estimates of the effect of morbidity on non-exempt prescription drug utilization were mixed. Both Lavers and O'Brien find a positive association when estimating over the full period. O'Brien fails, however, to find any association when estimating over the period 1979 - 1986, nor do RB when estimating over the period 1979 - 1985. The authors' use of the morbidity proxy --the monthly new claims for sickness and invalidity benefits -- is problematic because it may be correlated with the disturbance term in the regression equations. Morbidity may be endogenous to the model if higher levels of drug use are a determinant, not an outcome, of sickness rates. Even if morbidity is exogenous to the model, it may be influenced by factors unrelated to underlying morbidity (such as the value of paid sick time) and may therefore introduce measurement error. Both mechanisms could render all the estimates inconsistent. Because of data constraints, formal statistical tests for inconsistency of the estimators are not presented in any of the papers.

2.1.2 Data from the RAND Health Insurance Experiment

The Rand Health Insurance Experiment (HIE) data were derived from a large-scale controlled trial that randomly assigned participants from 6 cities across the U.S. into insurance plans with varying coinsurance rates and deductibles (Leibowitz *et al.* 1985). The HIE tracked the medical and drug expenditures, randomly assigned co-payment, health and demographic characteristics of enrollees for a 3 or 5 year period. The experiment enrolled a representative, random sample of families in six sites across the US; however for purposes of the study on drug use, families from only three sites were included in the sample. Only eligible members of families participated in the experiment. Eligibility was determined by the member's age (individuals were required to be under 65 at the end of enrollment), membership in the family at the start of the experiment (newcomers -- adoptees and newborns -- were ineligible), and participation in the study until at least the end of the first year. The in-patient expenditures of infants were entirely allocated to the mother for purposes of the analysis. Further, family income was required to be less than $56,000 (in 1983 U.S. dollars). All families in the sample were given fee-for-service medical coverage. Table 2-1 summarizes the distribution of participants into the insurance plans.

Table 2-1 Sample of Drug Analyses by Plan in the Health Insurance Experiment (HIE)

Coverage Type	Number of Enrollees	Percentage of Sample
Zero coinsurance (free care)	1,259	32%
25% coinsurance up to a limit (referred to as the Maximum Dollar Expenditure) of 5, 10, or 15% of previous year's family income, or $1000, whichever was less.	779	20%
50% coinsurance rate, subject to the MDE	296	8%
95% coinsurance rate, subject to the MDE	761	20%
95% coinsurance rate, up to an annual limit of $150 per person or $450 per family, whichever was less. All in-patient services were provided free of charge.	765	20%

Source: Leibowitz et al. (1985)

Control over the experimental design afforded the analysts several distinct advantages. First, the outcome variables -- the levels of drug utilization -- were observed regardless of their level. Drug insurance claims data, on the other hand, is incomplete if the level of utilization is only recorded if it exceeds a deductible level. In the event that expenditures are below the deductible level, expenditures are arbitrarily recorded as zero. Estimation must then proceed with typically more complicated and less robust estimators.

Second, the cost sharing subjects faced was orthogonal to any (possibly latent) confounding variables such as their demographic characteristics or self-perceived health status. In contrast, analysis of non-experimental data, such as the aggregated administrative time series data from the NHS, is perennially hampered

by the confounding effect of latent variables correlated with the variable of primary interest, the per-prescription charge. For example, in the context of the U.K. studies, it is conceivable that the upward trend in user charges is correlated with any increases in rates of hospitalization that would *ceteris paribus* tend to decrease the utilization of drugs among out-patients.

Self-selection was also avoided in the Rand study. Self-selection occurs when the sample of individuals is not a random sample from the population of interest. Leibowitz *et al.* (1985, page 1063) characterize the inference problem as follows:

> "Self-selection could bias results if, for example, more sickly people were more likely to select generous drug coverage. Using self-selected samples, we might improperly conclude that the high drug use of the sickly people was caused by their generous insurance coverage. Instead their poor health explained their high drug use and their insurance plan."

Self selection is only a problem when individuals are free to choose from a menu of insurance contracts, or indeed are free to opt out of the contract altogether. This problem does not adversely affect the analysis of data from the NHS because coverage is automatic and based on age (which clearly is not a choice variable). Instead, the problem usually manifests itself when data from voluntary, typically privately provided insurance contracts are used. The problem could manifest itself in the analysis of data from Medicaid recipients as well. Eligibility for Medicaid benefits is based on means tests. It is at least conceivable

that individuals with high expected use would choose to keep income below the cutoff so as to remain eligible for benefits.

One significant drawback of the HIE data was that the randomly assigned co-payment applied to both medical and prescription drug expenses. It was therefore not possible to identify the price elasticity of drug utilization from the price elasticity of medical care utilization. A finding that drug utilization is lower under the less generous insurance plans, for example, could indicate that individuals tend to have fewer physician consultations, or that they consume fewer drugs per consultation, or both.

For the purposes of estimating price elasticities, two dependent variables were measured: average per capita drug expenditures, and the number of prescriptions per capita. These variables were in turn related to a vector of explanatory variables: four binary variables representing the coinsurance rates (the free plan was the benchmark);[4] binary variables indicating three geographic locations of the participants (Seattle, Washington; Fitchburg, Massachusetts; and Franklin, Massachusetts); interactions between geographic location and coinsurance rate; and two binary variables representing age and sex: children (under the age of 18), and female adults. Male adults were the omitted category.

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[4] In the estimating equations the plans with varying maximum dollar expenditure (MDE) for a given coinsurance rate are aggregated because no MDE effect on utilization is observed in the site-year-specific analyses.

To allow the effect of these demographic influences to differ by site, interaction variables of site and demographics were included.

Estimation proceeded with the use of the "two-part model" advocated by Duan *et al.* (1983, 1984). According to simulation results reported in Duan *et al.* (1984), the procedure is particularly well suited to model micro level health care utilization data characterized by a large proportion of individuals who do not consume any drugs and skewness in the distribution of expenses among users. The two-part technique involves the estimation of two separate models: an equation explaining the binary outcome -- use versus non use of prescription drugs -- and an equation explaining the drug expenditures of the users. The authors found a probit model for the binary outcome and linear regression of the log of expenditures of users to be most compatible with their data. Mean drug expenditures, conditional on the vector of covariates, $\mathbf{x}_i$, are estimated using the decomposition:

$$E(DRUG_i|\mathbf{x}_i) = \Pr(DRUG_i > 0|\mathbf{x}_i) \times E(DRUG_i|DRUG_i > 0, \mathbf{x}_i)$$

As was expected, the number of prescriptions per capita was lower in the less generous plans, holding constant all other variables. Although arc elasticities were not reported, these can be estimated using data assembled in Table 2-2. On the basis of these calculations, it appears that drug utilization is price inelastic.

The arc elasticity estimates were in the range -0.72 to -0.34, depending on the magnitude of the price change.

Table 2-2 Expenditure and Quantity Consumed by Plan in the HIE

Plan	Mean Expenditure per capita (1983 U.S. Dollars)	Number of Prescriptions per capita	Arc elasticity estimate (relative to free plan)
Free	60.09	5.43	
25% coinsurance	45.64	4.43	-0.72
50% coinsurance	35.78	4.33	-0.40
95% coinsurance	34.08	3.63	-0.34

Source: Leibowitz et al. (1985)

These elasticity estimates are slightly larger in absolute value than the majority of those produced in the analysis of the U.K. NHS data. This could be attributable to co-payment rates in the HIE having been applied to both the medical and drug utilization. Because medical consultations are required for prescriptions to be dispensed, a co-payment applied solely to medical care utilization will, *ceteris paribus*, tend to lower prescription drug use.

The average cost per prescription did not seem to vary significantly across plans. The authors interpreted this as indicating that much of the plan difference in drug expenditures appeared to be related to the quantity of pharmaceuticals purchased, rather than to differences in the average prices of the drugs purchased

across the plans. Surprisingly, there was little plan response in factors that might affect average costs, such as the proportion of prescriptions filled with generic drugs.

2.1.3 Data from Managed Health Care Organizations

Two studies have analyzed the effects of prescription co-payments in the context of populations covered by managed health care organizations in the U.S. Smith (1993) investigated prescription drug utilization in a set of 212 employer groups covered by a national managed care organization. Insurance contracts administered to each of the employer groups differed with respect to the level of (fixed) drug co-payment per prescription and incentives for the use of generic drugs. Linear regression models of total prescription drug costs per person, number of prescriptions per person, and ingredient cost per prescription provided estimates of the effect of co-payments, as well as the characteristics of the market area (number of hospitals in the vicinity, and geographic identifiers), employer (firm size, industry) and employee (age, sex) on these measures of utilization. Individual data were not used; rather data were aggregated to the employer group level.

Ordinary least squares regression estimates indicated that the effect of co-payments differed in each of the models. Per capita expenditures of prescription

drugs were not significantly affected by co-payment. Total costs per person are, however, definitionally the product of number of prescriptions per person times the price per prescription, each of which is potentially affected by co-payment rates. Indeed it appeared that ingredient cost per prescription increased with higher co-payments while the number of prescriptions per person declined so as to offset each other. Several factors may operate to increase the average cost per prescription following a higher co-payment. First, if the co-payment is independent of the prescription ingredient cost, patients may request larger prescription sizes so as to reduce the average ingredient cost. Second, higher co-payments may result in some prescriptions not being covered. As Smith (1993) notes: "A $5 co-payment implies no insurance contribution to a $4 prescription, resulting in no claim and an "observed" decrease in use and increase in average price, without any actual changes." In addition, patients might refrain from filling prescriptions for less expensive drugs (which could be associated with lower quality or smaller expected effect on health status). It was not possible to differentiate between these alternative explanations due to data constraints.

The elasticity of the number of prescriptions per person with respect to price was -0.098, a smaller estimate (in absolute value) than those provided by other studies. Smith attributed this difference to the higher incomes of the individuals included in his study relative to those included in the U.K. data, a factor which economic theory suggests would tend to depress the elasticity estimate.

Harris *et al.* (1990) analyzed records of the utilization and cost of medications of 19,982 continuously enrolled beneficiaries under the age of 65 of a health maintenance organization (HMO) in Washington state. The availability of information on individual-level drug use, combined with substantial price variation in prescription-drug co-payment levels allowed for an investigation of the effect of drug co-payments on total drug utilization, drug utilization for selected therapeutic classes of drugs, and total cost incurred by HMO patients.

Conveniently, the price changes affected only a subset of the population of HMO enrollees -- State of Washington employees. To establish a baseline level of utilization, the records of drug utilization and cost of a group who had no drug co-payments during the entire study period were assembled. The group consisted of the employees and dependents of the 15 largest non-federal employee groups. The authors claim that selection of individuals into the study and comparison cohorts was orthogonal to any (potentially latent) personal characteristics, facilitating the identification of the effect of user charges on prescription drug utilization.

Individuals in the co-payment cohort faced substantial price variation. In the first year in the sample (7/82 - 6/83), there were no drug co-payments. In the next year (7/83 - 6/84), a $1.50 per prescription co-payment was introduced. This co-payment was doubled in the next year (7/84 - 6/85). In the final year of the study (7/85 - 6/86), the following benefit changes were made: (a) a $3 co-payment per *30-day supply* was instituted (previously, there was no limit on the size of the

prescription); (b) plan coverage of over the counter (OTC) drugs was limited; and (c) a $5 co-payment for all out-patient visits to physicians, physician assistants, nurse practitioners, optometrists and physical therapists was introduced, as was a $25 emergency room co-payment.

For every study subject, the following variables for each one year time period were recorded: number of prescriptions dispensed, drug ingredient cost, and average drug ingredient cost per prescription. Linear regression models were posited relating each of the dependent variables to co-payment dummy variables, and the following control variables: the enrollee's age, sex, number of years as an HMO enrollee, and the lagged value of the dependent variable. There were 19,982 subjects in the co-payment cohort and 23,164 subjects in the comparison cohort. No diagnostic tests are reported; parameter estimates pertaining to the demographic effects on utilization are also absent. A total of 1,027,350 prescriptions were dispensed to the two cohorts during the four year study period.

As was expected, utilization dropped when the higher drug co-payments were introduced. Using the utilization of the comparison group as a benchmark, the imposition of the $1.50 co-payment in the second year of the sample and the subsequent increase to $3.00 in the third year resulted in declines in the per capita prescriptions in the order of 10.7% and 10.6%, respectively. Restriction of the $3.00 co-payment for each 30 day supply of prescribed drugs combined with the introduction of physician visit co-payments led to a further 12% reduction in drug

utilization relative to the comparison cohort.[5] All tests of statistical significance of these utilization effects were significant at the P=0.0001 level. These parameter estimates are consistent with the unconditional trends in the annual per capita prescription growth. During the four year period, the co-payment cohort experienced a reduction in drug use (-11%) while drug use in the comparison cohort continued upward (+15.8%).

As was mentioned, a reduction in the number of prescriptions dispensed does not necessarily imply that program costs fall by the same proportion, because several factors may operate to increase the average cost per prescription. The authors found that substitution of expensive for less costly drugs occurred after the co-payments. For example, utilization of typically cheaper OTC preparations declined 25% following loss of coverage during the final study year. This and other factors could explain why the adjusted average ingredient cost per prescription was 17.6% higher in the co-payment group relative to the comparison group.

Overall, the co-payments reduced utilization enough so as to offset the increased average price per prescription. The net effect was therefore a decline in the annual drug costs (incurred by the HMO) per enrollee. After standardizing for age, sex and other demographic influences on utilization, per capita drug costs

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[5] Some caution is needed in the interpretation of this price response. The 12% reduction in drug utilization is potentially attributable to the increases in both the drug co-payment and the co-payment associated with physician consults.

declined 6.7%, 5.2%, and a further 8.8% relative to the comparison cohort following the $1.50 co-payment in year 2, $3.00 co-payment in year three and year four change in the benefit structure, respectively. ($P<0.01$ in the above tests.)

2.1.4 Data from the U.S. Medicaid Program

The final set of studies have examined the effect of co-payments in the context of U.S. Medicaid populations. Eligibility for Medicaid benefits is based primarily on age and income (beneficiaries are means tested and must be under 65 years of age). Again, the conclusions reached by these studies may not necessarily apply to older individuals.

The first of these studies was conducted by Soumerai *et al.* (1987) on records of the utilization and cost of medications of 10,734 continuously enrolled New Hampshire Medicaid beneficiaries over a 48 month period (January 1980 to December 1983). The authors examined the impact of price changes on the patient-level changes in the number of prescriptions filled for 16 drugs that "varied in their clinical importance and cost". The price changes involved an imposition of a limit of three paid prescriptions per month and its replacement a year later by a $1 co-payment.

The statistical analysis consisted of the estimation of linear regression models relating the number of constant-sized prescriptions filled,[6] average prescription size and the reimbursed drug costs to a linear time trend, and three dummy variables indicating the changes in the mean level of prescribing during an "anticipatory" precap period (month 20) and the periods during which the cap (months 21 to 32) and the co-payments (months 33 to 48) were in effect. The price changes were also free to affect the trend growth in the above dependent variables, through the addition of interaction terms. Generalized least squares was used to correct for the (assumed) serially correlated error terms. No demographic control variables were included in the regression (even though data on age, sex and income were available); instead, *ceteris paribus* conditions were established by examining the prescription drug utilization of 74,027 Medicaid enrollees in New Jersey, a population deemed to be similar to the study population, but where no co-payments were in effect.

The effects of user charges were estimated for several subpopulations varying in their frequency of drug use. These groups included "multiple drug users" -- individuals who had received an average of three or more prescriptions per month and at least one prescription every quarter in 1980 (n=860), "non drug users" (n=1,872) and "other drug users" (n=8,002). Multiple drug users represented only 8% of the total sample, yet consumed 47% of all prescriptions

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[6] Constant-sized prescriptions were defined as containing equal dosages of the drug.

filled in the base year (1980). This group tended to be composed of older (average age ± SD was 56±19 years), predominantly female (81%), long term drug users. Over half (56%) of the prescriptions prescribed to this group were cardiovascular agents.

As was expected, the total number of constant-size prescriptions dropped when the drug reimbursement limit and co-payment were introduced. Most of the decline was, however, attributable to the multiple drug users, who reduced their utilization 46% (from 5.2 to 2.8 constant-size prescriptions per month) following the 3-prescription reimbursement limit. Other patients reduced their use by 17% (from 0.7 to 0.58 constant-size prescriptions per month). After the cap was replaced by a $1 co-payment 12 months later, average prescription rates by multiple drug users rose both in level and trend to approximately 4.7 constant-size prescriptions by the end of the sample period, a rate below the initial 5.2 prescriptions per month. Utilization by others increased to pre-cap levels by the end of the sample period.

Utilization in the New Jersey comparison group remained stable at an average (±SD) of 1.2 ± 0.07 prescriptions per patient throughout the entire study period, suggesting that the changes in Medicaid benefits prompted the dramatic shifts in utilization observed in New Hampshire. The co-payments reduced Medicare expenditure commitments. Program expenditures fell from an average of

$50/beneficiary/month before the cap to $31 during the cap and rose to $40 under the $1.00 prescription co-payment policy.

Nelson *et al.* (1984) analyzed the number of prescriptions per capita for Medicaid recipients in South Carolina before and after the imposition of a $0.50 per-prescription charge. Data were collected on the utilization and cost of medications of 17,811 Medicaid beneficiaries over a 4 year period (January 1976 to December 1979). Only individuals who were continuously enrolled during 1976, and received reimbursement for at least 5 prescription were eligible for inclusion into the sample.

Quantitative analysis consisted of the estimation of linear regression models relating the number of prescriptions filled, average prescription size and the reimbursed drug costs to a linear time trend, and a dummy variable indicating the period during which the co-payment (January 1977 to December 1979) was in effect. The price change was free to affect the trend growth in the above dependent variables, through the addition of an interaction term. Cochrane-Orcutt estimation was used to correct for (again assumed) serially correlated error terms. No demographic or fixed effects variables were included in the regression even though age, sex, race and limited income information were available; instead *ceteris paribus* conditions were established by examining the prescription drug utilization of 27,841 Medicaid enrollees in neighbouring Tennessee, a population

deemed to be similar to the study population, but where no co-payments were in effect.

As was expected, the total number of prescriptions dropped when the drug reimbursement limit and co-payment were introduced. The estimated coefficient associated with the time trend variable indicated that both states were experiencing growth in the monthly mean number of claims per recipient prior to the co-payment (0.03 in South Carolina, 0.02 in Tennessee). The implementation of the co-payment in South Carolina significantly reduced the slope of the prescription utilization function so that there was effectively no trend growth. No significant change in the trend utilization function was reported in Tennessee. The authors also report that the intercept of the function decreased significantly in *both* states following the co-payment. The authors fail to provide any rationale for the decrease in the intercept in the comparison state. This casts some suspicion on whether the changes in the trend function observed in the test state represent responses to the imposition of the co-payment; this suspicion is exacerbated by the authors' failure to provide any details of their hypothesis testing (such as standard errors or *t*-ratios) beyond merely claiming significance at the five percent level.

The co-payment did not significantly affect the growth of Medicaid expenditures per beneficiary in the test state; only the intercept was reduced. This occurred in the control state (Tennessee), however as well, which again calls into question whether the price effect was solely responsible for this shift.

2.2 Incidence of User Fees by Individuals with Differing Levels of Health Status

Whereas all of the studies cited have provided information on the magnitude of the "moral hazard" effect of drug insurance, only a few have addressed the perhaps more substantive issues such as the incidence of the co-payment (the rate at which drugs are relinquished by individuals who differ in their medical need) or the effect of prescription drug co-payments on patient health status. Harris *et al.* (1990), Soumerai *et al.* (1987, 1994) and Reeder and Nelson (1985) attempted to address both questions. In Harris *et al.* (1987), the therapeutic categories of a subset of selected drugs were categorized into "essential" and "discretionary" categories. Essential drugs were defined as drugs whose withdrawal could have important effects on health status: antihypertensives, cardiac, diabetic, and thyroid agents. Discretionary drugs were prescribed for symptomatic relief, often on an "as needed" basis for self-limiting conditions: analgesics, nonsteroidal anti-inflammatory agents, cough and cold products, and skeletal muscle relaxants. The utilization of essential medications were monitored after the imposition of the co-payments to determine if patients taking these medications reduced consumption levels. If the utilization of essential medications is found to drop, then this suggests that individuals with lower levels of health

status are relinquishing potentially needed medications. Health status may therefore be adversely affected.

It should be noted that for the decrease in the use of essential medications to have an adverse effect of health status, it must first be established that the pre-co-payment utilization of these drugs was in fact medically warranted. Clearly, even essential medications can be inappropriately prescribed. Unfortunately, information on the clinical indications for the use of these drugs was not available; instead the authors proceeded on the assumption that at least some fraction of any relinquished essential drug consumption could have had a beneficial impact on patient health status.

Both Soumerai *et al.* (1987) and Harris found that utilization of discretionary-type drugs dropped by a larger margin than the use of essential drugs. Specifically, Harris reported that discretionary drug use dropped 17.3%, 19.2%, and a further 19.0% following the $1.50 co-payment in year two, $3.00 co-payment in year three and year four change in the benefit structure, respectively;[7] ($P<0.0001$ in all the above tests). Use of essential drugs in the co-payment cohort declined significantly only after the $3.00 co-payment in the third year. (A 13% decline relative to the comparison group was reported, $P<0.0001$.)

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[7] The number of discretionary prescriptions per patient per year in the copayment cohort actually declined slightly over years 2 to 4 (from 1.63 to 1.62). The number of discretionary prescriptions per patient per year in the comparison cohort increased 1.5% over the same period (from 1.97 to 2.00).

Moreover, the use of essential drugs over the study period in the co-payment cohort actually increased faster than in the comparison cohort.[8]

In the Soumerai *et al.* (1987) study drugs were classified into slightly different categories based on their expected effect on health status: effective, essential medications (withdrawal could have important effects on mortality or morbidity); effective non-essential symptomatic relief medications; and drugs of limited efficacy (slight or no superiority over placebo). Following the the 3-prescription/month limit imposed by the New Hampshire Medicare program, the number of constant-size prescriptions of less essential drugs dropped more sharply than did the volume of essential drugs dispensed. The authors report reductions of 28% in essential drug use, 38% in effective symptomatic relief drug use, and 58% the use of drugs of limited efficacy.

Soumerai *et al.* (1987) paid special attention to the effect of user charges of one particularly essential and costly medication -- insulin. Overall, the number of prescriptions per 100 patients per month dropped 28% (from 11.6 to 8.4). Further analysis was conducted on the prescriptions of a cohort of insulin dependent patients to determine whether precap doses were considered excessive, whether aggregate reductions were concentrated among a few patients, and the

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[8] The number of essential prescriptions per patient per year in the copayment cohort actually increased 41% over years 2 to 4 (from 0.17 to 0.24). The number of essential prescriptions per patient per year in the comparison cohort increased 32% over the same period (from 0.19 to 0.25).

process by which reductions in prescriptions occurred.[9] To address the first question, the cohort was divided into two subgroups: those whose utilization dropped only slightly (<10%) following the cap, and those with a larger drop in utilization (>30%). The authors argued that because their precap doses were similar, a reduction in excessive doses was not an underlying explanatory factor. In addition, it appeared that reductions in prescriptions among the most price-responsive group corresponded with reductions in total dosages administered: prescription sizes filled by this group did not rise so as to compensate.

Soumerai *et al.* (1994) provided additional evidence on the effects of the New Hampshire Medicaid three-prescription-per-month limit on the health status of schizophrenia patients in the State. The analysts merged the Medicaid claims records of the 268 patients with the clinical records of two community health centres (CMHCs) and the single state psychiatric hospital. The comparison group was comprised of the 1,959 schizophrenia patients in New Jersey. Identification of the effects on health status consisted of testing for an intercept shift in a trend line in CMHC and psychiatric hospital admissions of the study patients after the medication cap was imposed. The authors note that the increased use of mental health services may have represented an attempt to secure low cost medications, rather than a response to acute exacerbation of illness due to the discontinued

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[9] This cohort consisted of 79 continuously enrolled patients who were identified as regular insulin users (the individuals had more than 4 prescriptions filled in the year before the cap).

medicines use. Several institutional details were provided, however, which the authors feel renders the former explanation as unprobable.

Consistent with their earlier findings of the aggregate responses to the cap Soumerai *et al.* (1987), medications use (i.e., antipsychotic agents, antidepressants, anxiolytic and hypnotic agents) decreased 15-49%, depending on the drug. Interestingly, the per patient use of emergency mental health services and partial hospitalizations increased significantly after the cap, in the range 1.2 to 1.4 episodes per month. The authors conclude on the basis of these increases in mental health care use, that patient health status was adversely affected.

Reeder and Nelson (1985) indicated that after Medicare drug benefits in South Carolina were reduced, patients did not relinquish drugs which had immediate and unpleasant withdrawal effects (e.g., sedatives and analgesics), even though withdrawal from these drugs did not have adverse longer term health effects. In contrast, utilization of drugs used to treat serious but asymptomatic disease (e.g., diuretics for hypertension) was found to decline substantially.

2.3 Physician vs Patient Control over Drug Utilization

Analyzing whether decreases in the quantity and composition of drugs consumed following a user charge are largely patient- or physician-initiated can shed some light on the probable effects on patient health status. The patient

typically has less knowledge of what constitutes "rational" drug therapy than the physician. Therefore if a co-payment induced drop in utilization results primarily from consumer rather than physician decisions, (due to non-compliance with physician prescriptions or a lower propensity to initiate treatment) it increases the probability that the appropriateness of therapy is not improved (Hurley and Johnson 1991).

Several studies on medical noncompliance have demonstrated that not all written prescriptions are purchased, and not all purchased prescriptions are taken as prescribed (Begg 1984; Richardson 1986). The published evidence on the effects of prescription drug co-payments on patient compliance with prescribed drug regimens is, however, sparse. Col *et al.* (1990) analysed the reasons for noncompliance on the basis of interviews with 315 elderly patients admitted to an acute care hospital. A common reason for noncompliance was due to patients' ability and/or willingness to pay for their medications. Variables such as monthly cost of medications, opinion of the cost of medications, insurance coverage of medications, and income level were found to affect the risk of noncompliance as well as the risk of hospitalization due to noncompliance. Similar findings were reported by Brand *et al.* (1977).

Another possible patient response to increases in drug co-payment rates is in the reduction in the number of physician visits. Estimates of the effect of prescription drug co-payments on the number of physician visits are mixed. Lingle

et al. (1987) compared the utilization of several health services by Medicare recipients-- including home health care, physician visits and hospitalizations -- in a state where prescription drugs were insured (New Jersey)[10] and a state with no public subsidization of drugs for Medicare recipients (Pennsylvania). The authors found no significant differences in the relationships between the two study states for most health care services -- including physician services -- reimbursed under Medicare. One exception was hospital admissions (which accounts for a major proportion of Medicare reimbursements) which were lower in New Jersey. Kozma *et al.* (1990) monitored the utilization of a variety of health services by South Carolina Medicaid recipients before and after increases in the types of pharmaceuticals which were insured by Medicaid. In contrast to the findings reported by Lingle, this study found significant increases in the use of physicians' services after the formulary list was expanded.

2.4 Discussion

Most of the information on the effects of co-payments on drug utilization has been obtained from quasi-experimental settings. Typically the "natural experiments" involve examination of prescription drug utilization before and after the imposition of changes in reimbursement criteria in the context of various

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[10] A $2 copayment per prescription was paid by the patient.

insurance providers (i.e., U.K. National Health Service, U.S. Medicare Program, and U.S. managed health care organizations). In some cases, studies based on these administrative data sets have been hampered by problems of identification. The RAND Health Insurance Experiment produced the only data set which was based on a controlled experiment design. The experiment failed, however, to identify the changes in drug utilization which were due to changes in drug co-payments from those induced by medical care co-payments.

Regardless of study design the results seem to suggest that prescription drug use is price responsive, although the elasticity appears to be under one. Moreover, the estimates were robust to the form of the co-payment, i.e., fixed per-prescription charges and charges which vary with the total cost of the prescription. It should be noted, however, that the studies reviewed here have examined the price sensitivity of drug utilization by non-elderly populations. The degree to which the results obtained in these studies are generalizable to older populations is questionable.

Due to data limitations, there is no direct evidence on the health status effects of changes in prescription drug co-payments. Indirect evidence does suggest, however, that health status is adversely affected by copayment in some patient populations. First, there is some evidence to suggest that patient compliance with prescription regimens is affected by out of pocket expenses, as is the likelihood of patients' initiating physician consultations. In addition, some patients selectively refrain from reducing drug use on the basis of immediate

withdrawal effects, but not on the longer term health consequences of noncompliance. Indeed, some of the drugs relinquished after the imposition of user charges have potentially important effects on health status (e.g., insulin). Finally, it appears that the use of emergency medical care services in some patient populations increases after the imposition of paid prescription limits.

3. Effects of Drug Plan Eligibility on the Prescription Drug Use by Ontario Seniors

3.1 Introduction

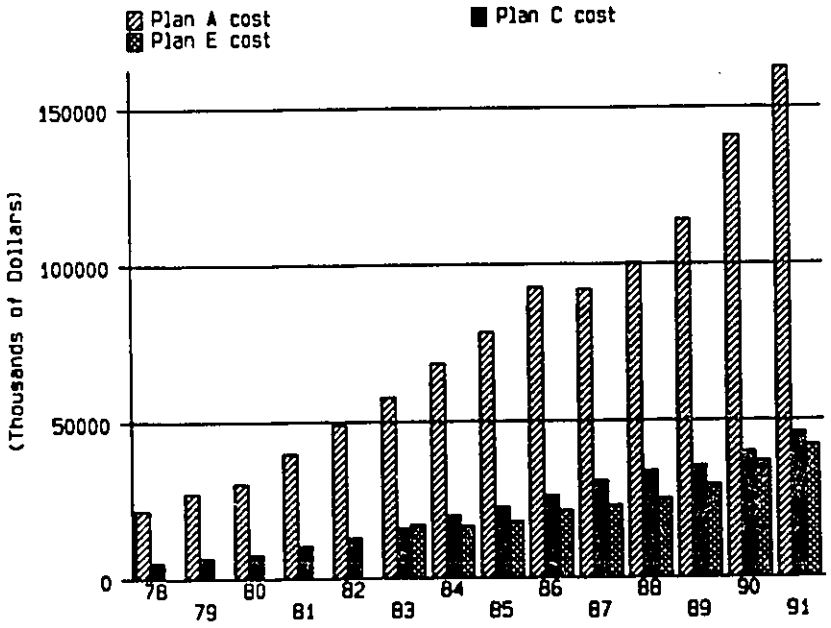
The utilization of prescription medicines is receiving increasing attention for a number of reasons. Pharmacological agents are important in the management of acute and chronic illness. Canadian general practitioners provide prescriptions in 21% to 86% of all patient consultations (Lexchin 1990). Advances in pharmacological technology have been matched by increases in utilization, especially among elderly populations (Institute for Clinical Evaluative Sciences 1994). There is widespread evidence, however, of less than ideal and even inappropriate prescribing behaviour by physicians and compliance and utilization behaviour by patients (Tully and Tallis 1991; Shorr and Bauwens 1990; Kofoed *et al.* 1989). The Canada Health Survey identified elderly people as the largest consumer group of anxiolytics, sedatives and hypnotics and found that the prevalence of individuals whose duration of therapy exceeded recommended levels was high (Dept. of National Health and Welfare 1981). A parallel policy issue is the rapid growth in expenditures on private and public sector drug insurance plans.

Drug utilization is a key component of physician-patient interactions and decision making. Third party payment schemes for drugs both in the private and public sectors have the potential to affect the behaviour both of physicians and patients. Thus an examination of the factors that affect the utilization of drugs is important both for testing economic theory concerning the behaviour of physicians and patients and for improving the evidential base for the formulation of policy on drug insurance.

There has been a growing interest in the utilization of prescription medicines for fiscal reasons. Increases in both the volume and prices of prescription drugs have caused public subsidization of drug expenditures to be one of the most rapidly increasing components of provincial health care spending. In Ontario, for example, prescription drug expenses for seniors -- paid for by the Ontario Ministry of Health Drug Benefit program -- rose from $212.2 million in the 1985-86 fiscal year to $645.6 million in 1992-93 (Institute for Clinical and Evaluative Sciences 1994). Rapid growth in expenditures on prescription drugs have not been restricted to Ontario. The average annual rate of increase in (nominal) expenditures on the Nova Scotia Pharmacare program between 1979 and 1988 was 18 per cent (Nova Scotia Government 1989). Similar trends have been observed in British Columbia, where Pharmacare expenditures have grown substantially over the last decade.

Within the B.C. Pharmacare program, subsidies to the various beneficiary groups have increased at differing rates. Public spending on prescription drugs for individuals 65 and older in particular (under the auspices of an insurance program known as Plan *A*) have increased at the fastest rate; the average annual growth rate in nominal expenditures between 1985-1991 was over 17 per cent (Grootendorst 1992). Only modest rates of increase have been observed in public spending for the other major beneficiary groups: social assistance recipients (Plan *C*), and persons under 65 who are not social assistance recipients (Plan *E*). (Figure 3-1.)

Figure 3-1 Annual British Columbia Pharmacare Expenditures on Plans A (65 and Over), C (Social Assistance Recipients) and E (Under 65)



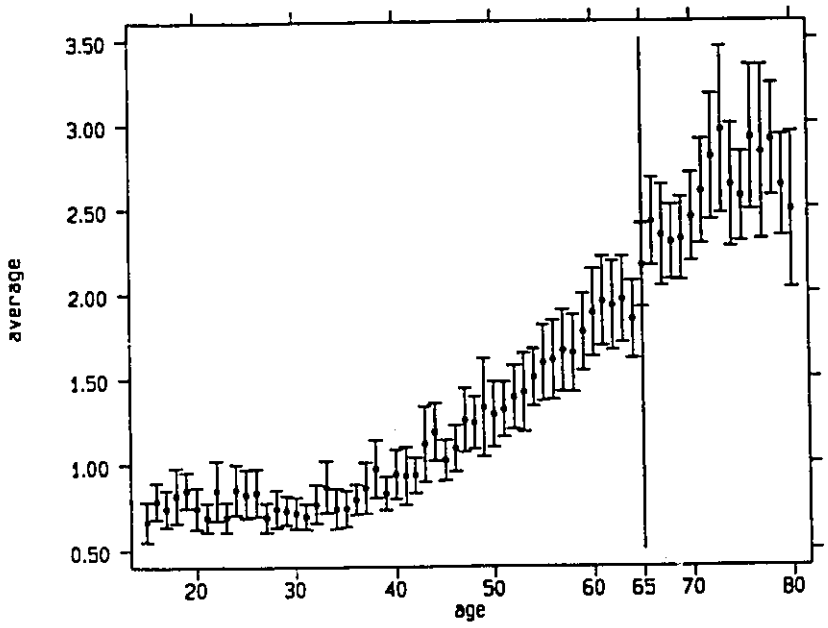
Source: B.C. Ministry of Health

One of the primary responses by provincial governments to rising drug expenditures has been to introduce or increase beneficiary co-payment requirements for out-patient drug consumption. In April 1987 the British Columbia Ministry of Health instituted a co-payment scheme for beneficiaries aged 65 or older. Similar measures are under consideration, or have already been implemented in New Brunswick, Saskatchewan and Ontario. The goal of these co-payment schemes has been to either reduce public expenditure or facilitate the redistribution of funds to enhance coverage for other beneficiary groups (e.g., the working poor). The introduction of user charges has potentially undesirable consequences, however, by way of discouraging the use of effective medications (thereby adversely affecting health outcomes) and exposing the beneficiary population to risk. Little is known about the effect of prescription charges on health services utilization in older populations.

This paper will address three issues. First, the price sensitivity of prescription drug utilization among elderly populations will be ascertained. Ontario residents over the age of 64 are eligible for publicly subsidized pharmaceutical drug insurance. The age-prescription drug utilization profile displayed in Figure 3-2 below suggests that there is an increase in utilization after drugs are provided free of charge. Cross-sectional data from the 1990 Ontario Health Survey (OHS) are used to evaluate the moral hazard effect of this age-based insurance, while holding constant possibly confounding factors such as

health status, income and other covariates. Information obtained may shed some light on the probable decreases in prescription drug utilization following the introduction or increase in prescription drug co-payments.

Figure 3-2 Mean Number of Different Drugs Consumed by Age, with 95% Confidence Intervals



Source: 1990 Ontario Health Survey

This paper will also examine the distributive effects of the public subsidy for prescription drugs. Does the provision of public prescription drug insurance favor individuals with lower levels of health status? Information gained here may provide some clues as to any adverse health consequences associated with the

introduction of prescription drug co-payments. If utilization increases are disproportionately higher among those with greater health care needs, and the results are symmetric to the case of an increase in co-payment, then reliance on co-payments may carry potentially adverse health consequences.

Drug utilization reflects joint physician-patient decision making. Although only physicians may prescribe medications, patients typically initiate episodes of treatment and are ultimately responsible for compliance with therapy. Information about these physician-patient interactions is limited. A final objective of this paper is to examine the specific utilization responses to the price change. Does the introduction of free drug insurance result in increases in patient episode initiation or substitutions of prescription for non-prescription drugs? Do changes in prescription drug co-payments primarily affect the probability of use, or do they affect intensity of use? Information obtained may shed some light on patient-initiated responses to changes in prescription drug co-payments. Again, if drug co-payments result in patients becoming less likely to initiate physician visits, then patient health status may be adversely affected.

Section 3.2 reviews the existing evidence regarding the effects of prescription drug co-payments on prescription drug utilization, and Section 3.3 discusses issues involved in addressing the three questions outlined above. The empirical models of the utilization of prescription and non-prescription drugs, and physician consultations are motivated in Section 3.4 and empirical results are

presented in Section 3.5. Section 3.6 offers some interpretation of the empirical results.

3.2 Modelling Drug Utilization

In all of the provinces of Canada, prescription drugs are prescribed only by physicians (including dentists) and are dispensed by registered pharmacists. The process of obtaining a prescription drug therefore involves initiation of a treatment episode by a patient and the prescription of the drug by the physician. Because utilization reflects both patient and physician decisions, then, shifts in the co-payment levels may alter the behaviour of both parties.

Lowering the prescription charge may affect patient demand by way of increasing physician consultations and/or improving compliance with physician-recommended drug therapy. Evidence from Col *et al.* (1990) and Brand *et al.* (1977) indicate that it is likely that lower user charges encourages patients to fill more of the prescriptions written by the physician -- both for refills of drugs consumed prior to a change in effective prices and for drugs prescribed after the price change.

The physician may also change prescribing habits once prescription drugs are available free of charge to the patient. The physician may prescribe additional drugs for the management of existing chronic conditions. Some pharmacological

agents produce undesirable side effects which may be remedied through the prescribing of additional drugs. For example, non-steroidal anti-inflammatory drugs are commonly used as part of the maintenance therapy of chronic arthritis. Prolonged use of these drugs may, however, produce undesirable side effects such as gastro-intestinal bleeding. To reduce the risk of this, misoprostol, a mucosal protective agent can be co-prescribed (Walt 1992). Given its considerable expense, the drug may only be prescribed for patients with insurance coverage.

The physician concerned with minimizing treatment cost both to him/herself and the patient may also alter the mix of inputs if there is some substitutability between prescription drugs and other health care inputs. For example, the lower relative price of prescription drugs may result in substitutions between prescription drugs and the physician's own time. This would reduce the cost to the physician. The cost to the patient would also be reduced through substitutions of prescription for non-prescription drugs. The physician may also be more likely to prescribe a medication with a perceived quality advantage over another therapeutically similar product. (One example is the prescribing of "brand name" drugs over typically less expensive "generic" drugs.) Finally, the physician might respond by altering the dosage strength of drugs which were consumed prior to the price change.

Having enumerated the channels through which utilization might respond, it is important to investigate the sensitivity of different utilization measurements to

each of these. This information is summarized in Table 3-3 below. Two measures commonly used in the empirical literature on drug utilization are real prescription drug expenditures and the number of prescriptions dispensed. Real expenditure is the weighted sum of consumption of a vector Q of drug products (which differ with respect to active ingredient, dosage strength, dosage form, and manufacturer), where the weights are the per unit prices P of the drugs. The use of real expenditure is sensitive to increases in total consumption of selected drugs and substitutions between low and high cost drugs after the price change. The other common instrument, the number prescriptions dispensed, lacks any price information and is therefore not sensitive to substitutions between high and low cost drugs. It is also insensitive to increases in the volume of drugs prescribed per prescription. Neither of these measures, by themselves, are able to distinguish among all the sources of utilization increases. A third measure of utilization, which is the one used in the 1990 OHS -- the number of different prescription drugs consumed in the 4 weeks prior to the survey -- is sensitive to fewer utilization responses. The OHS measure is simply a count of the number of nonzero elements in the vector Q. It lacks information on both the prices associated with the different drugs and the level of consumption of each of the drugs. It is therefore sensitive to neither increases in the volume of drugs consumed prior to the price change, nor to substitutions between high cost and low cost drugs. Its major advantage over the other two measures is that it

probably suffers from a lowest degree of recall bias on the part of survey respondents. More individuals are typically able to recall how many different drugs were recently consumed than the value of their drug purchases.[11] This measure is also particularly sensitive to multiple drug use which is increasingly becoming a pertinent policy issue. Finally, the question asked in the OHS specifically measures actual consumption rates. Expenditures record the purchase of drugs, which may not necessarily coincide with consumption.

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[11] A verification study conducted by Berk, Schur and Mohr (1990) concluded that only a small proportion of elderly respondents can provide accurate data on prescription drug expenditures. The study did not address the accuracy of the reporting of the number of different drugs taken by elderly respondents.

Table 3-3 Sensitivity of Different Instruments to Changes in Physician/Patient Behaviour

Change in utilization following the price change (providing ingredient cost & dispensing fee free of charge.)	Change in Measurement Instrument		
	Expenditure	Number of Prescriptions Dispensed	Number of Different Drugs Taken
1. Patient initiates episode of treatment	increase	increase	increase
2. Patient fills more prescriptions for drugs prescribed prior to the price change	increase	increase	increase / no change
3. Patient fills more prescriptions for drugs prescribed after the price change	increase	increase	increase
4. Physician increases the number of complementary drugs used for management of conditions.	increase	increase	increase
5. Physician substitutes prescription drugs for own time and other inputs, reducing his/her treatment cost	increase	increase	increase
6. Physician substitutes prescription drugs for non-prescription drugs, reducing patient treatment cost	increase	increase	increase
7. Physician substitutes brandname prescription drugs for generic prescription drugs	increase	no change	no change
8. Physician prescribes larger dosages of drugs administered prior to the price change	increase	no change	no change

The primary measurement instrument used in the OHS -- the number of different drugs taken -- lacks the specificity to distinguish among responses 1, 3, 4, 5, and 6 to the provision of free drugs at age 65. Data on the number of physician visits, and utilization of non-prescription drugs contained in the OHS are used,

however, to differentiate among some of these utilization responses. Models of the probability of a physician consultation in the last 12 months and the probability of non-prescription drug use in the last 14 days are estimated to determine how their utilization is affected by the provision of public insurance after the age 65. Specifically, if it is found that there is a statistically significant increase in the number of different drugs consumed after 65, but negligible responses in physician consults or non-prescription drug use, then the likely sources of utilization change are responses (3) improved patient compliance, (4) physician prescribing of complementary drugs and/or (5) physician substitutions of prescription drugs for other health inputs, such as physician time. There is no information on physician time spent per consultation, or patient compliance rates to facilitate analysis of these separate utilization channels. This lack of information prevents a precise decomposition of changes in utilization due to patient- and physician decisions, but it still potentially rules out patient-initiated changes in physician visits as a source.

3.2.1 The Distribution of Drug Consumption

The distribution of drug utilization reported in the 1990 OHS bears several important characteristics. The first characteristic is that the distribution is discrete, because the OHS counted the number of different drugs taken. Another characteristic of the distribution of drug consumption is that a large proportion of

individuals do not consume any prescription drugs. Table 3-4 indicates that over 40 percent of respondents did not report using prescription drugs in the 4 weeks prior to the Ontario Health Survey.[12] Inspection of the age-specific participation rates reported in Figure 3-3 reveals additional insights into the drug use patterns disaggregated by age and sex. First, the percentage using drugs increases substantially with age. Over 80% of respondents aged 66-71 reported using prescription drugs. The proportion of males who are users is typically smaller than the proportion of females who are users. Also, the proportion who are users among both sexes bears a non-linear relation with age.

Table 3-4 Distribution of Number of Different Drugs Consumed -- All Ages

Number Different Drugs	Frequency	%
0	13,894	43.3
1	8,669	27.0
2	4,857	15.2
3	2,062	6.4
4	1,197	3.7
5	570	1.8
6-10	671	2.1
11+	144	0.5
Total	32,064	100.0

Source: 1990 Ontario Health Survey

Note: These data were self-reported, and unweighted.

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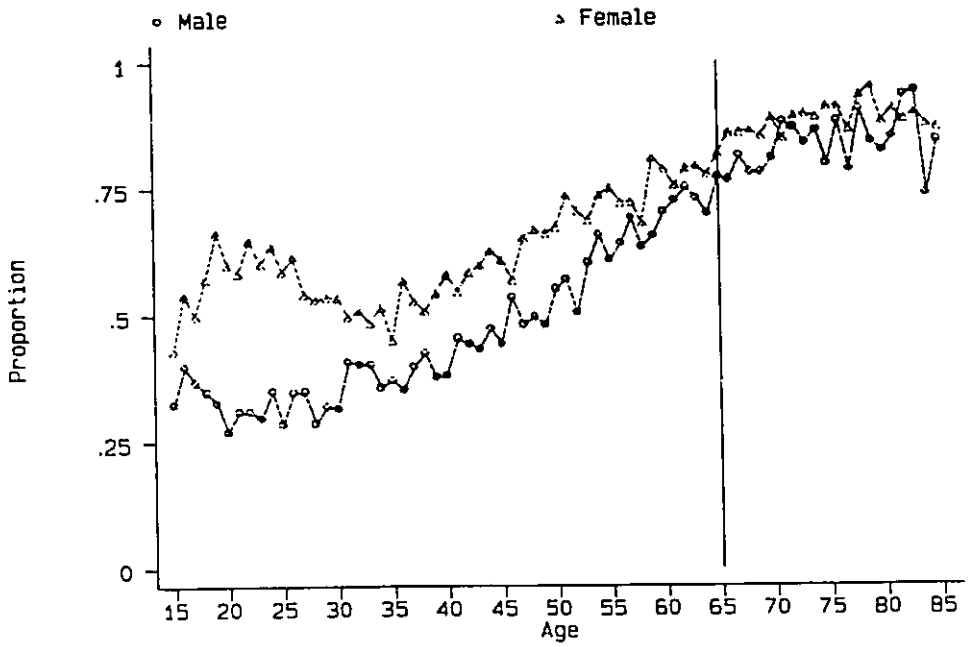
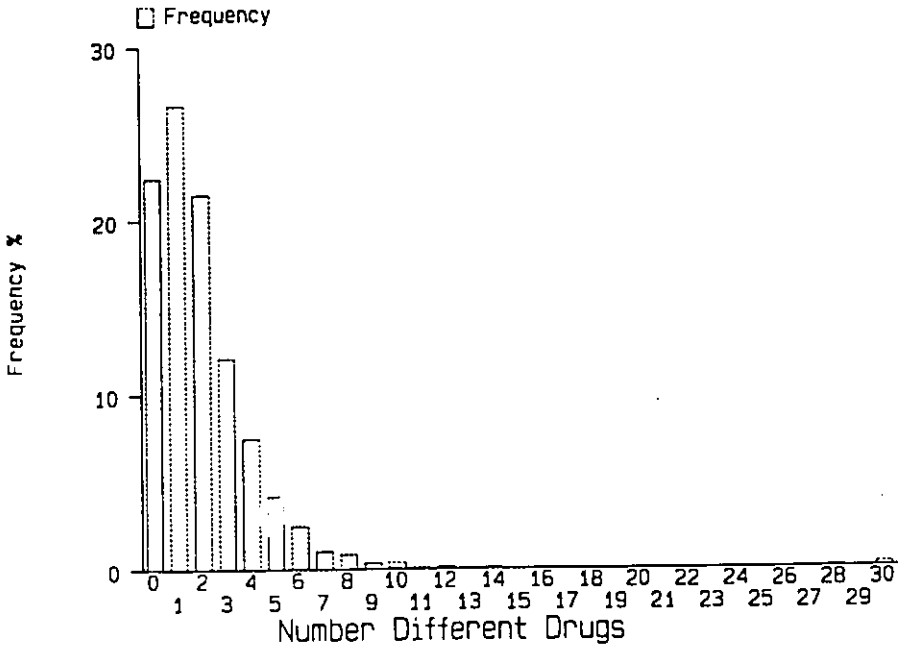
[12] Sampling weights have not been applied to these utilization data. These rates are therefore not equivalent at the population level. The weighted data are, however, very similar. For example, using the weighted data, 42.3 of respondents did not use any prescription drugs in the last 4 weeks.

Figure 3-3 Proportion Drug Users by Age and Sex



The distribution of drug consumption by individuals aged 55-75 is also skewed. As is evident from Figure 3-4, below, a large proportion of users consume a few different drugs, whereas a relatively small fraction of users consume a large number of different drugs (up to 30 in fact).

Figure 3-4 Distribution of the Number of Different Drugs Consumed by Individuals 55-75



3.2.2 Statistical Methods

Models of drug utilization must be consistent with the salient features of the distribution of drug expenditures discussed above: a rather large number of zeroes, skewness in the distribution of consumption of users and the discrete nature of the utilization measure.

3.2.2.1 Dealing with Discrete Dependent Variables

One approach to dealing with the analysis of data involving counts of events per time interval is to use the Poisson or negative binomial regression. Ordinary Least Squares (OLS) regression admits negative predictions which are inconsistent with non-negative data. Moreover, the disturbance terms associated with OLS regression models of count data are typically left-skewed, non-normal and heteroskedastic.[13] As counts must be integers as well as non-negative, maximum likelihood techniques based on discrete distributions are potentially more efficient, produce positive predictions, and may produce more powerful inference on the estimated parameters.[14]

The contribution to the likelihood of the *ith* observation of a Poisson-distributed random variable Y is:

$$f(y_i) = \Pr(Y_i = y_i) = \frac{\lambda_i^{y_i} \exp(-\lambda_i)}{y_i!}, \quad y_i = 0,1,2, \ldots \tag{3.1}$$

The density of Y_i is made conditional on the explanatory variables $\mathbf{x}_i$ by parameterizing the mean λ_i, as:

$$\ln \lambda_i = \mathbf{x}_i' \beta \tag{3.2}$$

---

[13] The heteroskedasticity arises because the variance of a Poisson variate with a small mean is less than the variance of one with a larger mean.

[14] It should be noted that the Poisson model converges in distribution to the standard normal when the parameter λ tends to infinity. However, the fact that the unconditional estimate of λ is relatively small, 2.5, suggests that the normal distribution may be a poor approximation in this case.

This particular transformation ensures that the estimated mean is positive. The log-likelihood function:

$$\ln L = \sum_i \left(-\mathbf{x}_i'\beta + y_i \ln(\mathbf{x}_i'\beta) - \ln y_i!\right)$$

is globally concave in β; iterative maximization algorithms usually achieve rapid convergence.

The Poisson model has the possibly unattractive restriction that the first and second conditional moments of the Poisson-distributed variable are both equal to λ_i. Hence:

$$E[y_i|\mathbf{x}_i] = Var[y_i|\mathbf{x}_i] = \lambda_i = \exp(\mathbf{x}_i'\beta).$$

Many types of count data are characterized by "overdispersion" meaning that the (conditional) variance exceeds the (conditional) mean. In these cases, the assumptions of the Poisson model are not satisfied and a more general specification should be adopted. Over-dispersion may be due to unobservable individual heterogeneity in drug consumption. The negative binomial regression model arises if this heterogeneity is modeled using the gamma probability distribution. Following the notation of Greene (1992, page 539), the density of the negative binomial is derived by adding an error term to the conditional mean of the Poisson (3.2):

$$\ln \lambda_i = \mathbf{x}_i'\beta + \varepsilon \qquad (3.3)$$

where exp(ε) follows a gamma distribution with mean one and variance α. Substituting (3.3) into (3.1) and integrating ε out of the expression yields the negative binomial density:

$$f(y_i) = \Pr(Y = y_i) = \frac{\Gamma(\theta + y_i)}{\Gamma(\theta) y_i!} u_i^{\theta} (1-u_i)^{y_i}, \quad y_i = 0,1,2, \ldots$$

where: $u_i = \frac{\theta}{\theta + \lambda_i}$, $\theta = \frac{1}{\alpha}$, $\Gamma(\cdot)$ = gamma function

The variance of the negative binomial distributed random variable y_i is:

$$Var[y_i] = E[y_i](1 + \alpha E[y_i])$$

Notice that the extra parameter α allows the mean to differ from the variance. The Poisson model is a special case of the negative binomial in which the variance parameter α is equal to zero (in which case the variance and mean of y_i are identical). A test for over-dispersion in the context of the Poisson model conveniently reduces to a *t*-test on the significance of the estimated value of α.

3.2.2.2 Dealing with Non-Consumption

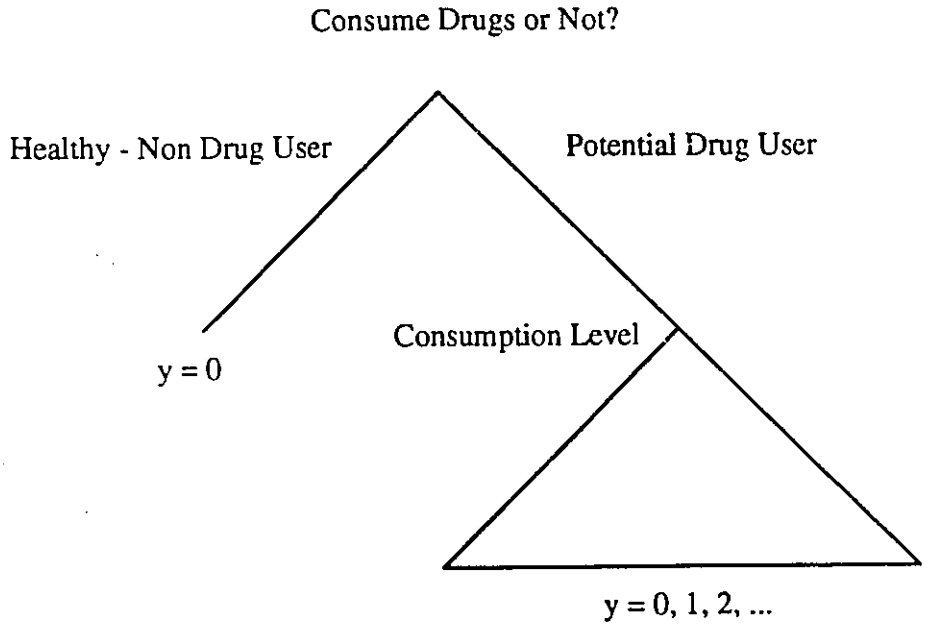
A variety of statistical methods are available to model health care utilization using micro-level data. A key element of these methods is their treatment of observations on zero consumption levels. Given the large proportion of zero consumption in health care utilization data, it is worth discussing some of the alternative models.

Most empirical corner solution models treat non-consumption as a strictly economic decision -- goods are not consumed when they are too expensive; people do not work unless they are adequately paid. As Pudney (1989) notes, however, non-consumption is often the result of decisions unconnected with the levels of prices and income. Most vegetarians do not abstain from eating meat because it is too expensive; many non-smokers would not smoke even if tobacco were a free good. The same logic could be applied to models of drug utilization. Many people who are healthy would not consume drugs at any price. Indeed, for otherwise healthy individuals, drug consumption may even be hazardous. People with a medical need, on the other hand, could experience a health status improvement from prescription drug use.

If the process describing consumption behavior of healthy individuals differs from those who are potential drug users, it does not make sense to apply the same model to the two groups. If it were possible to identify individuals based on their medically defined need for prescription drugs, then the easiest solution would be to estimate separate models for individuals who differ in their medical need. When this information is not available, however, some other mechanism must be used to discern between these groups. One approach is to estimate conditional probabilities that individuals are one of these two types. Two models using mixtures of discrete distributions proposed by Greene (1994), the zero altered Poisson (ZAP) and zero altered negative binomial (ZAN) model, appear

particularly well suited for the estimation of these models. The model consists of two behavioural processes depicted in the schematic below:

- a *regime generation process* which estimates a conditional probability that an individual is one of the two types discussed above: nondrug users and potential drug users, and
- a *Poisson* or *Negative Binomial Model* of the drug consumption of the potential drug users.



Zero consumption may arise in both regimes. For otherwise healthy individuals, however, non-consumption is, in general, automatic. Drug consumption would not be optimal even at a zero pr[illegible] Potential and actual drug users, on the other

hand, respond to prices and income in their consumption decision. Zero consumption is but one possible outcome at this stage.

Formally, the probability q_i of being a non drug user is made conditional on a vector of covariates $\mathbf{z}_i$:

$q_i = prob(nondruguser) = \Phi(\mathbf{z}_i' \delta)$

where $\Phi(\mathbf{z}_i'\delta)$ is the standard normal cumulative distribution function. The Poisson or negative binomial densities are used to model the consumption for potential drug users. As usual, the means of both of these distributions λ_i are made conditional on another set of covariates, $\mathbf{x}_i$ using the transformation $\lambda_i = \exp(\mathbf{x}_i'\beta)$. The other parameter, α, in the negative binomial model is assumed to be independent of these covariates.[15]

For the case of the ZAP model, the sample densities for drug consumption (y_i) are as follows:

$$prob(y_i = 0) = q_i + (1 - q_i)Poisson(\lambda_i = 0)$$
$$prob(y_i = j > 0) = (1 - q_i)Poisson(\lambda_i = j)$$

The mean and variance functions are, respectively:

$$E(y_i) = (1 - q_i)\lambda_i$$
$$Var(y_i) = (1 - q_i)(1 + \lambda_i q_i)\lambda_i$$

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[15] This restriction was rejected in the case of the negative binomial model and may therefore indicate a potential rejection in the case of the zero altered negative binomial model. Unfortunately, in the context of the ZANB model, conditioning α on a set of covariates increases the difficulty in obtaining model convergence. This generalized model was therefore not considered.

A Two-Part Model

It should be stressed that the purpose of the zero altered models outlined above is to retrieve consistent estimates of parameters describing the utilization behaviour of the potential and actual drug users. One equation in the model -- the regime generation process -- attempts to assign a probability that individuals are potential drug users (as opposed to non drug users). The conceptual distinction between the non-users and potential-actual drug users is not, however, always meaningful in practice. If all of the individuals in the sample had some medically-defined need for prescription drugs, then the same utilization model could be applied to them. Alternatively, the model may not even be estimable if it is not possible to quantify differences in individuals' medically-defined need for prescription drugs. If individuals are sufficiently homogeneous in their drug utilization behaviour, it may make sense to employ simpler estimation techniques.

The "two-part model" -- forwarded by Duan *et al.* (1983) -- appears to be a convenient method of estimation in this context. The essence of their statistical model is to decompose drug expenditures (y_i) into two observed random variates: "$y_i > 0$" and "$y_i \mid y_i > 0$" and specify a probability model appropriate for each random variable. The use of this decomposition affords the analyst some flexibility in picking an estimation technique which is consistent with features of the distribution of the variable of interest. Other estimation methods -- such as OLS -- do not appear to be as flexible (Duan *et al.* 1983). It should be stressed that the

interpretation of the parameters of the two-part and zero altered models differs. The zero altered model attempts to estimate parameters for the group of individuals with medical need (the potential and actual drug users). The two-part model, on the other hand, is best viewed as a tool to model the characteristics of the distribution of actual drug users.[16]

Maximum Likelihood Estimation of a Two-Part Model

The sample of n observations is partitioned so that the first N observations have positive expenses, and the last $(n\text{-}N)$ observations have no drug expenditures. The likelihood of the N users is:

$$L_i = \Pr(y_i > 0 | x_i) \times density(y_i | y_i > 0, x_i), \quad i = 1,\ldots,N \tag{3.4}$$

The likelihood of the $(n\text{-}N)$ individuals who do not consume drugs is:

$$L_i(\delta_1) = \Pr(y_i = 0 | x_i), \quad i = N+1,\ldots,n$$

The likelihood of the entire sample is therefore:

$$L = \prod_{i=1}^{N} \Pr(y_i > 0 | \mathbf{x}_i) \times density(y_i | y_i > 0, \mathbf{x}_i) \times \prod_{i=N+1}^{n} \Pr(y_i = 0 | \mathbf{x}_i) \tag{3.5}$$

A convenient feature of the likelihood function is that it factors into two multiplicative terms:

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[16] This has been the source of some confusion in the literature. See, for example, Hay and Olsen (1984).

$$L1 = \prod_{i=1}^{N} \Pr(y_i > 0 | \mathbf{x}_i) \times \prod_{i=N+1}^{n} \Pr(y_i = 0 | \mathbf{x}_i) \tag{3.6}$$

$$L2 = \prod_{i=1}^{N} density(y_i | y_i > 0, \mathbf{x}_i) \tag{3.7}$$

The first term depends exclusively on parameters in the model of the binary outcome equation: "$y_i > 0$"; the second term depends exclusively on parameters in the equation explaining expenditures of the users. Because of this separability, maximizing the likelihood is equivalent to maximizing the likelihood functions (3.6) and (3.7) separately.

Once parameter estimates have been obtained, it is possible to predict the drug utilization of an individual with characteristics $\mathbf{x}_i$ using:

$$E(y_i | \mathbf{x}_i) = \Pr(y_i > 0 | \mathbf{x}_i) \times E(y_i | y_i > 0, \mathbf{x}_i)$$

Duan *et al.* (1983) found the probit model for the binary outcome and linear regression of the log of expenditures of users to be most compatible with their medical care utilization data. The analyst is, however, free to choose models appropriate for the data set at hand; the separability properties of the likelihood are robust to arbitrary parameterizations of the two equations. For the purposes of modelling the OHS drug utilization data, the two-part model consisting of a probit model for the binary outcome data and both the Poisson and negative binomial regressions to model the number of different drugs consumed by the users were considered. Also considered as candidate models of the number of different

prescription drugs were the Poisson, and negative binomial regressions; the zero altered Poisson and zero altered negative binomial models.

Preliminary Analysis

Preliminary analysis indicated that the Poisson-type models (i.e., the Poisson regression model, two-part model in which the Poisson was used to model the drug consumption of the subsample of users, and the zero-altered Poisson model) were characterized by substantial over-dispersion. This was established by way of *t*-tests on the significance of the estimated value of α in the negative binomial models.[17] These models were therefore rejected in favor of the more general negative binomial specifications. Table 3-5 summarizes the probability density functions for the three candidate models.

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[17] The *t*-ratios associated with the null hypothesis that $\alpha = 0$ were between 8.12 - 18.41 in the three models, estimated over the male and female subsamples.

Table 3-5 Densities for Various Estimation Techniques

Model	Density for Zeroes	Density for Positive Values
Negative Binomial	u_i^{θ}	$\frac{\Gamma(\theta+y_i)}{\Gamma(\theta)y_i!}u_i^{\theta}(1-u_i)^{y_i}$
Zero Altered Negative Binomial	$q_i+(1-q_i)u_i^{\theta}$	$(1-q_i)\frac{\Gamma(\theta+y_i)}{\Gamma(\theta)y_i!}u_i^{\theta}(1-u_i)^{y_i}$
Two-part Model: Probit and Negative Binomial	$1-\Phi(\mathbf{z}_i'\delta)$	$\Phi(\mathbf{z}_i'\delta)\frac{\Gamma(\theta+y_i)}{\Gamma(\theta)y_i!}u_i^{\theta}(1-u_i)^{y_i}$

3.2.3 The Distribution of Non-Prescription Drug and Physician Utilization

Information on non-prescription drug utilization contained in the OHS is limited to whether or not any non-prescription drugs were used in the 14 days prior to the survey. Because the dependent variable is binary, the count data models discussed above are not appropriate. Instead, the probit specification was used to model the use of non-prescription medicines. There is more information on physician utilization contained in the OHS. The survey includes the total number of visits to a general practitioner or specialist in the past 12 months. This variable was, however, not used. Instead, the probability of any physician visits over this period was modelled because this outcome measure is likely to be subject to the greatest degree of patient control. The alternative, the total number of physician visits is more subject to physician influence. The graphs below display

the proportion of individuals taking a non-prescription drug in the last 14 days (Figure 3-5) and consulting with a physician over the last 12 months (Figure 3-6).

Figure 3-5 Probability of Any Non-Prescription Drug Use during Past Two Weeks by Age and Sex (Spline-Smoothed)

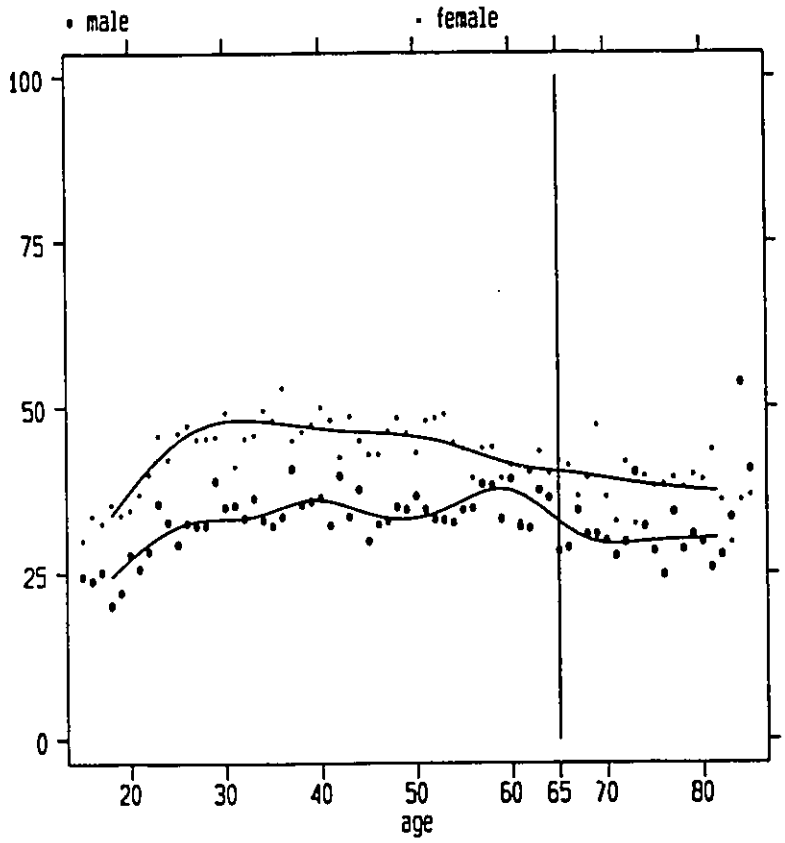
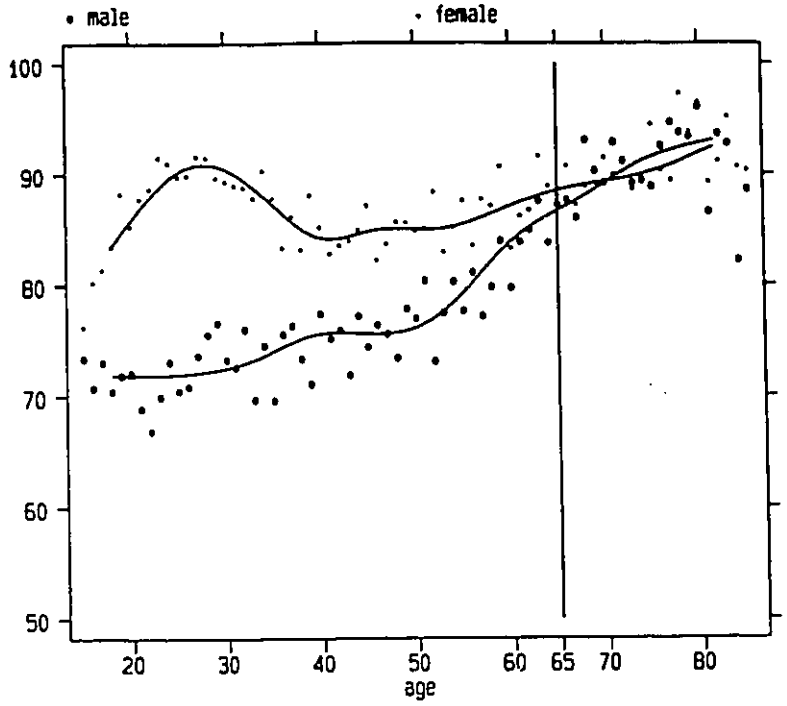


Figure 3-6 Probability of Any Physician Consult during Past Year by Age and Sex (Spline-Smoothed)



3.3 Modelling Technique

3.3.1 Selection of Model

With several plausible competing statistical models, some mechanism must be established to choose among them. In principle, it is possible to devise "goodness of fit" measures that are comparable across the models. These

performance measures, however, favor more complicated models that could over-fit the data (Duan *et al.* 1983). The additional complications in the models might be simply fitting artifacts of the particular sample and hence may not generalize to other samples. Instead the "split sample analysis" was conducted to devise performance measures.

The set of observations was randomly partitioned into estimation and forecast subsamples. Approximately 70% of the observations were allocated to the estimation subsample. All the models were fitted to this estimation subsample. Observations from the forecast subsample were then used to calculate predictions that could be compared to the actual values of the dependent variable. The differences between the predicted and actual number of different drugs form the basis of the mean squared error (MSE) performance measure. This measure is:

$$MSE_j = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_{ij} - y_i)^2$$

where the summation extends over the n individuals in the forecast subsample, $\hat{y}_{ij}$ is the predicted number of different drugs of the *ith* individual using the *jth* estimator and y_i is the actual number of different drugs consumed. The MSE measure takes on values from zero (indicating no forecast error) to positive infinity (indicating a rather poor fit).

The performance of the alternative models was assessed using a second method, the Vuong (1989) non-nested test. To test two competing probability models, f_1 and f_2, the statistic V is computed:

$$V = \frac{N^{1/2}\overline{m}}{s_m}, \text{where } m_i = \log\left[\frac{f_1(y_i)}{f_2(y_i)}\right]$$

This statistic (which is asymptotically normal) tests the null hypothesis that $E[m_i]=0$. An attractive feature of this test is in its ability to discriminate between the different models; a large positive value (e.g., greater than 1.96) favours model 1, whereas a large negative value favours model 2.

As Greene (1994) notes, testing the zero altered negative binomial against the negative binomial using this statistic allows us to make statements as to whether any excess zeroes are a consequence of the splitting mechanism or are due to unobserved heterogeneity. If the zero altered model is rejected in favour of the negative binomial, then the splitting model is rejected. If, in addition, the estimate of the "heterogeneity" parameter α in the negative binomial is found to be significant, then individual level heterogeneity may be at work. A finding that the negative binomial is rejected in favour of the zero altered model coupled with a finding that the estimate of α in the zero altered model is significant would indicate that both the splitting mechanism and individual heterogeneity in drug consumption

are operational. Finally, if the negative binomial is rejected in favour of the zero altered model and the estimate of α in the zero altered model is insignificant it would indicate that just the splitting mechanism is at work.

3.3.2 Sampling Frame of the OHS

The target population of the Ontario Health Survey was all residents of private dwellings in Ontario over the survey period January through December 1990 (Ontario Ministry of Health 1991). Residents of Indian reserves, inmates of institutions, foreign service personnel and residents of remote areas were excluded. Data were collected during all months of the year with the exception of July and December.

For the purposes of sampling, the population of Ontario was stratified by geographic regions known as Public Health Units (PHUs). Respondents were selected using a two-stage stratified cluster sampling frame designed to obtain 1000 completed responses per PHU. Each PHU is divided into urban and rural strata and each PHU/urban-rural strata is comprised of units called Enumeration Areas (EAs). At the first stage, a sample of EAs was selected from the urban and rural strata of each PHU. Larger EAs (in terms of occupied private dwellings) had a higher probability of selection. At the second stage of sampling, the sample of dwellings to be visited by the interviewers was selected from the listed EAs such

that the same number of dwellings was selected from each EA for a given stratum within a PHU.

Once a household was selected for inclusion into the survey, the questionnaire was administered in two stages. The first stage was an in-person interview with one respondent (referred to as the *index* respondent) in which the health status, health care utilization and socio-demographic information of all household members was collected. The index respondent responded both on behalf of himself or herself (self-report) and on behalf of other household members (acting as a proxy respondent). Supplementary information was then collected through self-completed written questionnaires left for each member of the household (aged 12 and older). The response rate for the interviewer portion of OHS was 87.5%. A further 77.2% of eligible respondents (12 years and older) completed the self-completed portion. The distribution of observations on each of the variables included in the analysis by respondent type (self- or proxy-reported) and by mode of administration of the survey (in-person interview or written, self-completed) is reported in Appendix A.

Because a large part of the survey data were collected from an index respondent serving as a proxy respondent for other household members, it is important to assess the extent to which measurement error could bias the parameter estimates. The literature on proxy-reporting suggests that proxy respondents typically under-report the burden of morbidity of pain, emotional

status, and other phenomenon that are not directly observable (Cannell, Marquis and Laurent 1977). Grootendorst, Feeny and Furlong (1994) investigated the extent of inter-rater agreement in the proxy and self-completed responses in the OHS. They conclude that the level of agreement for questions that assess readily observable phenomena is generally quite high. This contrasts to low levels of agreement for more subjective aspects of health status such as pain and emotional status.

The proxy reported variables used in the present analysis are age, sex, household income, household size, education, employment status, the number of chronic health problems and non-prescription drug use. Most of these variables are readily observed by the proxy respondent. Measurement error is therefore likely to be quite small for these variables with the possible exception of non-prescription drug use. Measurement error is likely to be substantial for health status, and prescription drug use. For this reason, the self-reported values of these variables are used in the analysis.

Grootendorst (1993) analysed the overall validity of the OHS. In general, the survey responses appear to have been coded and processed correctly. All skip patterns were observed. Intra-respondent response consistency was checked and found to be satisfactory. This applies both to the responses to the interviewer-administered and to the self-completed questions.

3.3.3 Selection of Regressors

The same set of regressors was used in all of the models considered. These can be divided into broad groups of variables: insurance dummies, access prices, health status and other demographics including income, age, sex, education.

3.3.3.1 Price Effects

It is important to capture the institutional characteristics that could have pertinent effects on drug utilization. The Ontario Drug Benefit Program (ODB) administered by the Ontario Ministry of Health (MOH) offers insurance to individuals on the basis of:

- *age* -- individuals 65 and older
- *income* -- social assistance recipients
- *disease* -- individuals with specific disorders (e.g., cancer, diabetes) or receiving specific drug therapy (e.g., AZT, cyclosporin)
- *other characteristics* -- residents of longterm care facilities, home care recipients.

There are no beneficiary co-payments in the ODB.[18] In Ontario, eligible drugs are itemized in a formulary or schedule. Reimbursement for drugs with similar active ingredients, dosage form and strength -- regardless of brand -- is fixed by the MOH and is based on the lowest price across all brands (Gorecki 1993).[19]

Eligibility for public drug coverage of both ingredient cost and dispensing fee was identified by the dummy variable *AGE65* that was assigned the value 1 if the individual is 65 years of age or older, 0 otherwise. Individuals who were deemed likely to be eligible for social assistance drug coverage were removed from the sample. (These individuals reported social assistance income as an income source.) The OHS excluded institutionalized individuals; the data have therefore been purged of those qualifying for in-patient drug coverage. No explicit control was made for those who qualify for disease-specific coverage on an out-patient basis.

Additional drug coverage (offered by private insurance firms or other government programs) is another potential source of price variation that should

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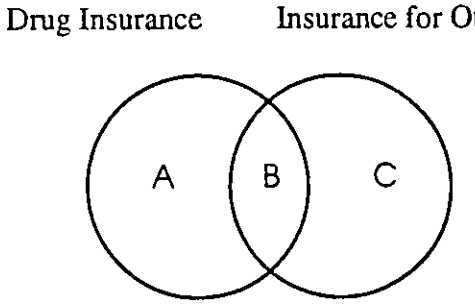
18 The other provinces and territories (with the exception of Nova Scotia) require co-payments, most commonly from seniors not receiving social assistance.

19 All provincial Ministries of Health (MOH) offer some form of subsidy for out-patient prescription drugs expenditures. The provincial programs, however, differ considerably with respect to eligibility criteria, co-payment rates, drugs that are covered, and the percentage of the price of a prescription that the government will subsidize (Anderson 1990).

logically be included as a covariate.[20] Unfortunately, the question asked in the OHS to identify respondents with additional drug coverage also includes individuals with non-ODB coverage for "other health services." The binary variable designed to identify other drug coverage, *DRUGINS*, may therefore introduce some measurement error. The schematic below represents the individuals identified by the variable *DRUGINS* (sections *A*, *B* and *C*). The group of interest is represented by the sections *A* and *B*. The ratio $(A+B)/(A+B+C)$ is the fraction of the individuals identified who have additional drug insurance coverage. The higher is this ratio, the lower the potential measurement error associated with the OHS variable.



Information on industry-level health insurance coverage data from Ontario indicated that measurement error may not be severe. The Canadian Life and

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[20] In Ontario, individuals over 65 are automatically eligible for ODB drug coverage. Individuals over 65 may, however, still carry additional drug coverage through employment related or retirement benefits. This insurance typically covers prescription drugs not covered by the ODB.

Health Insurance Association Inc., which represents 96% of all group health business and 88% of all individual health business in Canada, tabulates enrollment data by type of coverage (Canadian Life and Health Insurance Association Inc. 1994). For purposes of this measurement error analysis, "other health services" was taken to include non-publicly-insured health care expenses such as ambulance services, crutches, braces and other medical appliances, private duty nursing, services of non-medical practitioners, and hospital expenses.[21] Enrollment data by coverage type for Ontario are as follows:[22]

Individuals covered for drugs alone (*A*):	100,869
Individuals covered for other health care, including drugs (*B*):	5,165,913
Individuals covered for other health care, not including drugs (*C*):	292,987 - 808,350

The enrollment into category *C* had to be estimated. Depending on the estimate chosen, the fraction of individuals identified by the variable *DRUGINS* who have prescription drug coverage is between 87% - 95%.

The additional drug coverage variable may be also endogenous if individuals are selected into additional insurance coverage based on their *ex ante*

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[21] The other health services referred to in this question probably do not include dental or optical insurance, because insurance coverage for these were ascertained separately in the previous two questions in the OHS.

[22] These data do not include enrollment by two private insurers: Blue Cross and Green Shield. There may also be some double counting of individuals.

expected drug use. This selection can take place on both sides of the market, i.e., private insurers would prefer to insure those with low expected drug use, whereas those with high expected drug use would most like to be insured. Private drug coverage is not, however, directly purchasable; instead, it is usually obtained through employment-related benefits. The selection process may therefore have to operate through the employment decisions of both workers and firms. Endogeneity is only a problem then, if employers are particularly successful in differentiating between applicants who are heterogeneous in their *ex ante* expected drug use, or, alternatively, if "unhealthy" applicants succeed in gaining employment in firms with attractive drug benefits. Of course, even if these selection effects are operational, endogeneity may not prove to be serious if the private coverage constitutes a small percentage of the additional drug coverage identified in the survey question.

It is possible that the "*AGE65*" drug utilization response observed for individuals who have additional prescription drug insurance coverage is different from the response by those with no pre-existing coverage. If the terms of the private insurance held before age 65 are similar to the terms of the publicly-provided insurance, then there will be no change in effective coverage after reaching age 65. This implies that those with private coverage, who become eligible for public coverage upon turning 65, should not experience an increase in mean drug consumption, *ceteris paribus*. This can be formally tested in the model

by adding a new dummy variable *PRICEINT* that is the product of the public (*AGE65*) and other drug insurance variable (*DRUGINS*). If effective coverage does not change after turning 65, the coefficients on the *AGE65* variable and the *AGE65*DRUGINS* variables should sum to zero.[23]

Clearly the pecuniary cost of drugs is only one dimension of the cost of seeking care. Another cost would be the time price of seeking care. Individuals who are employed, for example, may incur a larger "time price" of going to the physician than retired people. The OHS includes information that could be used to identify differences in the time price of seeking care. Specifically, a question is asked which identifies the "normal activity" of the respondent during the previous 12 months. The possible responses are: working at a job, looking for work, going to school, keeping house, retired or other. It seems plausible that those working at a job face the highest cost of time of the five activity groups listed above. A binary variable identifying employed individuals was constructed and included as a covariate to control for this effect.

A potential difficulty with the use of the variable indicating employment status is that it may be correlated with the disturbances in the drug utilization equations. The reason is that some individuals might, even after conditioning on

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[23] Technically, if the model is $QRX = a_0 + a_1 AGE65 + a_2 DRUGINS + a_3 AGE65*DRUGINS +$ other regressors, then the increase in utilization at age 65 is approximated by: $\partial QRX / \partial AGE65 = a_1 + a_3 DRUGINS$. The hypothesis that those with additional drug coverage (i.e., $DRUGINS=1$) experience no increase in utilization at age 65 is then tested using the restriction: $a_1+a_3=0$.

all the exogenous variables, nonetheless retire early because of ill health. It is plausible that these people will be the same who use extra prescriptions (again conditioning on all the exogenous variables).

3.3.3.2 Health Status Effects

Health status is typically an important predictor in empirical models of health care utilization. As Manning *et al.* (1982) note in their review of the literature, health status often explains most of the variance in regression models of medical care utilization. More importantly, controlling for it can affect the magnitude of other estimated coefficients because of the correlations between health status and other regressors such as education, income and age.

The use of health measures in empirical models of health service utilization is problematic, however, because of the correlations between the health regressors and the disturbances in the utilization equation. It is well known that these correlations will likely render all of the parameter estimates inconsistent. These correlations may be nonzero because of measurement error or endogeneity of the health status regressors.

Measurement Error

It is not transparent how health status should be quantified. Health status is recognized as being a multi-dimensional concept, with distinguishable physical, mental, and social components. To the extent that all or several of these components have pertinent effects on drug use - operating through patient decisions (eg, initiation of treatment episodes, compliance) or physician decisions (eg, treatment for a chronic condition) - reliance on uni-dimensional measures of health status may introduce measurement error and/or omitted variables bias. Caution must be exercised, though, in the selection of these covariates. The temptation is to include an exhaustive list of variables associated with health status. In the interests of parsimony, the analyst would select several comprehensive measures of health status which encompass the dimensions influencing prescription drug use.

Another source of measurement error arises from the willful misreporting of health status levels. Butler *et al.* (1987) find evidence of measurement error in self-reported health status used as regressors in models of labour supply. This measurement error is found to vary systematically across different socioeconomic groups. The study notes (page 644): "... individuals who are not working tend to report their health incorrectly, perhaps owing to social pressure to justify not having a job."

A number of different measures of health status were included in the OHS. These measures can be categorized according to physical, mental and social components. In the physical health category, variables include the number and type of accidents incurred in the past 12 months, the number of restricted activity days in the last 14 days, and indicators of chronic or acute conditions. Also included are anthropometric measures (weight and height) which are important indicators of morbidity and longevity. Measures of social health status include the frequency and quality of interactions with friends and family members.

Several measures of overall health status were also used in the OHS. The level of self-assessed health status was ascertained with the following survey question: "In general, compared to other persons your age, would you say your health is: excellent, very good, good, fair, or poor." In addition, survey questions designed by Feeny *et al.* (1994) were used to assess functional capacity on eight health dimensions or attributes of health status of respondents: vision, hearing, speech, mobility/ambulation, manual dexterity, cognition (including memory and thinking ability), pain and emotion. For each of the eight attributes respondents were asked questions about their functioning that would allow them to be assigned to one of five or six levels of function per attribute. Questions assessing functional capacity of the first six attributes (vision, hearing, speech, mobility, dexterity, cognition) were asked of the index respondent. The latter two attributes, pain and emotion, were asked of both the index respondent and of each person themself, on

the basis of individual written questionnaires. Finally, behavioural and other factors which could have effects on health status were identified (nutritional intake, smoking, drinking, driving habits, narcotic drug use, occupational hazards and stress).

The health status measures used in the model included four dummy variables identifying the five levels of self-reported general health status[24] and a variable identifying the number of different health problems afflicting the individual. The comprehensive nature of the self-reported general health status has been documented in numerous studies. Numerous studies have demonstrated statistically significant relationships between variants of the self-report and other measures of health status, including physician assessments (e.g., Friedsam 1963; Maddox 1973; La Rue 1979; Linn and Linn 1980; Linn, Hunter and Linn 1980), measures of functional ability/disability (e.g., Tissue 1972; Nagi 1976; Linn and Linn 1980; Davies and Ware 1981), number and/or type of self-reported health problems, diagnoses or chronic diseases (e.g., Tissue 1972; Fillenbaum 1979; Linn and Linn 1980; Davies and Ware 1981), acute symptoms (Davies and Ware 1981) and composite measures of health status based on either self reports (Kaplan and Camacho 1983) or a combination of physician and self-reported conditions and health service utilization data (Mossey and Shapiro 1982). This variable has also been used extensively in empirical models of medical care utilization (Manning *et*

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[24] The omitted category is excellent health.

al. 1982). The number of different health problems variable has also been used in a variety of studies including Acton (1976), and Davis and Reynolds (1976). There is some evidence then, that the measures of health status chosen are reasonably valid.

To allow the price response to vary by health status level, interaction terms between the five health status variables and the binary variable indicating eligibility for public insurance -- *AGE65* are estimated. Preliminary analysis indicated that after conditioning on the interaction between *AGE65* and *NUMBPRB* -- the number of chronic health problems, the four other interaction terms were jointly insignificant in both parts of the two-part model.[25] The more restrictive specification was used instead.

Endogeneity

Correlation between the regressors and disturbances might also arise if the health status measures selected represent an outcome, rather than a determinant of drug use. As an example, Manning *et al.* (1982, page 147) critique the restricted activity days measure of health status: "Did one suffer from restricted activity and

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[25] Likelihood ratio statistics of the joint significance of these 4 variables computed from the probit models of prescription drug use were 4.6 (females) and 7.2 (males). The statistics computed from the negative binomial models of number of different drugs taken were 3.2 (females) and 8.31 (males). The five percent critical value is 9.49.

therefore seek care, or did the physician advise taking it easy?" Alternatively the problem arises if there are latent individual characteristics which affect both drug use and health status.

What can be said about potential endogeneity? The temporal dimension of the two questions may render the health status measures "pre-determined" variables that should then be treated as exogenous for estimation purposes. This is a result of the wording of the questions on drug use and health status. Whereas the drug use question asks about recent utilization (last 4 weeks), the health status question asks about your health status "in general". It is plausible that neither individuals' evaluation of their longterm health status nor the number of chronic health problems would be radically affected by recent drug use. On the other hand, it is plausible that latent variables correlated with health status and drug use are operational. This could lead to correlations between the regressors and disturbances. Chronic users of effective medications, for example, could realize an improvement in health status.

To deal with the correlation between the error terms and the regressors, instumental variables techniques are often used. This method requires "instruments": regressors correlated with health status, but uncorrelated with the disturbances in the prescription drug utilization equation. Because valid instruments are not readily available, a sensitivity analysis will be adopted. This method of dealing with the problem is more pragmatic: simply estimate the

reduced form model of the number of different drugs consumed (i.e., drop the potentially endogenous health status variables) and determine if the parameters of primary interest are sensitive to this.

3.3.3.3 Other Demographic Effects

Finally, dummy variables identifying levels of household income and individual educational attainment were included. (Binary variables were used because these variables were measured categorically in the OHS.) The log of household size was also added to deflate household income by household size, with the log used to accommodate nonlinearities in the household member resource function.[26]

Economic theory suggests that under certain types of consumer preferences, price responsiveness will be greater, the lower is one's income. The model was expanded to allow for this possibility with the addition of three variables interacting the ODB eligibility variable *AGE65* with the indicator variables of levels of gross household income. Preliminary analysis indicated that after conditioning on the interaction between *AGE65* and *NUMBPRB* -- the

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[26] These nonlinearities may exist because of the "public" nature of some goods and services consumed by the household, e.g., accommodations and transport. Once these goods are purchased, they provide (to a lesser or greater extent) the same service flow to each member of the household.

number of chronic health problems, the three additional interaction terms were jointly insignificant in both parts of the two-part model.[27] The insignificance of these variables is not entirely surprising given the strong correlation between health status and income.

3.3.4 Selection of Observations

3.3.4.1 Differences in Utilization by Sex

Given the marked gender difference in health care utilization patterns, a likelihood ratio test for homogeneity in the parameters of the male and female negative binomial drug utilization models was conducted. The test resulted in a decisive rejection of the null hypothesis (L.R.= 79.25, 20 d.f., $P<0.0001$), suggesting that the parameters of the models estimated over the male and female subsamples were significantly different. As a result, separate models for males and females were estimated.

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[27] Likelihood ratio statistics of the joint significance of these 3 variables computed from the probit models of prescription drug use were 2.2 (females) and 0.11 (males). The statistics computed from the negative binomial models of number of different drugs taken were 5.66 (females) and 2.00 (males). The five percent critical value is 7.82.

3.3.4.2 Differences in Utilization by Age

Individuals were restricted to be between 55 and 75 years, inclusive. This restriction served serveral purposes. First, the drug utilization behaviour of seniors is of primary interest to this study. Second, this avoided the problem of modelling substantial age-related variation in drug use before age 55, especially among females of reproductive age. After the age of 75, it appears that (average) drug use declines slightly with age. This may an artifact of the sampling process: to be eligible for inclusion, individuals must be healthy enough to avoid institutionalization or death. Lastly, this subsample was deemed to be the most informative in identifying the "price" effect from confounding effects. It appears that inference on the magnitude of the price effect depends critically on both the functional form for age chosen and the ages of the individuals used for parameter estimation.

Graphs of drug utilization by age and sex (Figure 3-7, below) clearly reveal a non-linear age-utilization pattern for both sexes. This pattern is also observed in graphs which isolate the effect of age on drug utilization in a "non-parametric" manner. Figures 3-8 and 3-9 graph the coefficients of age-specific dummy variables estimated from an OLS regression in which health status and demographic variables were also used as covariates. (The use of age-specific dummy variables is a useful exploratory device since it does not impose any

functional form restrictions on age, while at the same time controlling for the effects of variables correlated with age.) These graphs indicate that it might be difficult to choose a simple parametric form for age that is consistent over the entire age range.

One approach is to select an age range in which a simple functional form would work. Spline functions fitted to the estimated age-specific coefficients in Figures 3-8 and 3-9 appear fairly smooth and linear over the subsample 55-75.[28] The upper limit of this age range is also close to the life expectancy of males and females in Ontario.[29] For these reasons, untransformed age was used as a regressor and this particular subsample was chosen.

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[28] The spline function was fit over eight bands in the 15-64 age range and three bands in the 65-85 age range. (The smaller number of bands used was due to the small number of observations in the second age range.) This may have the effect of "over-smoothing" the estimated spline curve in this age range.

[29] Life expectancy at birth for Ontario males, based on 1986 Census data, is 73.49 years. Life expectancy at birth for Ontario females is 79.73 years (Canada 1989).

Figure 3-7 Mean Number of Different Drugs Consumed by Age and Sex

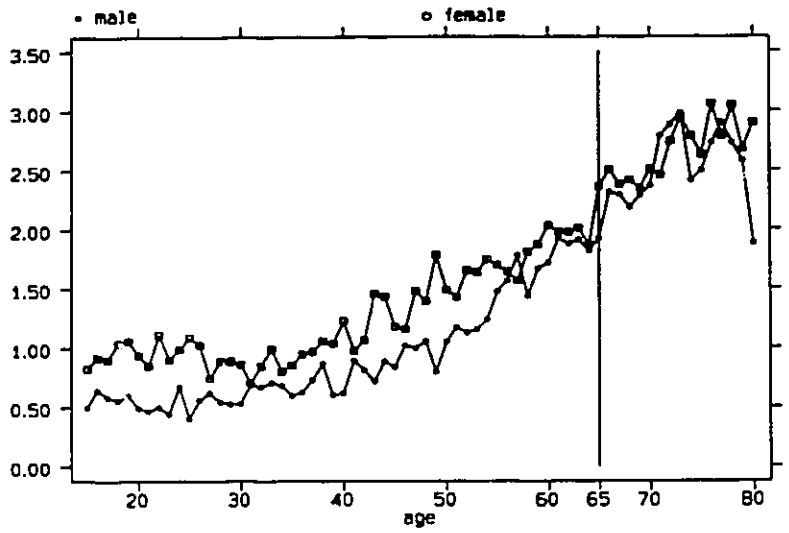

Figure 3-8 Age-Specific Effects on Drug Utilization: Males 15-85

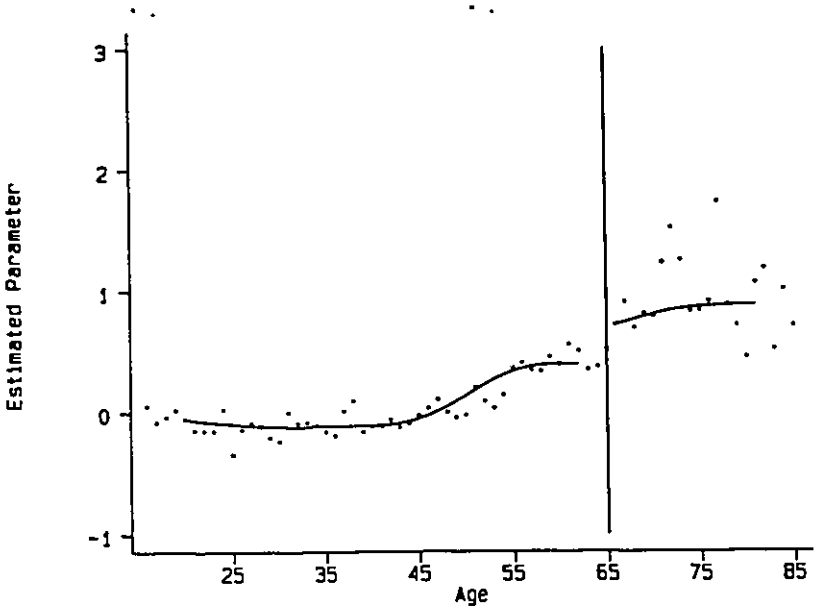

Figure 3-9 Age-Specific Effects on Drug Utilization: Females 15-85

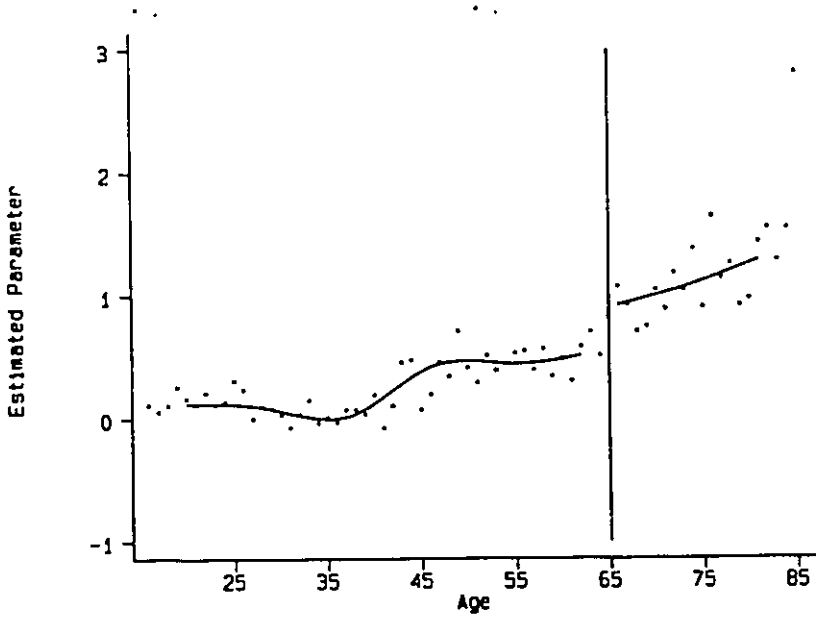

Table 3-6 Descriptive Statistics: Males and Females Age 55-75, Welfare Recipients Removed

Variable	Definition	Males				Females			
		Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
QTYDRUG1	Number of different drugs taken over the last 4 weeks.	2.02	2.71	0	30	2.11	2.33	0	30
QTYDRUG2	Number of different drugs taken over the last 4 weeks by users.	2.73	2.82	1	30	2.62	2.32	1	30
DRUGUSER	Dummy = 1 if prescription drugs were taken over the last 4 weeks.	0.74	0.44	0	1	0.81	0.40	0	1
NONRX14	Dummy = 1 if non-prescription drugs were taken over the last 14 days.	0.36	0.48	0	1	0.43	0.49	0	1
DOCUSER	Dummy = 1 if consulted with a physician over the last 12 months.	0.90	0.27	0	1	0.92	0.30	0	1
AGE65	Dummy = 1 if 65 or older.	0.46	0.50	0	1	0.47	0.50	0	1
DRUGINS	Dummy = 1 if covered by other drug insurance.	0.74	0.44	0	1	0.69	0.46	0	1
PRICEINT	*AGE65*DRUGINS*	0.34	0.47	0	1	0.34	0.47	0	1
WORKING	Dummy = 1 if main activity over past year was working at a job.	0.37	0.48	0	1	0.20	0.40	0	1
EXCLHLTH	Dummy = 1 if self-assessed health, relative to others same age: excellent.	0.12	0.32	0	1	0.11	0.32	0	1
VGHLTH	Dummy = 1 if self-assessed health, relative to others same age: very good.	0.31	0.46	0	1	0.34	0.47	0	1
GOODHLTH	Dummy = 1 if self-assessed health, relative to others same age: good.	0.34	0.47	0	1	0.36	0.48	0	1

Note: QTYDRUG1 = number of different drugs consumed by users and nonusers. QTYDRUG2 = number of different drugs consumed by users.

Table 3-6, *continued* Descriptive Statistics: Males and Females Age 55-75, Welfare Recipients Removed

Variable	Definition	Males				Females			
		Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
FAIRHLTH	Dummy = 1 if self-assessed health, relative to others same age: fair.	0.18	0.38	0	1	0.16	0.36	0	1
POORHLTH	Dummy = 1 if self-assessed health, relative to others same age: poor.	0.05	0.22	0	1	0.03	0.18	0	1
NUMBPRB	Number of health problems.	2.27	1.69	0	8	2.52	1.84	0	8
AGE65 NUMBPRB*	Interaction between ODB coverage and health status.	1.16	1.71	0	8	1.33	1.93	0	8
LHSIZE	Log household size.	0.76	0.35	0	2	0.64	0.40	0	2
INC1	Dummy = 1 if household income: $0-11,999.	0.05	0.23	0	1	0.11	0.31	0	1
INC2	Dummy = 1 if household income: $12,000-29,999.	0.38	0.48	0	1	0.43	0.49	0	1
INC3	Dummy = 1 if household income: $30,000-59,999.	0.38	0.49	0	1	0.34	0.47	0	1
INC4	Dummy = 1 if household income: $60,000 and over.	0.19	0.39	0	1	0.12	0.33	0	1
PRIMARY	Dummy = 1 if highest level of education completed: primary.	0.29	0.45	0	1	0.23	0.42	0	1
SOMEHIGH	Dummy = 1 if highest level of education completed: some highschool.	0.26	0.44	0	1	0.29	0.46	0	1
COMPHIGH	Dummy = 1 if highest level of education completed: highschool.	0.21	0.40	0	1	0.25	0.43	0	1
SOMEPOST	Dummy = 1 if highest level of education completed: some college, completed college, or some university.	0.13	0.34	0	1	0.18	0.39	0	1
UDEGREE	Dummy = 1 if highest level of education completed: university degree.	0.11	0.31	0	1	0.05	0.21	0	1
AGE		64.02	5.68	55	75	64.06	5.72	55	75

Source: 1990 Ontario Health Survey

3.4 Empirical Results

3.4.1 Model Selection Results

The set of observations was randomly partitioned into estimation and forecasting subsamples as follows:

	Males		*Females*	
Number of Observations Used for Estimation:	1,857	70%	2,174	70%
Number of Observations Used for Forecasting:	787	30%	942	30%
Total Number of Observations:	2,644	100%	3,099	100%

The results of the estimator selection exercise appear in Table 3-7 below. For both the male and female models, the two-part model consisting of a probit model for the binary outcome and a negative binomial model for the drug use on the subsample of drug users outperformed the other candidates. Interestingly the prediction errors were uniformly lower in the models estimated using females data. The zero altered model failed to converge when the regime generation process was a function of all of the regressors. To remedy this, zero restrictions were placed on all but the health status variables in the regime function. The model still predicted out of sample number of different drugs substantially worse than the others. The zero altered negative binomial model was also rejected when tested against the negative binomial model using the Vuong test statistic (V=-2.24 for

males and V=-5.64 for females; 5% critical value of two-tailed test= -1.96). This suggests that the conceptual distinction between "non drug users" and "potential users" may not be necessary for estimation purposes, at least for individuals between 55-75. It does appear to be the case, however, that there is substantial unobserved heterogeneity in drug utilization. The Poisson models were found to substantially underpredict the proportion of zeroes in the data (approximately 30% underprediction for females and 20% for males). The findings that the estimate of the parameter α in the negative binomial model was highly significant on the basis of its t-ratio (t=10.82 for males and t=10.77 for females; 5% critical value=1.96), together with the earlier rejection of the splitting function provide some support for this view.

These tests appear to reject the zero altered negative binomial and Poisson specifications in favour of the negative binomial model. It remained to be seen whether the rankings from the mean squared error exercise are consistent with the Vuong test. The negative binomial model was therefore tested against the two part model using the Vuong test. The test provided unambiguous support for the two part specification (V=-8.39 for males and V=-6.24 for females; 5% critical value=-1.96). The two-part model will be used for parameter estimation and policy simulation. Estimates from the other two models will be presented as well for comparison purposes.

Table 3-7 Mean Squared Error Statistics of Alternative Estimators: Males and Females

Model	Mean Squared Error - Males	Mean Squared Error - Females
Poisson Regression	6.983	4.821
Negative Binomial Regression	6.593	4.433
Zero Altered - Probit and Negative Binomial	7.657	5.975
Two-Part Model - Probit and Negative Binomial	6.168	4.375

3.4.2 Diagnostic Tests

A variety of diagnostic tests were performed on the two-part models to ensure that the parameter estimates and inferences drawn on them were reasonably robust to potential mispecifications. Specifically, assumptions regarding the form of the variance in the all the models, and assumptions about functional form in the probit models were tested.

The first set of tests concern the probit models of drug use - non use (both for prescription and non-prescription drugs) and for physician consults. The model generating the binary outcome I_i, which equals one if any drugs are consumed, and zero otherwise, can be thought of as arising from an underlying latent model of

drug utilization (q_i), where $\mathbf{z}_i$ is the vector of conditioning variables and δ is the vector of associated parameters:

$$q_i = z_i'\delta + \varepsilon_i$$
$$I_i = 1 \text{ if } q_i > 0 \text{ and } I_i = 0 \text{ if } q_i \leq 0$$
$$\varepsilon_i \sim N(0,1)$$

An assumption implicit in the estimation of the probit models of physician visits, prescription and non-prescription drug utilization is that the disturbances in the underlying latent model of drug utilization has constant (unit) variance. The assumption that the variance is constant across all observations ("homoskedasticity") may not, however, be realistic. Individuals with lower levels of health status may have higher variability in the latent level of drug utilization (q_i) than those with higher levels of health status.[30] Heteroskedasticity affects the consistency properties of both the covariance matrix *and* the vector of slope coefficients in the probit and negative binomial models. It is therefore important to test for its existence. These results contrast with both nonlinear and linear regression models, in which heteroskedasticity does not affect the consistency of the estimated (slope) coefficients.

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[30] One reason is that those with lower levels of health status might have either untreatable conditions (and report consuming only a few drugs) or be treatable with a large number of different drugs. Main therapeutic drugs generate side effects that induce additional prescriptions to ameliorate the side effects.

To accommodate heteroskedastic errors in the context of the probit model, the variance of the disturbances in the underlying model was generalized as follows (where $\mathbf{w}_i$ is the vector of covariates in the variance or "skedastic" function):

$$\varepsilon_i \sim N(0,[\exp(\mathbf{w}_i'\gamma)]^2)$$

The sample density for observations on users corresponding to this model is:

$$\text{Prob}(I_i = 1|\Omega_i) = E(I_i|\Omega_i) = \Phi\left(\frac{\mathbf{z}_i'\delta}{[\exp(\mathbf{w}_i'\gamma)]^2}\right) \tag{3.8}$$

When $\gamma = 0$, (3.8) reduces to the homoskedastic probit model:

$$\text{Prob}(I_i = 1|\Omega_i) = E(I_i|\Omega_i) = \Phi(\mathbf{z}_i'\delta) \tag{3.9}$$

The null hypothesis of homoskedasticity is easily tested using the likelihood ratio test. The vector of covariates in the skedastic function, $\mathbf{w}_i$, was initially set equal to those in the mean function, $\mathbf{z}_i$. Significant variables in the skedastic function were, however, limited to the four self-assessed health status dummies and the number of health problems. In the interests of parsimony, these five

variables were therefore used exclusively in all subsequent skedastic function specifications.

The negative binomial model can be generalized in a similar manner. The variance of the random variable y_i in the standard model is:

$$Var[y_i] = E[y_i](1+\alpha E[y_i])$$
$$= \lambda_i(1+\alpha\lambda_i)$$

As it stands now, the variance is not constant across observations, but is increasing in λ_i. This variance process may be further generalized by parameterizing $\alpha_i = \exp(\gamma_0 + \mathbf{z}_i'\gamma)$. In essence the standard negative binomial model restricts the pattern of heterogeneity in the occurence rate λ_i to be constant across individuals. This generalization allows the heterogeneity in λ_i to depend on the vector of health status covariates unique to the individual. Again, when $\gamma = 0$, the generalized model reduces to the usual negative binomial model.

The results of the tests on assumptions concerning the variances (i.e., $\gamma = 0$) for both probit and negative binomial models for prescription drug use, and the probit models of non-prescription drug use and physician visits using both the male and female subsamples are reported in Table 3-8 below. The null hypotheses are soundly rejected in each case, which lend some support for the more general specifications.

Table 3-8 Likelihood Ratio Tests for Heteroskedasticity

Model	Female Subsample	Male Subsample
Probit model of prescription drug use	LR=79.8	LR=77.3
Negative Binomial model of prescription drug use by users	LR=105.6	LR=65.2
Probit model of non-prescription drug use	LR=18.2	LR=24.6
Probit model of physician consultations	LR=25.5	LR=27.5

Note: the five percent critical value: $\chi^2(5)=11.07$

Tests for model mispecification outlined in Davidson and MacKinnon (1993) were also conducted on the probit models generalized for heteroskedasticity. The type of mispecification that the test has power against pertains to the form of the "transformation function" of the binary response models. The transformation function transforms the index x_i -- which itself is a function of the regressors and coefficients -- into the argument of the standard normal cumulative distribution function. The transformation function of the assumed model, the probit model generalized for heteroskedasticity, is simply the index itself:

$$E(I_i|\Omega_i) = \Phi(x_i) \qquad where \quad x_i = \frac{\mathbf{z}_i'\delta}{[\exp(\mathbf{w}_i'\gamma)]^2}$$

This maintained model is nested within the family of models:

$$E(I_i|\Omega_i) = \Phi\left(\frac{\tau(\psi x_i)}{\psi}\right) \tag{3.10}$$

which have more complicated transformation functions $\tau(\cdot)$. These functions may be of any general form so long as they are monotonically increasing in their argument, ψx_i, and satisfy the conditions: $\tau(0) = 0$, $\tau'(0) = 1$, and $\tau''(0) \neq 0$. It turns out that the assumed model (3.8) is a special case of the more general family of models when $\psi = 0$.

The natural testing strategy is to determine if the assumed value of ψ is significantly different from zero. If it is, then a more general transformation function should be used. Test statistics were calculated using a computational (also referred to as an "artificial") regression generalized for models of binary dependent variables. The test amounts to a *t*-test of significance of the square of the index x_i, evaluated at the restricted estimates, in the artificial regression. The test can be viewed as a Lagrange Multiplier test because the restricted estimates are being used. As Davidson and MacKinnon note, this test also bears a strong resemblance to the RESET test for mispecification of linear regression models. Just as is the case for the RESET test, however, a rejection of the null hypothesis does not indicate what the appropriate alternative model might be.

Table 3-9 reports the results of these tests. The failure to reject the null in any of the models produces some support for the specifications of the models explaining the decision to use prescription and non-prescription drugs. The models of physician use had slightly higher test statistics. Because these test statistics were modest in size, however, the models were not adjusted.

Table 3-9 Tests for Mispecification of Probit Models of Prescription and Non-Prescription Drug Use and Physician Consults

Model	Female Subsample	Male Subsample
Probit for prescription drug use	$t = 1.17$	$t = 1.59$
Probit for non-prescription drug use	$t = 0.89$	$t = 1.34$
Probit for physician consults	$t = 1.56$	$t = 2.17$

Note: the five percent critical value: $N(0,1)=1.96$

3.4.3 Parameter Estimation Results

Empirical results of the heteroskedasticity-adjusted two-part models, estimated over both the female and male subsamples are reported in Table 3-10. Heteroskedasticity-adjusted probit estimates of the models explaining non-prescription drug utilization and physician consults appear in Table 3-11. Pseudo R^2 measures of model fit based on the sample size, n, the maximized values of the

log likelihood functions evaluated at the unrestricted estimates (*LU*) and estimates restricted to be zero (*LR*) were calculated using the formula outlined in Magee (1990):

$$R^2 = 1 - \exp\left(\frac{-2*(LU - LR)}{n}\right).$$

Pseudo R^2 measures were roughly 0.25, which is similar to other models of prescription drug utilization estimated using cross-sectional data. The male models were fit slightly better than the female models. The pseudo R^2 of the models for non-prescription drug consumption was only 7%, but were slightly higher in the models of physician consultations (8% for females, 12% for males).

Table 3-10 Two-Part Model Estimates of Prescription Drug Utilization

Covariate	Females				Males			
	Probit		Neg. Binomial		Probit		Neg. Binomial	
	Coef.	*t-ratio*	Coef.	*t-ratio*	Coef.	*t-ratio*	Coef.	*t-ratio*
Constant	-0.841	*-0.82*	-0.074	*-0.25*	-2.631	*-2.79*	-0.127	*-0.34*
AGE65	0.133	*0.55*	0.097	*1.24*	-0.215	*-0.91*	-0.086	*-0.85*
DRUGINS	0.133	*1.05*	0.127	*2.83*	0.036	*0.28*	-0.058	*-1.02*
PRICEINT	-0.160	*-0.78*	-0.183	*-3.09*	0.086	*0.45*	0.085	*1.12*
WORKING	-0.143	*-1.25*	-0.045	*-1.03*	-0.073	*-0.71*	-0.059	*-1.30*
VGHLTH	0.607	*4.11*	0.065	*0.99*	0.314	*2.45*	0.180	*2.41*
GOODHLTH	0.984	*5.01*	0.249	*3.85*	0.566	*3.97*	0.374	*5.12*
FAIRHLTH	1.459	*4.11*	0.441	*6.52*	0.935	*3.91*	0.692	*8.79*
POORHLTH	1.905	*0.71*	0.779	*9.23*	1.400	*1.22*	0.899	*9.52*
NUMBPRB	0.929	*8.35*	0.065	*5.76*	0.857	*7.63*	0.079	*5.51*
HLTHINT	0.255	*2.78*	0.037	*2.70*	0.249	*2.67*	0.033	*1.80*
LHSIZE	-0.038	*-0.28*	0.101	*2.57*	0.213	*1.71*	0.013	*0.25*
INC1	0.131	*0.55*	0.100	*1.45*	-0.281	*-1.21*	0.282	*3.32*
INC2	-0.084	*-0.52*	0.075	*1.42*	-0.168	*-1.22*	-0.058	*-1.00*
INC3	-0.145	*-1.02*	0.001	*0.01*	-0.064	*-0.54*	-0.036	*-0.67*
PRIMARY	-0.665	*-2.88*	-0.047	*-0.64*	0.031	*0.19*	0.067	*1.01*
SOMEHIGH	-0.573	*-2.67*	-0.045	*-0.63*	0.090	*0.57*	0.019	*0.29*
COMPHIGH	-0.381	*-1.83*	-0.070	*-0.97*	0.032	*0.20*	0.007	*0.10*
SOMEPOST	-0.528	*-2.43*	-0.115	*-1.54*	0.179	*1.03*	-0.023	*-0.32*
AGE	0.006	*0.36*	0.006	*1.36*	0.024	*1.66*	0.007	*1.24*
Skedastic Function								
Constant	-	-	-0.709	*-2.16*	-	-	-17.959	*-5.13*
VGHLTH	0.118	*0.97*	-0.627	*-1.70*	0.012	*0.09*	15.739	*4.49*
GOODHLTH	0.133	*1 05*	0.063	*0.19*	-0.111	*-0.78*	16.300	*4.66*
FAIRHLTH	0.005	*0.03*	-1.887	*-1.18*	-0.309	*-1.82*	17.293	*4.94*
POORHLTH	-0.245	*-0.23*	1.349	*3.10*	-0.279	*-0.65*	17.376	*4.96*
NUMBPRB	0.206	*8.55*	-0.752	*-5.80*	0.239	*8.68*	-0.226	*-3.55*
Loglikelihood	-1152.30		-4479.01		-1125.10		-3644.69	
R Squared	0.22		0.23		0.25		0.27	
n	3,099		2,495		2,644		1,959	

Table 3-11 Probit Estimates of Non-Prescription Drug Utilization and Physician Visits

Covariates	Non-Prescription Drug Use				Physician Visits			
	Females		Males		Females		Males	
	Coef.	*t-ratio*	Coef.	*t-ratio*	Coef.	*t-ratio*	Coef.	*t-ratio*
Constant	1.318	*1.32*	0.349	*0.44*	0.657	*0.83*	0.794	*0.94*
AGE65	0.132	*0.54*	0.038	*0.22*	-0.094	*-0.56*	0.225	*1.07*
DRUGINS	-0.120	*-0.94*	-0.212	*-1.68*	0.185	*1.94*	0.048	*0.42*
PRICEINT	0.349	*1.72*	0.233	*1.41*	0.004	*0.03*	-0.018	*-0.10*
WORKING	-0.114	*-0.94*	0.056	*0.72*	-0.056	*-0.66*	-0.174	*-1.78*
VGHLTH	-0.114	*-0.70*	0.332	*1.50*	-0.005	*-0.03*	0.198	*0.98*
GOODHLTH	-0.216	*-1.20*	0.306	*1.34*	-0.086	*-0.42*	0.198	*0.94*
FAIRHLTH	-0.622	*-2.26*	-0.824	*-0.84*	-0.087	*-0.31*	0.384	*1.07*
POORHLTH	-0.753	*-1.35*	-0.068	*-0.14*	-0.248	*-0.47*	6.343	*0.04*
NUMBPRB	0.464	*4.76*	0.264	*2.28*	0.542	*4.61*	0.643	*5.34*
HLTHINT	-0.191	*-2.68*	-0.184	*-1.95*	0.090	*1.47*	0.023	*0.26*
LHSIZE	-0.330	*-2.38*	-0.338	*-2.03*	-0.054	*-0.54*	-0.038	*-0.36*
INC1	-0.506	*-2.05*	-0.749	*-1.94*	-0.023	*-0.13*	-0.688	*-3.05*
INC2	-0.267	*-1.67*	-0.028	*-0.28*	-0.057	*-0.48*	-0.356	*-2.43*
INC3	0.002	*0.02*	0.022	*0.26*	-0.039	*-0.36*	-0.241	*-2.03*
PRIMARY	-0.118	*-0.55*	-0.050	*-0.44*	-0.374	*-1.94*	-0.115	*-0.72*
SOMEHIGH	0.304	*1.42*	0.050	*0.45*	-0.375	*-2.00*	-0.144	*-0.92*
COMPHIGH	0.082	*0.40*	0.018	*0.16*	-0.324	*-1.75*	0.056	*0.35*
SOMEPOST	0.107	*0.51*	0.040	*0.34*	-0.135	*-0.73*	0.038	*0.21*
AGE	-0.032	*-1.96*	-0.015	*-1.25*	0.001	*0.12*	-0.005	*-0.36*
Skedastic Function								
VGHLTH	0.403	*1.67*	-0.387	*-0.81*	-0.312	*-1.56*	-0.126	*-0.67*
GOODHLTH	0.435	*1.79*	-0.490	*-1.04*	-0.453	*-2.28*	-0.294	*-1.57*
FAIRHLTH	0.277	*1.01*	0.425	*0.66*	-0.428	*-1.86*	-0.264	*-1.11*
POORHLTH	0.693	*1.46*	-0.264	*-0.39*	-0.668	*-1.36*	0.575	*0.04*
NUMBPRB	0.127	*3.16*	0.237	*3.56*	0.165	*5.32*	0.151	*4.57*
Loglikelihood	-1,977.9		-1,609.8		-737.85		-698.13	
R Squared	0.07		0.07		0.08		0.12	
n	3,066		2,614		3,039		2,592	

3.4.3.1 Effect of Public Drug Insurance on Drug and Physician Use

Estimates of the effect of publicly funded prescription drug insurance on the 4 dependent variables (probability of any prescription drug use, probability of any non-prescription drug use, number of prescription drugs taken by users and the probability of any physician consultations) depend on both health status (*NPROB:* the number of chronic health problems) and on whether or not the individual has additional drug insurance coverage (*DRUGINS*). Technically, if the model is:

$Y = a_0 + a_1 AGE65 + a_2 AGE65*NPROB + a_3 AGE65*DRUGINS$ + other regressors,

then the increase in utilization at age 65 is approximated by:

$\partial Y/\partial AGE65 = a_1 + a_2 NPROB + a_3 DRUGINS.$

Testing the hypothesis that those there is no overall effect ($\partial Y/\partial AGE65 = a_1 + a_2 NPROB + a_3 DRUGINS$=0) therefore depends on the estimated coefficients (a_1, a_2 and a_3) and on specific values for the two covariates.

Likelihood ratio (LR) tests of the hypothesis that there is no overall effect after the onset of eligibility for ODB coverage were conducted on both parts of the

two-part models (Table 3-12). Six different restrictions were imposed, each with a different combination of number of chronic health problems (*NPROB*=0,2,4) and indicator of additional drug insurance coverage (*DRUGINS*=0,1). The tests revealed that the statistical significance of the effect of ODB coverage on the probability of using any medicines increased, the greater the number of chronic health conditions. Males and females reporting a total of four chronic health conditions, for example, were found to have positive, significant increases in the probability of utilization, irrespective of their additional insurance coverage ($P<0.01$ in all tests). Individuals with no chronic health conditions, on the other hand, had negligible increases in probability of use after becoming eligible for ODB. The results for the level of use equations were mixed. Female drug users with no prior insurance coverage (*DRUGINS*=0) but suffering from 2 or more health problems had significant increases in utilization ($P<0.01$). Female drug users with prior insurance coverage (*DRUGINS*=1), on the other hand, did not significantly increase the number of drugs taken, irrespective of the number of health problems ($P>0.24$ in all tests). The effects of ODB eligibility on the level of use by male drug users was found to approach conventional levels of significance only for individuals with four or more health conditions and with additional insurance coverage ($P=0.06$).

Table 3-12 Likelihood ratio tests for zero increased probability or level of prescription drugs use after eligibility for ODB, by level of health status, prior drug insurance coverage and sex.

Restriction	Probability of prescription drug use		Number of drugs taken by Users	
	Females	Males	Females	Males
DRUGINS=0, NPROBS=0	0.2 (*P*=0.65)	1.0 (*P*=0.32)	1.5 (*P*=0.21)	0.7 (*P*=0.40)
DRUGINS=0, NPROBS=2	8.0 (*P*<0.01)	1.8 (*P*=0.18)	6.7 (*P*=0.01)	0.1 (*P*=0.81)
DRUGINS=0, NPROBS=4	12.8 (*P*<0.01)	6.4 (*P*<0.01)	14.7 (*P*<0.01)	0.3 (*P*=0.61)
DRUGINS=1, NPROBS=0	0.01 (*P*=0.98)	0.4 (*P*=0.53)	1.4 (*P*=0.24)	0.0 (*P*=0.99)
DRUGINS=1, NPROBS=2	5.8 (*P*=0.02)	4.4 (*P*=0.04)	0.0 (*P*=0.84)	0.8 (*P*=0.36)
DRUGINS=1, NPROBS=4	10.8 (*P*<0.01)	9.6 (*P*<0.01)	1.2 (*P*=0.28)	3.6 (*P*=0.06)

These six likelihood ratio tests were also conducted on the probit models of physician visits and non prescription drug use. Results appear in Table 3-13 below.

Table 3-13 Likelihood ratio tests for zero increased probability of non-prescription drug use and physician visits after eligibility for ODB, by level of health status, prior drug insurance coverage and sex

Restriction	Prob. of non-prescription drug use		Prob. of any physician visits	
	Females	Males	Females	Males
DRUGINS=0, NPROBS=0	0.2 (*P*=0.65)	0.01 (*P*=0.99)	0.36 (*P*=0.55)	1.26 (*P*=0.26)
DRUGINS=0, NPROBS=2	1.4 (*P*=0.24)	3.8 (*P*=0.05)	0.26 (*P*=0.61)	1.78 (*P*=0.18)
DRUGINS=0, NPROBS=4	6.4 (*P*=0.01)	10.4 (*P*<0.01)	1.34 (*P*=0.25)	1.10 (*P*=0.29)
DRUGINS=1, NPROBS=0	5.0 (*P*=0.03)	3.2 (*P*=0.07)	0.36 (*P*=0.55)	1.42 (*P*=0.23)
DRUGINS=1, NPROBS=2	0.2 (*P*=0.65)	0.4 (*P*=0.53)	0.34 (*P*=0.56)	2.18 (*P*=0.14)
DRUGINS=1, NPROBS=4	1.6 (*P*=0.21)	6.4 (*P*<0.01)	1.5 (*P*=0.22)	1.18 (*P*=0.28)

The parameter estimates associated with the model of the probability to take any non-prescription drugs, indicate that neither the *AGE65* variable nor the interaction of *AGE65* and *DRUGINS* are statistically insignificant on the basis of their respective *t*-ratios. The *t*-ratio for the variable *HLTHINT*, which is the interaction of *AGE65* and *NUMBRB*, was negative and statistically significant, indicating that declines in the probability of non-prescription drug use after ODB eligibility are greater, the lower is individuals' health status. The LR statistics reported in Table 3-13, however, indicate that this effect was pronounced only

among low health status (4 health problems) males and low health status females without additional drug insurance coverage.

The estimated effect of publicly funded prescription drug insurance on the probability of any physician visits was negligible. The test statistics indicate that there is no significant increase in the probability of physician visits for any combination of health status level or private drug coverage status at age 65. Eligibility for public insurance at age 65 was not found to increase the total number of visits either, on the basis of individual *t*-ratios associated with OLS estimates of the *AGE65* coefficient (Appendix B).

3.4.3.2 Effect of Public Drug Insurance by Estimator

Parameters estimated using the Poisson, negative binomial and zero altered negative binomial models are reported in Table 3-14 (females) and Table 3-15 (males). The results obtained using the two part specification do not appear to be robust to the choice of estimator. For females, *AGE65* was statistically significant on the basis of its *t*-ratios in all models. The *AGE65*NPROB* interaction was statistically insignificant and had the anticipated positive sign in only the zero altered model. Likelihood ratio tests of the hypothesis that the onset of ODB eligibility has no effect on utilization could only be rejected for an individual with 4 health problems and no additional drug insurance when estimated using the zero

altered negative binomial (P=0.031). For males, tests of this hypothesis were not rejected in any of the models (P>0.137).

Table 3-14 Poisson, Negative Binomial, and Zero Altered Negative Binomial Estimates of Prescription Drug Utilization: Females

Covariates	Poisson		Negative Binomial		Zero Altered Negative Binomial	
	Coef.	*t-ratio*	Coef.	*t-ratio*	Coef.	*t-ratio*
Constant	-0.845	*-3.06*	-0.917	*-2.58*	-0.566	*-1.45*
AGE65	0.282	*4.00*	0.296	*3.80*	0.239	*2.82*
DRUGINS	0.154	*3.70*	0.151	*3.24*	0.174	*3.37*
PRICEINT	-0.212	*-3.84*	-0.207	*-3.53*	-0.214	*-3.39*
WORKING	-0.090	*-2.20*	-0.076	*-1.47*	-0.045	*-0.75*
VGHLTH	0.306	*5.16*	0.302	*4.74*	0.240	*3.13*
GOODHLTH	0.574	*9.83*	0.571	*9.03*	0.455	*6.02*
FAIRHLTH	0.810	*12.98*	0.811	*11.43*	0.671	*8.23*
POORHLTH	1.151	*15.63*	1.159	*14.62*	1.022	*11.48*
NUMBPRB	0.132	*13.47*	0.147	*10.76*	0.119	*7.75*
HLTHINT	-0.003	*-0.22*	-0.012	*-0.72*	0.029	*1.56*
LHSIZE	0.086	*2.33*	0.086	*2.07*	0.090	*1.98*
INC1	0.120	*1.87*	0.126	*1.51*	0.138	*1.52*
INC2	0.055	*1.12*	0.069	*1.10*	0.085	*1.23*
INC3	-0.041	*-0.86*	-0.036	*-0.58*	-0.026	*-0.37*
PRIMARY	-0.157	*-2.32*	-0.187	*-2.54*	-0.101	*-1.23*
SOMEHIGH	-0.154	*-2.34*	-0.193	*-2.63*	-0.114	*-1.39*
COMPHIGH	-0.143	*-2.16*	-0.172	*-2.29*	-0.122	*-1.45*
SOMEPOST	-0.219	*-3.20*	-0.258	*-3.25*	-0.230	*-2.59*
AGE	0.009	*2.17*	0.010	*1.85*	0.007	*1.14*
log alpha			0.187	*17.89*	0.165	*13.54*
Splitting Function						
NPROBS					-0.688	*-12.59*

Table 3-15 Poisson, Negative Binomial, and Zero Altered Negative Binomial Estimates of Prescription Drug Utilization: Males

Covariates	Poisson		Negative Binomial		Zero Altered Negative Binomial	
	Coef.	*t-ratio*	Coef.	*t-ratio*	Coef.	*t-ratio*
Constant	-1.493	*-4.85*	-1.567	*-3.70*	-1.421	*-3.19*
AGE65	0.082	*1.00*	0.036	*0.41*	-0.176	*-1.86*
DRUGINS	-0.015	*-0.33*	-0.041	*-0.93*	-0.107	*-2.37*
PRICEINT	0.056	*0.90*	0.107	*1.48*	0.204	*2.78*
WORKING	-0.092	*-2.37*	-0.077	*-1.74*	-0.067	*-1.44*
VGHLTH	0.422	*5.71*	0.415	*4.74*	0.364	*3.57*
GOODHLTH	0.761	*10.57*	0.736	*8.64*	0.644	*6.53*
FAIRHLTH	1.174	*15.77*	1.169	*13.23*	1.071	*10.54*
POORHLTH	1.328	*15.84*	1.328	*12.36*	1.271	*10.67*
NUMBPRB	0.163	*14.50*	0.183	*12.44*	0.106	*6.87*
HLTHINT	-0.008	*-0.57*	-0.003	*-0.15*	0.010	*0.48*
LHSIZE	0.112	*2.61*	0.088	*1.59*	0.092	*1.60*
INC1	0.269	*3.93*	0.214	*3.01*	0.296	*3.98*
INC2	-0.096	*-1.92*	-0.108	*-2.06*	-0.088	*-1.60*
INC3	-0.022	*-0.49*	-0.032	*-0.57*	-0.017	*-0.28*
PRIMARY	0.058	*1.01*	0.087	*1.06*	0.092	*1.07*
SOMEHIGH	0.013	*0.22*	0.030	*0.37*	0.028	*0.32*
COMPHIGH	0.000	*-0.01*	0.005	*0.06*	0.007	*0.08*
SOMEPOST	0.008	*0.13*	0.015	*0.16*	0.002	*0.02*
AGE	0.014	*2.96*	0.015	*2.37*	0.020	*3.00*
log alpha			0.309	*18.25*	0.268	*14.64*
Splitting Function						
VGHLTH					-0.253	*-1.00*
GOODHLTH					-0.618	*-2.11*
FAIRHLTH					-0.597	*-1.25*
POORHLTH					-0.595	*-0.47*
NPROBS					-1.262	*-5.48*

3.4.3.3 Effect of Health Status in the Estimating Equations

The effects of health status on mean utilization appeared to be quite robust to alternative estimators. The variable measuring the number of different health problems was highly significant in all specifications for physician consults as well as prescription and non-prescription drug use. The indicator variables measuring levels of self assessed health status were also generally significant in the models of prescription drug use. The relative sizes of the coefficients on these variables indicated that, as expected, utilization increases as self assessed health status worsens. The effect of health status on the skedastic function was found to be mixed. In all of the heteroskedasticity robust probit models, the variance (of the underlying latent variable) was found to be increasing in the number of health problems, whereas this variable tended to decrease the variance of use amongst the subsample of users.

Estimates of the parameters of the zero altered model indicated that health status had different effects in the two equations of the model. Potential and actual drug users with larger number of chronic health problems were found to have take a larger number of drugs on average. However, increases in the number of health problems was found to lower the probability of an individual being designated as "healthy" or, equivalently, not in need of prescription drugs.

3.4.3.4 Endogeneity of Health Status and Labour Force Participation Variables

One of the potential difficulties with the use of the health status and labour force participation variables is that they may be correlated with the disturbances in the drug use equations. There are a number of reasons for this. It is possible that, after conditioning on all the exogenous variables, individuals may rate their health status as low only because they take a large number of drugs. Alternatively, individuals taking a large number of drugs may experience improvements in their health status. Individuals with poor health status may also retire earlier. The same individuals might be observed to consume a larger number of different drugs. In the absence of viable instruments for these variables, an alternative is to determine if the problem matters in practice by examining the reduced form estimates. The structural model and two different "reduced form" models estimated using OLS with heteroskedastic consistent standard errors are reported in Table 3-16. The first set of parameter estimates are from the structural model, the second column refers to the reduced form model in which all health status variables, or variables interacted with health status, are treated as endogenous, and the final column of parameter estimates treats just the "working" variable as endogenous.

The magnitudes of the effect of ODB coverage on number of drugs taken appeared to be sensitive to assumptions regarding the endogeneity of the health status variable. The estimate of the increase in the number of drugs taken using the structural model, evaluated at the sample averages for *DRUGINS* and

NUMBPRB, was 0.29 (females) and 0.21 (males). The estimate obtained when all health status variables were excluded was 0.66 (females) and 0.09 (males). The fit of the models (estimated by OLS) also dropped dramatically with the exclusion of the health status regressors. The R^2 statistic fell from 23% to 5% for females and from 24% to 5% for males. The estimates were less sensitive to assumptions concerning the endogeneity of the labour force participation variable. When this variable was excluded, the overall effect of ODB coverage, again evaluated at the sample averages for *DRUGINS* and *NUMBPRB*, was practically unchanged: 0.30 (females) and 0.23 (males).

Table 3-16 Structural and Reduced Form OLS Estimates of Prescription Drug Utilization: Females and Males

	Males						Females					
	Structural		Endog. Health		Endog. Working		Structural		Endog. Health		Endog. Working	
	Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio
Constant	-1.432	*-1.44*	-0.172	*-0.15*	-1.715	*-1.77*	-0.480	*-0.62*	0.532	*0.63*	-0.684	*-0.88*
AGE65	-0.176	*-0.58*	0.094	*0.32*	-0.155	*-0.51*	0.270	*1.20*	0.661	*3.16*	0.274	*1.22*
DRUGINS	0.003	*0.02*	0.178	*0.91*	0.003	*0.02*	0.271	*2.66*	0.406	*3.67*	0.261	*2.53*
PRICEINT	0.091	*0.37*	-0.024	*-0.09*	0.101	*0.42*	-0.436	*-2.41*	-0.471	*-2.39*	-0.424	*-2.33*
WORKING	-0.119	*-0.98*	-0.732	*-5.56*	-	-	-0.110	*-1.41*	-0.486	*-5.45*	-	-
VGHLTH	0.267	*3.46*	-	-	0.271	*3.49*	0.287	*2.81*	-	-	0.291	*2.83*
GOODHLTH	0.706	*7.67*	-	-	0.715	*7.87*	0.724	*6.49*	-	-	0.735	*6.47*
FAIRHLTH	1.856	*9.55*	-	-	1.874	*9.82*	1.421	*10.72*	-	-	1.437	*10.73*
POORHLTH	2.918	*9.06*	-	-	2.954	*9.06*	3.091	*7.51*	-	-	3.109	*7.54*
NUMBPRB	0.337	*7.65*	-	-	0.342	*7.87*	0.270	*9.97*	-	-	0.272	*9.95*
HLTHINT	0.142	*2.49*	-	-	0.137	*2.43*	0.128	*3.03*	-	-	0.125	*2.95*
LHSIZE	0.224	*1.56*	0.401	*2.34*	0.220	*1.53*	0.192	*1.42*	0.256	*1.81*	0.206	*1.51*
INC1	0.838	*1.80*	1.347	*2.65*	0.870	*1.88*	0.307	*1.52*	0.933	*4.17*	0.328	*1.64*
INC2	-0.172	*-1.17*	0.147	*0.90*	-0.139	*-0.98*	0.122	*0.86*	0.421	*2.87*	0.138	*0.99*
INC3	-0.046	*-0.42*	0.079	*0.63*	-0.027	*-0.24*	-0.054	*-0.57*	0.007	*0.07*	-0.044	*-0.47*
PRIMARY	0.132	*0.92*	0.658	*3.93*	0.126	*0.88*	-0.310	*-1.25*	0.043	*0.16*	-0.311	*-1.26*
SOMEHIGH	0.057	*0.47*	0.367	*2.61*	0.055	*0.46*	-0.284	*-1.22*	-0.016	*-0.06*	-0.288	*-1.24*
COMPHIGH	-0.005	*-0.04*	0.127	*0.98*	-0.006	*-0.05*	-0.268	*-1.15*	-0.110	*-0.45*	-0.273	*-1.18*
SOMEPOST	0.004	*0.03*	0.275	*1.93*	0.007	*0.06*	-0.418	*-1.81*	-0.235	*-0.95*	-0.426	*-1.86*
AGE	0.025	*1.54*	0.023	*1.26*	0.029	*1.75*	0.016	*1.30*	0.013	*0.97*	0.018	*1.51*
No. Obs.	2644		2644		2644		3099		3099		3099	
Adjusted R2	0.24		0.05		0.24		0.23		0.05		0.23	

3.4.4 Simulation Results

In order to evaluate the magnitude of the moral hazard effect of ODB coverage, a variety of simulation analyses were conducted. These simulations involved predicting mean number of different drugs consumed for individuals over the ages 50-80 (inclusive) both with and without eligibility for public insurance. Differences between these graphs were used to assess the price effect under various values of the remaining covariates. This method was used because the usual derivative methods are at best only approximately valid when the control variables are dichotomous (Caudill and Jackson 1989).

Five different age-utilization profiles were predicted using the estimates presented in Table 3-10, each with a different configuration of self assessed health status and number of health problems. Individuals in the highest level of health status had "excellent" self-assessed health status, and one health problem. Individuals in the second highest level had "very good" self-assessed health status, and two health problems. Remaining categories were similarly defined; the lowest health status configuration was "poor" self assessed health status and a total of five health problems. (The sample average number of health problems was approximately 2.5.) Individuals in the simulation held no additional drug coverage; the values of other covariates were held fixed at their sample means.

The simulation data is graphed in Figure 3-10 (females) and Figure 3-11 (males). The most striking feature of these graphs is the large increase in expected utilization accompanying worsened health status (again, as measured by self-assessed health status and number of health problems). Another feature is the different response in utilization following eligibility for public insurance by those with varying levels of health status. Whereas those with "excellent" health status were observed to exhibit only modest increases in utilization, those with "poor" health status had substantially larger responses.[31]

The magnitude of the price effects in each of the five health status levels is evaluated in Table 3-17 below. Within each health status level, the effects on the mean probability of drug use, level of drug use by users and total utilization, (defined as the product of the first two terms) are presented. Because the price effect is permitted to have different effects in the two components of the two-part model, it is interesting to determine whether one component has a predominant influence on utilization. The columns "% of total increase" indicate the proportion of the total increase in utilization observed which are due to changes in the probability of use and level of use among users.

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[31] It should be noted that at least part of the reason for the differential utilization response by individuals with different levels of health status is due to the functional form used to model the conditional number of different drugs consumed. Recall from equation (3.3) that the mean of the drug use by users is $\exp(x'\beta+\varepsilon)$. The derivative of this function with respect to the *ith* regressor x_i is $\beta_i \exp(x'\beta+\varepsilon)$ which is increasing (multiplicatively) in the level of x_i. Hence, even if there was no difference in the utilization response at age 65 by individuals with varying levels of health status, this functional form would demonstrate a larger response by those with lower levels of health status.

The prediction models revealed a number of points. First, at all levels of health status, the increase in overall utilization after ODB eligibility is predicted to be higher among females than males. For example, there was a 32.7% increase among females in good health compared to 7.8% in males. Indeed, the 95% confidence intervals around these increases suggested that the increases in drug use by males are statistically insignificant. Second, the utilization response at age 65 among females appears to be predominantly in the number of drugs being used by existing users rather than the probability of use. For example, the onset of public insurance increased expected utilization among females with very good health by 0.38 different drugs. Thirty five percent of this increase was due to increases in the probability of use following the price change, whereas 59% of the total increase was due to increases in the level of use by users. (The remaining 6% increase is due to changes in both the levels of use and probability of use.) Interestingly, as health status worsens, the price effect causes most of the marginal adjustments to take place in the level of use, rather than in the probability of use. Finally, there appears to be a gradient in utilization response at 65 by health status which appears to be mainly in the level of use rather than the probability of use, and more marked for females than males.

Table 3-18 predicts the changes in the probability of non-prescription drug use and any annual physician visits after eligibility for ODB coverage by health status level and sex. Again the simulations refer to an individual aged 65 without

additional drug insurance coverage. These data indicate that probability of any use (of both non-prescription medicines and physician consults) is lower among individuals with excellent or very good health. In contrast to the models of prescription drug use, however, there is no clear gradient in changes in the probability of physician visits or non-prescription drug use by health status level. Indeed, the biggest proportional declines in the probability of non-prescription drug use are found among males with very good or good health.

Figure 3-10 Predicted Increase in Prescription Drug Use by Females with Various Levels of Health Status after Eligibility for Public Drug Coverage

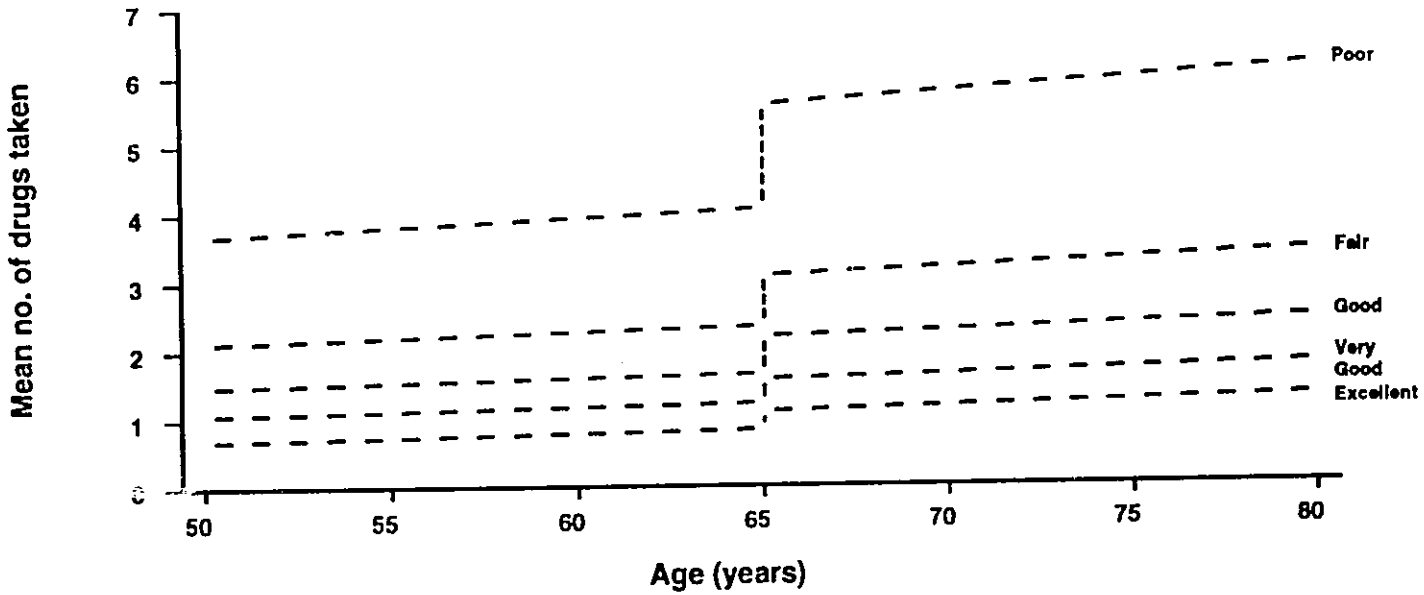

Figure 3-11 Predicted Increase in Prescription Drug Use by Males with Various Levels of Health Status after Eligibility for Public Drug Coverage

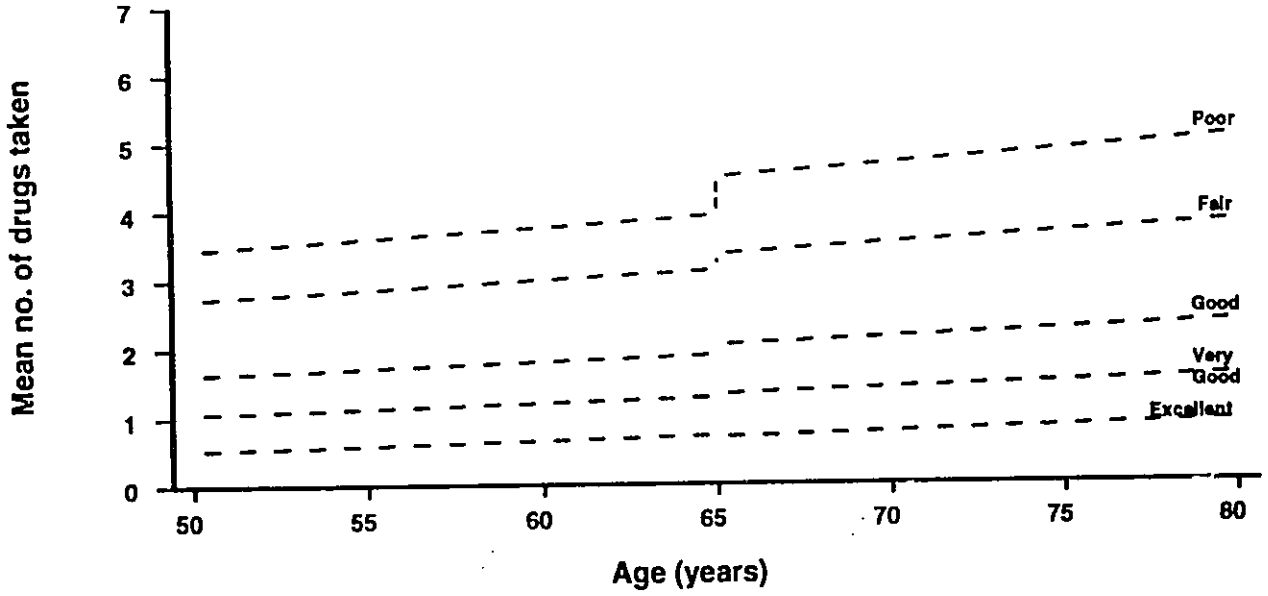

Table 3-17 Predicted changes in number of drugs taken after eligibility for ODB coverage by health status level and sex

Health Status Level	Model	Predictions - Females					Predictions - Males				
		No ODB coverage	ODB coverage	Change	95% conf. interval	% of Total Increase	No ODB coverage	ODB coverage	Change	95% conf. interval	% of Total Increase
Excellent	Prob. of Use	0.53	0.63	*0.10*		53	0.47	0.48	*0.01*		-51
	# Drugs by Users	1.60	1.82	*0.23*		40	1.50	1.42	*-0.08*		149
	Total Use*	0.84	1.14	*0.30*	0.08 - 0.53		0.71	0.69	*-0.02*	-0.22 - 0.17	
Very Good	Prob. of Use	0.68	0.76	*0.07*		35	0.66	0.69	*0.04*		159
	# Drugs by Users	1.75	2.08	*0.33*		59	1.94	1.90	*-0.04*		-56
	Total Use*	1.20	1.57	*0.38*	0.17 - 0.59		1.27	1.32	*0.05*	-0.20 - 0.30	
Good	Prob. of Use	0.73	0.79	*0.06*		26	0.74	0.79	*0.05*		84
	# Drugs by Users	2.25	2.76	*0.52*		68	2.55	2.58	*0.03*		15
	Total Use*	1.63	2.18	*0.55*	0.29 - 0.81		1.89	2.04	*0.15*	-0.20 - 0.50	
Fair	Prob. of Use	0.78	0.84	*0.06*		23	0.83	0.88	*0.05*		83
	# Drugs by Users	2.90	3.57	*0.67*		71	3.79	3.84	*0.04*		16
	Total Use*	2.27	3.00	*0.73*	0.37 - 1.10		3.13	3.36	*0.23*	-0.35 - 0.81	
Poor	Prob. of Use	0.87	0.92	*0.05*		15	0.78	0.82	*0.05*		41
	# Drugs by Users	4.34	5.75	*1.41*		81	5.05	5.45	*0.40*		55
	Total Use*	3.79	5.31	*1.52*	0.58 - 2.47		3.92	4.49	*0.57*	-0.27 - 1.40	

*Notes: *Total Use is the product of Probability of Use and Number of Drugs taken by Users. For purposes of this simulation, individuals were 65 years of age and held no additional drug insurance coverage. Values for the five health status levels are described in the text. The values of the remaining covariates were set equal to the respective sample means.*

Table 3-18 Predicted changes in probability of non-prescription drug use and physician visits after eligibility for ODB coverage by health status level and sex

Model	Health Status Level	Predictions - Females				Predictions - Males			
		No ODB coverage	ODB coverage	Change	% Change	No ODB coverage	ODB coverage	Change	% Change
Non-prescription Drug Use	*Excellent*	0.27	0.26	-0.01	-5.52%	0.30	0.27	-0.03	-10.20%
	Very Good	0.47	0.45	-0.03	-5.63%	0.49	0.38	-0.11	-22.36%
	Good	0.51	0.47	-0.03	-6.76%	0.55	0.42	-0.13	-23.84%
	Fair	0.51	0.46	-0.05	-10.19%	0.48	0.47	-0.02	-3.69%
	Poor	0.51	0.49	-0.02	-4.48%	0.52	0.47	-0.06	-10.67%
Physician Visits	*Excellent*	0.76	0.76	0.00	-0.12%	0.70	0.76	0.06	8.57%
	Very Good	0.91	0.93	0.01	1.35%	0.86	0.90	0.04	4.43%
	Good	0.96	0.97	0.01	1.32%	0.94	0.96	0.02	2.17%
	Fair	0.94	0.95	0.02	1.98%	0.94	0.95	0.02	1.89%
	Poor	0.98	0.99	0.01	1.01%	0.75	0.76	0.01	1.00%

Note: for purposes of this simulation, individuals were 65 years of age and held no additional drug insurance coverage. Values for the five health status levels are described in the text. The values of the remaining covariates were set equal to the respective sample means.

3.5 Discussion

The Ontario Ministry of Health reimburses the drug expenditures -- both ingredient cost and dispensing fee -- of individuals aged 65 and older. The "natural experiment" of providing zero co-payment medicines was exploited to investigate aspects of the drug utilization by individuals aged 55-75. Three sets of issues were of interest. First, what is the magnitude of the increase in utilization once drugs are provided free of charge? This question is of immediate concern to policy makers concerned with reducing public sector expenditure commitments. The larger is the price sensitivity, the greater the reduction in total spending and therefore public spending commitments following the introduction of a co-payment. It turns out that the effect of public drug insurance depends both on gender and whether or not the individual has pre-existing (such as privately-provided) drug insurance. Utilization increases at age 65 among those with existing coverage were smaller than those who were previously uninsured. Models of the number of different prescription drugs consumed suggest that the utilization of females (who have no additional drug coverage) increase in the range of 36 - 40 percent (depending on the health status of the individual) following the price change. Parameter estimates produced from data on males indicate a much smaller (and statistically insignificant) utilization response. Percentage increases in the

range 0 - 14 percent (again, depending on health status) were found.[32] These results suggest that a user pay policy will reduce the utilization of females (with a given level of health status) by a larger extent than that of males. The estimates are consistent with estimates provided in the literature that suggest that drug utilization is price inelastic, although no other published studies have provided price elasticity estimates for older adults or disaggregated these by sex.

The second issue of interest was the incidence of the subsidy. The data indicate that increased utilization will be concentrated primarily among individuals with lower levels of health status. Proceeding on the assumption that these behavioural responses are symmetric to the case of an increase in co-payment, we would predict that such a policy would result in commensurate utilization decreases primarily among persons with poorer health.

The prediction that co-payment will reduce utilization amongst those persons with lower health status raises a number of questions. On the face of it, if all use of medicines is appropriate therapy, then a policy which reduces use in less healthy persons may be regressive on those most in need of care. But our data cannot speak to the question of whether the drug use being induced or deterred by user charges is essential or appropriate because the appropriateness of a drug therapy is specific to each clinical situation and we had no information on which

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[32]This latter result was somewhat surprising because the unconditional mean use by males increased by a much larger margin (Figure 3-7). It is conceivable that these unaccounted increases were due to declines in health status.

drugs were being consumed, or the clinical indications for their use. Adverse behavioural responses among patients facing co-payments for prescription drugs were identified by Harris *et al.* (1990), Soumerai *et al.* (1987, 1994) and Reeder and Nelson (1985). All three studies reported that potentially needed medications were relinquished by enrollees in U.S. Medicaid programs and health maintenance organizations after the imposition of drug co-payments. Existing evidence suggests that patient health status may therefore be adversely affected by such a policy.

The third objective of the study was to identify specific behavioural responses to changes in drug co-payments. Patients facing lower drug costs might be more inclined to initiate treatment episodes, or increase compliance with physician prescription recommendations. Physicians, on the other hand, might increase the number of different drugs prescribed and/or substitute prescription drugs for other health care inputs (such as non-prescription drugs or the physician's time) because the relative prices of these other inputs have now risen. Knowledge of the source of the change in utilization is of some interest to policy makers for several reasons. Analyzing whether changes in the quantity and composition of drugs consumed following a user charge are largely patient- or physician-initiated can shed some light on the probable effects on patient health status. The patient typically has less knowledge of what constitutes "rational" drug therapy than the physician. Therefore if a co-payment induced drop in

utilization results primarily from consumer rather than physician decisions, (due to non-compliance with physician prescriptions or a lower propensity to initiate treatment) it increases the probability that the appropriateness of therapy is not improved (Hurley and Johnson 1991). If decreases in co-payments have a predominant effect on patient decision making, then it may be preferable to introduce alternative policies which target physicians, who are relatively better informed.

Due to data constraints, it was not possible to monitor patient compliance levels before and after the introduction of public prescription drug insurance. It was possible, however, to observe the probability of any physician visits over the course of a year, which is highly correlated with the probability of patient-initiation of treatment episodes. There were no increases in the probability of physician visits (or the total number of visits) after prescription drugs were provided free of charge observed for either males or females.[33] This result was anticipated after viewing a graph of the probability of physician use against age. The probit regression estimates confirmed this suspicion. This result is not surprising given that individuals probably are not primarily motivated to initiate episodes of treatment on the basis of out-of-pocket prescription drug costs. This finding is also consistent with the results of Lingle *et al.* (1987) who found that lowering

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[33] The results suggest that the probability of a physician consult is higher among those who carry private drug insurance.

prescription drug co-payments did not affect the number of physician visits by seniors in the New Jersey Medicare program.

The probability of non-prescription drug use fell after prescription drugs were provided free of charge; probabilities of use dropped 10% for males and 5% for females. But these effects were not significant at conventional levels.[34] On the basis of these results, the increased prescription drug utilization among older individuals appears to have operated through increased multiple drug prescribing, and/or substitutions of prescription drugs for other health inputs (such as physician own-time or surgery) on the part of physicians, possibly coupled with increased patient compliance with these post-65 prescription regimens.

It appears that the level of physician control over the utilization process is generally higher, the lower the level the patient health status. The preferred estimation technique produced estimates of the "price effect" on two separate components of utilization: the probability of utilization and the level of utilization (the number of different drugs taken) among users. The price change was found to increase both variables; however, among individuals with "poor" levels of health status, (with income and other demographic characteristics set at sample averages) the magnitudes differed considerably. Approximately 81% of the total utilization response among females (55% for males) was found to operate through

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34 The finding of limited substitution between non-prescription and prescription drugs is consistent with the findings of the RAND Health Insurance Experiment (Leibowitz *et al.* 1985).

adjustments in the level of use among existing drug users, who were likely under physician care. Only 15% of the utilization response among females (41% for males) was found to work through increases in the probability of use, which is likely to be highly correlated with the patient initiation of physician treatment. The proportion of the utilization change operating through increases in the probability of any use generally increased with the individuals' self assessed health status level. The finding is consistent with the observation that there are negligible increases in the probability of having any physician consults after prescription drugs were provided free of charge.[35] The data suggest therefore that there is some physician control over the increased utilization "induced" by a public subsidy of prescription drugs and that this influence increases for patients with lower levels of health status. Given the informational asymmetries between the physician and patient, this increase in utilization is consistent with a move from under-utilization toward appropriate levels of utilization. Again, it should be noted that the nature of the policy experiment under analysis involves the lowering of the drug co-payment, not the increase, so unless the behavioural responses are symmetric to the case of an increase in drug co-payments, definitive statements about the probable impacts

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[35] This finding contrasts, however, with results from the RAND Health Insurance Experiment, in which the effect of physician care co-payments among non-elderly (under 65) individuals with "average" health status and other characteristics was to decrease the probability of use. Intensity of use among users was not affected by an increase in co-payment rates.

on patient health status of a lowering or removal of public subsidy cannot strictly be made.

Choosing an empirical technique suitable for modeling the outcome measure of primary interest -- the number of different drugs consumed -- was dealt with at some length. The distribution of this variable is similar to distributions of the consumption of other health care services (e.g., physician and hospital services). Specifically, the distribution is discrete, contains a large proportion of zeroes (is left-skewed) and has a long right tail. This distribution mirrors the stylized fact that a large proportion of individuals do not consume any health care services; a small proportion of individuals, on the other hand, use a large number of services. An estimation technique advocated for modeling individual-level data with these characteristics -- the two-part model (Duan *et al.* 1983, 1984) -- was one of several candidate estimators and was found to perform well according to the split-sample forecast mean squared error (MSE) and Vuong (1989) model selection criteria. The model consists of a probit model of the use vs non-use of prescription medicines and a negative binomial model of drug use in the subsample of drug users.

This two-part model dominated the negative binomial regression model and the "zero altered model" on the model selection criteria. The zero altered model is useful when there exists a large proportion of zeroes and there is some evidence that there is heterogeneity between individuals reporting no drug consumption

over the survey period. This was thought to be the case with the OHS data set, in so far as some of the zeroes might represent individuals with no medical need, who had no intention of seeking health care, and others were individuals who may very well have had medical need, but did not seek care because of lack of insurance, or other reasons. The zero altered model is novel in that it models two separate processes which are assumed to have produced the observed distribution of drug utilization. First, a latent variable -- the probability that an individual is in need of health care -- is make conditional on a vector of covariates. Second, the mean utilization by those who are in need of health care (that is conditional on another set of covariates) is estimated.

Estimates from the zero altered model were consistent with prior hypotheses. For example, a regressor which appeared in both parts of the model, the number of health problems afflicting the individual, was associated with a lower probability that the individual was not in need of prescription drugs, but was associated with an increased level of drug utillization by those deemed in need of prescription drugs. There was some difficulty, however, in estimating a model which differentiated between indiv· ·als on the basis of medical need. This lack of model fit was reflected in poor MSE statistics and rejection of this model in favour of the two-part specification. One explanation is that there is insufficient variation in the quantifiable dimensions of medical need in the subsample of individuals of

interest -- men and women between 55 and 75 -- to identify the parameters of this model.

Health status is typically an important predictor in models of health care utilization. Indeed, this was the case for the models of the number of different prescription drugs consumed using OHS data. Additions of the number of health problems and indicator variables of self-assessed health status increased the proportion of explained variation in drug use (estimated by Ordinary Least Squares) from 5% to 23% (females) and from 5% to 24% (males).

The way in which health status was modeled in the estimating models proved to be important. Specifically, the standard homoskedastic probit models of prescription drug use was found to be rejected in favor of probit models in which the variance (of the disturbances of the underlying latent variable) was a function of self assessed health status and the number of health problems. This adjustment resulted in modest changes to the estimated parameters of the standard probit model. This generalized model also indicates that both the conditional mean and dispersion in the underlying latent level of drug use are increasing in the number of health problems. One reason is that those with lower levels of health status might have either untreatable conditions (and report consuming only a few drugs) or be treatable with a large number of different drugs. Main therapeutic drugs might generate side effects that induce additional prescriptions to ameliorate the side effects.

If health status is endogenous to the model, the properties of the parameter estimators may be adversely affected. It was not possible to test for inconsistency due to the possible endogeneity of these regressors; instead the reduced form model was estimated (using OLS) under the assumption that health status was endogenous to the model. It turns out that the magnitude of the increase in utilization after ODB coverage is somewhat sensitive to this assumption. This does not constitute evidence that parameters were estimated inconsistently, but should temper the interpretation of the results. The estimated ODB effect was robust, however, to assumptions regarding the endogeneity of labour force participation.

4. Effects of Drug Plan Eligibility on the Prescription Drug Use by British Columbia Seniors

4.1 Introduction

Universal health insurance in Canada provides first dollar coverage for all citizens for medical services such as hospital care and physician consultations. But universal public insurance does not extend to out-of-hospital prescription medicines. All provincial governments in Canada do, however, provide categorical drug insurance coverage with varying levels of co-payment and deductibles. The British Columbia Ministry of Health, through its Pharmacare program provides some drug insurance coverage for all residents, but the terms of the coverage depend on age. Prior to turning 65, Pharmacare reimburses only a portion of individuals' drug costs exceeding a deductible level. After their 65th birthday, however, all residents of B.C. are eligible for full coverage on the ingredient cost of prescription medicines.

Our study questions whether eligibility for zero co-payment medicines is associated with an increased rate of expenditures on prescription medicines, and estimates the magnitude of this increase. In addition, the relative contribution of

enhanced insurance coverage for seniors to public sector prescription drug expenditure growth is examined.

Longitudinal administrative claims data from the B.C. Ministry of Health Pharmacare and Medical Services Plan programs are used to estimate the relationship between the expected real ingredient cost per plan enrollee and eligibility for Pharmacare senior's benefits, while controlling for other covariates such as health status, age and gender. The contribution to expenditures due to the onset of insurance was identified by treating latent health status and other demographic characteristics as being an individual-specific constant effect on prescription drug use over the 8 year period individuals were observed. Because the dependent variable is censored, however, estimation of models incorporating these constant or fixed effects is problematic using standard statistical techniques. A non-parametric estimator designed to estimate models using censored data in the presence of fixed effects is used (Honoré 1992). These administrative data are not, however, infomative enough to fully identify this relationship. To overcome this, data from the 1990 Ontario Health Survey are used. This was a provincially-representative survey of the non-institutionalized population of Ontario designed to assess population health status and ascertain disease risk factors and use of health services.

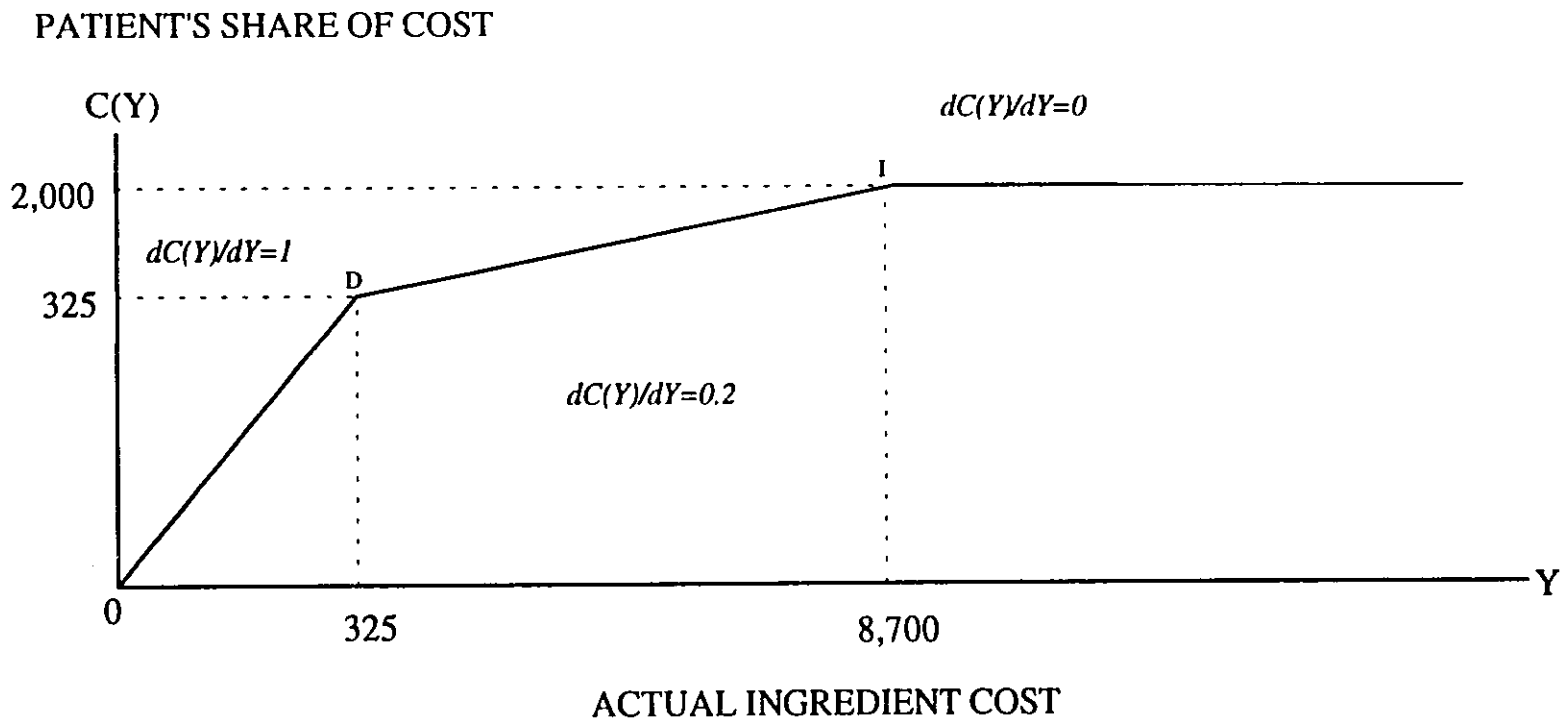
Section 4.2 describes the data used to address these questions and section 4.3 outlines the estimation strategy. Parameter estimates are presented in section 4.4. Section 4.5 concludes.

4.2 Data

Our data set tracks a group of people who, over the course of the 8 year period 1985-1992, reached the age of 65. This group of individuals was selected because the insurance contract administered by the Pharmacare plan changes at their 65th birthdate. Before the age of 65, these individuals were covered by "Plan E"; this contract reimburses 80% of all drug costs over a deductible, and provides 100% coverage on expenditures over a second threshold. After the age 65, the individual is covered under the more generous Plan A. This contract covers 100% of the ingredient cost and before 1988, 100% of the dispensing fee of any prescriptions. (Starting in April 1987, seniors were charged 75% of dispensing fees up to a maximum of $125 per calendar year.)

Figure 4-1 below illustrates the cost function in the years 1989-1990 applicable to individuals under 65. Consumers' cost is a concave, piecewise linear function of drug ingredient cost Y. The first kink in the function is the annual deductible (expenditures below this are paid entirely by the individual). The individual then pays 20% of drug expenses. From 1988 on, they pay this 20% only up to a maximum level, after which drugs are free.

Figure 4-1 Ingredient Cost Sharing Functions for Plan E Recipients: 1989-1990



Individuals in the sample were born in 1921, 1923 or 1925, turned 65 and therefore became eligible for Plan A coverage in 1986, 1988, or 1990, respectively. There will therefore be differences among individuals' insurance contracts in any given year. Table 4-1 below summarizes the individuals' marginal cost (C_Y) schedule by birth year and year of observation. The cells corresponding to the years in which the individuals reach age 65 are shaded, indicating that individuals will spend a fraction of the year in each of the insurance contracts Plan E and Plan A.

Table 4-1 Pharmacare Insurance Contracts by Birth Cohort and Year

	BORN 1921	BORN 1923	BORN 1925
1985	C_Y=1 if 0<Y≤200 C_Y=0.2 if 200<Y	C_Y=1 if 0<Y≤200 C_Y=0.2 if 200<Y	C_Y=1 if 0<Y≤200 C_Y=0.2 if 200<Y
1986		C_Y=1 if 0<Y≤200 C_Y=0.2 if 200<Y	C_Y=1 if 0<Y≤200 C_Y=0.2 if 200<Y
1987	C_Y=0	C_Y=1 if 0<Y≤275 C_Y=0.2 if 275<Y	C_Y=1 if 0<Y≤275 C_Y=0.2 if 275<Y
1988	C_Y=0		C_Y=1 if 0<Y≤300 C_Y=0.2 if 300<Y≤8800 C_Y=0 if 8800<Y
1989	C_Y=0	C_Y=0	C_Y=1 if 0<Y≤325 C_Y=0.2 if 325<Y≤8700 C_Y=0 if 8700<Y
1990	C_Y=0	C_Y=0	
1991	C_Y=0	C_Y=0	C_Y=0
1992	C_Y=0	C_Y=0	C_Y=0

4.2.1 Variables collected

Longitudinal administrative claims payment data on over 18,000 seniors over the period 1985-1992 are used. For each record, information on the nominal value of drugs, number of prescriptions dispensed, physical quantity of drugs and the drug dispensing fee reimbursed over the calendar year was collected.

A chain-linked Laspeyres price index from 1985-1992 was constructed to deflate annual nominal prescription drug expenditures. Price and quantity data used in estimating the price index were obtained from Pharmacare claims records.[36] Claims data from all of the Pharmacare categorical insurance programs were used with the exception of claims on Plan E. (Information on the prices and quantities of specific drugs are not reported on claims against this Pharmacare drug insurance plan.) The price index was calculated using a two step procedure. First, the year-to-year price indices were calculated. The basket of drugs ($Q_{\cdot}$) was

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[36] The drug price index estimated using Pharmacare claims data appears to be the most accurate index available. Alternative prices indices include the health and personal care component of the British Columbia Consumer Price Index (C.P.I.), the pharmaceutical component of the Industrial Product Price Index (I.P.P.I.), both compiled by Statistics Canada, and the Canada-wide Patented Medicines Price Index (P.M.P.I.) compiled by the Patented Medicines Prices Review Board. The problem with the health and personal care component of the B.C. C.P.I. and the pharmaceutical component of the I.P.P.I., which is a Canada-wide index of factory-gate prices of drug products, is that their baskets includes both non-prescription drug and/or non-drug items. These indices also fail to capture significant variation in prices paid by the public drug programs. Gorecki (1993), for example, documents the large difference in drug prices reimbursed by the B.C. Pharmacare program and the Ontario Drug Benefit program. The P.M.P.I. applies only to prescription drugs, but does not publish its price index on a provincial basis and also fails to include non-patented prescription medicines in its index basket. The drug price index estimated using Pharmacare claims data, on the other hand, does not suffer from any of these problems.

the base year consumption of a subset of drugs which were consumed in both years. (Injections, non-drugs, prosthetics and ostomy supplies were excluded.) The next step involved linking these indices. The index for any particular year *i* is the product of the year-to-year indices for all years from 1985 to year *i*.

Table 4-2 Pharmacare Prescription Drug Price Index

Year	Price Index
1985	0.9188
1986	1.0000
1987	1.0550
1988	1.1174
1989	1.1725
1990	1.2322
1991	1.3388
1992	1.3925

Information on the expenditures and quantity of medical services used was also obtained. These data were collected from the claims data base of the Medical Services Plan (MSP) of the B.C. Ministry of Health which provides publicly-funded first-dollar insurance for "medically necessary" health care services for all residents of the province, regardless of age, income or other characteristics. Over 2.3 million claims were grouped according to the specialty type of the physician who delivered the service (general practitioner, specialist), the location of the service (office, emergency room, hospital, other) and by type of service (minor surgery, non-minor surgery, cardiovascular surgery, diagnostic procedures, other)

and then aggregated to the patient-year level of observation. The sample of MSP data covers the period April 1, 1986 to March 31, 1992. There are therefore missing observations for 1985, the first three months of 1986 and the last 9 months of 1992.

Patient characteristics include age, sex and postal code. Limited information on patient income was also collected by merging individuals' MSP records with their Pharmacare records. MSP charges "premiums" for medical service insurance,[37] but charges lower rates on the basis of net income and other characteristics. This premium assistance is available to all residents regardless of age. It is possible to infer income categories of individuals based on the proportion of the premium which was subsidized by government. For example, in 1990, the following rate structure existed:

Adjusted Net Income	% of Insurance Premium Paid by Medical Services Plan
0 - 9,000	95%
9,001 - 11,000	75%
11,001 - 13,000	55%
13,001 - 15,000	35%
15,001 - 17,000	15%
17,000 and over	0%

[37] These charges bear little resemblance to premiums because they are not based on expected use and are not even required for insurance coverage.

Because the rate structure and the definition of income for purposes of subsidy changed over the sample period 1985-1992, it is difficult to calculate a consistently-defined level of income over the eight years. It is straightforward, however, to define income less precisely on the basis of the number of the eight years individuals received a certain level of premium assistance.

4.2.1.1 Additional Insurance Coverage

It is likely that some individuals in the sample, in particular those under 65 on Plan E coverage, had drug insurance coverage for prescription drug costs not covered by Pharmacare.[38] Effective insurance coverage for those with supplemental coverage will be more generous than those covered solely by Pharmacare. Unfortunately, information on supplemental coverage is not available. The insurance coverage variables will therefore be measured with some error.

[38] Private coverage is typically provided as an employment-related benefit. Some government programs (e.g., Department of Veterans Affairs) also provide coverage. Individuals usually cannot purchase supplemental drug coverage.

4.2.2 Selection Criteria

Individuals selected for analysis from Pharmacare records satisfied several criteria. First, as was mentioned, subjects were born in 1921, 1923 or 1925 and therefore turned 65 and became eligible for Pharmacare's Plan A coverage sometime during the sample period 1985-1992. Second, individuals were excluded if they were eligible for any other Pharmacare-administered prescription drug insurance. Eligiblity for these is based on receipt of social assistance benefits or residency in a long-term care facility. Finally, individuals in the sample came from single-person households. This restriction was necessary because Pharmacare Plan E reimburses total family drug expenditures and does not keep track of the claims incurred by individual family members. (Data limitations also prevented an analysis of the utilization of specific therapeutic classes of drugs after the change in insurance status.)

Restricting the analysis to single person households raises some concerns about the generalizability of the empirical results to all households in this age range. In particular, some males who never marry may have lower income, and possibly lower health status.[39] If this group comprises a large proportion of the sample, then this concern may be warranted. (It is also possible that the same

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[39] It is not clear which way the causality runs. Unwed males could be relatively unattractive due to characteristics which produce lower income or health. Alternatively, this could be due to lack of companionship and/or caring.

generalizability issues apply to those who were once married yet are single due to death, separation or divorce.) The data did not contain information on the reasons for the single person household status. However, demographic information for residents of Ontario are available from the 1990 Ontario Health Survey (OHS). Frequency tabulations of the reasons for being unmarried among non-institutionalized residents of Ontario aged 60-71 obtained from the 1990 OHS are reported below.[40] Sampling weights were applied to the raw data to ensure responses were generalizable to the population level.

Table 4-3 Distribution of Reasons for Being Unmarried: Ontario Residents 60-71 years

Marital Status	Females		Males	
	No. of Observations	Percentage	No. of Observations	Percentage
Never Married	26,220	13.8%	18,627	36.5%
Widow/Widower	128,747	67.8%	18,017	35.3%
Separated/Divorced	34,999	18.4%	14,349	28.1%
Total Singles	189,966	100.0%	50,993	100.0%

Source: 1990 Ontario Health Survey

These data indicate that of those women who were single at the time of the survey, the proportions who had never married are modest. A substantial

[40] As a group, single females represent approximately 35% of the total female population 60-71 years, while single males represent only 10% of the total male population 60-71 years.

proportion of single males, on the other hand, had never married. This raises some concerns that models estimated using data on non-married male residents of B.C. are not necessarily generalizable to the general population of males in the province.

Prescription drug utilization data on a total of 18,477 individuals (147,816 observations) were initially collected. A total of 1,103 individuals (8,824 observations) were, however, removed because of an error discovered in the prescription drug insurance claims files. (Some individuals were found to have positive expenditures in Plan *A* (over 65) when in fact they were younger than 65. Others were found to have positive expenditures in Plan *E* (under 65) when they were older than 65.) Of the remaining 17,374 individuals, it was discovered that information on sex was missing for 473. This left records on 10,422 females and 6,479 males. Of these females, 288 (2.7%) moved out of the province and 721 (6.9%) died sometime over the eight year period, leaving 9,413 "survivors" (a total of 75,304 observations). Of the 6,479 males, 121 (1.9%) moved out of the province and 955 (14.7%) died sometime over the eight year period, leaving 5,403 "survivors" (a total of 43,224 observations).

The sample retained for estimation therefore has been purged of individuals with data entry errors in any of the eight years or who moved or died over the eight years. The following table displays the number of observations in the estimation sample stratified by sex, birth year and the number of years in which premium assistance was received.

Table 4-4 Stratification of Sample by Sex, Birthyear and Premium Assistance Status

Stratification Variable						
Sex	**Females**			**Males**		
	75,304			43,224		
Birth Year	**1921**	**1923**	**1925**	**1921**	**1923**	**1925**
	28,368	24,520	22,416	14,752	14,680	13,792
Premium Assistance						
None	13,080	11,680	11,232	6,656	6,848	7,776
1-4 years	5,752	6,880	6,952	4,800	4,872	4,136
5-8 years	9,536	5,960	4,232	3,296	2,960	1,880

4.2.3 Descriptive Statistics

Table 4-5 and Table 4-6 below present descriptive statistics on real prescription drug ingredient cost stratified by sex, year of observation (1985-1992) and birthyear (1921, 1923 and 1925). Censored values were set equal to zero. This information is depicted graphically in Figures 4-2 to 4-4. Figure 4-2 displays real prescription drug expenditures by age and sex. The prominent feature of this graph is the large increase in expenditures after the age 65. This is undoubtedly due in part to the fact that pre-65 expenditure data is censored at year specific deductible levels. The data suggest that after the age 65, males have slightly larger expenditures than do females. Table 4-3 stratifies females' expenditures by year of

birth. This stratification reveals an interesting feature: individuals born later have higher expenditures at a given age than those born earlier. This effect is more apparent in the data on females than in the data for males portrayed in Table 4-4. One explanation of this birthyear difference is what Evans (1984) refers to as "technological extension". Over time the scope and application of medical technology expands so that "more can be done". The range of therapeutic interventions will therefore be larger for, say, individuals turning 65 in 1992 than those turning 65 in 1990 or 1988.

It is possible, however, that this effect is an artifact of the data. The rule for selection into the sample is based on surviving all eight years. This has the effect of removing unhealthy individuals from all 3 birth cohorts. But this will implicitly remove sicker individuals from the 1921 sample relative to the other cohorts, thereby lowering the average expenditures of the cohort. The reason is that the initial selection rule removed individuals who died at ages 68-71 from the 1921 cohort. Individuals born in 1925 who die during the same ages, on the other hand, are automatically included in the sample because these individuals are not observed after age 67. This selection effect might induce the expenditures of the survivors in the 1921 cohort to be lower than those born later. Figures 4-5 and 4-6 graph the expenditures of (respectively) females and males who survive to age 67. By using the same selection across the three cohorts, this attrition effect is

removed. Even after controlling for attrition, therefore, it appears that there are still "birthyear effects" at work.

There appeared to be some birthyear effects in the use of physician services as well. Figures 4-7 and 4-8 graph the mean number of annual general practitioner visits by age and birthyear. As was mentioned, medical services data are complete for the subperiod 1987-1991 only, so the data are not quite as informative as the prescription drug use data. These data do suggest, however, that individuals born later (1992) consult with the physician more often than those individuals born earlier (1988).

Table 4-5 Means, Standard Deviations and Frequencies of Real Drug Ingredient Cost by Year, Birth Cohort: Females

Calendar Year	Birth Year			
	1921	1923	1925	Total
1985	58.38	45.15	44.40	49.91
	221.94	187.11	188.64	201.46
	3,546	*3,065*	*2,802*	*9,413*
1986	104.85	53.84	47.79	71.25
	268.52	215.30	201.28	234.51
	3,546	*3,065*	*2,802*	*9,413*
1987	124.96	67.61	60.64	87.14
	231.69	250.98	257.38	247.61
	3,546	*3,065*	*2,802*	*9,413*
1988	154.29	123.58	68.40	118.72
	289.31	351.08	315.78	320.26
	3,546	*3,065*	*2,802*	*9,413*
1989	167.32	157.08	80.30	138.08
	292.46	300.37	339.57	311.99
	3,546	*3,065*	*2,802*	*9,413*
1990	203.39	189.99	151.72	183.65
	331.51	351.07	441.37	374.10
	3,546	*3,065*	*2,802*	*9,413*
1991	222.86	208.17	189.92	208.27
	350.00	358.63	351.94	353.63
	3,546	*3,065*	*2,802*	*9,413*
1992	250.23	237.59	216.08	235.95
	385.09	393.80	404.09	393.86
	3,546	*3,065*	*2,802*	*9,413*
Total	160.79	135.38	107.41	136.62
	306.89	316.88	330.08	317.93
	28,368	*24,520*	*22,416*	*75,304*

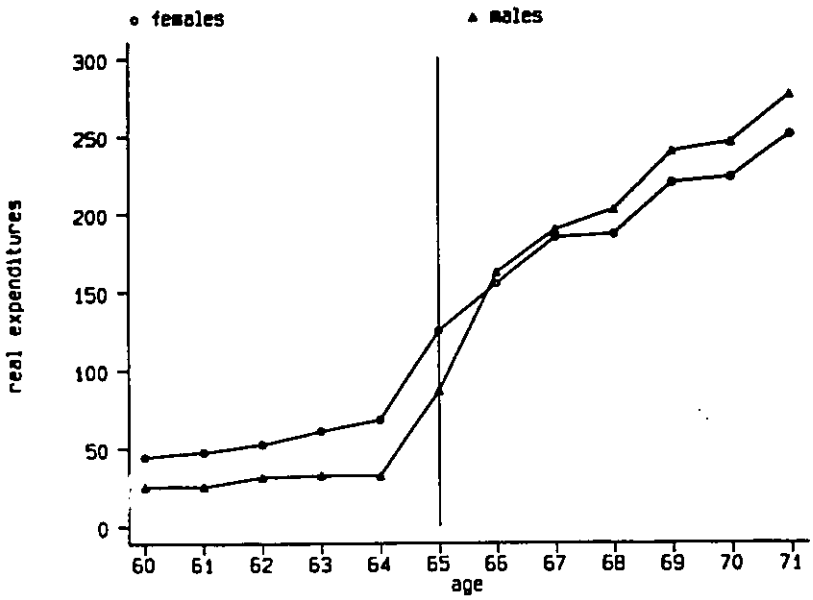
Note: the first entry is the mean, the second is the standard deviation and the final entry is the frequency.

Table 4-6 Means, Standard Deviations and Frequencies of Real Drug Ingredient Cost by Year, Birth Cohort: Males

Calendar Year	Birth Year			
	1921	**1923**	**1925**	**Total**
1985	30.29	28.23	25.38	28.02
	190.62	157.32	161.41	170.63
	1,844	*1,835*	*1,724*	*5,403*
1986	79.92	30.44	25.81	45.85
	260.95	165.18	170.07	205.73
	1,844	*1,835*	*1,724*	*5,403*
1987	149.57	30.79	34.98	72.67
	328.70	182.62	193.43	251.37
	1,844	*1,835*	*1,724*	*5,403*
1988	170.49	76.98	35.10	95.53
	371.89	234.76	208.81	288.10
	1,844	*1,835*	*1,724*	*5,403*
1989	191.35	154.56	36.27	129.37
	397.83	308.80	215.76	324.83
	1,844	*1,835*	*1,724*	*5,403*
1990	233.74	192.25	102.91	177.90
	465.28	359.77	316.41	390.72
	1,844	*1,835*	*1,724*	*5,403*
1991	245.26	212.48	182.40	214.07
	452.09	500.51	397.71	453.74
	1,844	*1,835*	*1,724*	*5,403*
1992	275.61	244.50	205.43	242.65
	547.24	532.91	436.18	509.98
	1,844	*1,835*	*1,724*	*5,403*
Total	172.03	121.28	81.04	125.76
	399.71	345.70	289.26	350.98
	14,752	*14,680*	*13,792*	*43,224*

Note: the first entry is the mean, the second is the standard deviation and the final entry is the frequency.

Figure 4-2 Real Drug Expenditures by Age and Sex



Source: BC Ministry of Health Pharmacare

Figure 4-3 Real Drug Expenditures by Age and Birthyear: Females

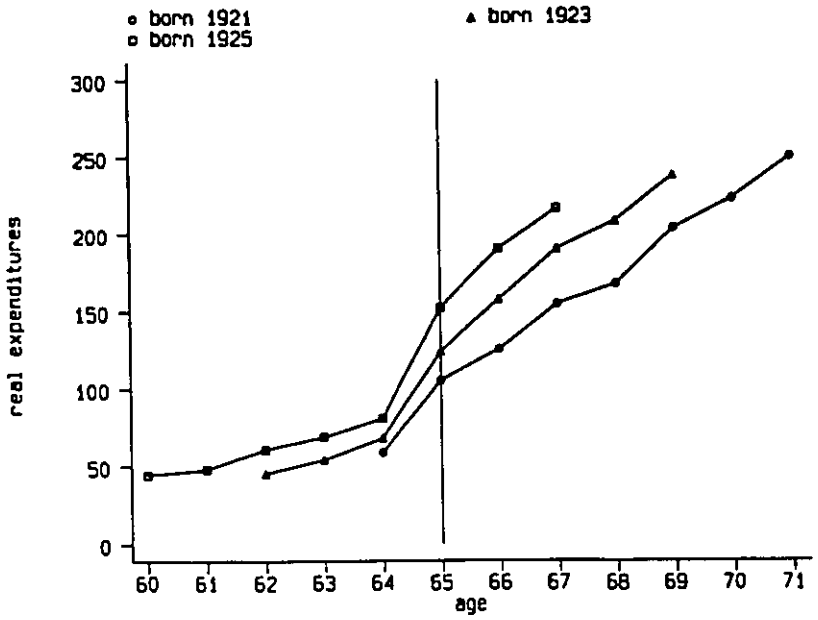


Figure 4-4 Real Drug Expenditures by Age and Birthyear: Males

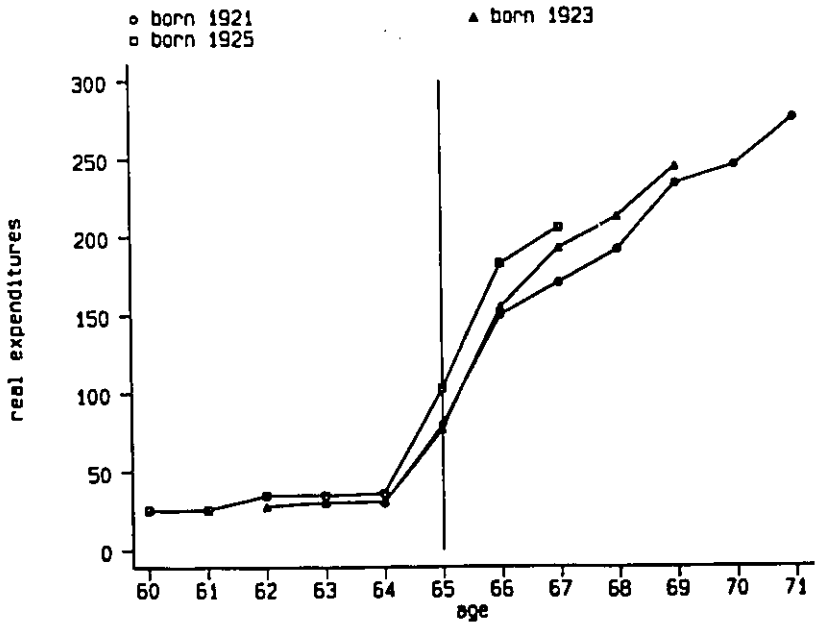


Figure 4-5 Real Drug Expenditures by Age and Birthyear: Females Surviving to 67 Years

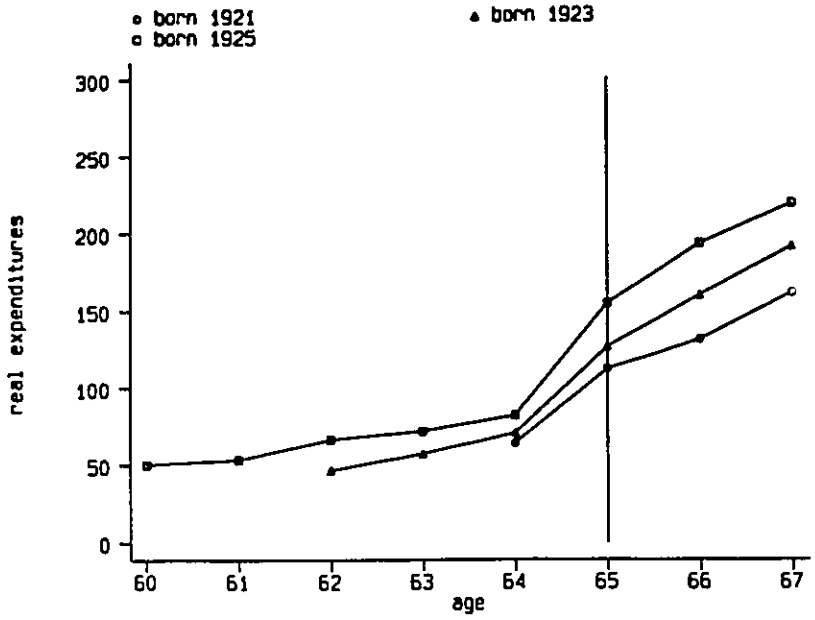


Figure 4-6 Real Drug Expenditures by Age and Birthyear: Males Surviving to 67 Years

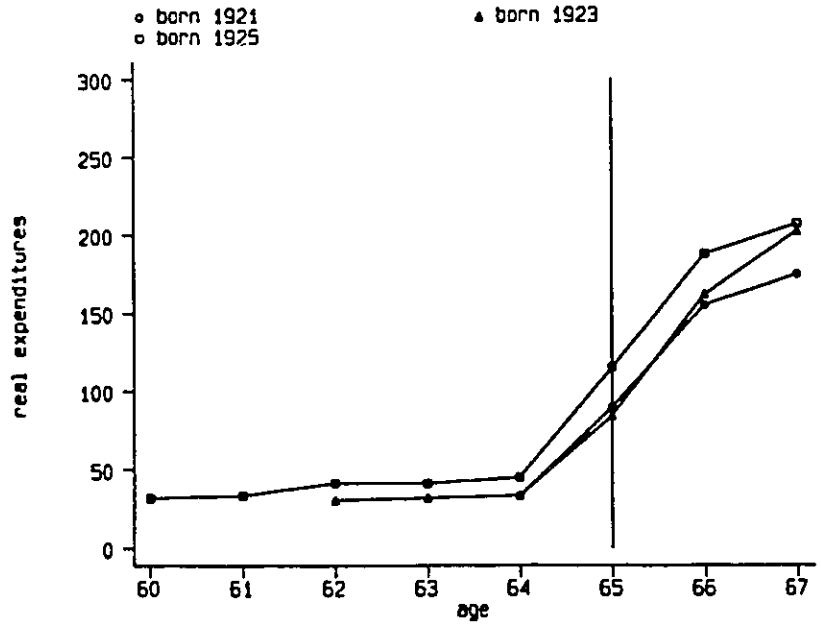


Figure 4-7 Average Annual GP Visits by Age and Birthyear: Females

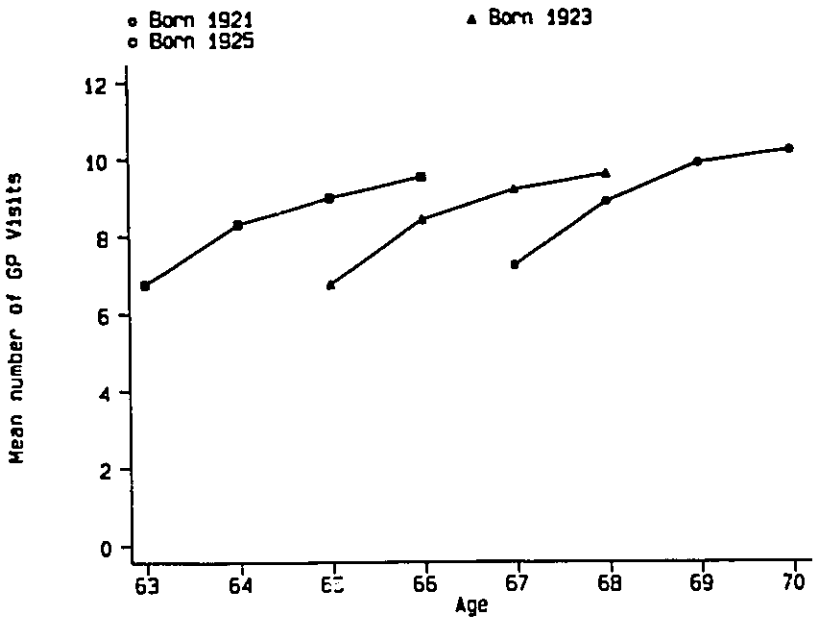
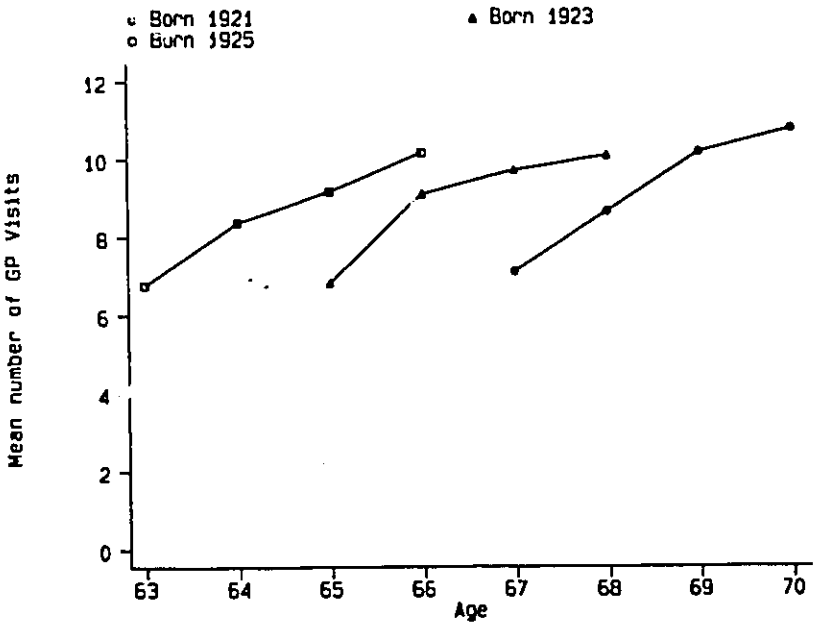


Figure 4-8 Average Annual GP Visits by Age and Birthyear: Males



The set of graphs shown in Figures 4-9 through 4-14 display expenditure stratified by sex, birthyear and the number of years that premium assistance for medical insurance premiums were received. Recall that eligibility for premium assistance is tied to income, so that in general, individuals receiving assistance for a greater number of years will have lower income. It appears that males born in all three years (Figures 4-10, 4-12 and 4-14) and females born in 1925 (Figure 4-13) who do not receive any form of premium assistance over the 8 years have lower expenditures than those who receive assistance for one or more years. Females born in 1923 (Figure 4-11) receiving premium assistance for 5 to 8 years had higher expenditures than those receiving 4 or fewer years assistance. Finally, there were no clear differences between those receiving and not receiving premium assistance among females born in 1921 (Figure 4-9).

Figure 4-9 Real Drug Expenditures by Years Receiving Premium Assistance: Females Born 1921

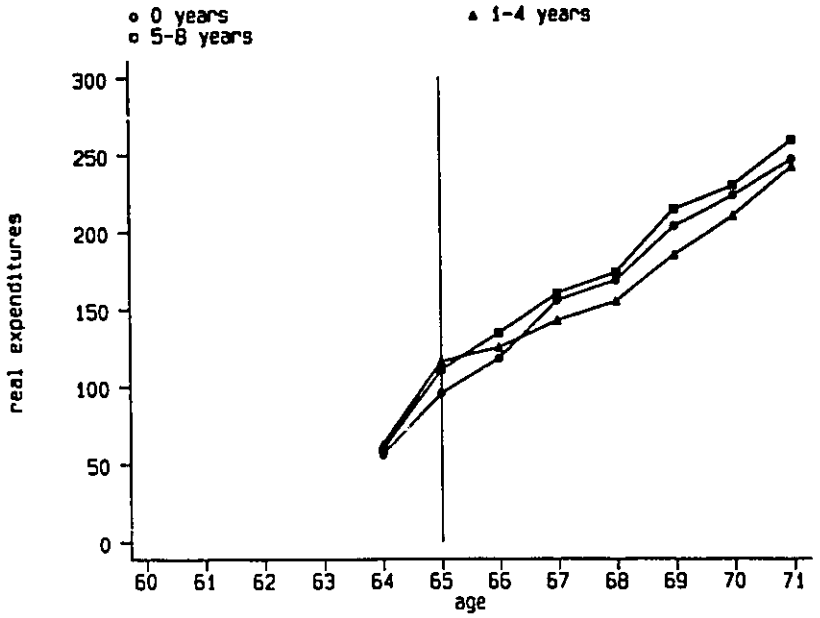


Figure 4-10 Real Drug Expenditures by Years Receiving Premium Assistance: Males Born 1921

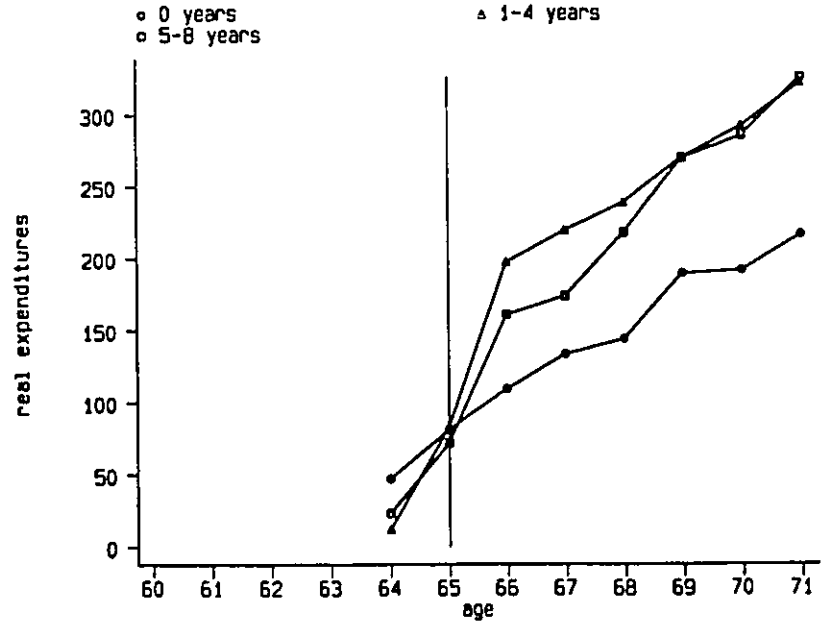


Figure 4-11 Real Drug Expenditures by Years Receiving Premium Assistance: Females Born 1923

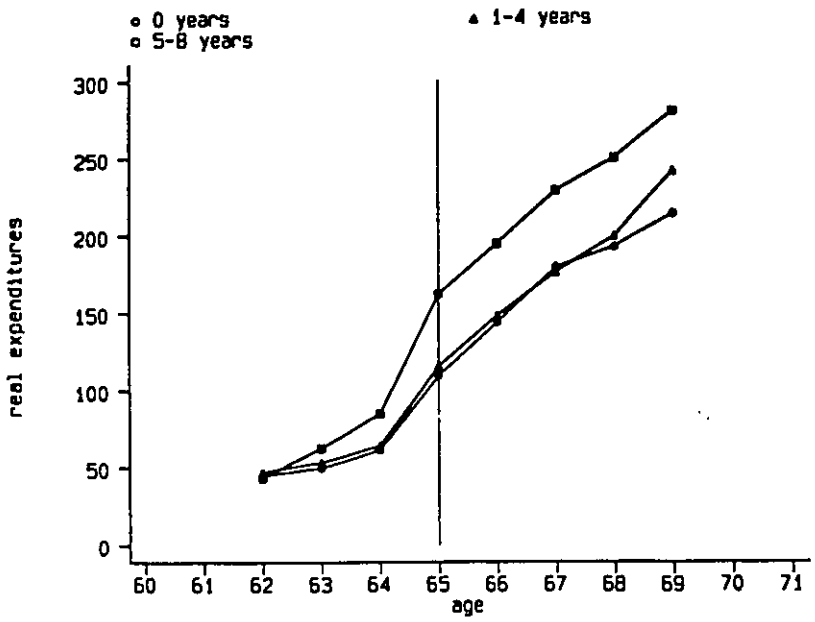


Figure 4-12 Real Drug Expenditures by Years Receiving Premium Assistance: Males Born 1923

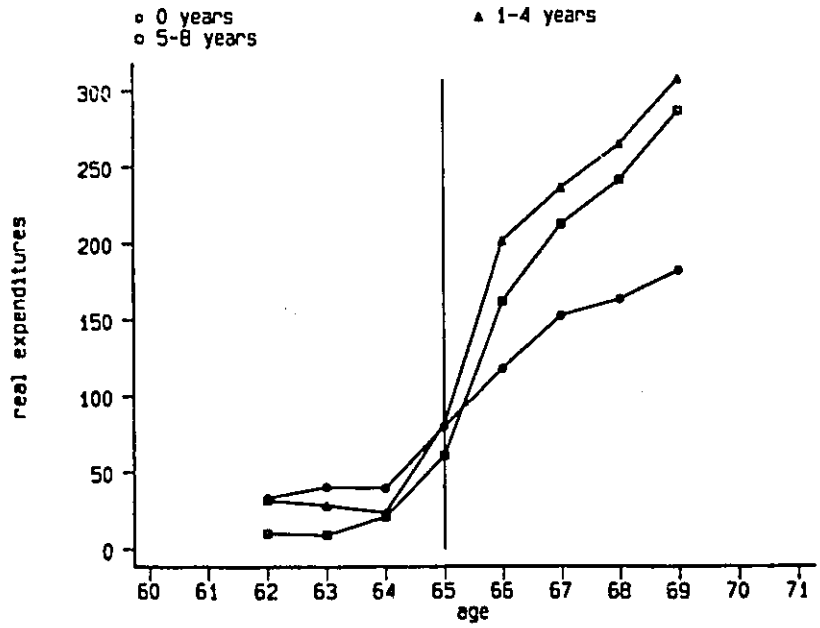


Figure 4-13 Real Drug Expenditures by Years Receiving Premium Assistance: Females Born 1925

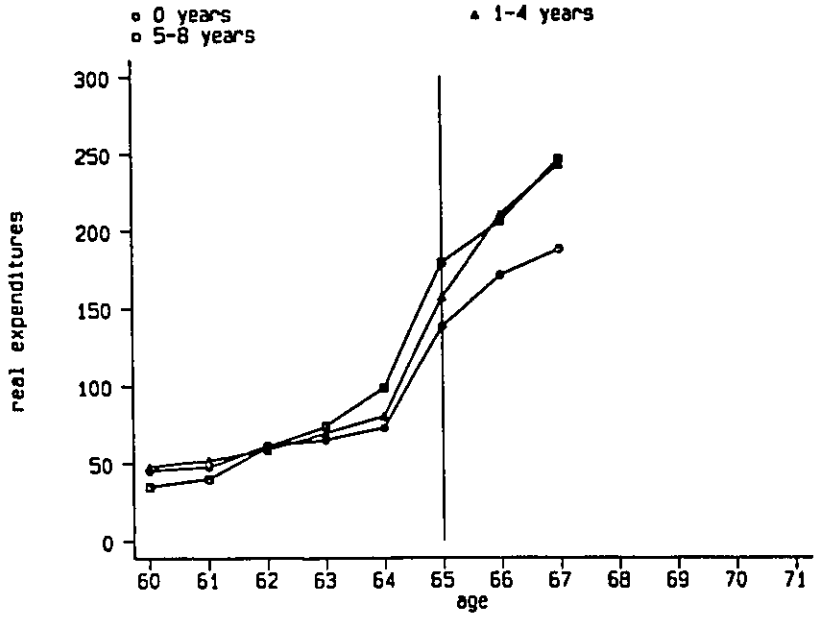
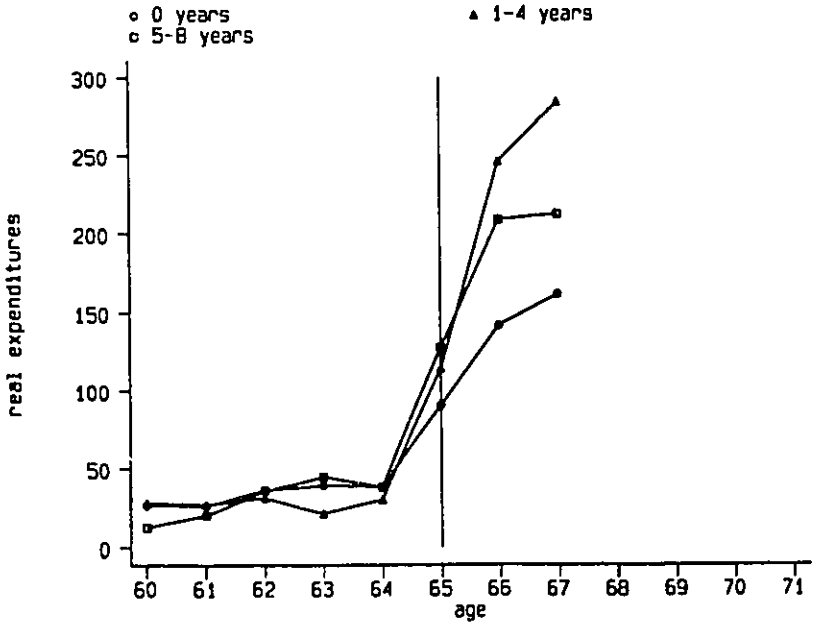


Figure 4-14 Real Drug Expenditures by Years Receiving Premium Assistance: Males Born 1925



Appendix C reports the frequency tabulations of real prescription drug expenditures in the follow categories: $0, $1-$50, $51-$100, $101-$200, $201-$300, $301-$400, $401-$500, $501-$1,000, $1,001-$2,000, $2,001-$5,000, and greater than $5,000. Censored observations were arbitrarily assigned the value $0. The distribution of reported expenditures appears to be highly left skewed. A large proportion of observations (roughly 90%) reported expenditures under $500. The data also indicate that relatively more males than females were observed to have extremely large real expenditures (greater than $5,000). This skewness is undoubtedly due in part to the influence of censoring because there are relatively fewer zeroes reported in subsamples in which individuals were observed to spend fewer years in Plan E (from which reported expenditures are censored). Censoring is not, however, the sole reason. Appendix D plots histograms of log expenditures for individuals reporting positive expenditures in each of the subsamples. A normal distribution with mean and variance estimated using the sample data has been superimposed. The distribution of log expenditures appears to be roughly symmetric; it follows therefore that even the uncensored observations are left skewed.

4.3 Modelling Technique

The modelling approach used here is quite simple. No behavioural model of drug utilization is posited; instead, a reduced form equation is estimated relating real expenditures on drug ingredient cost to a variable indicating eligibility for Pharmacare Plan A benefits at age 65, while holding constant age, sex, income, health status. Variations in the terms of the Pharmacare insurance contracts (e.g., deductible levels) of those under 65 are not explicitly modelled, nor is the introduction of the Plan A dispensing fee in 1987. Empirical implementation of this simple model is hampered, however, by issues of identification of the price effect at 65 from confounding influences, attrition bias and estimation of fixed effects using censored data.

4.3.1 Identification of the Insurance Effect on Prescription Drug Expenditures

The effect of eligibility for Pharmacare insurance coverage on real prescription drug expenditures might be confounded with several other factors which may coincide with individuals' 65th birthdate. A prominent example is the deterioration of health status associated with aging which might increase drug consumption. In addition, retirement, which usually occurs between 60-70 years, might lower the opportunity cost of consulting physicians (in terms of foregone

labour income). Increased physician contacts may, *ceteris paribus*, increase the amount of drugs consumed. Finally, advances in the medical arts increase the range of medical interventions available to the physician. One might expect increases in the volume of drugs consumed as medications become available for previously untreatable conditions or as new drugs reduce the morbidity associated with side effects. Of course, one would expect these advances to increase gradually over time. However, it is at least a possibility that the adoption of new drugs coincide with an individual's 65th birthday.

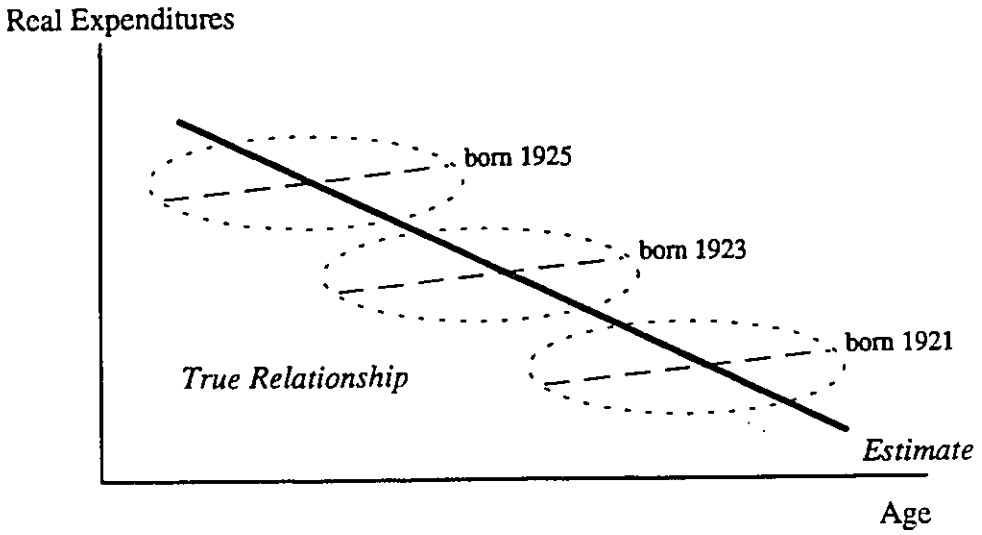
4.3.1.1 Identification of Insurance Effect from Health Status Deterioration

The effect of health status on drug utilization is modelled using two variables: an individual-specific effect (α_i), assumed to remain constant over the 8 years and a trend effect (*AGE*), which is common to all individuals. A more general model would allow the trend effect to differ by individual, but this is not possible with the estimation method used. Still, the approach adopted appears to be a parsimonious means of capturing the effects of health status on drug utilization. Individual differences in health endowments probably explains a greater proportion of the variance in prescription drug expenditures than differences in individuals' rate of health status deterioration over the 8 year window.

It is worth noting that *any* unchanging individual characteristics which affect the consumption of medicines will be absorbed into the estimated fixed effect. Health status endowments are but one effect. The degree of access to physicians' services and therefore prescription medicines, assuming it remains constant over the 8 years, will also be incorporated into the fixed effect. Patterns of health care utilization also differ by sex and will therefore will be incorporated. An individual's birthyear may also affect drug consumption. Individuals born later have the opportunity to use a greater variety of medicines, as medications become available for previously untreatable conditions or as new drugs reduce the morbidity associated with side effects. This effect of birth year on drug consumption is also captured in the fixed effect.

If this individual heterogeneity was ignored (i.e., restricting $\alpha_i=\alpha_0$), but was correlated with other covariates, such as age, then the estimates would be inconsistent. If, for example, individuals born in later years have higher drug expenditures and bigger fixed effects for reasons outlined above, then the effect of age on drug expenditures will be biased downwards. This is illustrated in the diagram below. The hatched lines represent the expenditure-age profiles on individuals born in three different years. At a given age, individuals born later will have higher expenditures. The bold line represents the misleading estimated relationship which is obtained if this heterogeneity is ignored.

Figure 4-15 Bias due to Omitting Fixed Effects



Source: Adapted from Hsiao (1986, page 7)

Identification of the insurance eligibility effect on drug expenditures from effects due to lower health status does depend on the trend effect being linear over the eight year period. The assumption that health status is constant over the 8 year period is, however, untestable using these administrative claims data because health status is not measured. Analyzing the time path of health status reported by respondents to the 1990 Ontario Health Survey with characteristics similar to those included in the B.C. data set (not married and between 60-71 years) could offer some insights into the validity of this assumption. (It should be recognized that this approach has its limitations as well because, strictly speaking, one cannot

make valid longitudinal inferences on a cross-sectional data set if there are cohort effects.)

Regression models were estimated to determine if there is a decline in health status at age 65 using data from the 1990 Ontario Health Survey on single, widowed, separated or divorced individuals who were 60-71, inclusive. Several dimensions of these individuals' health status were analyzed: number of chronic health problems, number of restricted activity days in the last two weeks, self assessment of health status (binary indicator of excellent or very good health, and binary indicator of fair or poor health) and satisfaction with health status (binary indicator of high degree of satisfaction, binary indicator of no satisfaction at at all.) A binary variable *AGE65*, equal to one if age was 65 or older, was constructed to test for a downward shift in trend health status after 65. Linear regression was used to estimate the first two models and probit was use to estimated the binary response models. Heteroskedasticity-robust standard error formulas were used in all models. A total of 1,800 observations were used for estimation. Based on the insignificance of the *t*-ratios of the *AGE65* variables, there does not appear to be an abrupt deterioration in any of these measures of health status at the 65th birthdate for these individuals. This lends some support to assumption of a linear decline in health status over the 60-71 range.

Table 4-7 Estimated Models of Health Status using 1990 Ontario Health Survey Data

VARIABLE	*Description*	*Coefficient Estimate*	*t-ratio*	*sample mean*	*std dev.*	*min*	*max*
NUMBPRB	Number of Chronic Health Problems			2.38	1.92	0	8
AGE		0.01	0.60	65.77	3.39	60	71
AGE65	=1 if age>64	0.11	0.62	0.63	0.48	0	1
CONSTANT		1.34	0.88				
SUMCTBD	Number of Restricted activity days			1.17	3.39	0	14
AGE		0.02	0.39	65.77	3.39	60	71
AGE65	=1 if age>64	-0.23	-0.82	0.63	0.48	0	1
CONSTANT		0.22	0.08				
EX-VG	=1 if excellent or very good health			0.37	0.48	0	1
AGE		-0.01	-0.33	65.77	3.39	60	71
AGE65	=1 if age>64	-0.01	-0.10	0.63	0.48	0	1
CONSTANT		0.04	0.04				
FAIR-POOR	=1 if fair or poor health			0.18	0.38	0	1
AGE		0.01	0.37	65.77	3.39	60	71
AGE65	=1 if age>64	-0.02	-0.16	0.63	0.48	0	1
CONSTANT		-1.37	-1.16				
SAT	=1 if very satisfied with health status			0.31	0.46	0	1
AGE		0.02	1.16	65.77	3.39	60	71
AGE65	=1 if age>64	0.01	0.12	0.63	0.48	0	1
CONSTANT		-1.80	-1.70				
UNSAT	=1 if very unsatisfied with health status			0.02	0.15	0	1
AGE		0.03	0.93	65.77	3.39	60	71
AGE65	=1 if age>64	-0.34	-1.34	0.63	0.48	0	1
CONSTANT		-4.00	-1.76				

4.3.1.2 Identification of the Insurance Effect from Changes in the Opportunity Cost of Time

The second omitted variable identified above is the implicit access price of physician consultations. In the absence of proxies for the access price of health care (e.g., information on employment and wage rates for the individuals in the sample, or age-specific rates of retirement of individuals in the general population), it may be impossible to separate the access price effect from the money price effect. Data on retirement behaviour obtained from the 1990 Ontario Health Survey (OHS) suggest that retirement is not coincident with the 65th birthdate; for example, 8% of male respondents and 6% of females were still in paid employment at age 67. Retirement is therefore not perfectly confounded with turning 65. Moreover, results from the estimated models of drug utilization among Ontario seniors using OHS data indicated that labour force participation did not significantly affect the probability of respondents' having any physician consults in the 12 months prior to the survey or the number of different drugs taken over the 4 weeks prior to the survey. It appears that this measure of the opportunity cost of time does not have large effects on physician visits or drug utilization.

4.3.1.3 Identification of the Insurance Effect from Technological Change

If technological advances influence the drug consumption of older adults in the sample in the same way regardless of their age, then drug consumption of all individuals should increase by the same proportion. Therefore one would expect that a new drug introduced in, say, 1986 which increases the drug utilization of those who just turned 65 (i.e., those born in 1921) would increase the utilization of those who are 63 and 61 as well. Pooling individuals born in the three years (1921, 1923 and 1925) and adding birthyear dummies should therefore control for this effect.

4.3.2 Attrition Bias

Individuals who leave the plan due to migration or death have been dropped from the sample. Approximately 7% of females and 15% of males died over the 8 year period. Failure to account for this attrition could adversely affect the properties of the estimators. If death and (outpatient) drug expenditures are positively correlated, then the probability of remaining in the sample depends on the value of the dependent variable. In this case, the disturbance term will have a non-zero mean and ML estimates will be rendered inconsistent. Data on the drug expenditures of those who died over the 8 year sample period 1985-1992 indicate

that this may very well be the case. Table 4-8 presents tabulations of real Plan E and A ingredient cost by full calendar years of life remaining and sex. These data suggest that expenditures are higher, the closer the one is to death. (Real expenditures are lower for individuals with "0 full calendar years of life remaining" because they were typically observed for less than one year.) It is also possible, albeit less likely, that individuals who move out of the province might also represent a self-selected group of atypically healthy individuals.

Table 4-8 Tabulations of Real Ingredient Cost by Years to Death, Sex

# full calendar years of life remaining	Females			Males		
	Mean	Std. Dev.	Freq.	Mean	Std. Dev.	Freq.
0	234.30	448.01	710	161.92	446.57	942
1	276.40	466.83	635	223.59	514.21	848
2	214.44	437.66	554	172.93	460.71	739
3	177.01	366.28	472	144.95	401.73	600
4	154.15	370.18	390	85.30	253.79	476
5	134.92	338.99	310	73.58	240.41	347
6	150.56	399.74	226	69.23	296.52	222
7	108.92	277.65	124	34.40	168.46	128
8	67.67	224.44	11	0.00	0.00	13
Total	202.34	415.78	3,432	148.97	417.28	4,315

Note: Each group in the table contains the groups below.

To correct for selectivity bias, a model of attrition behavior must be developed. To do so, a set of instrumental variables are required which explain the

probability of attrition (death) but are unrelated to drug use. Candidate instruments are difficult to find and are not available in this data set. Potential variables might include risk factors which could lead to an instant premature death (e.g., driving while impaired, failure to use seatbelts, certain occupational hazards) or alternatively indicators of specific diseases with high mortality rates and for which no pharmacotherapy is available. Instruments falling into the latter category are, however, almost impossible to find. While there still are numerous uncurable diseases (e.g., AIDS, end-stage cardiac and lung disease), medicines are nonetheless commonly used in palliative care.

4.3.3 Fixed effects Tobit models

The analysis of this administrative data was complicated by the peculiarities of the structure of the Pharmacare benefit system. Because individuals under the age of 65 faced a deductible, only those individuals with sufficiently large drug expenditures submitted a claim and registered positive drug expenditures. Annual purchases which were lower than the deductible level are unknown (censored) - arbitrarily set equal to zero or the deductible level. It is well known that estimation using standard regression models will not produce consistent parameter estimates when applied to data censored at these year-specific deductible amounts because the expected value of the disturbance term is nonzero.

Maximum likelihood (ML) methods are usually employed to produce consistent parameter estimates when the dependent variable is censored. Although estimation is usually straightforward, using censored longitudinal data may pose problems if each cross-sectional unit (i.e., individual) has a constant or "fixed" effect on the dependent variable. The problem is that there are typically only a few time series observations with which to estimate each of the individual-specific intercept dummies. Even if there are a large number of individuals, the desirable properties of ML estimates are only realized when the number of time series observations per individual grows large. ML estimates of these fixed effects using only a few time series observations may therefore be inconsistent. While it is true that the fixed effects estimates are not of primary interest, the inconsistency in these estimates will adversely affect the estimates of interest since in general, these "interesting" parameter estimates are correlated with the fixed effects.

The extent to which asymptotic theory provides a good guide in practice clearly depends on the nature of the data (e.g., sample size, choice of regressors). Simulation methods are one means of investigating this issue for specific estimation problems. Monte Carlo evidence reported by Heckman and MaCurdy (1980) suggests that the problem may not always be severe. This conclusion was based on a fixed effects probit model in which eight time series observations per cross-sectional unit were available. Even if the incidental parameters problem does not arise for the present analysis, however, one is still left with the practical

problem of estimating thousands of fixed effects parameters. (If the data were not censored, this problem could be avoided by first-differencing the data, thereby eliminating the fixed effects.) In addition, if the fixed effects are estimated using tobit, observations for individuals with censored observations in all years must be discarded because the corresponding fixed effect estimate is infinite.

4.3.3.1 A tobit model for panel data - Pantob

An alternative to estimating fixed effects in the tobit model is to use the "Pantob" estimator developed by Honoré (1992). This estimator has several advantages over ML. First of all, estimates are consistent (as the number of *individuals* grows large, holding the number of time series observations fixed) in the presence of fixed effects and can be shown to be asymptotically normal; hypothesis tests can therefore be conducted using conventional procedures. Second, hundreds of fixed effects parameters are not actually estimated. Third, the estimators require far less structure on the form of the distribution of the disturbances than ML estimates. The disturbances need only be identically and independently distributed and homoskedastic for each individual. This feature is quite attractive because the tobit model is quite sensitive to the assumptions of normality and homoskedasticity across both individuals and years (Horowitz and Neumann 1989; Moon 1989). The distribution of real drug expenditures graphed

in Appendix D indicates that the normality assumption may be inconsistent with these data.

The Pantob estimator exploits the assumption that for an individual, the actual (uncensored) drug expenditures in each of the eight years are independently and identically distributed, after conditioning on the covariates. This implies that two symmetry conditions must hold. Honoré demonstrates that these symmetry conditions are, in turn, the necessary conditions for the minimization of two objective functions. The Pantob estimators minimize these objective functions. Details of the estimation technique are provided in Appendix J.

The fact that the data contain observations on a large number of individuals appears to meet one of the requirements for consistency. In addition, for Pantob estimates to be consistent, errors must be independent and homoskedastic for observations on the same individual. Even if there is serial correlation, however, the estimates may still be consistent if the fixed effect captures some dependence between the error terms. Honoré notes (page 534) that the restrictions on the disturbance process are satisfied if the error terms are jointly normal with equal variance but arbitrary positive correlation.[41] The assumption that the variances of the disturbances remain constant across time may be problematic. As individuals age and health status worsens one might expect the range of medications which

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[41] Dependent normals with positive correlation can be written as a (normal) fixed effect plus independent normals - the dependence can be captured in the fixed effect

could be used in the management of disease to increase as well. Data from the 1990 OHS indicate that this might be likely. Models of drug utilization estimated using these data indicated that the variance of the underlying behavioural models of probability of any drug use and the number different drugs taken by users increased, the lower was health status. Another limitation is that Pantob permits censoring at zero only. In other words, the observed dependent variable Y_{it} is subject to the censoring rule: $Y_{it}=\max\{0,Y_{it}^*\}$ where Y_{it}^* is the actual (latent) dependent variable. But censoring thresholds in the Pharmacare data set vary with the calendar year of the observation. Modifications to the estimating equations must therefore be made.

4.4 Empirical Results

4.4.1 Analysis of Year Effects on Drug Utilization

In order to evaluate the behaviour of expenditures over time, Pantob was used to estimate the effects of year-specific indicator variables on real drug expenditures. This method was preferred to graphing the raw data because Pantob controls for both censoring and individual level effects. It should be noted that this model attempts to explain variations in the latent, not reported, drug expenditures. Graphs of these year effects may nonetheless provide information on the functional

form for the model including the linearity of age and the behaviour of expenditures after the change in insurance status at age 65. Separate models were estimated on the subsamples stratified by sex, birth year (1921, 1923, and 1925), and whether or not premium assistance for medical services had been received during the 8 year period: 1985-1992.

This model can be written as:

$$IngEA^*_{it} = \alpha_i + \gamma_t + \varepsilon_{it} \qquad (4.1)$$

where:

$IngEA^*_{it}$	actual real expenditures on prescription drugs taken by individual i over calendar year t
$IngEA_{it}$	observed (censored) real expenditures = $\max(IngEA^*_{it}, c_{it})$
c_{it}	real deductible facing individual i in year t
α_i	the "fixed effect" on drug expenditures for individual i
γ_t	coefficient on the year "t" dummy
ε_{it}	disturbance term $\varepsilon_{it} \sim IID(0,\sigma_i^2)$

The censoring thresholds (i.e., the real deductibles, c_{it}) vary by year. Censoring values are displayed below.

Year	Nominal Deductible	Real Deductible
1985	$200	$218
1986	$200	$200
1987	$275	$261
1988	$300	$268
1989	$300	$256
1990	$325	$277

Pantob permits censoring at zero only. To adapt the model to the form of censoring allowed by Pantob, the censoring threshold could be subtracted from both sides of the equation. The censoring process now becomes: $IngEA_i = \max(IngEA^*_{it} - c_{it}, 0)$. This amounts to subtracting c_{it} from the observed dependent variable. In this model, the effect of c_{it} is absorbed in the coefficient on the year dummies.

Drug expenditures in the year in which the individual turn 65 are the sum of both censored Plan E (under 65) and uncensored Plan A (65 and older) expenditures. But Pantob requires that total annual expenditures be subject to the same censoring process. Treating the (usually positive) annual expenditures as being censored, for example, will inflate the estimate of the year effect. Alternatively, if expenditures in this transition year are treated as being uncensored, the year effect will be under-estimated. The solution adopted was to

artificially censor the annual expenditure in the transition year at the real Plan E deductible for that year.

As described in Appendix J, there are actually several Pantob estimators, each associated with the minimization of a different loss function. Pantob year effect estimates are based on the minimization of the quadratic loss function. Minimization proceeded in two stages. The first step consisted of using the downhill simplex method to locate the neighbourhood of the minima. The Newton-Raphson method was then used to refine these estimates, taking the set of estimates from the first stage as starting values.

Pantob estimates of the year effects on drug utilization for individuals in 12 subsamples are summarized in Figures 4-16 to 4-19 below. Values of c_a (specific to each birth cohort) have been added to the estimated year effects to retrieve estimates of γ_r. These graphs reveal a number of points. First, the assumption that the effect of age on utilization is linear seems to be reasonably consistent with the data. Second, the earlier observation that the drug utilization profiles of individuals born in later years (e.g., 1925) are higher than the profiles of those born earlier (1921, 1923) is evident in these data as well. Finally, it appears that in a number of subsamples there was only a temporary increase in drug expenditures at 65 with consumption reverting to pre-65 trend levels by age 66. This effect was most pronounced in the 6 female subsamples. The drug expenditures of males on

premium assistance, on the other hand, appeared to increase permanently after the onset of Plan A benefits.

4.4.2 Modelling Utilization Behaviour Around Age 65

These graphs of drug consumption over time suggest that the onset of Plan A benefits has two effects on drug use. One effect is the permanent upwards shift in the drug use profile, which was observed primarily among males receiving premium assistance. The other is a temporary increase in use in the year of the onset of Plan A eligibility, followed by a reversion to pre-65 trends in the following years. A number of models of physician/patient behaviour are consistent with the permanent upwards increase in drug utilization once insurance benefits are improved. These models are less convincing in explaining the temporary upwards shift in utilization at 65.

Figure 4-16 Pantob-Estimated Age/Year Effect on Real Drug Expenditures for Females not receiving Premium Assistance, by Birthyear

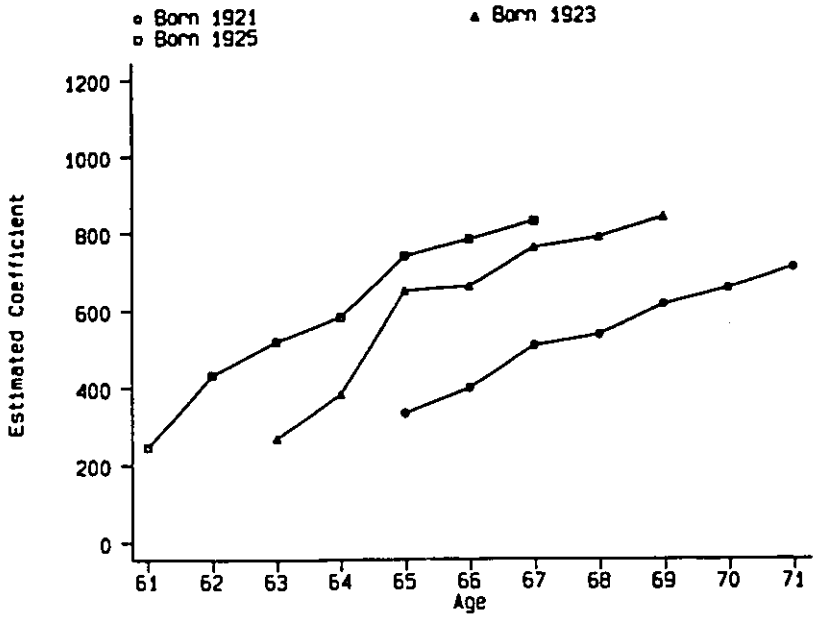


Figure 4-17 Pantob-Estimated Age/Year Effect on Real Drug Expenditures for Females receiving Premium Assistance, by Birthyear

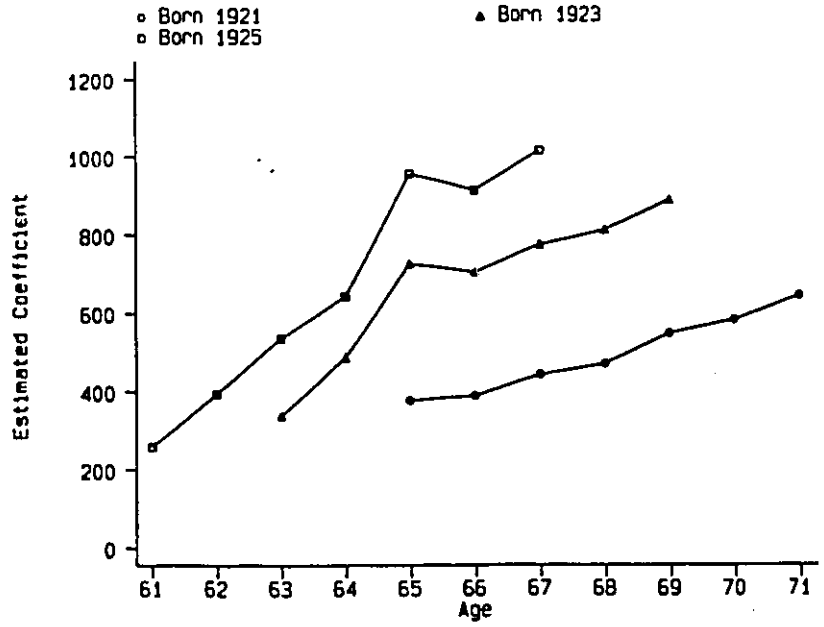


Figure 4-18 Pantob-Estimated Age/Year Effect on Real Drug Expenditures for Males not receiving Premium Assistance, by Birthyear

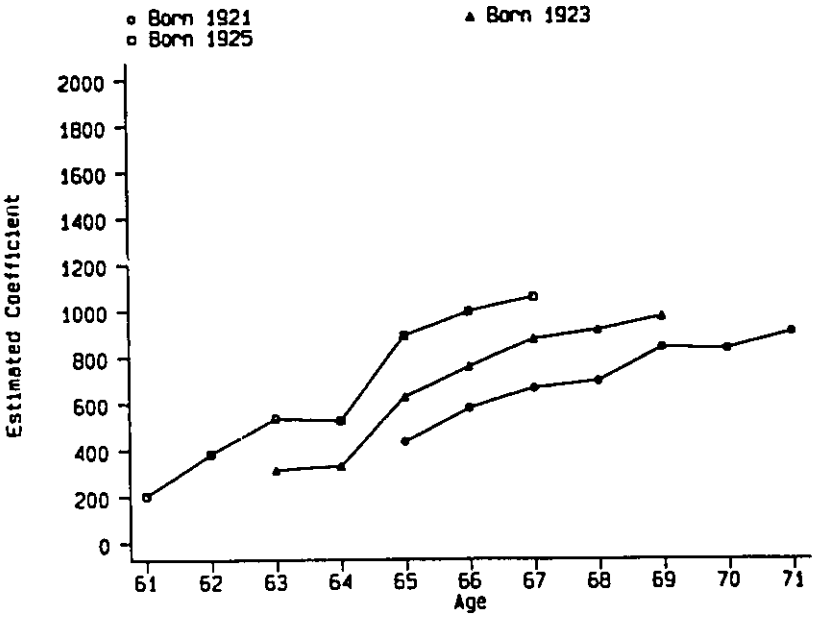
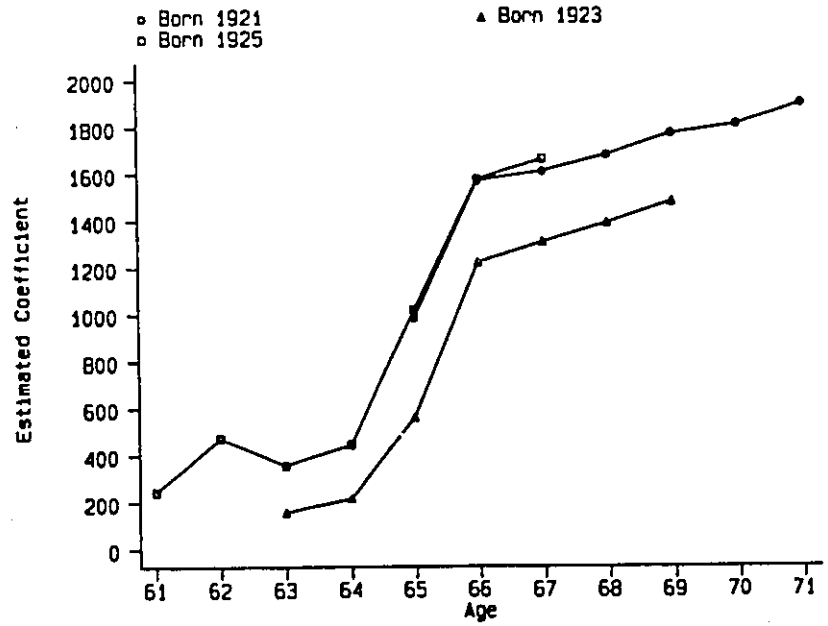


Figure 4-19 Pantob-Estimated Age/Year Effect on Real Drug Expenditures for Males receiving Premium Assistance, by Birthyear



One explanation of this phenomenon is that the change in drug insurance benefits at 65 does not alter drug prescribing and compliance patterns. Instead, the price change causes a temporary intertemporal substitution of drug consumption. It is intuitively plausible that individuals who are reaching their 65th birthday in a few months might delay filling prescriptions until their 65 birthday because drugs are less costly then. This might be responsible for the temporary increase in expenditures observed in the year individuals reach 65.

There are, however, limits on the time frame in which this substitution is feasible. Individuals cannot forgo the use of what they or their physicians perceive to be potentially needed medications indefinitely. This delay in consuming medicines can plausibly commence no earlier than 12 months before the 65th birthdate. On the other hand, if these graphs above serve as any indication, individuals must be delaying consumption no later than 6 months before the 65th birthdate. The intuition for this is based on the observation that individuals in the sample are born, on average, in the middle of the year. If individuals begin to forgo medications less than 6 months prior to their 65th birthdate and consume these within the 6 months after their 65th birthdate, then there will be no net effect on total expenditures for the calendar year in which they reach 65 years. Only if the anticipatory period begins 6 months prior to the 65th birthdate, so that consumption is (on average) delayed in the *previous* calendar year, will there be a temporary increase in the calendar year in which individuals reach 65 years. The

data do support the notion that there is a temporary upwards increase in expenditures in the year in which individuals from some subsamples turn 65. There is less support, however, for the offsetting anticipatory decline in expenditures in the year in which these individuals turn 64.

Another complication is that incentives for substitution depend on the total annual expenditures for individuals made in each calendar year while they are still in the pre-65 "anticipatory" period. Recall that individuals with expenditures under the deductible level face a marginal drug cost of 100%, while those who have exceeded their annual deductible face a marginal drug cost of only 20%. Moreover, the marginal drug costs may vary in this anticipatory period. For example, suppose that an individual's birthdate is November 1 and begins to substitute expenditures a full 12 months prior to her 65th birthday. Suppose further that she has drug expenditures exceeding her annual deductible by her 64th birthdate. Her marginal cost is only 20% for the remaining two months of the year, but will increase to 100% on January 1. Marginal drug cost will only decline back to 20% if she happens to exceed her deductible by November 1.

It is convenient to distinguish between transitory and permanent effects on consumption on the basis of parametric tests. Permanent effects would be evidenced by a significant coefficient on a dummy indicating the period that individuals were eligible for Plan A insurance benefits. The "transitory" effects such as the one discussed above requires a fair amount of structure on the

substitution response. In order to model this, consumption was assumed to decline in the 12 month period starting at the individual's 64th birthday until the individual's 65th birthday. It is likely that the rate of substitution will be higher, the closer the individual is to eligibility for Plan A benefits. There are two reasons for this. First, the perceived health costs of postponing the use of prescribed medications are lower, the shorter is the delay period. Second, the marginal drug costs individuals are required to pay is probably 100% in the calendar year of their 65th birthdate and will typically be lower in the previous calendar year. The reason is that it is less likely that individuals' expenditures accumulated over the portion of the year in which they are under 65 and in Plan E exceeds the annual deductible. On the other hand, it is more likely that individuals have exceeded their deductible in the previous calendar year and are paying only 20% of drug costs on the margin. To accomodate this, a dummy variable was constructed, the value of which decreased from 0 at the individual's 64th birthday to -2 at the individual's 65th birthday. (See Figure 4-20.) Drug consumption that is postponed during the previous year is then made up after the 65th birthdate, until the 66th birthdate. Again, most of this utilization occurs directly after the onset of Pharmacare eligibility. This is reflected by the value of the dummy which declines from a value of +2 at the 65th birthday to 0 at the 66th birthday. It was assumed that *total* drug expenditures over the 64th and 65th year are unaffected; instead consumption has simply been shifted between the pre-insurance year and the post

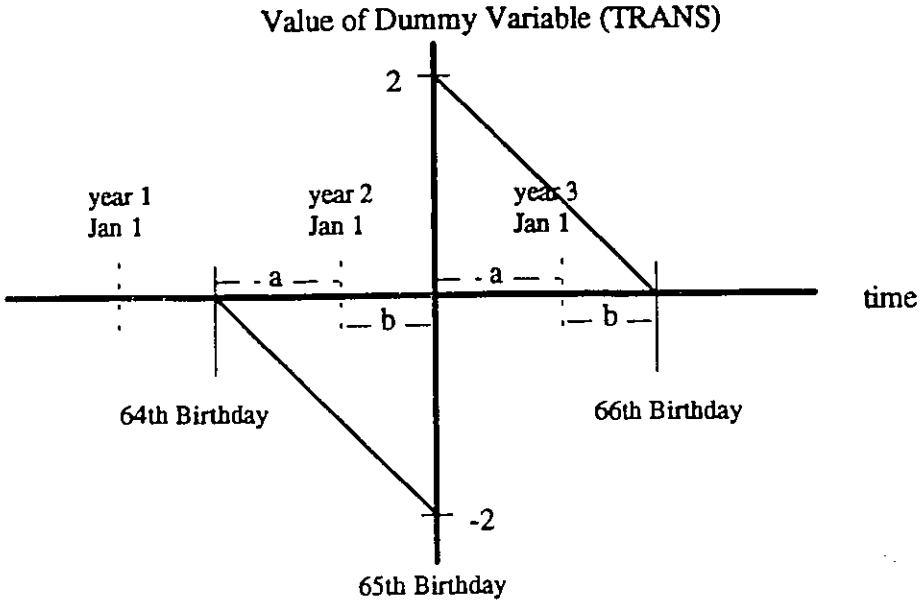
insurance year. (Technically, the area in the lower left triangle (-1) exactly offsets the area in the upper right triangle (+1).) Implicit in this model is the assumption that the real interest rate is zero. The higher the real interest rate, the greater the incentive for foregoing drug consumption until the second period.

The value of the dummy variable must be appropriated over the unit of observation - the calendar year. Integrating the area in the triangles for each calendar year produces the general formula for the value of the dummy for individual i in year t ($TRANS_{it}$):

$$TRANS_{it} = pr65_{it}^2 - pr64_{it}^2$$

where $pr65_{it}$ is the proportion of calendar year t individual i is 65, and $pr64_{it}$ is the proportion of calendar year t individual i is 64. For example, in the diagram below, the proportion of year 2 spent at age 65 is the distance a, and the proportion of year 2 spent at 64 is the distance b.

Figure 4-20 Construction of the Variable to Identify Temporary Effects on Utilization Induced by the Change in Insurance Status



In order to accommodate permanent effects on drug utilization, a variable was constructed indicating the proportion of the year t individual i was age 65 or older and therefore eligible for Plan A Pharmacare benefits ($PERM_{it}$).

4.4.2.1 Implementation of Pantob

In order to run Pantob, the empirical model must be modified. The model to be estimated is:

$$IngEA^*_{it}=\alpha_i+\beta_1 AGE_{it}+\beta_2 PERM_{it}+\beta_3 TRANS_{it}+\varepsilon_{it} \qquad (4.2)$$

where:

$IngEA^*_{it}$	actual real expenditures on prescription drugs taken by individual i over calendar year t
$IngEA_{it}$	observed (censored) real expenditures = $\max(IngEA^*_{it}, c_t)$
c_t	real deductible facing individual i in year t
α_i	the "fixed effect" on drug expenditures for individual i, by definition any effect which remains constant over time t
AGE_{it}	age of individual i at end of year t
$PERM_{it}$	proportion of the year t individual i was eligible for Pharmacare benefits
$TRANS_{it}$	$pr65^2_{it} - pr64^2_{it}$
$pr64_{it}$	the proportion of year t individual i was 64 years old
$pr65_{it}$	the proportion of year t individual i was 65 years old
ε_{it}	disturbance term $\varepsilon_{it} \sim IID(0,\sigma_i^2)$ [42]

To adapt the model to the form of censoring allowed by Pantob c_{it} is subtracted from the observed dependent variable and added as an additional regressor:

$$IngEA^*_{it} - c_{it} = \alpha_i + \beta_1 AGE_{it} + \beta_2 PERM_{it} + \beta_3 TRANS_{it} + \beta_4 c_{it} + \varepsilon_{it} \qquad (4.3)$$

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[42] Note that the assumed form of the disturbance term permits heteroskedasticity across individuals.

The censoring process now becomes: $IngEA_{it} = \max(IngEA^*_{it} - c_{it}, 0)$. If the model is correctly specified, the coefficient on c_{it}, β_4, should be equal to -1.

Given the heterogeneity in the responses to eligibility for Plan A benefits observed in Figures 4-16 to 4-19, it may be preferable to let the coefficients vary by subsample. It is not possible, however, to add interaction terms to allow these coefficients to vary by individuals' fixed characteristics (e.g., sex, birthyear). Fixed effects estimators cannot estimate the separate effects of variables which do not change over the panel for a given individual because the influence of these variables are absorbed into the fixed effect. Instead, parameter heterogeneity will be handled by partitioning the sample by sex, birth year (1921, 1923, 1925), and whether or not premium assistance for medical services had been received during the 8 year period: 1985-1992. Separate estimates will be produced for these 2*3*2 =12 subsamples.

Estimates of the parameters and standard errors appear in Table 4-9 below. The column "*t*-ratio" is the test statistic associated with the hypothesis that the coefficient on all variables except c_{it} is zero. The *t*-ratio corresponding to c_{it} is the test statistic associated with the hypothesis that the coefficient on the censoring variable, β_4, is -1. Also reported is "Signif. Test", a chi-squared-distributed test statistic of the null hypothesis that the regressors are jointly insignificant. This was

easily rejected in each of the models. The minimized value of the loss function and the number of observations are also reported.

It appears that in most of these preliminary models, the onset of Plan A Pharmacare drug coverage at age 65 is associated with a permanent upwards increase in drug utilization. The *t*-ratios associated with the *PERM* variable were generally statistically significant at conventional levels. The small *t*-ratios associated with the *TRANS* regressors, on the other hand, indicated that the specified pattern of inter-temporal substitution of drug expenditures was not operational. The magnitude of the estimated permanent effect on real drug expenditures varied by subsample. In general, the increase in utilization for males was larger than the increase observed for females. Also, males receiving premium assistance were observed to have larger increases in utilization than males not receiving premium assistance. This effect was not evident among females. Finally, in the subsamples stratified by sex and premium assistance coverage status, there appeared to be no gradient in the increases in utilization by birthyear.

In most of the models using observations on males, the estimates of the coefficient on the censoring threshold, β_4, were not significantly different from -1. (The exception was the model estimated using data on males born in 1923 receiving premium assistance. The estimate for this group was -2.) The estimates of β_4 for the six female subsamples, on the other hand, were all significantly greater than -1.

Table 4-9 Pantob Estimates of Effect of Insurance on Prescription Drug Expenditures

Subsample: Born 1921, No Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	66.45	11.94	5.57	55.49	4.91	11.29
Perm	287.50	166.50	1.73	314.00	103.10	3.05
Trans	37.98	54.43	0.70	-62.54	37.21	-1.68
C_{it}	-0.76	0.53	0.45	-0.31	0.27	2.56
Objective Fn.	2.08E+09			2.69E+09		
Signif. Test	51.80 *P<0.001*			255.40 *P<0.001*		
No. Obs.	6,656			13,080		

Subsample: Born 1923, No Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	64.65	35.84	1.80	49.08	10.76	4.56
Perm	391.10	146.70	2.67	451.00	110.70	4.07
Trans	54.64	62.54	0.87	-67.48	42.19	-1.60
C_{it}	-0.66	0.29	1.17	-0.17	0.24	3.41
Objective Fn.	2.99E+09			2.29E+09		
Signif. Test	27.70 *P<0.001*			143.70 *P<0.001*		
No. Obs.	6,848			11,680		

Table 4-9, continued

Pantob estimates of Effect of Insurance on Prescription Drug Expenditures

Subsample: Born 1925, No Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	73.45	45.66	1.61	91.58	29.63	3.09
Perm	574.60	319.20	1.80	257.60	157.10	1.64
Trans	75.91	118.00	0.64	-14.02	62.45	-0.22
C_{it}	0.05	0.53	1.99	0.01	0.30	3.39
Objective Fn.	1.37E+09			2.54E+09		
Signif. Test	48.60 *P<0.001*			92.10 *P<0.001*		
No. Obs.	7,776			11,232		

Subsample: Born 1921, Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	62.85	9.32	6.74	49.31	4.65	10.62
Perm	1,144.00	397.30	2.88	283.20	66.80	4.24
Trans	-73.00	62.66	-1.17	-6.67	26.12	-0.26
C_{it}	-1.04	0.80	-0.05	-0.09	0.21	4.34
Objective Fn.	2.75E+09			3.63E+09		
Signif. Test	134.20 *P<0.001*			276.70 *P<0.001*		
No. Obs.	8,096			15,288		

Table 4-9, continued

Pantob estimates of Effect of Insurance on Prescription Drug Expenditures

Subsample: Born 1923, Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	84.98	14.32	5.93	53.89	7.21	7.47
Perm	504.10	156.50	3.22	436.40	85.58	5.10
Trans	47.83	49.42	0.97	-134.00	37.50	-3.57
C_{it}	-2.19	0.43	-2.80	-0.01	0.16	6.23
Objective Fn.	1.57E+09			2.52E+09		
Signif. Test	140.60 *P<0.001*			247.20 *P<0.001*		
No. Obs.	7,832			12,840		

Subsample: Born 1925, Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	43.82	61.51	0.71	88.86	19.18	4.63
Perm	1,082.00	400.20	2.71	472.70	139.90	3.38
Trans	-66.27	164.10	-0.40	-18.80	61.80	-0.30
C_{it}	-1.04	0.51	-0.07	0.30	0.24	5.48
Objective Fn.	1.21E+09			1.93E+09		
Signif. Test	73.80 *P<0.001*			214.70 *P<0.001*		
No. Obs.	6,016			11,184		

4.4.3 Sensitivity Analysis

Several alternative models were estimated to determine how the estimates of primary interest, *PERM*, were affected by model specification. The "baseline" model imposed restrictions on both (i) the adjustments to the censoring thresholds necessary to allow for estimation by Pantob and (ii) the treatment of expenditures around the individuals' 65th birthdate. The baseline model allowed for Pantob censoring by including an additional regressor c_{ir}. The estimated value of β_4 was, however, significantly different from -1 in all the subsamples of females. This finding perhaps indicates a model mispecification, although the exact nature of the mispecification is unclear. If the estimates of β_4 were found to be less than -1, for example, then it could be argued that increases in the Plan *E* real deductible levels were depressing drug utilization. The exact opposite was, however, found to be the case. An alternative method of satisfying the censoring requirements of Pantob is to artificially censor all observations (both Plan *E* and Plan *A* observations) at the highest deductible level facing individuals in the sample. The censoring threshold will therefore be constant. This will result in a loss of information, but will at least indicate if the estimates are robust to the arbitrary modifications to the model made to facilitate estimation using Pantob. Appendix I reports the information lost due the artificial censoring of the dependent variable. Approximately 14% of total expenditures were artificially censored; the actual

information loss varied between 11.2% and 17.4%, depending on the subsample. This censoring affected roughly one quarter of all observations.

The model of the substitution response induced by the onset of Plan *A* coverage at age 65 could also be incorrect. The estimates reported in Table 4-9 indicate that *TRANS* was non-significant in the estimating equations. In order to sharpen the focus on the estimation of the permanent effect, observations on years in which individuals reached 65 years were removed and the models were re-estimated.

A total of three sets of additional models were estimated. The first model, which appears in Appendix E, imposed the alternative censoring process. Appendix F reports the estimates based on excluding observations in which individuals reach 65 years. Finally, Appendix G imposes both restrictions together. The estimates of the effect of Plan A coverage on prescription drug utilization from the four models is summarized in Table 4-10.

Estimates produced from the subsamples excluding observations on the years in which individuals reached 65 years were particularly sensitive. Dropping this observation proved to be problematic for estimation using observations on individuals born in 1921 because this left only one observation on individuals under 65 and not receiving Plan *A* coverage. Because baseline expenditures were difficult to establish, estimates of the variable *PERM* were therefore highly imprecise.

Parameter estimates and inferences made on these estimates using observations on females were sensitive to the choice of modification used to permit Pantob censoring. This is not entirely surprising given that estimates from the females subsamples also appeared to reject the initial technique used to adjust for the form of censoring allowed by Pantob (i.e., adding c_{it} and restricting its coefficient to equal -1). This may constitute some evidence that the models for females are somehow mispecified; if the model were correctly specified, the form of adjustment used should not matter.[43] There were less dramatic fluctuations in the estimates of *PERM* from the male subsamples; the same subsamples appeared to be consistent with the original Pantob censoring. Regardless of the specification chosen, the estimates seem to suggest that males on premium assistance sustain a permanent increase in real drug expenditures after eligibility for Plan *A*. Using the estimates from Model 4, which arguably provides the "cleanest" set of estimates, the remaining subsamples do not have statistically significant permanent increases in utilization.

Appendix F reports the Tobit estimates of model 4. Both Pantob and Tobit account for the fact that expenditures are left censored at real deductible levels. Tobit, however, restricts all the fixed effects parameters to equal zero. Comparison of the Tobit estimates to the Pantob estimates may therefore indicate

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[43] The loss of information due to artificially censoring in principle could lead to an efficiency loss, but should not affect the consistency properties of the estimators.

the importance of modeling fixed effects. Of course, the distributional assumptions inherent in the two models differ, with Tobit imposing more stringent requirements (i.e., normality). A finding that estimates differ substantially could therefore indicate that Tobit's restrictions on either the conditional mean function or the assumed distribution of the disturbances are incorrect. The Tobit estimates were found to be larger in magnitude than the Pantob estimates. They were all also statistically significant at conventional levels, suggesting that at least one of these explanations could be operational.

Table 4-10 Summary of Increases in Expenditures after Plan A Eligibility

Subsample			Estimate of Increase in Expenditures				Range	
			Shading indicates significance at the 5% level.					
Sex	**Received Premium Assistance?**	**Birth Year**	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Min**	**Max**
Female	*No*	*1921*	314	-17	-25	-55	-55	314
	No	*1923*	451	126	434	72	72	451
	No	*1925*	258	-214	52	-74	-214	258
Female	*Yes*	*1921*	283	-100	-7	-53	-100	283
	Yes	*1923*	436	95	553	12	12	553
	Yes	*1925*	473	-113	287	-22	-113	473
Male	*No*	*1921*	288	25	-42	89	-42	288
	No	*1923*	391	123	125	139	123	391
	No	*1925*	575	102	957	178	102	957
Male	*Yes*	*1921*	1,144	964	6	1082	6	1,144
	Yes	*1923*	504	610	601	642	504	642
	Yes	*1925*	1,082	1,114	1388	992	992	1,388

	Estimation Method	Regressors
Model 1	Pantob	*AGE, PERM, TRANS, Ct*
Model 2	Pantob	*AGE, PERM, TRANS*
Model 3	Pantob	*AGE, PERM, Ct*
Model 4	Pantob	*AGE, PERM*

Notes

Artificially censored obs. on 65th year.

Artificially censored all obs. at highest deductible

Excluded observations on the 65th year.

Artificially censored all obs. at highest deductible and excluded observations on the 65th year.

4.4.4 Effects of Insurance on Pharmacare Expenditures

It is important to distinguish the effects of expanding insurance coverage to senior populations on the actual (unobserved) prescription drug expenditures from the effects on reported expenditures, which are equivalently the value of claims against the Pharmacare insurance plan. Estimates of the effect of insurance on actual expenditures increases will in general over-estimate the effects of insurance eligibility on reported drug use. This is evident when the estimates of the increase in expenditures presented in Table 4-10 above are compared to the unconditional reported data plotted in Figures 4-2 to 4-14. The expected increase estimated using Pantob is over $1,000 for some subsamples, yet this is not consistent with the graphs which suggest, in some cases, increases an order of magnitude lower.

It is possible to estimate the effects of insurance on claims against Pharmacare by using the Pantob estimates. The Pantob estimates of model 4 presented in Table 4-10 above correspond to the following model:

$$IngEA^*_{it} = \alpha_i + \beta_1 AGE_{it} + \beta_2 PERM_{it} + \varepsilon_{it} \qquad (4.4)$$

or more succinctly as:

$$IngEA^*_{it} = X_{it}\beta + \varepsilon_{it} \qquad (4.5)$$

where $IngEA^*_{it}$ is the latent or actual expenditures of individual i during year t, X_{it} is the matrix of observations on all covariates and β is the corresponding parameter vector. Observed expenditures $IngEA_{it}$ are governed by the censoring process: $IngEA_{it} = \max(IngEA^*_{it} - c, 0)$, where c is the highest deductible level observed over the 8 year sample period.

McDonald and Moffitt (1979) give formulae for the expected value of observed values of drug expenditures, $IngEA_{it}$, which depend on the assumed Gaussian distribution of the disturbances ε_{it}, where $\varepsilon_{it} \sim N[0,\sigma^2]$. Dropping subscripts for notational convenience, the formula is:

$$E(IngEA) = X\beta F(Z) + \sigma f(z) \tag{4.6}$$

where $z = X\beta/\sigma$, $f(z)$ is the probability density function of the error distribution evaluated at z and $F(z)$ is the cumulative density function of the error distribution also evaluated at z, which is equivalently the probability of being below the censoring threshold. The expected value of drug expenditures on above limit observations is:

$$E(IngEA \mid IngEA > 0) = X\beta + \frac{\sigma f(z)}{F(z)} \tag{4.7}$$

Equations (4.6) and (4.7) are related as follows:

$$E(lngEA\ ) = F(z)E(lngEA\ |lngEA\ > 0) \tag{4.8}$$

Application of these formulae is hampered by lack of information on both Pantob predicted expenditures and the error term distribution. Lack of information on the error distribution is not a problem unique to Pantob. In order to calculate these formulas, normality of the error distribution will be assumed. Pantob does not provide fixed effects estimates because these cannot be consistently estimated; predictions on the value of the latent expenditures can therefore not be calculated unless some additional assumptions are made. The maintained hypothesis is that the average value (over all observations and individuals) of the fixed effect is equal to the difference between the average value of observed expenditures in 1985 and the prediction of the observed part of the model:

$$c + \beta_1 AGE_{it} + \beta_2 PERM_{it}$$

evaluated at sample average values.

Because Pantob imposes minimal restrictions on the error distribution no estimate of the variance of the error distribution is calculated. One solution is to use the error variance calculated from Tobit regressions of the models. Because

normality has already been assumed, the only additional restriction required to adopt this approach is that setting the fixed effects parameters to zero will not adversely affect the variance estimates.

Table 4-11 and Table 4-12, below, present estimates of the effect of insurance eligibility on the 12 subsamples. Derivative methods were not used because the covariate of interest *PERM*, is dichotomous. The estimate of the increase due to Plan A coverage was instead calculated as the difference in expected use by a 65 year old with average fixed effects who was eligible for coverage and the expected use by an individual with the same characteristics who was ineligible for benefits. The columns under the heading Pantob latent expenditures refer to the effect of insurance on actual expenditures (equation 4.5). The second set of three columns calculate the effect on reported or observed expenditures, which is also the effect of insurance on Pharmacare claims (equation 4.6). The final set of columns refer to the effect of insurance on individuals whose expenditures exceed the deductible limit (equation 4.7). In Table 4-11, estimates of β are calculated by Pantob and Tobit estimates of the error variance, σ^2 are used. Table 4-12 uses Tobit estimates of both σ and β.

Table 4-11 Effects of Plan A Eligibility on Latent and Observed Expenditures - Pantob Estimates with Sigma estimated by Tobit

Subsample			Pantob Latent Expenditures			Pantob Observed Expenditures			Pantob Observed Expenditures above Limit		
Sex	Received Premium Assistance?	Birth Year	Insured	Non-Insured	*Change*	Insured	Non-Insured	*Change*	Insured	Non-Insured	*Change*
Female	*No*	*1921*	-226.56	-171.70	*-54.86*	175.27	196.46	*-21.19*	472.61	489.46	*-16.85*
	No	*1923*	7.84	-63.70	*71.54*	340.52	305.67	*34.85*	676.02	650.44	*25.59*
	No	*1925*	157.00	231.40	*-74.40*	548.91	591.03	*-42.12*	991.90	1,021.81	*-29.91*
Female	*Yes*	*1921*	-180.43	-127.56	*-52.87*	189.08	210.78	*-21.69*	478.73	495.59	*-16.86*
	Yes	*1923*	-21.13	-32.65	*11.52*	300.31	294.70	*5.61*	613.88	609.76	*4.12*
	Yes	*1925*	215.33	237.71	*-22.38*	490.90	504.23	*-13.34*	830.76	840.17	*-9.41*
Male	*No*	*1921*	-234.11	-323.27	*89.16*	304.36	269.27	*35.10*	742.02	714.37	*27.65*
	No	*1923*	19.65	-119.75	*139.40*	475.92	408.57	*67.35*	939.25	889.72	*49.52*
	No	*1925*	311.85	133.55	*178.30*	633.87	531.08	*102.79*	1,045.58	972.76	*72.81*
Male	*Yes*	*1921*	-109.77	-1,191.77	*1,082.00*	303.96	37.57	*266.39*	673.78	411.88	*261.89*
	Yes	*1923*	221.86	-420.04	*641.90*	489.92	195.69	*294.23*	823.59	602.57	*221.03*
	Yes	*1925*	845.64	-146.76	*992.40*	1,012.33	404.40	*607.93*	1,329.57	896.85	*432.71*

Note: simulation refers to an individual aged 65 years with and without Plan A insurance coverage.

Table 4-12 Effects of Plan A Eligibility on Latent and Observed Expenditures - Tobit Estimates

Subsample			Tobit Latent Expenditures			Tobit Observed Expenditures			Tobit Expenditures above limit		
Sex	Received Premium Assistance?	Birth Year	Insured	Non-Insured	*Change*	Insured	Non-Insured	*Change*	Insured	Non-Insured	*Change*
Female	*No*	*1921*	-926.44	-1,062.29	*135.85*	27.93	17.89	*10.04*	314.34	292.74	*21.60*
	No	*1923*	-1,165.51	-1,313.96	*148.45*	32.06	21.52	*10.54*	382.53	359.32	*23.21*
	No	*1925*	-1,381.71	-1,912.29	*530.59*	67.78	24.78	*43.01*	570.91	485.60	*85.31*
Female	*Yes*	*1921*	-921.87	-1,028.27	*106.40*	26.73	18.77	*7.95*	308.16	291.18	*16.98*
	Yes	*1923*	-1,006.79	-1,173.57	*166.78*	35.87	22.34	*13.53*	364.63	337.51	*27.12*
	Yes	*1925*	-1,049.69	-1,388.73	*339.03*	61.33	28.29	*33.04*	467.31	409.37	*57.94*
Male	*No*	*1921*	-1,429.28	-1,699.21	*269.92*	38.65	21.14	*17.51*	466.60	425.66	*40.94*
	No	*1923*	-1,626.86	-2,005.45	*378.59*	43.37	20.38	*22.99*	528.62	472.40	*56.22*
	No	*1925*	-1,497.86	-2,208.28	*710.41*	52.95	12.35	*40.60*	541.74	438.45	*103.29*
Male	*Yes*	*1921*	-939.59	-1,906.54	*966.95*	67.08	5.17	*61.92*	457.66	313.81	*143.85*
	Yes	*1923*	-1,096.05	-1,809.74	*713.69*	53.01	8.63	*44.38*	449.85	343.56	*106.29*
	Yes	*1925*	-1,180.76	-2,335.68	*1,154.92*	100.12	10.99	*89.13*	623.86	443.02	*180.84*

As the data in Table 4-11 indicate, the effects of insurance eligibility on reported expenditures are much more modest than the effects on latent expenditures. Examination of the increases among males receiving premium assistance, which were earlier deemed to be statistically significant, indicates that the estimated increase among the observed expenditures of males in the 1921 cohort are roughly just 25% of the increase in latent expenditures ($266 versus $1,082). The corresponding proportions for the 1923 and 1925 cohorts are 46% ($294 versus $642) and 61% ($608 versus $992) respectively.

The reduction in the estimated increase in prescription drug expenditures are extreme when one compares the predicted latent and observed expenditures using Tobit (Table 4-12). Indeed, the estimated changes in observed expenditures are well below 10% of the increase in the latent expenditures. The tobit predictions should not be over-interpreted, however, given that tobit is probably not the right statistical model for these data. The predictions of observed expenditures for insured and uninsured individuals and the change in expenditures, for example, appear to be somewhat downward biased relative to the unconditional data. These findings appear to be consistent with the implications of failure to control for fixed effects discussed in Section 4.3.

These estimates confirm that the provision of prescription drug insurance for seniors will have only small effects on the volume of prescription drug claims against the Pharmacare Insurance Plan A for the majority of the individuals in the

sample. Indeed, there were generally statistically insignificant effects for females. Using the data reported in Table 4-11, males not receiving any premium assistance were observed to increase expenditures between $35 and $103 (depending on the birthyear). Males on premium assistance, who have lower income on average, received additional public subsidy in the range $266 - $608 (again depending on the birthyear). Interestingly, the magnitude of the increase in utilization among males is higher, the later the individuals' birthdate.

4.5 Discussion

The effects of Government subsidies for seniors' prescription drug expenses is of significance for policy purposes. First, the responsiveness of prescription drug use to the drug insurance subsidy represents a source of growth on publicly subdized drug expenditures. More importantly, the removal of financial barriers to care may induce additional drug utilization which could have beneficial effects on patient health status. The results in this paper can address the fiscal implications, but are of limited informativeness in addressing the effects of additional drug use on patient health status.

To address the former issue, the annual real prescription drug expenditures of a panel of British Columbian seniors over the years 1985-1992 were analyzed. Even though these individuals were born in different years, 1921, 1923 or 1925,

they all reached 65 years of age sometime during the sample period and therefore became eligible for a Ministry of Health subsidy of 100% of the ingredient cost of their prescription drugs. Prior to this time, the Government reimbursed only a fraction of their drug expenditures over a deductible limit.

The distinguishing feature of the statistical methodology is in the use of a new estimator which permits consistent estimation in the presence of fixed effects on drug utilization. The following conclusions were drawn from the empirical results:

(1) The effect of the additional subsidy of prescription drugs at the 65th birthdate depended on the characteristics of the individuals and in some cases, the estimation technique chosen. Annual claims against the Government insurance plan by males with lower levels of income were observed to increase permanently after eligibility for subsidy. This result was reasonably robust to the estimation technique and specification chosen. On the basis of the preferred estimation technique, the extent of the increase was in the range $266-$608 (1986 dollars) depending on the individuals' birthyear. The magnitude of the increase in utilization among other individuals depended on the estimation technique. Using results from the preferred technique, the onset of insurance did not affect the drug utilization behaviour of females (both receiving and not receiving premium assistance). Annual prescription drug insurance claims by males not receiving

premium assistance increased modestly ($35 - $103) yet these were not statistically different from zero.

(2) There appeared to be a temporary increase in real drug expenditures during the year individuals turned 65. This phenomenon appeared to be consistent with individuals delaying filling prescriptions which were issued prior to their birthday until after their birthdate, at which time the cost to them was lower. Although this appeared to be an intuitively plausible explanation, the specified behavioural model was not found to be consistent with the data.

(3) Despite the uncertainty as to the effects of price changes on utilization, there were some more robust findings. First, utilization increased with age, a finding which is consistent with a large body of existing health services research. Second, there were important year effects on real prescription drug expenditures such that individuals reaching a given age in 1992 used more drugs and physician services than those reaching the same age in 1990 and 1988. The *increase* in the value of prescription drug claims after the onset of Plan A coverage was also found to be higher among males turning 65 in 1992 than males turning 65 in 1990 and 1988.

The balance of the evidence suggests that for most of the individuals analyzed in this sample, the introduction of additional insurance coverage at 65 is probably a relatively minor contribution to overall expenditure increase. Prescription drug claims by males with low income, however, appeared to increase substantially after the provision of insurance. This result is interesting given that individuals with low income probably face the highest financial barrier to prescription drugs prior to Plan A eligibility. *A priori*, one would therefore expect their utilization increases to be highest of all groups after Plan A eligibility. Why the same behavioural response was not observed among low income females is unclear.

From a fiscal viewpoint, the largest contribution to growth in Pharmacare expenditures was not found to be due to the extension of insurance benefits *per se*, but rather due to "year effects". On average, each year the real drug expenditures of all individuals (regardless of age), increased 17%. Similar increases were observed in the use of physicians' services over time. One potential explanation for this phenomenon is technological advance: over time the scope and application of medical technology expands so that "more can be done". This interpretation of the data is consistent with Anderson *et al.* (1993) who found that a little over one third of the total increase in B.C. Pharmacare Plan A expenditures on prescription drugs between 1981/82 and 1988/89 was the result of the use of new drugs.

Anderson *et al.* (1993, page 205) note that the large increases in prescription drug expenditure growth due to increases in percapita utilization over time is consistent with the experience with other health services: "The finding that changes in utilization rates among the elderly are more influential than changes in demographics in driving increased utilization of prescription drugs is consistent with previous findings for physician (Barer *et al.* 1989) and acute-care hospital services (Anderson *et al.* 1990) in British Columbia. Previous work on drug utilization in Saskatchewan shows a similar pattern (Quinn, Baker and Evans 1992)."

The results are of course conditional on the maintained hypotheses. These include assumptions that the stochastic terms of the model are independent and homoskedastic, and that missing information on the extent of insurance coverage of those under 65 years has not introduced substantive measurement error into the insurance coverage variable. In addition, the analysis was restricted to individuals who came from single person households and who did not die over the sample period, raising questions as to the generalizability of these results to the larger population of all elderly (married and non-married, surviving and non-surviving) in British Columbia.

5. Conclusions

The elderly are the fastest growing segment of the North American population and also have the highest rates of health care utilization. These two forces have contributed to a growing interest in health care policy for this age group, especially on the issue of prescription drug coverage. Provincial governments in Canada all provide some level of subsidy for prescription drug expenditures incurred by the elderly, although the level of subsidy varies considerably. There is a growing interest by provincial governments in modifying the level of subsidy for medicines taken outside of the hospital by way of changing co-payment rates or eligibility criteria (Hurley and Johnson 1991).

Despite the interest in prescription drug coverage for the elderly and the development of a range of universal coverage plans in Canada, there is very little empirical evidence regarding the effects of prescription drug insurance on prescription drug use in this group. The populations studied in the existing literature have typically been non-elderly (and from jurisdictions outside of Canada). The degree to which this evidence can be generalized to the elderly, who are the heaviest users of medicines, is unclear.

This paper has attempted to shed light on this issue by examining the effects of enhanced prescription drug coverage on seniors from two provinces:

Ontario and British Columbia. Prior to turning 65, individuals in B.C. incurring large drug expenditures are eligible for a partial subsidy. There is no such public subsidy for Ontarians under 65, except for those covered by the Ontario Drug Benefit plan for other reasons such as low income or disease status, although some individuals do have coverage through private insurance plans. After turning 65, however, seniors from Ontario and B.C. are automatically extended full insurance coverage for drug ingredient cost under the auspices of, respectively, the ODB and B.C. Ministry of Health Pharmacare programs.

Longitudinal administrative claims data from the B.C. Ministry of Health Pharmacare program and cross sectional survey data from the 1990 Ontario Health Survey were used. Because selection into the experiment (i.e., turning 65) is not based on the decisions of the participants, this change in insurance status served as a relatively clean experiment to learn about the following specific effects of extending prescription drug insurance coverage to the elderly.

5.1 Effects of Insurance Coverage on Prescription Drug Utilization.

Previous analyses on non-elderly populations have demonstrated that prescription drug utilization appears to be somewhat sensitive to price, although the price elasticity appears to be well under one. This appears to be the case for seniors in these provinces as well. What the previous studies have not emphasized,

however, is the tremendous heterogeneity in the price responses observed. In this study, in Ontario the utilization responses among those with prior drug coverage was generally smaller than those who had no prior coverage. This was not surprising. The marked gender differences in utilization response observed was, however, not entirely expected. In Ontario the utilization responses among females without prior coverage (as measured by the changes in the number of different drugs taken) were significantly larger than that for males. Increases in the range 0.3 to 1.52 different drugs, representing relative increases of 35 - 40%, depending on the female's characteristics, were observed. Utilization responses for males were smaller, and generally statistically insignificant.

Claims data from B.C. Pharmacare provided somewhat contradictory evidence. In that province, significant permanent utilization responses were observed primarily among low income males. The remaining individuals did appear to increase utilization during the year in which they turned 65 and became eligible for benefits, although this effect was not sustained. This phenomenon appeared to be consistent with individuals delaying filling prescriptions which were issued prior to their birthday until after their birthdate, at which time the cost to them was lower. Although this appeared to be an intuitively plausible explanation, the specified behavioural model was not found to be consistent with the data.

In order to reconcile these divergent pieces of evidence regarding the gender differences in utilization responses, it should be recognized that the study

cohort from B.C. was confined to the population of non-married individuals in the province. It may be that the behaviour of this group is not generalizable to the larger population of elderly in B.C. Further, the instrument used to measure utilization among the B.C. residents was real prescription expenditures. This was somewhat different from the utilization measure used for the Ontario study.

5.2 Effects of Insurance Coverage on Public Drug Insurance Expenditures

One of the primary responses of provincial governments to rising drug expenditures on seniors has been to introduce or increase beneficiary co-payment requirements (Hurley and Johnson 1991). Given the *zeitgeist* of current health policy, it is important to assess the relative contribution to expenditure growth of publicly reimbursed pharmaceuticals. Evidence provided by Anderson *et al.* (1993) suggests that expenditure growth on physician services, hospital services and pharmaceuticals for the elderly is not primarily due to factors such as demographic shifts (such as the aging population) or enhanced insurance coverage. Instead, the authors contend that there are important "year effects" on consumption of these services such that holding insurance and demographic composition fixed, seniors now are consuming more of a larger array of products than seniors only a few years ago. Given the extent of provider control over

utilization patterns (Stoddart *et al.* 1993), it is unlikely that this is primarily a patient-initiated development.

Corroborating evidence was produced from analysis of the administrative claims data from the B.C. Ministry of Health Pharmacare program. The largest contribution to growth in Pharmacare expenditures was not found to be due to the extension of insurance benefits *per se*, but rather due to these "year effects". On average, real expenditures of all seniors at a given age increased by 17% each year. Similar temporal effects were observed in data on the number of annual general practitioner visits by the same individuals. On the other hand, insurance coverage resulted in negligible increases in Pharmacare claims for most of the subsamples examined. Notable exceptions were low income males whose real expenditures increased permanently in the range $266-$608 (1986 dollars) after becoming eligible for coverage.

5.3 Effects of Enhanced Insurance Coverage on Drug Program Objectives

There are mixed views on the merits of using patient cost sharing to allocate pharmaceuticals and other health care services. Some analysts (e.g., Feldman and Dowd 1991, 1993; Manning *et al.* 1987; Feldstein 1973; Pauly 1969) favour the use of some patient cost sharing. Their view is that insurance

encourages additional consumption which is socially undesirable due to the fact that the social value placed on its utilization (as measured by consumers' willingness to pay) is lower than its resource cost. One of the important assumptions underlying this view is that consumers' willingness to pay can be retrieved from observed utilization data.

Other analysts (e.g., Rice 1992, 1993; Stoddart *et al.* 1993; Evans 1983) argue that the contribution to social welfare of this additional health care consumption cannot be quantified using utilization data due to the fact that consumers' willingness to pay is not identified. The reason is that patients cannot assess the effects of health care on health status, which is the "final" consumption good, due to informational problems.

Patient cost sharing therefore will not necessarily improve the allocation of health care resources and might impose several potentially undesirable social consequences. First, to the extent that cost sharing has a deterrent effect on use and to the extent that cost sharing does not selectively deter the use of services with negligible effects on health status, patient health status may be adversely affected. Second, individuals are exposed to the financial risk associated with becoming ill and in need of pharmaceuticals. Finally, the burden of financing health care expenditures falls upon those who are ill. Given the positive correlation observed between health status and income level in Canada (Canadian Institute for Advanced Research 1991), lower income individuals are forced to pay

a relatively higher proportion of costs than are higher income individuals. These effects conflict with the primary objective of provincial pharmacare programs, which is to relieve the financial burden of drug therapy with the implicit, and sometimes explicit, aim of improving health status.

None of the existing studies have provided conclusive evidence on the effects of varying levels of prescription drug co-payments on patient health status. Indirect evidence does suggest, however, that health status is adversely affected by co-payment in some patient populations. This study was also unable to identify changes in patient health status attributable to enhanced insurance coverage, but it was able to add to the body of indirect evidence regarding health status effects and equity effects of providing insurance coverage.

The model of prescription drug utilization among Ontario seniors provided estimates of the effects of ODB eligibility on patients with differing levels of health status. Prior to the onset of ODB coverage, individuals with lower levels of health status were observed to consume a larger number of different drugs. After turning 65 and becoming eligible for ODB coverage, individuals with lower levels of health status experienced the largest increases in number of drugs taken. Distributional objectives of the ODB program therefore appear to be satisfied in so far as individuals with poorer health are receiving proportionately more medicines. In addition, analysis of the responses by B.C. seniors indicated that males with lower levels of income were observed to have the largest increases in medicines use after

the subsidy was extended. Proceeding on the assumption that these behavioural responses are symmetric to the case of an increase in co-payment, it seems likely that such a policy would result in commensurate utilization decreases primarily among persons with poorer health.

The prediction that co-payment will reduce utilization amongst those persons with lower health status raises a number of questions. On the face of it, if all use of medicines is appropriate therapy, then a policy which reduces use in less healthy persons may be regressive on those most in need of care. But our data cannot speak to the question of whether the drug use being induced or deterred by user charges is essential or appropriate because the appropriateness of a drug therapy is specific to each clinical situation and we had no information on which drugs were being consumed, or the clinical indications for their use. It seems plausible, however, that a positive fraction of the services induced or deterred by co-payments satisfy the criteria of appropriateness and may therefore have important consequences for patient health status.

To learn more about the probable effects on patient health status after co-payments are lowered, specific behavioural responses to changes in drug co-payments were identified. Patients facing lower drug costs might be more inclined to initiate treatment episodes, or increase compliance with physician prescription recommendations. Physicians, on the other hand, might increase the number of different drugs prescribed to treat conditions and/or substitute prescription drugs

for other health care inputs (such as non-prescription drugs or the physician's time) because the relative prices of these other inputs have now risen. Analyzing whether changes in the quantity and composition of drugs consumed following a user charge are largely patient- or physician-initiated can shed some light on the probable effects on patient health status. The patient typically has less knowledge of what constitutes "rational" drug therapy than the physician. Therefore if a co-payment induced drop in utilization results primarily from consumer rather than physician decisions (due to non-compliance with physician prescriptions or a lower propensity to initiate treatment), it increases the probability that the appropriateness of therapy is not improved (Hurley and Johnson 1991). If decreases in co-payments have a predominant effect on patient decision making, then it may be preferable to introduce alternative policies which target physicians, who are relatively better informed.

Due to data constraints, it was not possible to monitor the effects of changes in insurance coverage on patient compliance with therapy nor to observe patient-physician interactions directly. Evidence from the OHS does, however, narrow the set of plausible patient-physician responses to the enhanced insurance coverage. First, elderly Ontario women were observed to increase the number of different drugs taken after becoming eligible for ODB coverage. In addition, there were no effects observed on annual physician consultations (either probability of

any visits or the number of visits) or on the use of non prescription medications by either sex.

On the basis of these results, the increased prescription drug utilization among older individuals appears to have operated through increased multiple drug prescribing, and/or substitutions of prescription drugs for other health inputs (such as physician own-time or surgery, but not non prescription drugs) on the part of physicians, possibly coupled with increased patient compliance with these post-65 prescription regimens.

It also appears that the level of physician control over the utilization process is generally higher, the lower the level of patient health status. The preferred estimation technique produced estimates of the "insurance coverage effect" on two separate components of utilization: the probability of utilization and the level of utilization (the number of different drugs taken) among users. The proportion of the utilization change operating through adjustments in the number of drugs taken by those already receiving pharmacotherapy, and therefore likely already under physician supervision, increased, the lower the level of patient health status. The proportion of the utilization change operating through changes in the probability of taking any medications (which is probably highly correlated with patient initiation of treatment episodes) was observed to be correspondingly lower, the lower the level of patient health status.

The evidence produced from this research therefore suggests that extending drug insurance coverage to seniors will increase the consumption of pharmaceuticals. The subsidy, however, benefits primarily individuals with lower levels of health status. In addition, the data suggest that there is some physician control over the increased utilization "induced" by a public subsidy of prescription drugs and that this influence increases for patients with lower levels of health status. Given the informational asymmetries between the physician and patient, this increase in utilization is consistent with, but not *prima facie* evidence of, a move from under-utilization toward appropriate levels of utilization.

The equity and health status objectives of the provincial pharmacare programs in Ontario and B.C. appear to be satisfied. There is growing concern, however, at the growing demands these programs make on public funds. Attempts to lower program expenditures by increasing the level of patient co-payment in these plans may very well be successful but may also compromise the stated program objectives. As Hurley and Johnson (1991) outline, there are several other policy tools available which might achieve the goal of expenditure control but at the same time minimize the adverse effects on equity and patient health status. These include policies which attempt to improve physician prescribing patterns (by, for example, providing better information on the clinical indications for the use of specific drugs) and policies which attempt to control drug prices (such as mandatory substitution of generic drug equivalents, or direct price regulation).

These policies are all technically more difficult to implement than co-payment policies. Because they do not require patients to relinquish drugs on the basis of willingness or ability to pay, however, program objectives are more easily preserved.

6. Appendices

Appendix A Number of Observations by Mode of Survey Administration and Proxy- vs. Self-Report, Ontario Health Survey, 1990

Variables	General Description	No. of Obs.	Interviewer-Administered		Self-Administered
			on behalf of self	as a proxy	
qtydrug1, qtydrug2, druguser	prescription drug utilization	5,743	-	-	5,743 (100%)
nonrx14	non-prescription drug utilization	5,680	3,567 (63%)	2,113 (37%)	-
docuser	physician utilization	5,743	3,599 (63%)	2,144 (37%)	-
vghlth, goodhlth, fairhlth, poorhlth	self-assessed health status	5,743	-	-	5,743 (100%)
numbprb	number of health problems	5,743	3,599 (63%)	2,144 (37%)	-
hsize	household size	5,743	3,599 (63%)	2,144 (37%)	-
drugins	additional drug coverage identifier	5,743	3,599 (63%)	2,144 (37%)	-
working	identifier of working as full time activity	5,743	3,599 (63%)	2,144 (37%)	-
inc1, inc2, inc3	household income levels	5,743	3,599 (63%)	2,144 (37%)	-
primary, somehigh, comphigh, somepost	education levels	5,743	3,599 (63%)	2,144 (37%)	-
age		5,743	3,599 (63%)	2,144 (37%)	-

Source: 1990 Ontario Health Survey

Appendix B OLS Estimates of Number of Annual Physician Consultations: Females and Males

	Females		Males	
Covariates	Coef.	t-ratio	Coef.	t-ratio
Constant	-5.241	-1.63	3.882	0.86
AGE65	-0.829	-1.02	0.517	0.56
DRUGINS	0.164	0.35	-0.121	-0.24
PRICEINT	0.280	0.42	-0.064	-0.09
WORKING	-0.419	-1.23	-0.346	-0.94
VGHLTH	-0.097	-0.29	0.802	2.48
GOODHLTH	1.380	3.64	2.715	5.99
FAIRHLTH	3.893	6.48	5.917	8.11
POORHLTH	8.805	7.08	12.441	5.17
NUMBPRB	1.163	8.18	1.188	5.12
HLTHINT	0.054	0.28	-0.118	-0.44
LHSIZE	-0.131	-0.31	-0.176	-0.40
INC1	-0.929	-1.18	0.705	0.78
INC2	-0.448	-0.95	0.328	0.55
INC3	-0.814	-2.10	-0.348	-0.67
PRIMARY	1.163	2.38	-1.360	-1.31
SOMEHIGH	0.320	0.71	-1.824	-1.86
COMPHIGH	0.380	0.86	-1.994	-2.06
SOMEPOST	0.470	0.87	-1.515	-1.52
AGE	0.126	2.47	-0.008	-0.12
Adj.R Squared	0.14		0.20	
n	3,039		2,592	

Source: 1990 Ontario Health Survey

Appendix C Frequency Distribution of Real Prescription Drug Expenditures

Subsample: Born 1921, No Premium Assistance

	Males			Females		
Range	Frequency	%	Cumulative %	Frequency	%	Cumulative %
$0	3,435	51.6	51.6	5,197	39.7	39.7
$1-50	1,153	17.3	68.9	2,607	19.9	59.7
$51-100	406	6.1	75.0	1,080	8.3	67.9
$101-200	407	6.1	81.1	1,118	8.6	76.5
$201-300	318	4.8	85.9	751	5.7	82.2
$301-400	207	3.1	89.0	505	3.9	86.1
$401-500	165	2.5	91.5	430	3.3	89.4
$501-1,000	385	5.8	97.3	1,019	7.8	97.2
$1,001-2,000	143	2.2	99.4	342	2.6	99.8
$2,001-5,000	29	0.4	99.9	31	0.2	100.0
$5,001+	8	0.1	100.0	0	0.0	100.0
Total	6,656	100.0		13,080	100.0	

Subsample: Born 1923, No Premium Assistance

	Males			Females		
Range	Frequency	%	Cumulative %	Frequency	%	Cumulative %
$0	4,571	66.8	66.8	6,757	57.9	57.9
$1-50	729	10.7	77.4	1,642	14.1	71.9
$51-100	285	4.2	81.6	570	4.9	76.8
$101-200	315	4.6	86.2	677	5.8	82.6
$201-300	202	3.0	89.1	412	3.5	86.1
$301-400	143	2.1	91.2	328	2.8	88.9
$401-500	125	1.8	93.0	309	2.7	91.6
$501-1,000	335	4.9	97.9	701	6.0	97.6
$1,001-2,000	127	1.9	99.8	240	2.1	99.6
$2,001-5,000	14	0.2	100.0	43	0.4	100.0
$5,001+	2	0.0	100.0	1	0.0	100.0
Total	6,848	100.0		11,680	100.0	

Source: BC Ministry of Health Pharmacare

Appendix C, continued Frequency Distribution of Real Prescription Drug Expenditures

Subsample: Born 1925, No Premium Assistance

	Males			Females		
Range	Frequency	%	Cumulative %	Frequency	%	Cumulative %
$0	6,309	81.1	81.1	8,299	73.9	73.9
$1-50	415	5.3	86.5	847	7.5	81.4
$51-100	178	2.3	88.8	350	3.1	84.5
$101-200	193	2.5	91.2	355	3.2	87.7
$201-300	119	1.5	92.8	198	1.8	89.5
$301-400	87	1.1	93.9	175	1.6	91.0
$401-500	80	1.0	94.9	195	1.7	92.8
$501-1,000	257	3.3	98.2	569	5.1	97.8
$1,001-2,000	119	1.5	99.8	185	1.7	99.5
$2,001-5,000	18	0.2	100.0	55	0.5	100.0
$5,001+	1	0.0	100.0	4	0.0	100.0
Total	7,776	100.0		11,232	100.0	

Subsample: Born 1921, Premium Assistance

	Males			Females		
Range	Frequency	%	Cumulative %	Frequency	%	Cumulative %
$0	3,461	42.8	42.8	5,178	33.9	33.9
$1-50	1,333	16.5	59.2	3,530	23.1	57.0
$51-100	545	6.7	66.0	1,313	8.6	65.6
$101-200	649	8.0	74.0	1,590	10.4	76.0
$201-300	422	5.2	79.2	925	6.1	82.0
$301-400	306	3.8	83.0	662	4.3	86.3
$401-500	277	3.4	86.4	517	3.4	89.7
$501-1,000	724	8.9	95.3	1,169	7.7	97.4
$1,001-2,000	309	3.8	99.1	360	2.4	99.7
$2,001-5,000	66	0.8	100.0	44	0.3	100.0
$5,001+	4	0.1	100.0	0	0.0	100.0
Total	8,096	100.0		15,288	100.0	

Appendix C, continued Frequency Distribution of Real Prescription Drug Expenditures

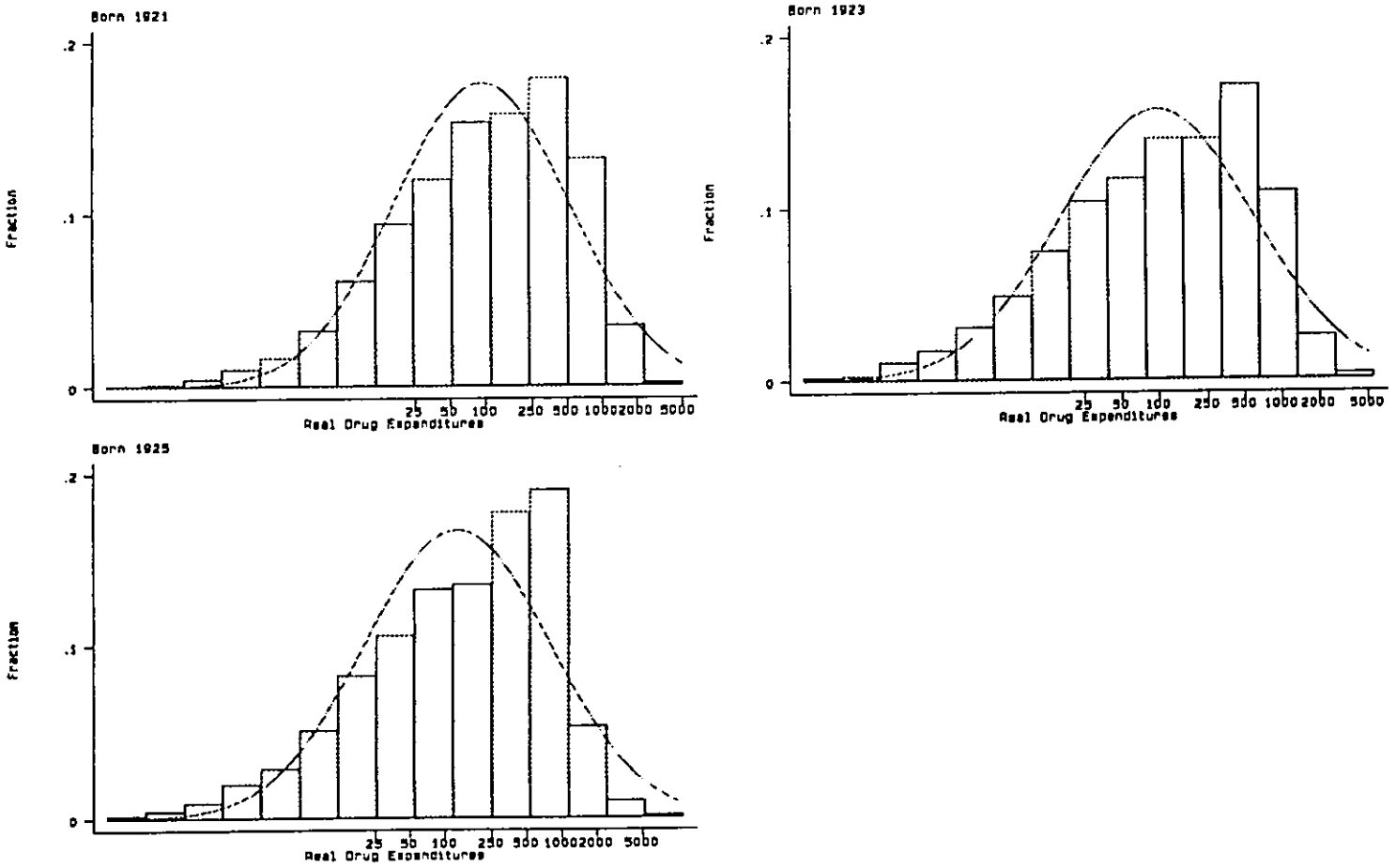
Subsample: Born 1923, Premium Assistance

	Males			Females		
Range	Frequency	%	Cumulative %	Frequency	%	Cumulative %
$0	4,612	58.9	58.9	6,599	51.4	51.4
$1-50	927	11.8	70.7	1,984	15.5	66.9
$51-100	364	4.7	75.4	739	5.8	72.6
$101-200	473	6.0	81.4	856	6.7	79.3
$201-300	294	3.8	85.2	559	4.4	83.6
$301-400	229	2.9	88.1	446	3.5	87.1
$401-500	186	2.4	90.5	383	3.0	90.1
$501-1,000	498	6.4	96.8	920	7.2	97.2
$1,001-2,000	209	2.7	99.5	296	2.3	99.6
$2,001-5,000	40	0.5	100.0	58	0.5	100.0
$5,001+	0	0.0	100.0	0	0.0	100.0
Total	7,832	100.0		12,840	100.0	

Subsample: Born 1925, Premium Assistance

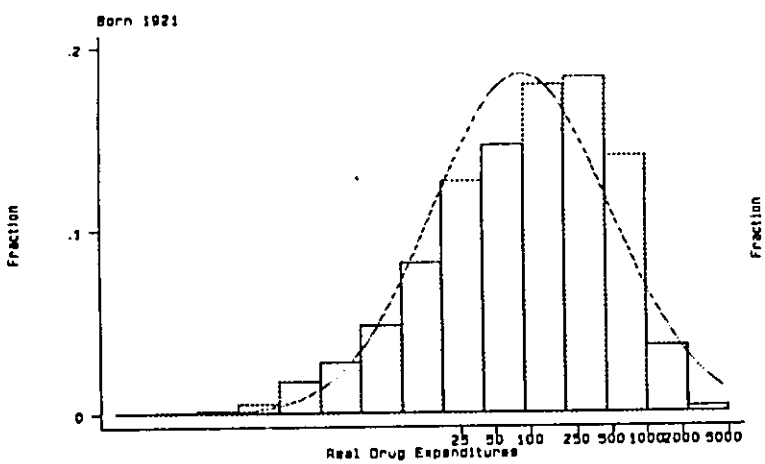
	Males			Females		
Range	Frequency	%	Cumulative %	Frequency	%	Cumulative %
$0	4,542	75.5	75.5	7,625	68.2	68.2
$1-50	439	7.3	82.8	1,023	9.2	77.3
$51-100	172	2.9	85.7	396	3.5	80.9
$101-200	185	3.1	88.7	452	4.0	84.9
$201-300	111	1.9	90.6	286	2.6	87.5
$301-400	86	1.4	92.0	194	1.7	89.2
$401-500	84	1.4	93.4	219	2.0	91.2
$501-1,000	238	4.0	97.4	683	6.1	97.3
$1,001-2,000	131	2.2	99.5	261	2.3	99.6
$2,001-5,000	28	0.5	100.0	44	0.4	100.0
$5,001+	0	0.0	100.0	1	0.0	100.0
Total	6,016	100.0		11,184	100.0	

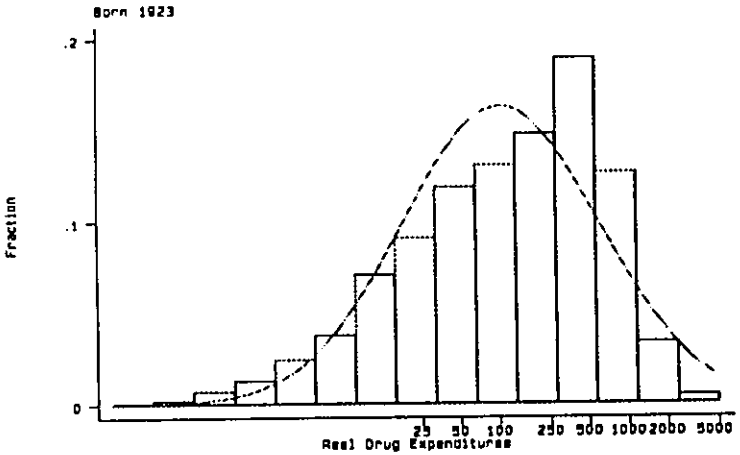
Appendix D Histograms of Log Real Drug Expenditures: Females not Receiving Premium Assistance

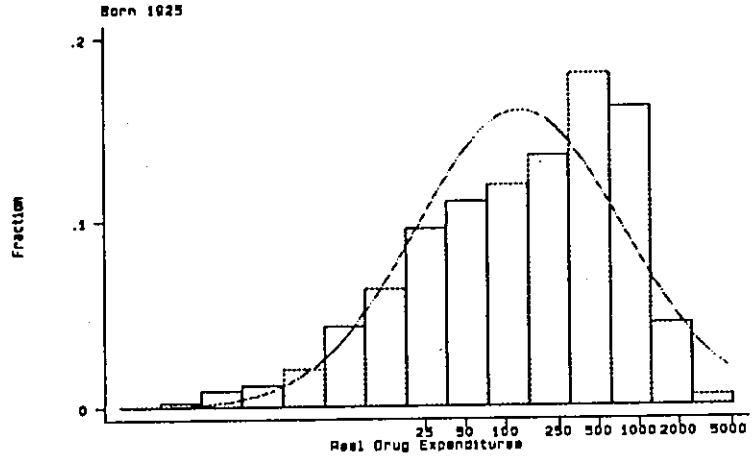


Source: BC Ministry of Health Pharmacare

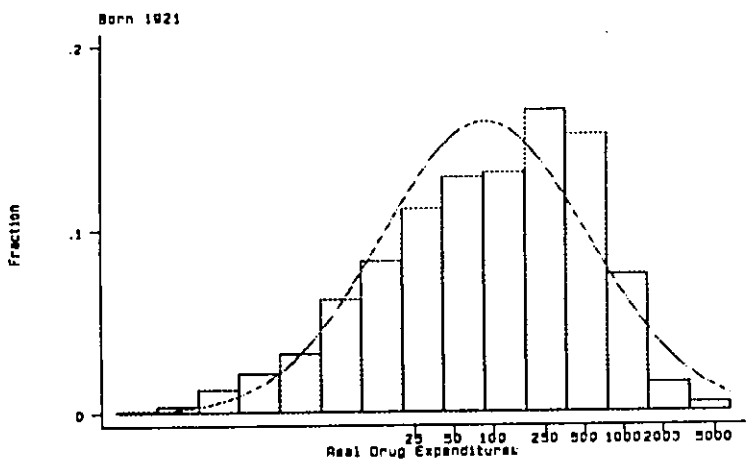
Appendix D, continued Histograms of Log Real Drug Expenditures: Females Receiving Premium Assistance

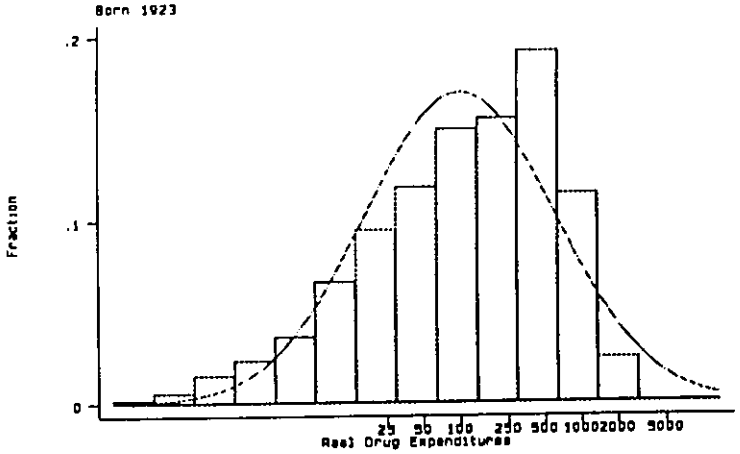


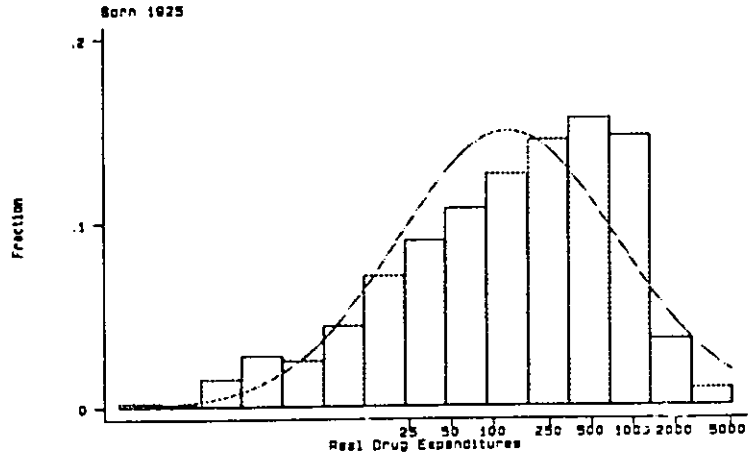




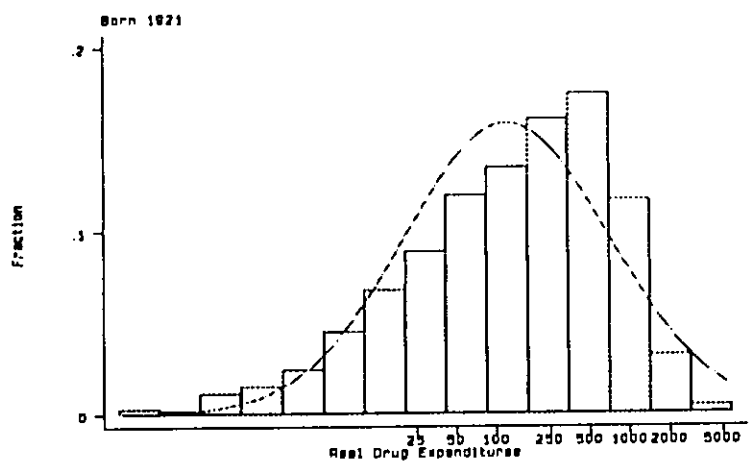
Appendix D, continued Histograms of Log Real Drug Expenditures: Males not Receiving Premium Assistance

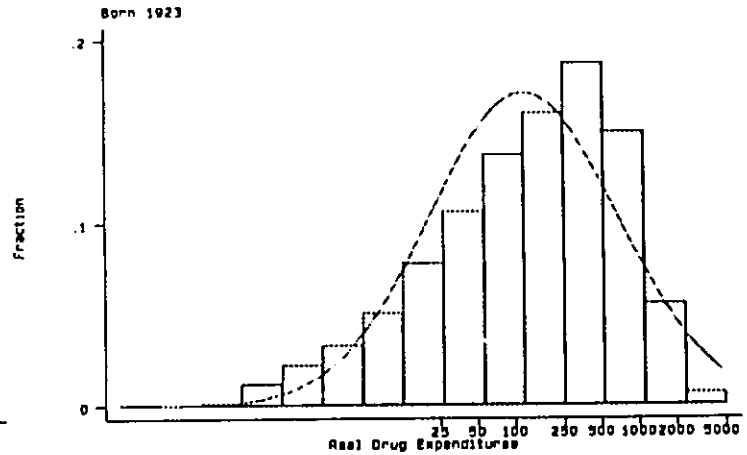


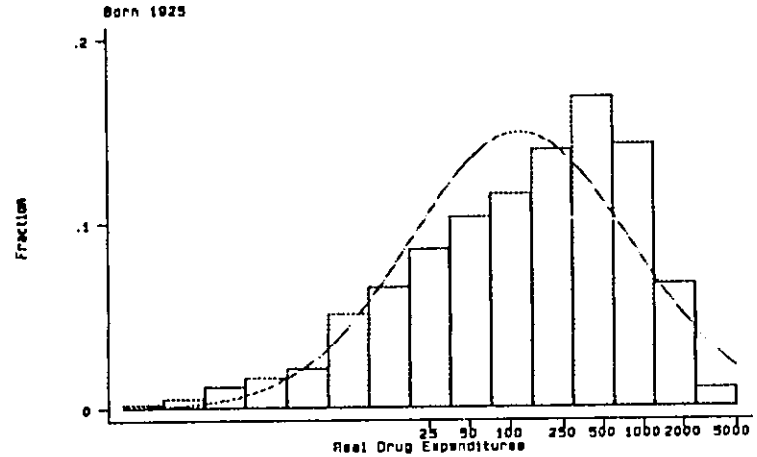




Appendix D, continued Histograms of Log Real Drug Expenditures: Males Receiving Premium Assistance







Appendix E Pantob Estimates of Effect of Insurance on Prescription Drug Expenditures - *All observations artificially censored*

Subsample: Born 1921, No Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	100.80	20.88	4.83	83.43	7.78	10.73
Perm	25.27	165.00	0.15	-17.33	66.07	-0.26
Trans	118.10	85.33	1.38	8.66	43.40	0.20
Objective Fn.	1.79E+09			2.19E+09		
Signif. Test	30.40	*P<0.001*		148.40	*P<0.001*	
No. Obs.	6,656			13,080		

Subsample: Born 1923, No Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	105.60	73.41	1.44	74.37	18.29	4.07
Perm	122.80	201.30	0.61	125.90	97.49	1.29
Trans	169.10	110.20	1.53	12.47	60.41	0.21
Objective Fn.	2.81E+09			2.01E+09		
Signif. Test	13.90	*P<0.001*		56.80	*P<0.001*	
No. Obs.	6,848			11,680		

Source: BC Ministry of Health Pharmacare

Appendix E, continued Pantob estimates of Effect of Insurance on Prescription Drug Expenditures - *All observations artificially censored*

Subsample: Born 1925, No Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	114.60	49.12	2.33	139.30	38.66	3.60
Perm	102.40	251.00	0.41	-214.00	172.50	-1.24
Trans	250.10	154.90	1.62	203.90	82.75	2.46
Objective Fn.	1.28E+09			2.41E+09		
Signif. Test	25.30	*P<0.001*		38.90	*P<0.001*	
No. Obs.	7,776			11,232		

Subsample: Born 1921, Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	96.40	14.20	6.79	72.47	7.94	9.12
Perm	963.90	260.40	3.70	-100.00	45.63	-2.19
Trans	-56.85	100.90	-0.56	112.20	36.25	3.09
Objective Fn.	2.34E+09			2.98E+09		
Signif. Test	96.60	*P<0.001*		112.40	*P<0.001*	
No. Obs.	8,096			15,288		

Appendix E, continued Pantob estimates of Effect of Insurance on Prescription Drug Expenditures - *All observations artificially censored*

Subsample: Born 1923, Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	130.20	24.48	5.32	74.61	11.38	6.56
Perm	610.40	154.80	3.94	94.80	81.17	1.17
Trans	40.19	63.38	0.63	-95.60	51.19	-1.87
Objective Fn.	1.37E+09			2.25E+09		
Signif. Test	83.70	*P<0.001*		103.00	*P<0.001*	
No. Obs.	7,832			12,840		

Subsample: Born 1925, Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	41.00	63.19	0.65	144.80	22.06	6.56
Perm	1,114.00	392.30	2.84	-113.30	109.80	-1.03
Trans	-98.94	169.50	-0.58	185.40	65.10	2.85
Objective Fn.	1.14E+09			1.81E+09		
Signif. Test	51.60	*P<0.001*		114.00	*P<0.001*	
No. Obs.	6,016			11,184		

Appendix F Pantob Estimates of Effect of Insurance on Prescription Drug Expenditures - Observations at age 65 removed, *TRANS* dropped

Subsample: Born 1921, No Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	62.26	10.49	5.94	56.34	4.37	12.89
Perm	-41.64	1.10E+11	0.00	-25.45	8.54E+07	0.00
Ct	-2.36	5.05E+08	0.00	-1.56	3.93E+05	0.00
Objective Fn.	1.58E+09			2.05E+09		
Signif. Test	31.30	*P<0.001*		246.80	*P<0.001*	
No. Obs.	5,824			11,445		

Subsample: Born 1923, No Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	65.23	34.97	1.87	53.73	8.42	6.38
Perm	124.90	337.90	0.37	434.20	173.70	2.50
Ct	-1.76	1.46	-0.52	-0.02	0.64	1.54
Objective Fn.	2.45E+09			1.65E+09		
Signif. Test	22.30	*P<0.001*		135.60	*P<0.001*	
No. Obs.	5,992			10,220		

Source: BC Ministry of Health Pharmacare

Appendix F, continued Pantob Estimates of Effect of Insurance on Prescription Drug Expenditures - *Observations at age 65 removed, TRANS dropped*

Subsample: Born 1925, No Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	53.67	32.14	1.67	95.08	22.89	4.15
Perm	957.10	472.30	2.03	51.63	211.60	0.24
Ct	1.37	1.59	1.49	-0.65	0.71	0.49
Objective Fn.	9.78E+08			1.71E+09		
Signif. Test	47.30	*P<0.001*		87.10	*P<0.001*	
No. Obs.	6,804			9,828		

Subsample: Born 1921, Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	63.25	8.00	7.91	48.07	4.23	11.36
Perm	6.46	1.6E+11	0.00	-7.41	5.10E+07	0.00
Ct	-6.72	7.3E+08	0.00	-1.36	2.35E+05	0.00
Objective Fn.	2.20E+09			2.75E+09		
Signif. Test	74.50	*P<0.001*		259.00	*P<0.001*	
No. Obs.	7,084			13,377		

Appendix F, continued Pantob Estimates of Effect of Insurance on Prescription Drug Expenditures - *Observations at age 65 removed, TRANS dropped*

Subsample: Born 1923, Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	79.00	11.92	6.63	59.62	6.14	9.71
Perm	601.30	622.00	0.97	552.90	142.10	3.89
Ct	-1.97	2.70	-0.36	0.75	0.52	3.35
Objective Fn.	1.29E+09			1.83E+09		
Signif. Test	121.80	*P<0.001*		215.90	*P<0.001*	
No. Obs.	6,853			11,235		

Subsample: Born 1925, Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	48.62	35.11	1.39	98.48	16.42	6.00
Perm	1,388.00	698.50	1.99	286.50	196.70	1.46
Ct	0.22	2.41	0.51	-0.12	0.67	1.31
Objective Fn.	8.92E+08			1.33E+09		
Signif. Test	63.60	*P<0.001*		196.40	*P<0.001*	
No. Obs.	5,264			9,789		

Appendix G Pantob Estimates of Effect of Insurance on Prescription Drug Expenditures - *Observations at age 65 removed, TRANS dropped, All Observations Artificially Censored*

Subsample: Born 1921, No Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	98.28	20.00	4.91	89.83	7.48	12.01
Perm	89.16	140.30	0.64	-54.86	49.00	-1.12
Objective Fn.	1.32E+09			1.59E+09		
Signif. Test	30.60	*P<0.001*		161.80	*P<0.001*	
No. Obs.	5,824			11,445		

Subsample: Born 1923, No Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	106.00	76.08	1.39	85.92	14.21	6.05
Perm	139.40	176.40	0.79	71.54	74.64	0.96
Objective Fn.	2.28E+09			1.37E+09		
Signif. Test	8.50	*P<0.001*		61.30	*P<0.001*	
No. Obs.	5,992			10,220		

Source: BC Ministry of Health Pharmacare

Appendix G, continued Pantob Estimates of Effect of Insurance on Prescription Drug Expenditures - *Observations at age 65 removed, TRANS dropped, All Observations Artificially Censored*

Subsample: Born 1925, No Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	97.75	37.72	2.59	107.20	26.89	3.99
Perm	178.30	190.00	0.94	-74.40	117.80	-0.63
Objective Fn.	8.92E+08			1.58E+09		
Signif. Test	24.00	*P<0.001*		34.30	*P<0.001*	
No. Obs.	6,804			9,828		

Subsample: Born 1921, Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	96.64	12.37	7.81	75.14	7.77	9.67
Perm	1,082.00	329.00	3.29	-52.87	39.48	-1.34
Objective Fn.	1.82E+09			2.14E+09		
Signif. Test	77.60	*P<0.001*		121.20	*P<0.001*	
No. Obs.	7,084			13,377		

Appendix G, continued: Pantob Estimates of Effect of Insurance on Prescription Drug Expenditures - *Observations at age 65 removed, TRANS dropped, All Observations Artificially Censored*

Subsample: Born 1923, Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	119.90	20.76	5.78	91.45	10.16	9.00
Perm	641.90	128.60	4.99	11.52	62.35	0.18
Objective Fn.	1.09E+09			1.55E+09		
Signif. Test	79.40	*P<0.001*		108.10	*P<0.001*	
No. Obs.	6,853			11,235		

Subsample: Born 1925, Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	70.41	41.70	1.69	120.90	17.73	6.82
Perm	992.40	280.90	3.53	-22.38	81.79	-0.27
Objective Fn.	8.32E+08			1.20E+09		
Signif. Test	45.10	*P<0.001*		98.80	*P<0.001*	
No. Obs.	5,264			9,789		

Appendix H Tobit Estimates of Effect of Insurance on Prescription Drug Expenditures - Observations at age 65 removed, TRANS dropped, All Observations Artificially Censored

Subsample: Born 1921, No Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	93.38	11.92	7.83	70.24	5.31	13.22
Perm	268.54	91.10	2.95	137.24	39.43	3.48
Constant	-7,332.25	773.30	-9.48	-5,190.29	343.91	-15.09
Objective Fn.	-10,904.85			-25,146.05		
Signif. Test	175.40			437.91		
Pseudo R^2	0.80%			0.86%		
No. Obs.	5,824			11,445		

Subsample: Born 1923, No Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	79.87	23.64	3.38	77.58	12.14	6.39
Perm	378.59	120.65	3.14	151.75	61.17	2.48
Constant	-6,660.01	1,496.91	-4.45	-5,812.02	769.47	-7.55
Objective Fn.	-7,556.96			-15,501.42		
Signif. Test	207.57			402.38		
Pseudo R^2	1.35%			1.28%		
No. Obs.	5,992			10,220		

Source: BC Ministry of Health Pharmacare

Appendix H, continued Tobit Estimates of Effect of Insurance on Prescription Drug Expenditures - *Observations at age 65 removed, TRANS dropped, All Observations Artificially Censored*

Subsample: Born 1925, No Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	30.77	25.13	1.22	27.31	17.55	1.56
Perm	710.41	127.13	5.59	528.66	89.42	5.91
Constant	-3,653.73	1,563.81	-2.34	-3,128.28	1,090.53	-2.87
Objective Fn.	-5,378.05			-10,920.60		
Signif. Test	256.09			263.99		
Pseudo R^2	2.33%			1.19%		
No. Obs.	6,804			9,828		

Subsample: Born 1921, Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	69.61	8.34	8.34	71.61	4.83	14.82
Perm	966.70	87.25	11.08	106.57	35.61	2.99
Constant	-5,994.16	543.29	-11.03	-5,244.79	312.98	-16.76
Objective Fn.	-17,922.11			-29,783.62		
Signif. Test	549.88			512.70		
Pseudo R^2	1.51%			0.85%		
No. Obs.	7,084			13,377		

Appendix H, continued Tobit Estimates of Effect of Insurance on Prescription Drug Expenditures - *Observations at age 65 removed, TRANS dropped, All Observations Artificially Censored*

Subsample: Born 1923, Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	91.17	16.11	5.66	80.00	10.27	7.79
Perm	708.43	87.16	8.13	166.51	51.80	3.21
Constant	-7,191.75	1,021.84	-7.04	-5,835.61	650.38	-8.97
Objective Fn.	-11,049.10			-19,754.86		
Signif. Test	819.36			609.78		
Pseudo R^2	3.58%			1.52%		
No. Obs.	6,853			11,235		

Subsample: Born 1925, Premium Assistance

	Males			Females		
Variable	**Estimate**	**Std. Err.**	**t-ratio**	**Estimate**	**Std. Err.**	**t-ratio**
Age	43.99	30.68	1.43	63.00	13.52	4.66
Perm	1,154.92	153.60	7.52	339.93	67.00	5.07
Constant	-4,640.98	1,911.86	-2.43	-4,928.70	843.60	-5.84
Objective Fn.	-5,153.12			-12,635.15		
Signif. Test	524.67			432.26		
Pseudo R^2	4.84%			1.68%		
No. Obs.	5,264			9,789		

Appendix I Loss of Information due to Artificial Censoring Drug Expenditures

Subsample: Females Born 1921 No Premium Assistance

	No. Obs.	Mean	Std. Dev.	Min.	Max.
All obs.	13,080	158.36	304.72	0.00	3,848.88
Yit > 0	7,883	262.77	355.87	0.06	3,848.88
Cit > *Yit* >0	4,956	64.66	58.74	0.06	217.59
Yit ≥ *Cit*	2,927	598.20	395.31	217.82	3,848.88

Percentage of observations artificially censored: 37.9%
Percentage of total expenditures artificially censored: 15.5%

Subsample: Females Born 1923 No Premium Assistance

	No. Obs.	Mean	Std. Dev.	Min.	Max.
All obs.	11,680	124.14	308.71	0.00	5,502.54
Yit > 0	4,923	294.52	419.46	0.14	5,502.54
Cit > *Yit* >0	3,187	74.68	72.52	0.14	268.33
Yit ≥ *Cit*	1,736	698.11	487.57	268.48	5,502.54

Percentage of observations artificially censored: 27.3%
Percentage of total expenditures artificially censored: 16.4%

Subsample: Females Born 1925 No Premium Assistance

	No. Obs.	Mean	Std. Dev.	Min.	Max.
All obs.	11,232	98.91	342.53	0.00	11,145.88
yit>0	2,933	378.78	585.97	0.13	11,145.88
cit>yit>0	1,717	77.37	73.73	0.13	276.87
yit>=cit	1,216	804.37	715.02	277.38	11,145.88

Percentage of observations artificially censored: 15.3%
Percentage of total expenditures artificially censored: 12.0%

Source: BC Ministry of Health Pharmacare

Appendix I, continued Loss of Information due to Artificial Censoring Drug Expenditures

Subsample: Females Born 1921 Premium Assistance

	No. Obs.	Mean	Std. Dev.	Min.	Max.
All obs.	15,288	162.86	308.73	0.00	4,664.16
$Yit > 0$	10,110	246.27	351.55	0.03	4,664.16
$Cit > Yit > 0$	6,624	65.32	59.90	0.03	217.45
$Yit \geq Cit$	3,486	590.11	413.74	217.76	4,664.16

Percentage of observations artificially censored: 43.3%
Percentage of total expenditures artificially censored: 17.4%

Subsample: Females Born 1923 Premium Assistance

	No. Obs.	Mean	Std. Dev.	Min.	Max.
All obs.	12,840	145.61	323.80	0.00	4,956.68
$Yit > 0$	6,241	299.56	411.82	0.10	4,956.68
$Cit > Yit > 0$	3,956	76.97	73.44	0.10	268.47
$Yit \geq Cit$	2,285	684.94	468.60	268.78	4,956.68

Percentage of observations artificially censored: 30.8%
Percentage of total expenditures artificially censored: 16.3%

Subsample: Females Born 1925 Premium Assistance

	No. Obs.	Mean	Std. Dev.	Min.	Max.
All obs.	11,184	115.94	316.87	0.00	5,127.40
yit>0	3,559	364.34	474.41	0.13	5,127.40
cit>yit>0	2,098	80.37	76.40	0.13	277.15
yit>=cit	1,461	772.11	507.77	277.28	5,127.40

Percentage of observations artificially censored: 18.8%
Percentage of total expenditures artificially censored: 13.0%

Appendix I, continued Loss of Information due to Artificial Censoring Drug Expenditures

Subsample: Males Born 1921 No Premium Assistance

	No. Obs.	Mean	Std. Dev.	Min.	Max.
All obs.	6,656	139.14	382.46	0.00	6,554.55
$Yit > 0$	3,221	287.53	509.55	0.13	6,554.55
$Cit > Yit > 0$	2,033	60.87	59.07	0.13	217.60
$Yit \geq Cit$	1,188	675.40	678.09	218.02	6,554.55

Percentage of observations artificially censored: 30.5%
Percentage of total expenditures artificially censored: 13.4%

Subsample: Males Born 1923 No Premium Assistance

	No. Obs.	Mean	Std. Dev.	Min.	Max.
All obs.	6,848	101.24	349.14	0.00	13,561.90
$Yit > 0$	2,277	304.47	552.09	0.14	13,561.90
$Cit > Yit > 0$	1,468	76.97	73.60	0.14	268.14
$Yit \geq Cit$	809	717.28	764.26	269.55	13,561.90

Percentage of observations artificially censored: 21.4%
Percentage of total expenditures artificially censored: 16.3%

Subsample: Males Born 1925 No Premium Assistance

	No. Obs.	Mean	Std. Dev.	Min.	Max.
All obs.	7,776	70.37	264.82	0.00	5,161.79
yit>0	1,467	373.03	508.88	0.21	5,161.79
cit>yit>0	885	82.91	77.59	0.21	275.96
yit>=cit	582	814.18	566.66	278.45	5,161.79

Percentage of observations artificially censored: 11.4%
Percentage of total expenditures artificially censored: 13.4%

Appendix I, continued Loss of Information due to Artificial Censoring Drug Expenditures

Subsample: Males Born 1921 Premium Assistance

	No. Obs.	Mean	Std. Dev.	Min.	Max.
All obs.	8,096	199.07	411.41	0.00	5,860.04
Yit > 0	4,635	347.72	493.94	0.15	5,860.04
Cit > *Yit* >0	2,617	68.69	61.49	0.15	217.53
Yit ≥ *Cit*	2,018	709.56	568.88	217.71	5,860.04

Percentage of observations artificially censored:	32.3%
Percentage of total expenditures artificially censored:	11.2%

Subsample: Males Born 1923 Premium Assistance

	No. Obs.	Mean	Std. Dev.	Min.	Max.
All obs.	7,832	138.81	341.73	0.00	4,950.81
Yit > 0	3,220	337.62	465.77	0.07	4,950.81
Cit > *Yit* >0	1,984	82.21	74.99	0.07	268.37
Yit ≥ *Cit*	1,236	747.59	532.38	268.69	4,950.81

Percentage of observations artificially censored:	25.3%
Percentage of total expenditures artificially censored:	15.0%

Subsample: Males Born 1925 Premium Assistance

	No. Obs.	Mean	Std. Dev.	Min.	Max.
All obs.	6,016	94.84	317.56	0.00	4,731.00
yit>0	1,474	387.09	546.45	0.13	4,731.00
cit>yit>0	886	78.30	76.52	0.13	277.09
yit>=cit	588	852.36	616.22	280.00	4,731.00

Percentage of observations artificially censored:	14.7%
Percentage of total expenditures artificially censored:	12.2%

Appendix J Heuristic Explanation of the Pantob Estimator

The Pantob estimators exploit the assumption that the disturbances are identically and independently distributed. Honoré used a simple model in which there are only two time series observations per individual (i.e., T=2) to explain how these symmetry conditions can be used to define the estimators.

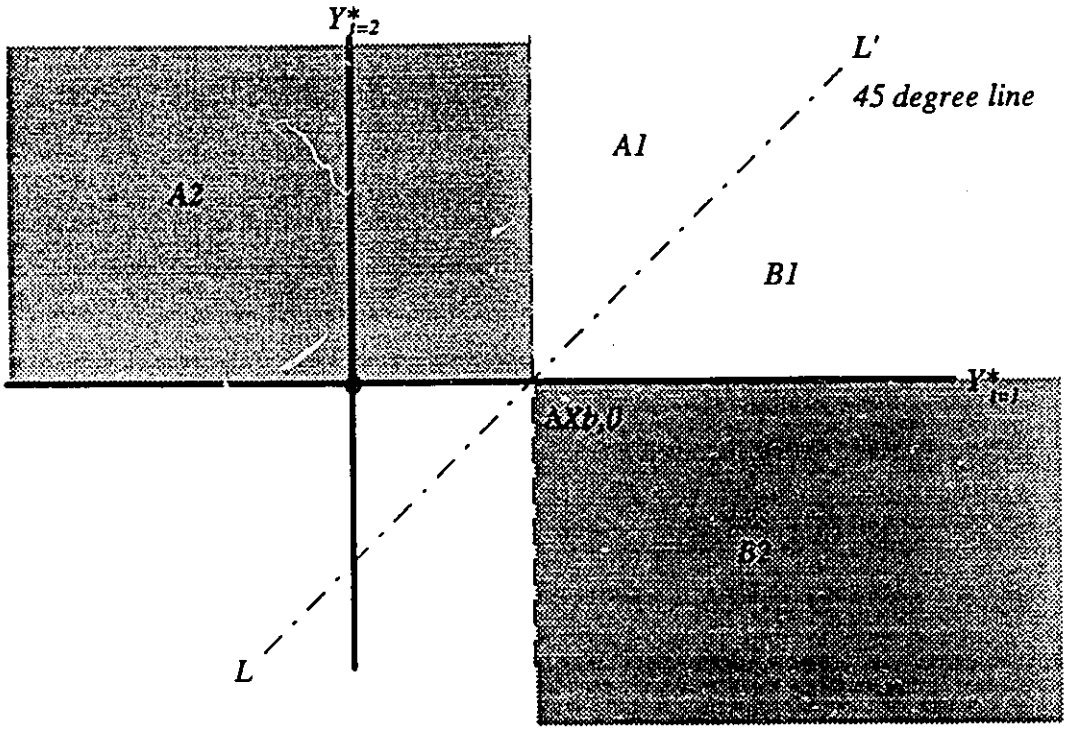
The model is $Y_t^* = \alpha + X_t\beta + \varepsilon_t$ (t = 1,2) and Y_t^* is the actual (latent) dependent variable. The observed dependent variable Y_t is subject to the censoring rule: $Y_t = \max\{0, Y_t^*\}$. The set of pairs of (Y_1^*, Y_2^*) are plotted in Figure 6-1 below. If ε_1 and ε_2 are identically and independently distributed, then the distribution of (Y_1^*, Y_2^*) conditional on (X_1, X_2) is symmetric around the 45 degree line through $(X_1\beta, X_2\beta)$, or equivalently, through $(X_1\beta - X_2\beta, X_2\beta - X_2\beta) = (\Delta X\beta, 0)$. This line LL' is graphed in (Y_1^*, Y_2^*)-space.

The assumption of symmetry in the distribution of observations in the regions A ($A = A1 \cup A2$) and B ($B = B1 \cup B2$) gives rise to two restrictions which hold for both the actual and observed dependent variable. Restriction (1): the probability that (Y_1, Y_2) falls in A equals the probability that (Y_1, Y_2) falls in B. This condition can be expressed mathematically as:

$$E\left[\left(1\{(Y_1,Y_2)\in A_1\cup A_2\}-1\{(Y_1,Y_2)\in B_1\cup B_2\}\right)\Delta X\right]$$
$$=E\left[\left(P\left((Y_1,Y_2)\in A|X_1,X_2\right)-P\left((Y_1,Y_2)\in B\,|X_1,X_2\right)\right)\Delta X\right]$$
$$=0 \qquad (1)$$

where $1\{.\}$ represents the indicator function.

Figure 6-1 Symmetry Conditions Exploited by the Pantob Estimator



Restriction (2): the expected vertical distance from points in A to the line LL' is the same as the expected horizontal distance from points in B to LL'. (The expected vertical distance is the sum over all points in the region A of the vertical

distance between the point and the line, $-(Y_1 - Y_2 - \Delta X\beta)$, times the probability density of the points.) Technically:

$$
\begin{aligned}
& E\left[1\{(Y_1,Y_2)\in A_1\cup B_1\}(Y_1-Y_2-\Delta X\beta)\Delta X\right] \\
&= E\left[\begin{pmatrix} 1\{(Y_1,Y_2)\in A_1\}(Y_1-Y_2-\Delta X\beta) \\ -1\{(Y_1,Y_2)\in A_2\}(Y_2-\max\{0,-\Delta X\beta\}) \\ +1\{(Y_1,Y_2)\in B_1\}(Y_1-Y_2-\Delta X\beta) \\ -1\{(Y_1,Y_2)\in B_2\}(Y_1-\max\{0,\Delta X\beta\}) \end{pmatrix}\Delta X\right] \\
&= 0
\end{aligned}
\tag{2}
$$

Honoré notes (page 538) that the proposed estimators of the censored fixed effects regression model are defined by minimization of objective functions that have as first order conditions that the sample analogs of (1) and (2) respectively are satisfied. The Pantob parameter estimators minimize the generically-defined objective function: $\Sigma_i\, s(y_1, y_2, \Delta X\beta)$, where:

$$
s(y_1,y_2,\Delta X\beta) = \begin{cases} \Xi(y_1)-(y_2+\Delta X\beta)\xi(y_1) & \text{if } \Delta X\beta \le -y_2 \\ \Xi(y_1-y_2-\Delta X\beta) & \text{if } -y_2 < \Delta X\beta < y_1 \\ \Xi(-y_2)-(\Delta X\beta - y_1)\xi(y_2) & \text{if } y_1 < \Delta X\beta \end{cases}
$$

and $\Xi(.)$ is a symmetric convex function, $\xi(.)$ is the derivative of $\Xi(.)$ and y_1, y_2 are the realized values of Y_t.

Each choice of loss function $\Xi(.)$, when minimized, will yield a different panel tobit estimator. For the estimator based on condition (1) (symmetry in the probability density), $\Xi(d)=|d|$ -- an absolute value loss function, which is piecewise linear and convex in β. For the estimator based on condition (2) (symmetric mean distance), $\Xi(d)=d^2$ -- a quadratic loss function, continuously differentiable and convex in β. The final estimator is a polynomial loss function which is a combination of the quadratic and absolute value loss functions. This loss function contains an extra user-defined parameter θ. Formally,

$$\Xi(d,\theta)=\begin{cases}15(\theta d)^2-5(\theta d)^4+(\theta d)^6 & \text{if } -1\le\theta d\le 1\\ 11-16(1+\theta d) & \text{if } \theta d\le -1\\ 11+16(\theta d-1) & \text{if } 1\le\theta d\end{cases}$$

When the parameter θ approaches 0, the loss function converges to the quadratic:

$$\lim_{\theta\to 0}\frac{\Xi(d,\theta)}{15\theta^2}=d^2$$

When this parameter approaches ∞, the loss function converges to the absolute value loss function.

$$\lim_{\theta \to -\infty} \frac{\Xi(d,\theta)}{16\theta} = |d|$$

Minimization of these objective functions is straightforward since all are convex functions of β. Estimation of the variance-covariance matrix is straightforward for the case of the quadratic loss function because the Hessian can be computed analytically. The variance-covariance matrix of the absolute value and polynomial loss functions cannot be computed analytically; numerical derivatives are therefore used.

The estimators proposed here are easily generalizable to the case where $T>2$. Honoré notes that if $\{\varepsilon_{i,t}\}_{t=1}^{T}$ are i.i.d., then both restrictions 1 and 2 must hold for all pairs of observations s, t. This gives $KT(T-1)/2$ orthogonality conditions than can be used to estimate β. Optimal weights can be constructed to give the orthogonality conditions.

7. References

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