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PRESCRIPTION DRUG UTILIZATION: MORAL HAZARD, ADVERSE SELECTION, AND THE ROLE OF CONSUMER MEDICAL CARE PREFERENCES

by

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ABSTRACT

Three important trends in prescription drugs utilization motivated this research: 1) rapidly increasing prescription drug expenditures, 2) increasing insurance coverage for prescription drugs, and 3) increasing consumer access to medical information, potentially resulting in more consumer influence on decisions about prescription drugs. The main objectives of this study were to measure the effects of prescription drug insurance coverage and medical care preferences on prescription drug utilization.

The study had a cross-sectional and descriptive design, and data were collected via mail survey. Surveys were sent to a random sample of 3,500 Wisconsin consumers age 50 and older. Preferences for using medical care were defined as being on a continuum, from stronger self-treating preferences to stronger help-seeking preferences, and were assessed using a nine item summated scale. Data were analyzed using a two part model: 1) the probability of any prescription drug use in the last 30 days, and 2) the number of prescription drugs or the cost of prescription drugs used by individuals who had used at least one prescription drug. Logistic regression was used in the first part of the model, and Poisson regression and ordinary least squares regression were used in the second part of the model. Models controlling for adverse selection also were estimated.

The usable response rate for the survey was 48.8 percent. The preference scale had a mean of 25.6, a standard deviation of 6.8, and a range of 9 to 45 out of a possible 9 to 45, with higher scores representing stronger help-seeking preferences. Correlations between the preference scale and demographic and health status variables all were 0.210 or less.

In the first part of the model, individuals with insurance coverage for prescription drugs were 1.7 times more likely than uninsured individuals to have used at least one prescription drug in the last 30 days. In the second part of the model, insured individuals used 12 percent more prescription drugs and had 46 percent greater prescription drug costs than uninsured individuals. When adverse selection risk was controlled, the insurance coefficient decreased 11 percent for the model predicting the probability of any prescription use, 18 percent for the model predicting the number of prescription drugs used, and 26 percent for the model predicting the cost of prescription drugs used. A standard deviation increase in the preference scale (more help-seeking), increased the odds of using at least one prescription drug by a factor of 1.9, increased the number of prescriptions used by 13 percent, and increased the cost of prescription drugs used by 17 percent. There was a significant interaction effect between insurance and preferences in the model predicting the number of prescription drug used. In that model, the insurance effect was not significant in individuals with self-treating references.

The results suggest that both medical care preferences and insurance coverage for prescription drugs have significant effects on prescription drug utilization. These results have important implications for policy makers, insurers, and providers of health care.

CHAPTER 1

INTRODUCTION

The proportion of prescription drug expenditures in the United States paid for by public or private insurance has increased from 4 percent in 1960 to 66.1 percent in 1996 (Health Care Financing Administration [HCFA] 1998). Although the expanded insurance coverage likely has improved access to needed medications, there is concern that it also has contributed to the rapid growth in prescription drug expenditures, from $2.7 billion in 1960 to $62.2 billion in 1996 (HCFA 1998). Insurance lowers consumer out-of-pocket costs for prescription drugs, and therefore may increase both the number and cost of prescriptions used by consumers. Although there has been extensive research on the effect of insurance coverage on prescription drug use, previous research has failed to account for consumer preferences. The main objective of this study was to examine the effects of insurance and consumer medical care preferences on prescription drug use.

The rate of growth in prescription drug expenditures began to escalate rapidly in the early 1980s. This change was accompanied by a shift in how prescription drugs are paid for, from consumer direct payment to primarily third party payment (Figure 1.1). Interestingly, the increased rate of growth in prescription drug expenditures in the early 1980s came shortly after the increased rate of growth in the percentage of prescription drug expenditures paid for by third parties (Figure 1.2). Although this does not prove causality, it does suggest that there may be some relationship between prescription drug expenditures and insurance coverage. This raises concerns about inequitable access to prescription drugs between

Figure 1.1 Prescription Drug Expenditures by Payment Type[1]

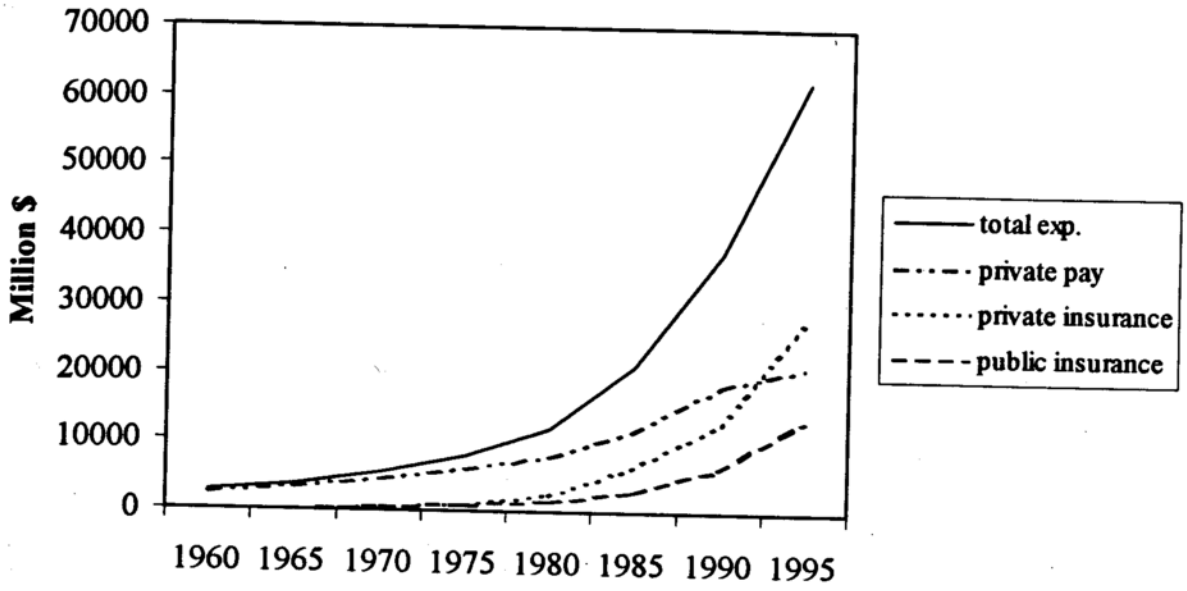
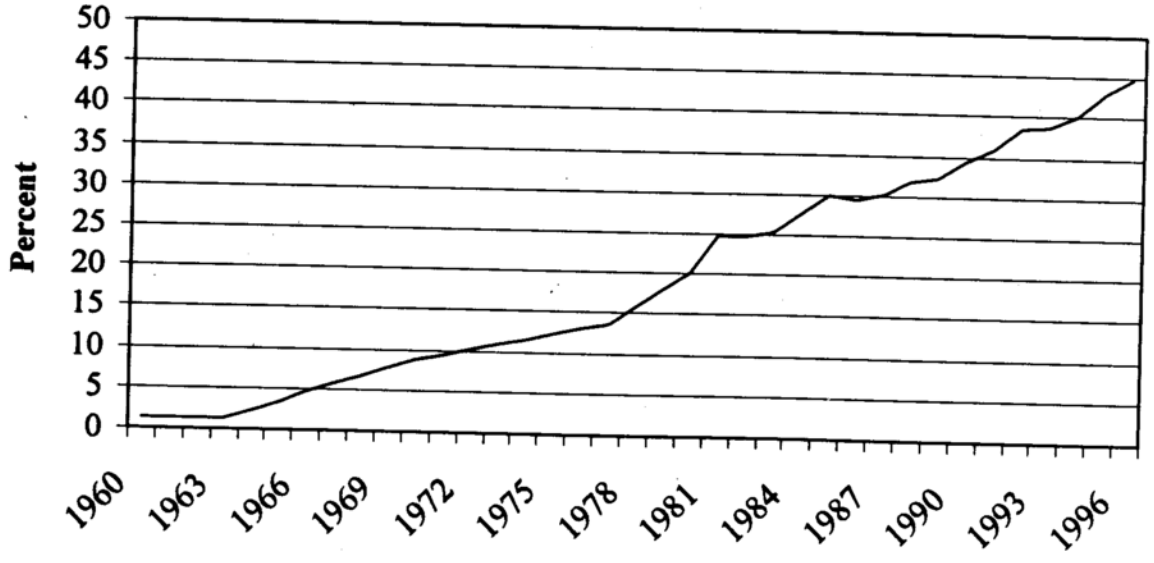


Figure 1.2 Percent of Prescription Drug Expenditures Paid by Private Insurance[1]



1. Health Care Financing Administration (1998). National Health Care Expenditures 1960 - 1996. Online. Http://www.hcfa.gov/stats/stats.htm [20May1998].

insured and uninsured individuals. Data from the Medical Expenditure Panel Survey (MEPS), showed that uninsured individuals were less likely to have obtained a prescription drug than individuals with either public or private insurance (Kraus et al. 1999). In a study of prescription drug utilization among Medicare beneficiaries, insured individuals used an average of 20.3 prescriptions per year and uninsured individuals used an average of 15.3 prescriptions (Davis et al. 1999)

There are two primary types of insurance coverage for prescription drugs, indemnity and service benefit. Consumers with indemnity insurance typically pay the full price of the prescription at the pharmacy, and then are reimbursed later by the insurance company. Under service benefit plans, consumers usually pay either a fixed dollar amount per prescription (copayment) or a fixed percentage of the price (coinsurance), and the pharmacy submits a claim to the insurance company for the remainder of the price. It is estimated that 66 to 81 percent of prescription drug plans use this reimbursement system (Copeland 1999). For both types of plans, consumers pay less than the full cost of the prescription and this may result in greater prescription drug utilization, or moral hazard (Pauly 1968). However, for service benefit plans, not only do consumers pay less than the full cost of the prescription, but they may not even be aware of the full cost. This may be one factor fueling the introduction of new, high-priced technologies (Goddeeris and Weisbrod 1985). Thus, insured individuals may use more prescription drugs and more expensive prescription drugs. In this study, data on number of prescriptions and total prescription costs were collected to examine both the quantity and intensity effects of insurance on prescription drug use.

Moral hazard is not the only potential problem associated with insurance coverage

for prescription drugs. Adverse selection, defined as "the tendency of high risks to be more likely to buy insurance or to buy larger amounts of insurance" (Cummins et al. 1982), also may be a problem. In the prescription drug insurance market, high risks are consumers who expect to have high prescription drug expenditures. Adverse selection may result in low risks purchasing incomplete insurance coverage or no coverage (Akerlof 1970). This leaves more high risks in the insured pool, and this in turn results in higher prescription drug expenditures in the insured population. Thus, the adverse selection effect is the same as the moral hazard effect, making it difficult to obtain an unbiased estimate of the moral hazard effect. In this study, primary data on source of insurance was collected and used to account for adverse selection effects.

There is a considerable body of research on the effects of insurance on prescription drug utilization, but most researchers have used large secondary databases with minimal information on patient characteristics. This approach assumes that patients do not have a significant impact on the demand for prescription drugs. However, even though they must obtain prescription orders from physicians or other prescribing health care professionals, there are many ways that patients may influence the demand for prescription drugs. In fact, patients' participation in health care decisions may be increasing. There has been a push to change from a medical model of health care decision making to a more client-centered approach (Chewning and Sleath 1996). Under a client-centered model, decision making is a collaboration between the patient and the health care professional. Consumers now have greater access to medical information, via self-help references and Internet information sources, and this may increase their participation in decisions about prescription drugs. In

addition, consumers have become the targets of intense direct-to-consumer marketing efforts by pharmaceutical manufacturers. This should increase consumers' awareness of different types of prescription drugs, and may increase demand. As a result of these changes, consumer preferences potentially are becoming an important factor in prescription drug utilization.

Consumers may have very different preferences for using medical care, and this may affect their use of prescription drugs. In this study, medical care was defined as treatment for a health problem obtained through the formal health care system, specifically physician services or prescription drugs. Consumer medical care preferences can be thought of being on a continuum. I proposed that one end of the continuum would be "self-treaters," who would much rather treat health problems themselves or see if the problem will resolve on its own. They will seek physician help only if the problem is very serious, and prefer to avoid taking prescription drugs. At the other end of the continuum would be "help-seekers[1]," who prefer to seek physician help whenever they have any health problem and are uncomfortable managing an illness on their own. They are very comfortable taking prescription drugs, and in fact may feel they need to take prescription drugs to recover from most illnesses. Although it is possible that consumer preferences for using physician services and prescription drugs form separate dimensions of a medical care preferences scale, both types of preferences potentially are important factors in prescription drug utilization.

In addition to affecting prescription drug utilization directly, medical care preferences

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1. The term help-seeking has been used by researchers in other disciplines, but in this study it refers to someone who prefers to seek help from the formal medical care system rather than self-treat a health problem.

may influence the effect of insurance on prescription drug utilization. Consumers who prefer to self-treat probably will not use a lot more medical care in general, and prescription drugs in particular, just because their out-of-pocket costs are lower. In contrast, consumers who believe in visiting a doctor and using prescription drugs every time they get sick may increase their use of medical care significantly in response to the lower out-of-pocket costs resulting from insurance coverage. For help-seekers, financial constraints may be the strongest factor limiting their use of medical care. If those constraints are removed or reduced by insurance, these individuals may have very high medical care utilization.

Research Objectives:

There were four research objectives of this study.

1) To examine the effect of health insurance on prescription drug utilization, controlling for consumer medical care preferences.

2) To separate the moral hazard insurance effect from the adverse selection insurance effect.

3) To measure the direct effects of consumer medical care preferences on prescription drug utilization.

4) To examine whether consumer medical care preferences moderate the effect of health insurance coverage on prescription drug utilization.

CHAPTER 2

REVIEW OF LITERATURE

This chapter is divided into two main parts, the theoretical framework used for the study and a review of pertinent literature. Two theoretical models were used as the framework for the study. The primary model was an economic utility model, and it was used to illustrate potential effects of insurance and medical care preferences on prescription drug utilization. To examine the effects of insurance and preferences more accurately, other variables that affect the use of prescription drugs were controlled in the study. The second model was a three stage model of prescription drug utilization, and it was used to conceptualize and categorize these control variables.

The literature review is divided into four main sections. The first section describes research on the price elasticity of demand for prescription drugs. The second section focuses on insurance, and is subdivided into research on the effect of insurance on prescription drug use, research on the effect of insurance on physician utilization, and research on adverse selection in the health insurance market. The third section covers past research on the effects of consumer medical care preferences and health beliefs on physician utilization and prescription drug utilization. The final section presents research on other variables potentially affecting prescription drug utilization, and was limited to variables actually measured in the study. The chapter concludes with a summary of the significance of the study, and the hypotheses tested.

I. Theoretical Framework

Utility Model - Effect of Insurance:

Economists use utility models to illustrate how consumers choose to allocate their resources. Utility is defined as "a measure of the consumers' level of satisfaction with various combinations of consumer goods" (Folland et al 1993), and is a function of the goods and services consumed. For simplicity, utility often is defined as a function of two goods; the good of interest, and a composite good representing all other goods and services that could be consumed. More utility is better, and thus consumers try to achieve the highest possible utility level, subject to their financial constraints. Indifference curves are used to summarize consumer preferences, and combinations or "bundles" of goods that are on the same indifference curve provide the same level of utility to the consumer. It is generally assumed that indifference curves are: 1) downward sloping, 2) convex to the origin and 3) non-crossing. If these conditions are met, utility is maximized at the point of tangency between an indifference curve and the budget constraint.

In the case of medical care, a consumer's utility is said to be a function of medical care (M) and a composite good (X) that represents all other goods. For this study, medical care was defined as treatment for a health problem obtained through the formal medical care system, and was restricted to physician services and prescription drugs. Consumers maximize their utility subject to their budget constraints, where the budget constraints are functions of the price of medical care, the price of the composite good, and the consumers' incomes.

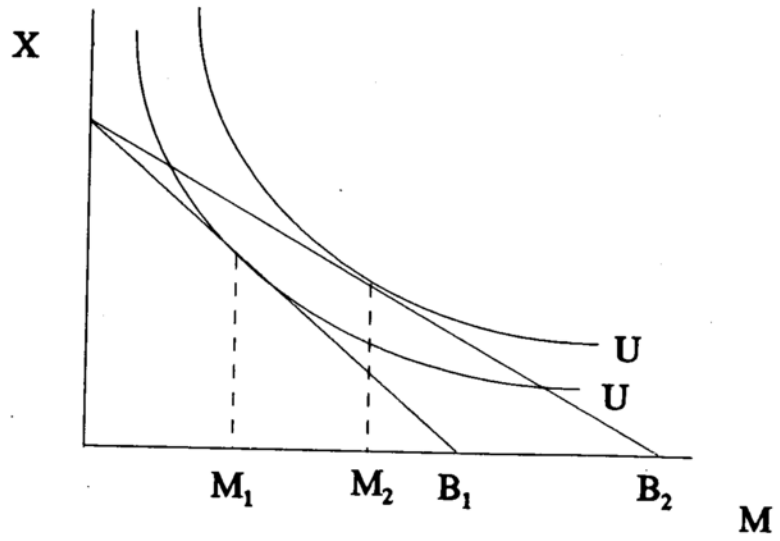
max U(X, M)

s.t. $p_1X + p_2M = y$

where p_1 = price of M
p_2 = price of X
y = income

This is shown graphically in Figure 2.1, where the x-axis represents units demanded of medical care M, and the y-axis represents units demanded of the composite good X. Each indifference curve U shows combinations of medical care and the composite good that provide the same level of utility to the consumer[2]. The budget constraint B_1 is the budget

Figure 2.1 Utility Model of Insurance Effect on the Use of Medical Care



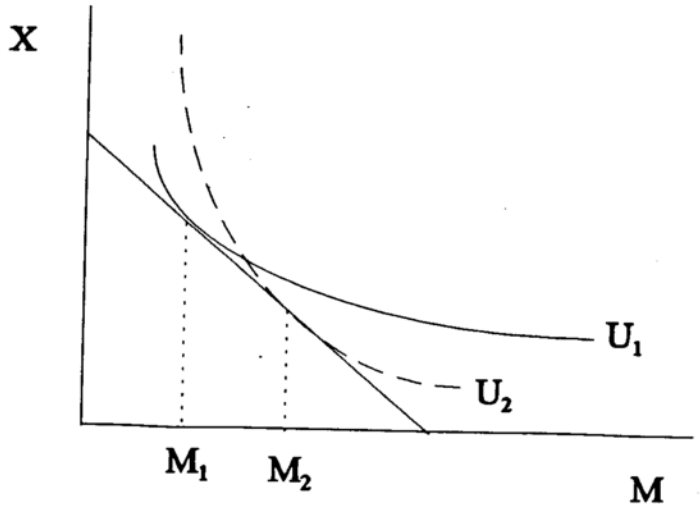
[2] Grossman (1972) proposed that demand for health care is derived from the demand for health. This theory suggests that utility is a function of health U(H,X) instead of medical care U(M,X). However, for this study it will be assumed that the indifference curves U(M,X) have the same general shape as the indifference curves U(H,X) and thus the demand for medical care can be used as a proxy for the demand for health (Phelps 1992).

constraint for an uninsured individual, and the quantity of medical care demanded (M_1 units) is determined by the point of tangency between B_1 and U. For an insured individual, the price of medical care is lower, and therefore his/her budget constraint (B_2) is shifted out along the M axis. Assuming the indifference curves for insured individual and uninsured individuals are the same shapes, the insured individual will demand M_2 units of medical care, with $M_2 > M_1$. This insurance effect on consumption has been termed moral hazard (Pauly 1968).

Utility Model - Effect of Preferences:

Consumers' preferences for using medical care are important because they determine the shapes of their indifference curves. The direct effect of this on the demand for medical care is shown in Figure 2.2. U_1 is an indifference curve for a self-treater, someone who prefers to avoid using physician services or prescription drugs whenever possible. This

Figure 2.2 Utility Model of the Effect of Preferences on the Use of Medical Care

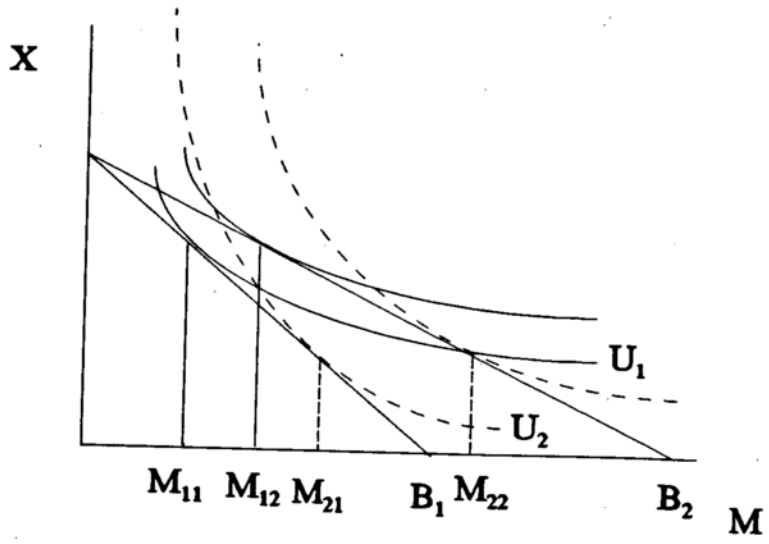


individual would rather spend more of his/her income on non-medical care goods, and will demand M_1 units of medical care. U_2 is an indifference curve for a help-seeker, someone who prefers to seek professional medical care in response to an illness. The help-seeker prefers to allocate more of his/her resources for medical care. Under the same budget constraint as the self-treater, the help-seeker will demand M_2 units of medical care, with $M_2 > M_1$. It was hypothesized that preferences would lie along a continuum, but for simplicity, the model does not show the continuum of preferences. Instead it depicts possible utility curves for individuals with strong self-treating and help-seeking preferences.

Utility Model - Interaction Effect of Insurance and Preferences:

In addition to having a direct effect on the use of medical care, preferences also may moderate the effect of insurance on the use of medical care (Figure 2.3). Individuals who

Figure 2.3 Utility Model of the Interaction Effect of Preferences and Insurance on the Use of Medical Care



prefer to treat most health problems on their own probably will not use a lot more medical care just because they have insurance coverage. In contrast, individuals who have strong preferences for seeking professional medical care when they have a health problem may use significantly more medical care in response to the lower out-of-pocket costs resulting from insurance. Having insurance shifts the budget constraint from B_1 to B_2. This increases the self-treater's use of medical care from M_{11} to M_{12} and increases the help-seeker's use of medical care from M_{21} to M_{22}. Thus, the predicted moral hazard effect is greater for the help-seeker than for the self-treater, $(M_{12} - M_{11}) < (M_{22} - M_{21})$.

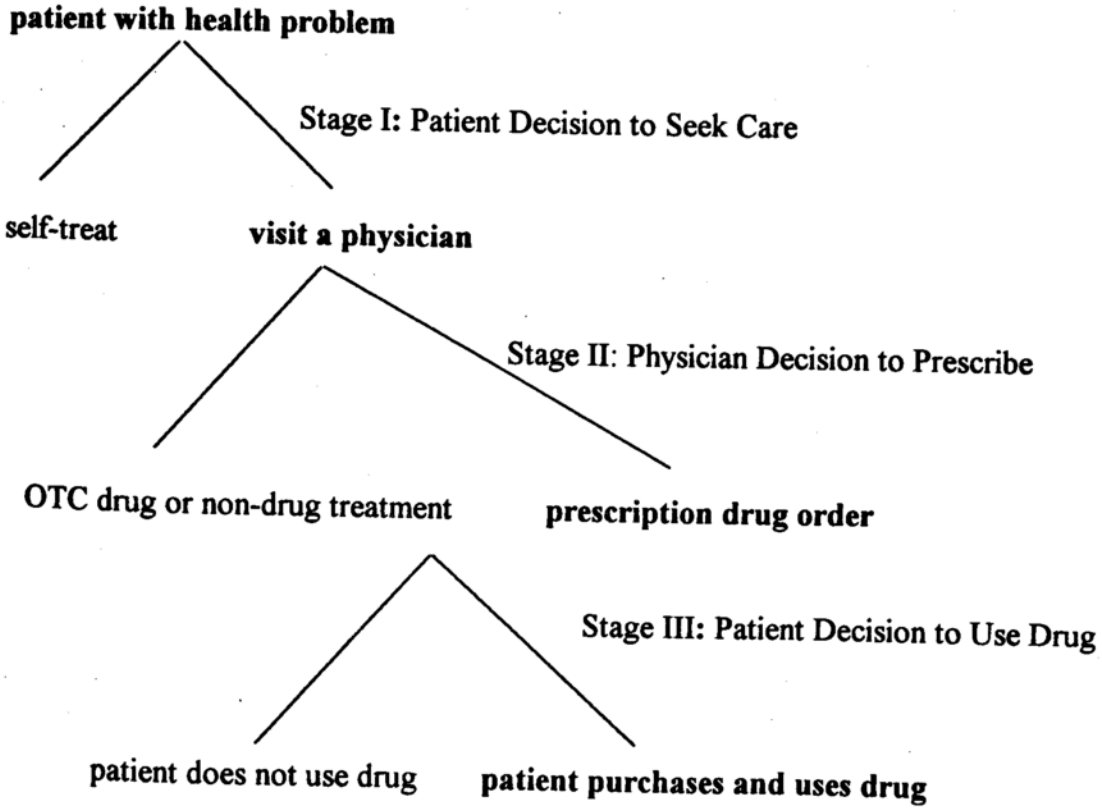
Model of Prescription Drug Utilization:

In order to measure insurance and preference effects on prescription drug utilization accurately, it was necessary to control for other variables that effect prescription drug utilization. The demand for any type of medical care is a complex phenomenon and there are many variables potentially affecting the use of medical care in general, and prescription drugs in particular. A three stage model of prescription drug utilization was proposed as a way to conceptualize and categorize these variables. This model is an extension of Feldsteins' (1966) two stage model of the demand for medical care.

In the first stage of Feldstein's model, patients with health problems decide whether to visit a physician. If they decide to seek physician help, in the second stage of the model the physician combines various components of medical care into a treatment plan for the patient. Feldstein classified variables affecting the use of medical care into patient variables and physician variables, and proposed that patient variables affect both stages of utilization but physician variables affect only the second stage. He further classified patient variables

into economic, cultural-demographic, and need variables. Feldstein's model is useful because it brings to bear the notion that obtaining medical care is not a single stage process. For prescription drug utilization, I proposed a third stage, whereby after obtaining a prescription from the physician, the patient decides whether to purchase and use the medication. Figure 2.4 illustrates this three stage decision model of prescription drug utilization.

Figure 2.4 Three Stage Decision Model of Prescription Drug Utilization



All three stages of the model are important, because for a prescription drug to be used: 1) the patient must visit a physician or other prescribing health professional, 2) the physician

must write a prescription order, and 3) the patient must choose to purchase and use the prescription. Even though a prescription order must be obtained from a health professional, patient factors are important in all three stages of the utilization model. In the first stage, patients must decide whether to seek help or treat the illness on their own. In the second stage, patients may influence the physician's prescribing decision. For example, a patient may request a prescription order or they may request a brand name drug. In the third stage, patients make the ultimate decision about whether to purchase and use the medication. Both insurance status and preferences potentially affect consumer decision at all three stages. The model also provides a framework to categorize other variables that may affect prescription drug utilization.

Stage I Variables:

Variables affecting the initial decision to seek care potentially include: incidence of illness, perceptions of illness, monetary and time costs for using physician services, income, and patient preferences for using physician services and prescription drugs. Incidence of illness is important because physician visits, except routine preventive care visits, are in response to health problems. Individuals with more frequent illnesses or chronic health problems would be expected to visit the physician more often. Perceptions of illness also are important, because a patient's decision to seek physician help in response to a health problem may be related to how serious they perceive the illness to be. An individual with a given set of symptoms may feel that the problem is minor and that it is not necessary to see a physician. Another individual with the same set of symptoms may perceive them to be very serious and believe that a physician should be consulted.

Monetary and time costs also may affect a patient's decision to seek physician help. If the monetary cost of the physician visit is low, patients may be more likely to choose to seek physician help. If the monetary cost is high, patients may feel that the cost outweighs the benefit, or they may simply be unable to afford the cost. Income plays a role in this because it is more likely that low income individuals will be unable to afford to pay the cost of a physician visit. If physician visits are normal economic goods, theory suggests that ceteris paribus, high income individuals would use more physician services than low income individuals (Folland et al. 1993). Individuals with higher hourly wage rates also will have greater opportunity costs for missing work, because time off from work results in more foregone wages. However, individuals in low paying jobs may find it more difficult to afford to take time off from work, or may not have sick leave. Insurance for physician services is a factor because it lowers the monetary cost of using physician services. Time costs are another potentially important factor because individuals who have to travel farther to see a physician may use their services less often. Employment status also may be a factor affecting time costs, because it may be difficult for some employed individuals to take time off work to visit a physician.

Patient preferences also are important. Some individuals may prefer to self-treat illnesses whenever possible. This could be because they dislike doctors or do not like to use prescriptions drugs. Alternatively, self-treating preferences may result from patients believing that they have enough knowledge to treat the illness themselves. They may have had the same symptoms previously and feel confident that they can handle them without physician help. These individuals also may choose to self-treat unless they believe there is an

effective treatment that can be obtained from the doctor. Other individuals may have strong preferences for seeking physician help. They may be very uncomfortable managing an illness by themselves. They may visit the physician as much for reassurance as for treatment of the illness. Some individuals also may have a strong belief in the effectiveness of prescription drugs, and may feel they need prescription drugs to recover from most illnesses. Both preferences for using physicians and preferences for using prescription drugs may be important in this stage. Individuals who want to use a prescription drug may visit a physician expressly to obtain a prescription order. Conversely, individuals who prefer not to take prescription drugs may avoid visiting a physician because they think that the physician merely will prescribe a drug.

Stage II Variables:

In the second stage, variables that may affect physician prescribing decisions include: type and severity of illness, physician beliefs, knowledge and preferences, prescription drug costs, and patient preferences. Type of illness is important because prescription drugs are not available to treat all types of illnesses. Severity of illness also may be important, both in the decision to prescribe, and in the type of drug prescribed. For example, if a patient has borderline high blood pressure, the physician may recommend diet and exercise instead of a prescription drug. However, if a patient has extremely high blood pressure, the physician may start prescription drug therapy immediately. The physician also may choose a different type of high blood pressure medication for very high blood pressure than for moderately high blood pressure.

Physician variables also are important in physicians' prescribing decisions (Eisenberg

1979; Zelnio 1982; Eisenberg 1985; Schwartz et al. 1989). Some physicians may prefer to use non-drug strategies whenever possible, or take a watchful waiting approach. Other physicians may prefer to prescribe a medication whenever possible. This may be because they believe the patient expects it, or it may just be an easy way to end a visit. Physician preferences also may affect the type of drug prescribed (Eisenberg 1979). Physicians may prefer to use products that they have experience with, or they may prefer to use the newest therapy. Some physicians may prefer not to prescribe generic drug products. Physician knowledge also is important because physicians must be aware of a new prescription drug to prescribe it. Finally, the type of practice setting may affect physician prescribing decisions. Physicians in a managed care environment may have financial incentives to prescribe fewer drugs or less expensive drug products, or they may have their prescribing restricted by formularies.

Patient preferences and prescription drug costs also may be important in this stage of utilization. Patient prescription drug preferences are important because patients influence physician decisions (Schwartz et al. 1989). For example, they may request that a prescription order be written, or they may request a specific drug. With increasing direct-to-consumer advertising by pharmaceutical manufacturers, it is expected that consumers will begin to know more specific product names. Alternatively, some individuals may tell their physician that they do not want to use a prescription drug to treat their illness. Drug cost may be another factor in physician prescribing (Lilja 1976). Physicians may be more likely to prescribe a low cost drug for uninsured patients (Mott and Kreling 1998). Uninsured patients also may request that a non-drug therapy be tried first.

Stage III Variables:

Variables potentially affecting the patient's initial decision to purchase and use a prescription drug include: monetary and time costs for obtaining prescription drugs, income, and patient preferences. The decision to continue using a prescription drug may be influenced by the cost of the prescription, the patient's income, and the patient's experience with the drug. For example, patients may discontinue taking the drug if they experience many side effects (Chewning In Press; Chewning 1994). Patient preferences for using prescription drugs are important, because even if a physician writes a prescription order, the patient may choose not to purchase and use the prescription. Patients who prefer not to use prescription drugs may accept a prescription order from the doctor simply because they do not want to argue or disagree with him/her. Research has suggested that unclaimed prescription rates vary from 0.5 percent to 2.7 percent (McCaffrey et al. 1998).

Monetary and time costs are important both in the initial decision to purchase the prescription and the decision to continue using the prescription. When a patient takes a prescription order to a pharmacy and discovers what the prescription costs, he or she may decide that the drug is too expensive to purchase. Patients may decide not to get any drug at all, or they may ask if there is a less expensive drug available. Insurance coverage is a factor in this, because insurance shields patients from the full cost of the drugs. Insured patients not only pay less than the full cost for prescriptions, but they also may not be aware of the full cost of the drug. Consequently, there is little incentive for them to request a less expensive alternative.

Cost may be an even larger factor in the decision to continue to use a drug. Patients

may be willing and financially able to purchase an expensive drug once, but may not be willing or able to continue purchasing that drug on a regular basis. If an expensive chronic medication is prescribed, the patient may: 1) discontinue the medication, 2) request to be switched to a less expensive medication or 3) use less of the medication. In this study, insurance was used as a proxy for the monetary cost of obtaining a prescription. Time costs also may be important. Many insurance companies restrict prescription quantity to a one month supply, and consequently patients may need to travel to the pharmacy every month to obtain medications that are used regularly. This may be a problem if patients have to travel long distances to get to the pharmacy, or if they have difficulty finding transportation to the pharmacy.

It is important to clarify that the purpose of this study was not to provide a comprehensive test of this model. Many variables in the model could be the sole focus of a study, and have been studied more thoroughly in other disciplines. The full model is proposed in the hope that it may be useful for future research on prescription drug utilization. For this study, only general prescription drug utilization was measured, and as a result it was not feasible to attempt to measure all variables in the model. Specifically, variables that were disease specific, or pertained to the use of specific prescription drugs were not included. The focus of this study also was on patient variables, not physician variables. This study also did not attempt to measure at what stage in the process the variables were important.

II. Review of Literature

The review of literature is divided into four main sections. The first section describes research on the price elasticity of demand for prescription drugs and other types of health care. The second section focuses on insurance, and is subdivided into research on the effect of insurance on prescription drug use, research on the effect of insurance on physician utilization, and research on adverse selection in the health insurance market. Some of this research has been done in elderly populations, and these individuals often have Medicare and supplemental Medicare insurance. To aid in understanding and interpreting this literature, descriptions of the Medicare program and Medicare supplemental insurance policies are provided in Appendix A.

The last two sections focus on variables, other than insurance, that effect prescription drug utilization. The third section addresses earlier research on the effect of consumer medical care preferences and health beliefs on health care utilization. The final section reviews the effects of other variables on prescription drug utilization. This section is not intended to provide a comprehensive review of the prescription drug utilization literature. Researchers in other disciplines, in particular sociology, have studied many of the non-economic variables extensively. This section is intended to provide in depth coverage of control variables measured in previous economic studies of prescription drug utilization and some examples of research in this area from other disciplines. The scope was restricted to variables that actually were measured in the study.

Price Elasticity of Demand for Health Care:

In order for insurance coverage to affect prescription drug use, the demand for

prescription drugs must be somewhat responsive to price. One way to assess responsiveness to price is to measure the price elasticity of demand, defined as the percentage change in quantity demanded resulting from a one percent change in price (Nicholson 1994). There have been several researchers who have attempted to measure the price elasticity of demand for prescription drugs, most of whom used National Health Service (NHS) data from Great Britain. O'Brien (1989) used NHS data to perform a time series regression analysis of prescriptions purchased from 1969 to 1986. During that period there was considerable variation in the copayments paid by consumers, including some consumers that were exempt from charges the entire time. O'Brien reported a price elasticity of demand of -0.33 over the entire period, signifying that for every 10 percent increase in price there was a 3.3 percent decrease in the quantity demanded. Price elasticities of demand in the one to zero range are considered inelastic (Nicholson 1994).

There have been two other studies that measured the price elasticity of demand for prescription drugs using NHS data. Lavers (1989) used monthly prescription data from 1971 to 1982, and controlled for the relative price of substitutes for prescription drugs, population income, level of sickness benefit, eligibility, and seasonal effects. He reported a price elasticity of demand between 0.15 and 0.20. Ryan and Birch (1991) used monthly data from 1979 to 1985. Their dependent variable was number of prescriptions per 1000 population and their independent variables were: prescription charge, price of substitutes, level of earnings, number of general practitioner physicians, morbidity proxy, month dummy variables, and lagged utilization. They reported a short run price elasticity of demand of -0.109 and a long run price elasticity of -0.09. This estimate is more inelastic than the

estimates from the other two studies.

In a United States study, Smith (1993) used data from a national prescription drug service to calculate the price elasticity of demand for prescription drugs. The data were composed of prescriptions from many different employer groups, with copayments ranging from $1 to $8 per prescription. Smith reported a price elasticity of demand of -0.098. This price elasticity of demand is very close to the value reported in the Ryan and Birch study. All of the studies suggest that the price elasticity of demand for prescription drugs is relatively, but not completely inelastic. However, this may be related to the small range of prices used in these studies.

Table 2.1 compares price elasticities of demand for prescription drugs with price elasticities of demand for other types of health care. The price elasticity of demand for prescription drugs and physician services seem similar, although demand for prescription

Table 2.1 Selected Research on Price Elasticity of Demand for Health Care

Study	Type of Health Care	Price Elasticity of Demand
O'Brien (1989)	prescription drugs	-0.33, -0.68
Lavers (1989)	prescription drugs	-0.15 to -0.20
Ryan and Birch (1991)	prescription drugs	-0.090, -0.109
Smith (1993)	prescription drugs	-0.098
Newhouse and Phelps (1976)	physician office visits	-0.081
Keeler et al. (1988)	outpatient care	-0.17 to -0.31
Keeler et al. (1988)	hospital care	-0.14 to -0.17
Newhouse and Phelps (1976)	hospital length of stay	-0.062

drugs may be slightly more elastic. The price elasticity of demand for inpatient services probably is somewhat more inelastic than the demand for outpatient services.

Effect of Insurance on Prescription Drug Utilization:

Research on the effects of insurance on prescription drug utilization and cost can be classified into three main categories: 1) longitudinal research on prescription drug use before and after a change in insurance status, 2) cross-sectional comparisons of prescription drug use for insured and uninsured individuals, and 3) research on how the structure of insurance benefits (e.g., type of cost sharing) has affected prescription drug use. Most of these studies have examined the effect of insurance on the quantity, and not the cost, of prescription drugs used by consumers.

Some researchers have used a longitudinal design to measure the effect of implementing prescription drug insurance coverage. Weeks (1973) used survey and prescription record data to measure the change in prescription drug use after a prepaid drug plan (with copayment) was introduced. Prescription drug use was measured for one week periods before and after the insurance change, with the post-change measurement occurring six weeks after the insurance change. A second round of data was collected after the copayment amount was reduced from $2.00 to $1.07. Weeks reported that the mean number of drugs prescribed per person per study period increased from 1.42 to 1.53 after implementing the insurance benefits. The mean subsequently increased from 1.56 to 1.70 after the copayment amount was reduced. However, the study was limited by the short reference period and possible confounding from seasonal effects.

Smith and Garner (1974) used a pre-post design to examine the effect of

implementing Medicaid[3] coverage on prescription drug use. The authors used pharmacy prescription records and patient interview data to examine the change in the number of prescriptions and prescription expenditures from a three month period before Medicaid coverage was implemented and the same three month period one year later. Data were collected for a sample of 241 patients. They found that the average number of prescriptions dispensed per patient in the three month period increased from 5.43 to 9.48. The average prescription expenditure increased from $18.96 to $42.54. Seasonal effects should not have been a problem because the same three month period was used before and after the coverage was implemented.

Gianfrancesco et al. (1994) examined prescription drug use for new entrants into an insurance plan with drug coverage. Prescription drug use in the study group (n=1,818) was compared with prescription drug use for individuals already enrolled in the program (n=1,841), who were chosen to match key characteristics of the study group. Data were obtained from both groups for a three year period, and both groups had a $5.00 copayment for prescription drugs. Over the three years, per capita expenditures for prescription drugs increased 59 percent for the new entrants group and 41 percent for the comparison group. The per capita number of prescriptions increased 35 percent for the new entrants and 23 percent for the comparison group. The authors concluded that approximately two-thirds of the difference in per capita expenditures between the two groups was due to greater

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[3] Medicaid is a government sponsored program that pays medical care costs for the poor. It is funded by both Federal and State funds, and coverage and eligibility requirements vary by state. All 50 states provide coverage for prescription drugs (National Pharmaceutical Council 1998).

numbers of prescriptions and one-third was due to a higher cost per prescription. The difference between the two groups was greatest in the first year of entry into the program, and then gradually decreased over the three years.

Grootendorst et al. (1997) used a two part econometric model to examine the effect of the Ontario Drug benefit plan on prescription drug use. This plan provides prescription drug insurance coverage to seniors, beginning at age 65. Self-reported data on the number of prescription drugs used over a four week period were obtained from the 1990 Ontario Health Survey, for a sample of individuals aged 55 to 75 (n = 9,370). The effect of the insurance was tested by including a dummy variable set equal to 1 for persons age 65 and older. Both the probability of any prescription drug use and the number of drugs used were examined. The authors concluded that the effect of insurance depended on health status. Individuals with four chronic conditions had significant increases in the probability of using a prescription drug and the number of prescription drugs used. Conversely, individuals with no chronic conditions did not have significant increases either in probability of use or level of use after implementing the insurance coverage.

Researchers also have studied the effect of insurance on prescription drug utilization using cross-sectional comparisons between insured and uninsured individuals. In one of the earliest studies, Greenlick and Darsky (1968) compared one year of prescription records for individuals in a prepaid drug plan with prescription records for a sample of individuals in the same community. They reported that individuals in the prepaid plan used more prescriptions and more expensive prescriptions than the individuals in the community. The age adjusted number of prescriptions per year was 4.20 for persons in the prepaid plan and 2.19 for

persons in the community. The average cost per prescription was $3.96 for the prepaid plan and $3.78 for the community. It is possible that some individuals in the community sample were insured, however, prescription drug insurance was relatively uncommon at the time of the study so this should not have been a significant problem.

Wolfe and Goddeeris (1991) examined the effect of Medicare supplemental (Medigap) insurance on prescription drug use in the elderly using data from the 1969 to 1979 Retirement History Surveys. They used regression analysis to compare prescription drug expenditures over a one year period for individuals with only Medicare insurance (n=475) to individuals with Medigap insurance (n = 1,403). They found that the group with Medigap insurance had higher prescription expenditures than the group with only Medicare coverage. However, when the correlation with previous years expenditures was allowed to be non-zero, the insurance coefficient was not significant. A problem with this study was that individuals were asked to report all of their medical expenditures over the past year, both expenses that they paid and expenses paid by their insurance. These data may not have been accurate, because it is difficult for people to remember their expenses over that long of a period, and they may not have known the amount paid by their insurer.

Coulson et al. (1995) also examined the effect of supplemental Medicare coverage on prescription drug utilization. They used 1990 self-reported data from a sample of Pennsylvania residents with Medicare (n = 4,509). A two week reference period was used for reporting prescription drug use. They found both own price-effects from prescription drug coverage and cross-price effects from physician supplemental coverage on prescription drug utilization. Having supplemental physician insurance increased the number of

prescriptions used in a two week period by 0.56, and having both supplemental physician coverage and supplemental prescription drug coverage increased use by 1.42 prescriptions. They also analyzed a group with coverage for prescription drugs provided by the state's Pharmaceutical Assistance for the Elderly (PACE) plan. This plan provided prescription drug coverage for low income elderly (with a $6.00 copayment), and was more generous than the typical Medigap prescription drug coverage. With PACE insurance, prescription drug use increased by 1.05 prescriptions and with PACE plus supplemental physician coverage, use increased by 1.42 prescriptions.

Coulson and Stuart (1995) re-analyzed data from the same study, using a Hausman test to examine whether insurance was an endogenous variable. They found evidence that insurance was endogenous, and as a result used a model where past hospitalization was a proxy for unobserved variables affecting insurance choice. They found that PACE enrollees used 0.29 more prescriptions over a two week period than elderly without supplemental insurance. Having PACE insurance led to significantly higher probability of any prescription drug use, as did supplemental Medicare insurance for physician visits. Private supplemental insurance for prescription drugs did not significantly affect prescription drug use, suggesting that the increased prescription drug use in individuals with supplemental prescription insurance reported by Coulson et al. (1995), resulted from adverse selection. None of the insurance variables significantly affected the number of prescriptions per prescription user.

Lassila et al. (1996) examined prescription drug use in an elderly rural population. Data were collected from 1,360 individuals aged 65 and older via in home interviews. The interviewees were asked to provide information on any prescription drugs they currently

were taking. Insurance coverage was classified as having any insurance coverage for prescription drugs. Polytotomous logistic regression models were used to measure the effect of the independent variables on prescription drug use, where an odds ratio greater than one represented increased likelihood of greater prescription drug use. They found that the effect of insurance on prescription drug use was significant, with insured individuals being 2.6 times as likely to have greater prescription drug use.

Most researchers studying the effects of insurance coverage on prescription drug use have examined quantity effects (probability of use or number of prescriptions used) and not intensity effects (cost of prescription drugs used). In one study that did report intensity effects, Mott and Kreling (1998) examined the association between insurance type and prescription drug cost. They audited a random sample of 6,120 new prescription orders from 10 independent pharmacies. Private third party prescriptions had the highest mean cost per dose, $0.83 compared to $0.60 for uninsured prescriptions. This appeared to result from the higher probability of brand name drug use for third party prescriptions. In the logistic regression model, the odds of the prescription being dispensed with a brand name product for a third party prescription were 1.71 times that of an uninsured prescription.

Insurers often design their insurance plans to include incentives for consumers to use fewer prescriptions or less expensive prescriptions. These incentives may include cost sharing, such as copayments or coinsurance, or limits on the number of prescriptions that can be obtained. A number of researchers have examined the effect of these incentives on the number and cost of prescription drugs used by insured individuals.

A seminal study in this area was the RAND Health Insurance experiment, designed

to measure the effect of cost sharing on consumer demand for health services (Leibowitz, Manning and Newhouse 1985; Manning et al. 1987). In this experiment, families in six cities were randomly assigned to health insurance plans with 0, 20, 50, or 95 percent coinsurance, although there was a maximum out-of-pocket amount after which there was no charge for services. The maximum annual out-of-pocket expense was 5, 10, or 15 percent of family income, up to $1,000. A total of 7,791 individuals, all under the age of 62, participated in the study. Inpatient expenses, outpatient physician expenses and prescription drug expenses were examined for three or five year periods.

The amount of health care consumed was affected by the amount of cost sharing. Total per capita health care expenses were about 45 percent higher for the free plan than for 95 percent coinsurance plan, and the cost sharing appeared to affect the number of contacts with providers more than the cost per contact. The effect of the cost sharing on prescription drug use was even greater. Per capita prescription drug expenditures increased steadily as the percentage of cost sharing decreased, with expenditures in the free plan about 60 percent higher than the plan with 95 percent coinsurance (Leibowitz, Manning and Newhouse 1985). This also appeared to be due to an increased number of prescriptions used in the free plan, not higher costs per prescription.

The RAND study was unique in that consumers were randomly assigned to insurance plans. Theoretically, this should eliminate selection bias, and thus the insurance effects can be attributed completely to moral hazard. However, there were several limitations of the study. One major limitation is that elderly subjects were excluded from the study, and they are frequent users of prescription drugs. Other limitations of the study are higher rates of

refusal to participate in the non-free plans, confounding of site with plan, and a failure to report health care expenditures for the pre-experimental period (Welch et al. 1987). In spite of these limitations, the RAND study provides strong evidence that increased cost sharing decreases health care expenditures, in particular outpatient expenditures such as physician or prescription drug expenditures.

There are other studies that provide support for this conclusion. Nelson et al. (1984) used data from the South Carolina Medicaid program (n = 17,811) to examine the effect that implementing a $0.50 copayment had on prescription drug use. The researchers used the Tennessee Medicaid population (n = 27,841), that did not have a copayment, as a control group. They reported that the average number of prescriptions per Medicaid recipient in South Carolina decreased 2.8 percent over the three years after the copayment was implemented, compared to a 17.8 percent increase in Tennessee. The effect of the copayment differed, depending on the therapeutic class of the prescription (Reeder and Nelson 1985). Although the copayment was relatively small, Medicaid recipients have lower incomes than the general population, and thus the effect of the copayment probably was larger than it would have been in a non-Medicaid population.

The effect of copayments on prescription drug use also has been studied in a Health Maintenance Organization (HMO) setting. Harris et al. (1990) used data from a staff model HMO to examine prescription drug utilization under different copayments. They used a pre-post with control group design to analyze prescription records over a four year period. The study cohort was 19,982 beneficiaries under the age of 65 who experienced copayment changes. The comparison cohort was 23,164 beneficiaries who had no copayments during

the study period. Implementing a $1.50 copayment decreased the number of prescriptions relative to the comparison group by 10.7 percent. Increasing the copayment to $3.00 resulted in an additional 10.6 percent reduction. The effects of the prescription copayments were larger for drugs classified as discretionary than for drugs classified as essential. In the final year of the study, prescription copayments were combined with copayments for physician visits and this resulted in a 12 percent reduction in the number of prescriptions relative to the control group.

Effect of Insurance on Use of Physician Services:

Use of prescription drugs is linked closely with use of physician services, and as a result, it is useful to examine the effects of health insurance coverage on the use of physician services. Link et al. (1980) compared the effect of Medicare supplemental insurance and Medicaid relative to Medicare alone, using data from the 1976 Health Interview Survey. They used a Tobit estimation technique to examine the effect of supplemental insurance on the number of physician visits in the last year (n = 8,239). For individuals with no chronic conditions, both private supplemental insurance and Medicaid coverage significantly increased the number of physician visits, from 1.79 to 2.53 and from 1.79 to 2.68 respectively. For individuals with some chronic conditions, only Medicaid was significantly different from Medicare, increasing the average number of physician visits from 8.59 to 9.61.

McCall et al. (1991) also examined the effect of supplemental Medicare coverage on the use of physician services. They used a sample of Medicare beneficiaries in six states who had both Parts A and B coverage and were not eligible for Medicaid (n = 2,456). Having supplemental coverage significantly increased the use of Part B (physician) services. The

effect of the supplemental coverage was greatest for individuals in fair or poor health, who used 42 percent more physician services compared to individuals without Medigap coverage. The effect of supplemental insurance was greatest for first dollar policies.

Hurd and McGarry (1997) used data from the Asset and Health Dynamic Survey to examine the effect of insurance on the use of physician services in an elderly population (n=7,327). They compared physician use for individuals with only Medicare Part A coverage to individuals with both Part A and B coverage, individuals with Medicare plus supplemental coverage, and individuals with Medicare plus Medicaid coverage. The authors reported that having more insurance increased the probability of having at least one physician visit. For the number of physician visits, the only type of insurance coverage that was significant was having Medicare and Medicaid, which increased the number of visits in the last year by 0.72 compared with having only Medicare coverage.

Although most of the studies of the insurance effect on the use of physician services are cross-sectional comparisons between individuals with different levels of insurance, one study reported the effects of implementing a copayment for physician services. Jung (1998) used data from a Korean population to examine the effect of implementing a per-visit copayment on outpatient medical care utilization, including physician visits and prescription drug use. The data were from a sample of 10,170 employees of a large company. Illness episode data, annual medical care utilization data, and total expenditures were analyzed. He found that implementing the copayment significantly decreased the probability of using any outpatient services, but appeared to increase the cost per visit. Per illness episode, physician visit rates declined 8.4 percent but the cost per visit increased 9.8 percent.

In some of the studies reviewed previously in the section on effects of insurance on prescription drug utilization, researchers also examined the effect of health insurance on physician utilization. In the RAND study, Manning et al. (1987) found that expenditures for physician services in the free plan were about 66 percent higher than expenditures in the 95 percent coinsurance plan. This effect was slightly higher than the 60 percent greater prescription drug expenditures in the free plan. Wolfe and Goddeeris (1991) reported that individuals with supplemental Medicare insurance had greater physician expenditures than those without supplemental insurance. The moral hazard effect in this study also was greater for physician expenditures than it was for prescription expenditures.

Insurance for physician visits should increase the use of prescription drugs because prescription drugs typically are ordered by a physician. Physician visits and prescription drugs are complements, and thus a positive cross-price effect of physician insurance coverage on prescription drug utilization is expected. A few researchers have measured this cross-price effect directly. In the Coulson and Stuart (1995) study described earlier, coverage for outpatient physician services increased the probability of prescription drug use by 5 percent. This is less than the 11 percent increase resulting from insurance coverage for prescription drugs. In the Jung (1998) study, implementing a per visit copayment for physician services decreased the number of medication days per illness episode by 3.5 percent.

Adverse Selection in the Health Insurance Market:

One difficulty in measuring the moral hazard effect of insurance on prescription drug use is adverse selection. Individuals who expect high prescription drug expenditures may be

more likely to purchase insurance and as a result, higher expenditures in an insured population may be due to moral hazard or adverse selection. This means that if adverse selection is not accounted for, estimates of the moral hazard effect may be biased. From an econometric perspective, there is concern about endogeneity because unobservable determinants of insurance choice may affect prescription drug utilization. Several researchers have examined whether there is evidence for adverse selection in the health insurance market.

Price and Mays (1985) examined adverse selection in the Federal Employees Health Benefits Program (FEHBP) for the years 1981 through 1984. They analyzed data from 20 of the FEHBP plans, containing 85.5 percent of the approximately 3.8 million federal worker and retirees enrolled in FEHBP. They estimated what premiums would have been if there was no adverse selection, and then compared their estimates with the actual premiums. In their model, they accounted for moral hazard effects using estimates from the Rand Health Insurance Experiment. Selection effects for most plans were more than 10 percent, and the authors concluded that the selection effects were significant and persistent over time.

Browne (1992) used data from the National Medical Expenditure Survey (NMES) to examine whether there was evidence for adverse selection in the individual health insurance market. This market consists of individuals who purchase a health insurance policy directly from the insurer. Browne compared the amount of insurance coverage purchased in the individual market to the amount that would have been predicted, based on what was purchased in the group market. There is presumed to be minimal adverse selection in the group health insurance market, because this insurance is provided largely through employers.

He found that the amount of insurance purchased in the individual market was significantly less than would have been predicted from the group market purchases. This finding is consistent with adverse selection.

Browne and Doerpinghaus (1993) examined adverse selection in the market for individual medical insurance. They used National Medical Care Expenditure Survey (NMCES) data from 1977 and 1978 to determine whether low risk individuals purchase less complete insurance coverage than high risk individuals. Individuals were defined as low risk if none of the members of their household reported being in poor health. Low risk and high risk individuals purchased policies with similar cost sharing provisions, but high risks received more benefits per dollar of premium than low risks. The authors concluded that these findings were consistent with the presence of adverse selection.

Browne and Doerpinghaus (1994) also examined adverse selection effects in the Medicare supplemental insurance market. They used NMES data to determine whether individuals with high and low levels of risk purchased different levels of Medigap coverage. In the study, high risk individuals were those who reported that they were in poor health. Coverage purchased by low risk and high risk individuals was not significantly different when coverage was measured by policy provisions and when coverage was measured by the policy premium. However, they found that low risks received fewer indemnity benefits from their coverage than high risks. The authors concluded that low risks would purchase more insurance if adverse selection were not present in the market.

Some researchers have tried to examine or control for adverse selection when estimating insurance effects on health care utilization. One of these studies was the

previously discussed Wolfe and Goddeeris study (1991). They estimated two separate regression equations of the demand for health care, first assuming zero correlation with previous health care expenditures, and then allowing the correlation to be non-zero. This allowed previous health expenditures to function as a proxy for unobservable determinants of insurance choice. They found that the insurance coefficient was significant in the first equation, but became non-significant after allowing for correlation with past health care expenses. This suggests that the significant insurance coefficients in the first equation may have been due to adverse selection. However, they also found that individuals with supplementary insurance had better self-reported health than those without supplemental insurance, which is inconsistent with selection bias based on health status. Wealth appeared to be a stronger factor in whether supplemental insurance was purchased. The authors concluded that there is some adverse selection in the Medigap market, but the effect is not very large.

Coulson and Stuart (1995) also used past health care utilization as a proxy for insurance choice in a model of the demand for prescription drugs. A description of the data used in the study was provided previously. The authors stated that standard econometric techniques for handling endogenous variables have performed poorly in studies of the effect of insurance on health care utilization, and therefore chose to use a variation of the model used in the Wolfe and Goddeeris (1991) study. They created a proxy variable to capture prior health status, using data on past hospitalizations and Medicare Part A payments, and then used the Hausman test to examine the endogeneity of the insurance variable both with and without the proxy variable. They found that insurance choice was correlated with the

error term when the proxy was excluded, and uncorrelated when the proxy was included. The authors concluded that using the proxy variable addressed the endogeneity problem, but they did not make specific conclusions about adverse selection.

The Coulson et al. (1995) study discussed early used a different approach to control for potential adverse selection bias. They used a two-stage procedure, in which parameters of a multinomial logit model of insurance choice are estimated in the first stage, and then used in a nonlinear least squares model predicting the use of prescription drugs. An estimate of a parameter indicating the presence or absence of adverse selection bias is obtained in the second stage of the model. This parameter was not significant in the study, suggesting that adverse selection bias was not present. The coefficients obtained in the two stage model were similar to the coefficients obtained in a simple nonlinear least squares model, also suggesting that adverse selection bias was not an issue.

Long (1994) examined prescription drug expenditures for insured and uninsured Medicare beneficiaries using 1987 NMES data. To examine whether the increased expenditures in the insured group were due to adverse selection or moral hazard, he first compared individuals with employer sponsored Medigap coverage that did not include prescription drug coverage to individuals with employer sponsored Medigap coverage that did include prescription drug coverage. He assumed that selecting into an employer group based on anticipated prescription drug expenses during retirement was unlikely, and therefore any difference in prescription drug spending between these two group should primarily be a moral hazard effect. He then examined the difference in expenditures between individuals who had non-employer sponsored Medigap plans that did not include

prescription drug coverage and those who had non-employer sponsored Medigap plans that included prescription drug coverage. Long found that there was no insurance effect in the employer sponsored Medigap groups, and thus concluded that the 26 percent greater prescription drug expenditures in the non-employer sponsored Medigap group were entirely due to adverse selection.

There are many researchers that have examined consumer choice of insurance plans. Although a complete review of this literature is beyond the scope of this study, there are two studies examining choice of Medigap coverage that are relevant. In the Hurd and McGarry study (1997) discussed earlier, the authors examined whether having Medigap insurance was related to health status. If adverse selection is present, individuals in poorer health should be more likely to have Medigap insurance. The authors used a probit model to estimate the probability of having Medigap insurance. They found that self-reported health status did not significantly affect the probability of having Medigap insurance, which is not consistent with the presence of adverse selection. Income and wealth effects were significant, with wealthier individuals being more likely to have Medigap insurance. The strong income effect is consistent with other research. One limitation of this study was that information was not available on whether the Medigap insurance was obtained through a former employer or purchased individually.

Vistnes and Banthin (1997) used 1987 NMES data to examine Medicare beneficiaries' demand for supplemental insurance. This study was unique because the authors included attitudes toward medical care and risk as predictors in the model. They found that attitudes toward medical care had as large an effect on the demand for

supplemental insurance as self-reported health status, the presence of specific health conditions, and income. This study also was important because the authors examined the demand for prescription drug coverage specifically. They found that medical care attitudes, education level, and the presence of specific medical conditions significantly affected the demand for prescription drug coverage. It seems logical that if attitudes toward medical care affected the demand for prescription drug insurance coverage, they also would affect the use of prescription drugs directly.

Summary of Research on Insurance Effects on Prescription Drug Use:

Research has shown that although the price elasticity of demand for prescription drugs is in the inelastic range, it is not completely inelastic. Insurance lowers the out-of-pocket cost of prescription drugs for consumers and thus, insurance coverage should result in increased prescription drug use. The literature on the effect of prescription drug insurance on prescription drug use provides evidence to support this conclusion. In longitudinal research, implementing insurance has been shown to increase the use of prescription drugs. In cross-sectional comparisons of insured and uninsured individuals, prescription drug use was higher in insured individuals. Insurance coverage also appears to increase the use of physician services, and this would be expected to increase prescription drug utilization. Research also has shown that the amount of cost sharing affects prescription drug use in an insured population, with prescription drug use decreasing as the amount of cost sharing increases.

In spite of the substantial body of research on the effect of insurance on prescription drug use, problems with previous research and gaps in the literature create a need for

additional research. One problem with previous research is how adverse selection was handled. Research on adverse selection in the health insurance market has had inconsistent results. Researchers comparing insurance purchases in group and non-group markets have found evidence of adverse selection. However, other studies on the demand for health insurance have found that health status is not a significant factor in predicting insurance choice. This suggests that adverse selection is not a problem, or that adverse selection results from something other than health status.

The issue of adverse selection also has been addressed in some research on the insurance effect on prescription drug utilization. The methods used to address the problem have been almost as numerous as the studies that have examined the problem. Many researchers have ignored the potential for adverse selection. Others have controlled for the possible endogeneity problem using past health care utilization as a proxy for unobservable determinants of insurance choice. However, this approach assumes that health status is the only unobservable determinant of insurance choice and this may not be the case. Vistnes and Banthin (1997) found that health care attitudes had as strong of an effect of insurance choice as health status. Coulson et al. (1995) and Long (1994) used somewhat unique methods to control for selection, and had completely opposite results. Long reported that the insurance effect was due entirely to adverse selection, and Coulson et al. reported that the adverse selection effect was not significant.

Some of the contradictions in the literature may result partly from whether the researchers are examining health insurance in general or prescription drug insurance in particular. They also may be a function of the different methods used to study adverse

selection. Regardless, there does not appear to be definitive conclusions on either how important it is to control for adverse selection, or what method to use. Consequently, more research is needed to determine whether estimates of the insurance effect on prescription drug use are biased by adverse selection. In this study, the extent of the bias was measured explicitly.

Another problem with past research on the effect of insurance coverage on prescription drug utilization is that researchers typically have relied on secondary databases that contain very few patient variables. In particular, previous research has failed to account for the possible effects of medical care preferences. Consumer preferences for using physician services and prescription drugs potentially affect all three stages of the prescription drug use model, and yet previous research on the effect of insurance on prescription drug utilization either has ignored preferences, or tried to measure them indirectly, using demographic information such as age, gender, and race. These variables probably are inadequate measures of consumer preferences, and instead may capture differences in the incidence of illness. Consequently, there is a need to examine the insurance affect on prescription drug use, accounting both for adverse selection and consumer medical care preferences.

Consumer Medical Care Preferences:

Consumer medical preferences or health beliefs generally have been ignored not only in research on insurance effects, but also in most multivariate studies of prescription drug utilization. As a result of the lack of research, and because physician utilization and prescription drug utilization are related, the literature review was expanded to include

research on the effects of health beliefs on physician utilization. However, a comprehensive review of research on the effects of health beliefs on the use of specific types of physician services or other health behaviors was beyond the scope of this literature review. This study was a multivariate study of general prescription drug utilization and thus the more narrowly focused studies were less relevant. As a result, the literature review was restricted to multivariate research on the effect of health beliefs on general physician utilization and prescription drug utilization. The main goals of this section were to: 1) discuss the relationship between health beliefs and medical care preferences, 2) present research on the effects of heath beliefs on the use of physician services and prescription drugs, and 3) summarize and discuss limitations of previous research.

Health beliefs are defined as "attitudes, values, and knowledge that people have about health and health services that might influence their subsequent perceptions of need and use of health services" (Anderson 1995, p. 2). Preferences in general, and medical care preferences in particular, can be thought of in a slightly different way. Individuals' preferences reflect the relative values that they assign to any goods and services, and medical care preferences reflect the values that they assign to medical care goods and services specifically. For this study, medical care was defined as physician services or prescription drugs. Individuals who place a low value on physician services or prescription drugs would prefer to allocate more of their resources to other goods and services, and would prefer not to use physician services or prescription drugs in response to a health problem. In contrast, individuals who place a high value on medical care would prefer to use physician services or prescription drugs in response to a health problem.

Health beliefs and medical care preferences are related, in that preferences for using health care potentially result from individuals' health beliefs. For example, some individuals may have negative attitudes toward physicians. This may result in these individuals assigning a low value to physician services, and therefore preferring to self-treat rather than seek physician help when they have an illness. Conversely, individuals who believe that physicians are very knowledgeable may prefer to seek physician help in response to a health problem. Some individuals may believe that prescription drugs have many side effects, and thus prefer not to use them. Preferences also can be considered somewhat broad in scope, as they likely result from many different attitudes and beliefs.

Research on physician utilization has focused on health beliefs rather than preferences. However, due to the relationship between health beliefs and preferences, the effects of health beliefs on health care utilization likely are related to the effects of medical care preferences on health care utilization. Common types of health belief used in health care utilization studies are attitudes, either toward physicians or general health care. Another type of health belief used frequently is health locus of control, defined as a person's belief that their health is determined by their own behavior (Wallston et al. 1976). Health locus of control (HLC) originally was proposed as a unidimensional measure, with one end of the scale representing individuals with an internal HLC and the other representing individuals with an external HLC. Internals believe that their health is under their control while externals believe their health is under the control of outside forces such as chance or other people. The scale subsequently was modified to create a multidimensional scale with internal, powerful others, and chance dimensions (Wallston and Wallston 1978).

Table 2.2 summarizes research on the effect of health beliefs on health care utilization. Wirick (1966) examined how attitudes toward seeking early medical care affected physician utilization and prescription expenditures, using data from a 1958 survey of Michigan households (n = 1000 households). The attitude measure was a single item about "whether one should go to the doctor at the first sign of trouble or wait to determine whether minor symptoms will disappear." The scale for the item was not provided in the article. Attitude toward early medical care did not significantly affect physician utilization, but it was significant in the model for prescription drug expenditures, with individuals who preferred to wait to seek care having less prescription drug expenditures than individuals who preferred to seek care immediately.

Bice and White (1968) measured the tendency to use medical care and its effect on use of physician services. They used interview data from three different populations: a city and surrounding rural district in England, a county in Vermont, United States, and a commune and surrounding area in Yugoslavia. An index of tendency to use medical care was constructed based on individuals' responses to what they would do if they experienced three health problems. Individuals were dichotomized into low and high tendency to use medical service, with high tendency being individuals who said they would visit a physician. It was unclear exactly how the index was constructed or whether individuals had to say they would visit a physician for all three health problems before they were classified as "high tendency." Tendency to use medical care was not a significant predictor of the use of physician services for any of the populations, and explained only about 2 percent of variance.

Anderson (1968) proposed a model of health services utilization that has been used

Table 2.2 Summary of Selected Research on the Effect of Health Beliefs on Health Care Utilization

Study	Health Belief Measure	# Items	Items Listed	Utilization Measure
Wirick (1966)	attitude toward early medical care	1	yes[1]	physician utilization prescription drug expenditures*
Bice and White (1968)	tendency to use medical care	3	yes[1]	physician utilization
Anderson (1975)	health care attitudes (4 types)	?	no	physician utilization
Stoller (1982)	health care attitudes	4	yes	physician utilization*
Sharp et al. (1983)	attitude toward symptoms attitudes toward using doctors	11 4	yes yes	physician utilization[2] physician utilization
Maeland & Havik (1989)	health locus of control	11	no	physician utilization (post-MI)*
Strain (1991)	degree of medical skepticism internal health locus of control external health locus of control	4 4 4	yes yes yes	physician utilization (elderly)* physician utilization (elderly) physician utilization (elderly)
Wolinsky and Johnson (1991)	worry over health control over health	1 1	yes yes	physician utilization (elderly)* physician utilization (elderly)
Bazargan et al. (1998)	internal locus of control chance locus of control powerful other locus of control	6 6 6	yes yes yes	physician utilization (elderly)* physician utilization (elderly)* physician utilization (elderly)*
Fiscella et al. (1998)	skepticism toward medical care	4	yes	physician utilization* hospitalizations*

* Authors reported that the health belief measure had a significant effect on health care utilization.

1. An incomplete description of items was given.
2. Interaction effect of actual symptoms and attitudes toward symptoms on physician utilization was significant.

widely in subsequent studies on health care utilization. He categorized factors affecting the use of health services into predisposing, enabling, and need variables. In this model, health beliefs are predisposing factors. The type of health belief measure used in research based on the Anderson model typically has been attitudes, either toward physicians or toward health care in general. In one of his earlier studies, Anderson (1975) tested the model using 1971 interview data. He tested four health belief measures: value of health services, value of doctors, knowledge of disease, and response threshold. More detailed information about the scales was not provided. None of the health belief measures significantly affected physician utilization. Kravitz (1975) used the same data to examine the effect of attitudes in subgroups of the population. She individually analyzed 10 attitude questions, and found that attitudes were related to physician utilization in some populations, namely blacks above the near poverty line and individuals over age 65.

Matthew and Feather (1976) constructed four different indices of health-related attitudes: perceived availability of care, skepticism toward medicine, skepticism toward physicians and dependency in illness. They examined the proportion of people with high scores on these indices and population rates of physician use in a Canadian population. The only information provided on the attitude indices was that they were constructed from a random sequence of questions with "yes" or "no" response categories. Neither the wording of the items nor the number of items used in the indices were provided. The authors also did not directly test the effect of attitudes on physician utilization. They merely reported physician use rate and the percent of "high" scorers on the attitude measures for individuals in four different areas of Canada. As a result, no conclusions about the effect of attitudes on

physician utilization could be made. They did report some variability in the percent of high scorers on some of the attitude measures across the different areas.

Stoller (1982) examined the effect of health care attitudes on physician utilization in individuals aged 65 and older, using the Anderson model as a framework. Health care attitudes were measured using four items, measured on dichotomous scales of agree or disagree. Each attitude item was entered into the regression model separately. Agreeing with the items "I have my doubts about some things doctors say to you" and "a person understands his own health better than most doctors do," significantly decreased physician utilization. Agreeing with the item "some aches and pains you might as well get used to, because they are not important," significantly increased physician utilization but agreeing with the item "older persons have to expect a lot of aches and pains" did not have a significant effect.

Sharp et al. (1983) studied how attitudes toward symptoms and attitudes toward physicians affect the use of physician services. They analyzed telephone interview data from the 1980 Illinois Health Survey, where physician use was measured as the number of times a physician was seen in the last twelve months. Attitudes toward physicians were measured using a four item Likert scale and attitudes toward symptoms were measured by asking respondents to report whether a doctor should be seen for each of eleven symptoms (yes or no). Their responses were summed to create a single index for each type of attitude. The authors reported that neither attitude measure significantly affected physician utilization. However, they found that the interaction between actual symptoms experienced and attitudes toward symptoms had a significant effect on physician utilization.

Wolinsky and Johnson (1991) tested the Anderson model in an older population. They analyzed 1984 data from the Longitudinal Study on Aging (LSOA) for a sample of 5,151 individuals aged 70 and over. Physician utilization was measured as whether there was contact with a physician in the last twelve months, and if there was contact, how many visits. They used two single item measures to capture "worry over health status" and "control over future health." Both items were dichotomized for analysis, worried vs. not worried and control vs. no control. Worry over health increased both the likelihood of physician contact and the number of physician visits. Control over future health did not significantly affect physician utilization.

Strain (1991) examined the effect of "medical skepticism" and health locus of control on the use of physician services in an elderly population. She used interview data from individuals aged 50 and over who resided in Manitoba, Canada (n= 743). Physician utilization was measured by asking respondents to report the number of times they saw a doctor in the last year and degree of medical skepticism was assessed with four items measured on three point scales. Internal and external health locus of control each were assessed with four items, measured on three point scales. The items in each scale were generated from a larger pool of items using factor analysis. Degree of medical skepticism significantly affected the number of physician visits, with individuals who were more skeptical having fewer physician visits. Neither the internal nor the external HLC scales had a significant effect on physician utilization.

Health locus of control has been used in other studies on physician utilization. Maeland and Havik (1989) examined whether a shortened version of the HLC scale affected

short term and long term use of physician services in post-myocardial infarction (MI) patients (n = 383). Short term use was defined as the number of physician consultations within 6 months after the MI and long term use was the number of consultations within 3 to 5 years. They used an 11 item HLC scale, but the items and the type of scale were not given in the article. They found that long term use of physician services was affected significantly by HLC, with patients who reported less belief in internal HLC using more physician services. The same effect was seen in short term physician use, but it was not statistically significant.

Bazargan et al. (1998) also examined how HLC affected physician utilization, but their population was elderly African Americans (age 62 or older) who were residents of New Orleans, Louisiana (n = 1,114). The study was based on the Anderson model, and the authors examined the effect of internal HLC, chance HLC, and powerful other HLC scales on the number of physician visits in the past six months. Each of the HLC scales was composed of 6 items, measured using a 6 point Likert format. They reported that greater physician utilization was related significantly to a lower level of internal HLC and a higher level of powerful others HLC. Chance HLC was not related significantly to the number of physician visits. This study was notable in that 55 percent of the variance was explained by the full model.

In the most recent study, Fiscella et al. (1998) examined the effect of skepticism toward medical care on utilization of physician and hospital services. They surveyed a nationally representative sample of United States residents age 25 and older. Their medical care skepticism measure was four health attitude items, measured on five point Likert scales

(coefficient alpha = 0.69). More skepticism was associated with fewer physician visits, fewer hospitalizations, and lower total annual health care expenditures. A one standard deviation increase above the mean skepticism score resulted in a 14 percent reduction in health care expenditures. A one standard deviation decrease from the mean skepticism score resulted in a 15 percent increase in expenditures.

Summary of the Effect of Health Beliefs and Preferences on Health Care Utilization:

Several conclusions can be drawn from the review of research on the effect of health beliefs on health care utilization. The first conclusion is that there is very little multivariate research on the effect of health beliefs on prescription drug use. In all of the multivariate studies of the effect of health beliefs on health services use, only Wirick (1966) included a measure of prescription drug use. This is surprising, because the effect of health beliefs on prescription drug use may be stronger than their effect on physician utilization. Visiting a physician involves only an initial decision, while using a prescription drug requires an initial decision to use the drug and subsequent daily decisions about whether to continue taking the drug. Thus, there are more opportunities for health beliefs to affect decisions about prescription drug use. This does not imply that there has been a complete lack of research on how health beliefs affect prescription drug use. There has been research on how health beliefs affect certain types of drug use behavior, for example compliance. However, these types of studies were less relevant for my study because their methodologies were very different from a multivariate study on health care utilization.

Another conclusion from the review of this literature is that the effects of health beliefs on health care use have been inconsistent. In most of the earlier research, health

beliefs, usually attitudes, did not affect physician use significantly. However, in later research, there were some significant effects. Research on the effect of health locus of control on physician utilization also has had mixed results. Having a strong internal HLC has been shown to have no effect on physician use (Strain 1991) and has been shown to decrease physician use (Maeland and Havik 1989; Bazargan et al. 1998).

There are many possible reasons for the lack of consistently significant health belief effects on health care utilization. One possibility is that the health belief measures were unreliable or did not capture the construct adequately. There is good reason to believe that this is the case. The "attitude" measures used often have been only single item or a few items. Very little assessment of the reliability or validity of these measures has been reported. Researchers often have failed to report the internal consistency of the measures, or to conduct factor analysis to determine whether the construct is unidimensional or multidimensional. There also has been almost no discussion of how the attitude measures were conceptualized or developed. The exception to this is the HLC scale. This scale has theoretical underpinnings and the reliability has been tested in many studies.

There potentially is a different reason HLC has had mixed effects on physician utilization. The HLC scale is designed to measure whether individuals believe their health is under their own control (Wallston et al. 1976). Believing that your health is under your control may result in different effects on physician utilization. Individuals who believe their health is under their control would be expected to engage in behavior that they believe would improve their health. They may use a lot of medical care because they believe that this is the best way to improve their health (e.g., regular preventive care visits).

Alternatively, they could believe the best way to improve their health is to have a healthy lifestyle and use alternative therapies. Consequently, it is not surprising that HLC has had mixed effects on health care utilization.

There are other possible reasons why health belief variables have not been significant in some of the past research. Mechanic (1979) provides an excellent discussion of possible reasons why health belief variables are significant in many sociological studies on physician use, but not significant in large scale multivariate studies of physician utilization. He suggests that the methodology (qualitative vs. quantitative and processual vs. cross-sectional), and differences in concept measurement may be factors. However, even if health beliefs do not significantly affect physician utilization, they still may affect prescription drug utilization. In the three stage model of prescription drug use described earlier, health beliefs potentially are important at all three stages. They may affect the patient's decision to seek care from a physician (Stage I), the physician's decision to prescribe a drug (Stage II) and the patient's decision to purchase and use the drug (Stage III). Physician utilization is only the first stage in this process, and thus there are more opportunities for prescription drug use to be affected by health beliefs.

Past research has focused almost exclusively on health beliefs and not preferences. This raises the question of why use preferences instead of health beliefs. There are two main reasons why preferences are a better choice for my study. First, preferences fit within the economic utility model being used to illustrate the effects of insurance on prescription drug use. Preferences frequently are referred to in economic utility theory, they just usually are not measured explicitly. The second reason is that preferences are more general than most

of the health belief measures and likely are formed from many types of health beliefs. For example, consider individuals who prefer to self-treat rather than go to the doctor for most health problems. These individuals may dislike physicians, or they may believe they can treat the illness, or they may believe home remedies work well enough, etc. The preference to self-treat may have been formed from one of these beliefs or a combination of these beliefs. My study focuses on general prescription drug utilization, and thus the broader preference measure may be more useful than a very specific health belief measure.

Other Variables Affecting Prescription Drug Utilization:

The focus of this study was on the effects of health insurance and medical care preferences on prescription drug use, however, it would have been impossible to measure these effects accurately without controlling for other variables that affect prescription drug use. This portion of the literature review discusses control variables that have been used in previous research on prescription drug utilization. The scope of this portion of the literature review was restricted to variables that were measured in the study.

One important control variable is incidence of illness. Incidence of illness sometimes has been measured directly, using self-reported health status or number of type of medical conditions. These variables universally have been found to be significant. Self-reported health status has been used frequently, and individuals reporting poorer health consistently have been found to use more prescription drugs (Wolfe and Goddeeris 1991; Coulson and Stuart 1995; Coulson et al. 1995; Grootendorst 1995; Grootendorst et al. 1997). Studies that have used number of medical conditions also have found that prescription drug use increased as the number of reported conditions increased (Coulson and Stuart 1995; Coulson

et al. 1995; Grootendorst 1995; Grootendorst et al. 1997). Being hospitalized, and the number of days hospitalized also have been shown to affect prescription drug utilization significantly (Coulson and Stuart 1995; Lassila 1996). Given the strong effects of incidence of illness variables, a weakness of many earlier prescription drug utilization studies is that they did not control for these variables directly.

Incidence of illness also has been measured indirectly, using demographic variables such as age and gender. The effect of age on prescription drug utilization has been mixed, with some researchers reporting that age was not significant (Grootendorst et al. 1997 and Jung 1998), some reporting that older age increased prescription drug use (Greenlick and Darsky 1968; Stuart and Coulson 1993; Lassila 1996) and one reporting that older age decreased prescription use (Coulson and Stuart 1995). The researchers who found significant age effects typically did not control for health status. The exception to this was Coulson and Stuart (1995), who did control for health status and interestingly, found that older age was associated significantly with decreased prescription use. However, this was an elderly population, and this effect may have been due to sicker individuals not surviving to an older age. Gender also has had mixed effects on prescription drug utilization. Coulson and Stuart (1995) and Lassila et al. (1996) reported that gender was not significant. Stuart and Coulson (1993) and Grootendorst et al. (1997) reported that females were more likely to use prescriptions and Greenlick and Darsky (1968) reported that females used greater numbers of prescriptions.

Income has been included in some of the research on prescription drug utilization, and it also has had mixed effects. Lassila (1996) reported that income did not affect

prescription drug use significantly. Coulson and Stuart (1995), Grootendorst et al. (1997) and Jung (1998) reported that lower income was associated with less prescription drug use. Stuart and Coulson (1993) found both positive and negative income effects. Being in the second lowest income category decreased the level of prescription use in users relative to the lowest category, but being in the fourth lowest income category significantly increased the probability of any prescription drug use. Wolfe and Godeeris (1995) found that greater nonbequeathable wealth significantly increased prescription drug expenditures.

Significance of the Study:

Although there has been extensive economic research on the effect of insurance coverage on prescription drug utilization, most of the studies omitted potentially important variables and/or failed to account for adverse selection. Most researchers have used large databases of prescription records that contained very little information on patient characteristics. This study provides information on how important those missing variables are. In particular, previous research on the effect of insurance on prescription drug use has failed to account for consumer medical care preferences. In my study, consumer preferences for using physician services and prescription drugs were measured explicitly. Both the direct effect of these preferences on prescription drug use and the interaction effect of insurance and preferences on prescription drug use were measured.

Preferences have not been examined in previous multivariate studies of prescription drug utilization, but related health belief measures have been included in research on physician utilization. Results of these studies have been mixed, but there were problems with many of the health belief measures used. Even if preferences do not have a significant

effect on physician utilization, they still may affect prescription drug utilization. Furthermore, it is possible that the interaction effect of preferences and insurance on prescription drug use might be significant, even if preferences do not have a direct effect. The preference scale that was developed also may be useful in research on physician utilization.

A better understanding of preferences also may be useful in designing cost control strategies and promoting more efficient and equitable use of health care services. Individuals with extreme help-seeking preferences may use unnecessary medical care, and may need to be educated about when health problems can be self-treated. Individuals with strong preferences for self-care may avoid or postpone necessary medical care. This eventually may result in more expensive care because an illness was not found in the early stages, and thus these individuals may need to be encouraged to seek care. A significant interaction effect of insurance and preferences would suggest that preferences should be considered when designing the structure of insurance benefits.

Another contribution of my study is the method that was used to account for adverse selection. Most previous research on the effect of insurance on prescription drug use either has ignored adverse selection, or has used a variety of econometric techniques for handling endogenous variables. As discussed previously, previous research has been inconclusive. In my study, the method used was based on methods employed in previous research on adverse selection in the health insurance market (Browne and Doerpinghaus 1994) and on the method used in the Long (1994) study. This method used data on source of insurance, and did not assume that health status is the only variable correlated with insurance purchase.

The method helped determine how much estimates of the moral hazard effect were biased by adverse selection.

A final contribution of my study is that it provides additional information on some aspects of the insurance effect on prescription drug utilization that have had little previous attention. Very few studies have differentiated own price effects of insurance for prescription drugs from cross price effects of insurance for physician services. In this study I attempted to measure both of these effects separately. Understanding the magnitude of these effects is very important for policy decisions such as expanding Medicare to include prescription drug benefits. Very little research has been done on how specific types of prescription drug benefits effect prescription drug utilization, and the data on type and amount of cost sharing that were collected in this study will allow for future analysis of the importance of benefit structure.

Hypotheses:

Study hypotheses were separated into four groups. The first group of hypotheses, H1 to H3, pertain to the first research objective, to measure the effect of insurance coverage on prescription drug utilization. These hypotheses were based on the economic utility model described in the section on theoretical framework. A concern with measuring the insurance effect on prescription drug utilization is that the estimates will be biased upward because of adverse selection in the market. Previous research has provided some evidence that this is a problem, so the second research objective was to examine whether there was evidence for adverse selection in the prescription drug insurance market. The second set of hypotheses, H4 to H6, pertain to this objective.

In the economic utility model, preferences for using medical care determine the shape of indifference curves and thus should affect prescription drug utilization. The third set of hypotheses, H7 to H9, relate to the third objective of measuring the effect of preferences on prescription drug utilization. The utility model also predicts that insurance coverage for prescription drugs will have a greater effect on prescription drug utilization in individuals with help-seeking preferences than it will for individuals with self-treating preferences, and the last set of hypotheses, H10 to H12, were used to test this prediction.

H1: Prescription drug insurance/physician insurance coverage will increase the probability of using at least one prescription drug.

H2: Prescription drug insurance/physician insurance coverage will increase the number of prescription drugs used by individuals who have used at least one prescription drug.

H3: Prescription drug insurance/physician insurance coverage will increase the total cost of prescription drugs used by individuals who have used at least one prescription drug.

H4: The effect of prescription drug insurance coverage on the probability of using at least one prescription drug will be less for individuals at low risk for adverse selection than for individuals at high risk for adverse selection.

H5: The effect of prescription drug insurance coverage on the number of prescription drugs used by individuals who have used at least one prescription drug will be less for individuals at low risk for adverse selection than for individuals at high risk for adverse selection.

H6: The effect of prescription drug insurance coverage on the total cost of prescription drugs used by individuals who have used at least one prescription drug will be less for individuals at low risk for adverse selection than for individuals at high risk for adverse selection.

H7: The probability of using at least one prescription drug will increase as medical care preferences become more help-seeking.

H8: The number of prescription drugs used by individuals who used at least one prescription drug will increase as medical care preferences become more help-seeking.

H9: The total cost of prescription drugs used by individuals who used at least one

prescription drug will increase as medical care preferences become more help-seeking.

H10: The effect of prescription drug insurance coverage on the probability of using at least one prescription drug will be less for individuals with self-treating preferences than for individuals with help-seeking preferences.

H11: The effect of prescription drug insurance coverage on the number of prescription drugs used by individuals who have used at least one prescription drug will be less for individuals with self-treating preferences than for individuals with help-seeking preferences.

H12: The effect of prescription drug insurance coverage on the total cost of prescription drugs used by individuals who have used at least one prescription drug will be less for individuals with self-treating preferences than for individuals with help-seeking preferences.

CHAPTER 3

METHODS

A cross-sectional retrospective descriptive design was used for the study, and data were collected from Wisconsin consumers age 50 and over via mail survey. This chapter is divided into three main sections: 1) questionnaire development 2) data collection and 3) data entry and analysis. The first section describes the variables used in the study and how the questionnaire was pre-tested and pilot tested. Pilot testing the questionnaire was necessary to refine the preference measure and assess overall and item nonresponse rates. The pilot test was relatively large scale because of sample size requirements for preference scale analysis, and key results from it are reported in this section. The second section describes data collection methods, including the population and sample for the study. The final section of this chapter reports methods for data entry and analyses.

I. Questionnaire Development

A twelve page survey booklet was developed for use in this study. The questionnaire was designed to obtain self-reported data on: prescription drug use, health insurance coverage, medical care preferences, and other variables potentially affecting prescription drug utilization. The study methodology was a mail survey, and therefore the questionnaire was designed to be completed by consumers in their homes, without help from the researcher.

Prescription Utilization Variables:

Two measures of prescription drug utilization were used: 1) number of prescriptions

and 2) total cost of prescriptions. Number of prescriptions was used because it provides information on the quantity of prescriptions used, and it is relatively easy for consumers to report. It also has been used frequently in other studies, so results can be compared. A problem with number of prescriptions is that is does not capture differences in the cost of prescriptions used, or intensity of use. Health insurance coverage may affect both the quantity of use and the intensity use, so it is important to measure both. Total cost of prescriptions captures both quantity and intensity effects, but is more difficult to measure than number of prescriptions.

To obtain data on the number of prescriptions used, consumers were asked to report the number of different prescription drugs used in the last thirty days. Berk, Schur, and Mohr (1990) raised concerns about whether consumer self-reports of number of prescription drugs used are valid. They found that consumers could not recall accurately the number of prescriptions used in the last six months. However, a thirty day reference period should reduce problems with consumers' recall, and has been found to be less problematic (Polit and Sharp 1983; Crichton et al. 1978).

Consumers were asked to report the number of different prescription drug they used, rather than the number they purchased, because the number purchased might be confounded with prescription size, and therefore with insurance status. Prescription size may be related to insurance status because insured individuals often have prescription quantity restrictions that force them to purchase smaller size prescriptions more frequently. As a result, insured individuals may appear to purchase a larger number of prescriptions. For example, insured individuals on a chronic medication may purchase it once each month because they are

restricted to a month supply, whereas uninsured individuals may purchase several months supply at a time. Consequently, when asked to report the number of prescription drugs purchased in the last month, uninsured individuals may report "none," because the prescription was purchased several months ago.

Collecting data on the cost of prescriptions used is more difficult. Consumers could be asked to report the amount they spent for prescriptions in the last thirty days, but this approach has several problems. One problem is that this information is difficult for consumers to report. First, it may be difficult for consumers to recall exactly how much they spent on prescriptions, even for a thirty day reference period. Even if they can recall accurately what they spent on prescriptions, this amount may not reflect the true cost because insured consumers do not pay all of their prescription drug costs, and probably do not even know their total drug costs. Another problem is that the amount they spent on prescription drugs in the last thirty days is confounded by prescription size. People who purchased larger quantities will have spent more on prescriptions, even though they did not use more.

As a result of these problems, consumers were asked to list name and strength, directions for use, and quantity used for all of the prescription drugs used in the last thirty days. The total cost of the prescriptions was calculated from this list using reimbursement and drug cost pricing references. Details on how this was done are provided in the data analysis section. There was some concern that consumers would be unwilling or unable to provide a list of their prescriptions, so this was tested in the pilot study. Although asking consumers to list their prescriptions increased respondent burden, it provided important

information on intensity of use and provided a way to check the validity of the self-reported number of prescriptions used.

Health Insurance Variables:

Insurance type was determined by asking consumers to report: 1) whether they have insurance that covers all or part of the cost of physician visits, and 2) whether they have insurance that covers all or part of the cost of prescription drug costs. The information on insurance for physician visits was included to measure cross-price effects of physician insurance on prescription drug use. Consumers also were asked whether they belonged to a Health Maintenance Organization (HMO), because physicians in an HMO setting may have different incentive structures and prescribing restrictions than non-HMO physicians.

Some additional information was collected for consumers with prescription drug insurance. This information was intended for future research and was not used in the dissertation analysis. These individuals were asked to report the type of cost sharing (copayment, coinsurance, deductible) and the amount of cost sharing. They also were asked who sent in the claims to the insurer, because individuals whose pharmacies send in the claim for them usually do not see the cost of the drug. and this may increase moral hazard effects. As a way to verify the reported information, consumers were asked to report the name of their plan. Although plan information was not known for all reported plans, some of the more popular plans had cost sharing provisions that were known to the researcher.

To determine adverse selection effects of insurance, information also was collected on source of insurance (employer, individual policy, government program, or other). Individuals whose insurance was from an employer were asked to report how many

employees the employer had, using break points of 10, 25 50, 100 , and 500. Categories were provided to make the question easier for respondents to answer, and the break points were chosen based on levels that could be distinguished by respondents and that would provide meaningful information. Consumers with prescription drug insurance were asked if there was any time in the last year when they did not have insurance for prescription drugs, how many plans they had to choose from, and if any of the health insurance plans they chose from did not have prescription drug coverage. Consumers who did not have prescription drug insurance were asked to report the main reason why they did not have insurance. Choices were provided for this question to make it easier to answer.

Consumer Medical Care Preferences:

A nine item scale, developed for this study, was used to measure consumer medical care preferences. All items were measured on five point Likert scales. The preference scale was intended to capture general preferences for using prescription drugs and physician services, and therefore was not disease or symptom specific. A description of how the scale was developed is provided in a separate section later in this chapter.

Control Variables:

It is important to control for incidence of illness, because prescription drug use is highly correlated with both the number and severity of illnesses. A single item health status scale was used as a global measure of impact of illness. Respondents were asked to report their health, relative to others their own age, using the EVGFP scale (excellent, very good, good, fair, poor). This measure was used because it has performed well in past research on health care utilization (McCall et al. 1991; Wolfe and Goddeeris 1991; Coulson et al. 1995;

Hurd and McGarry 1997; and Grootendorst et al. 1998). Use of a longer health status measure, such as the SF-36, was ruled out because it would have lengthened the survey considerably.

The other measure of incidence of illness was the number of chronic conditions. This information was obtained by asking providing respondents with a list of chronic conditions and asking them to check any that a doctor ever has told them they have. The chronic conditions included on the list were frequently occurring medical conditions that typically are treated with prescription drugs. The list was obtained based on the researcher's knowledge, past studies, and data from a Wisconsin city on the incidence of various diseases and the percent of individuals with that disease being treated with prescription drugs.

A problem with assessing the effect of incidence of illness variables on prescription drug utilization is that the relationship is bi-directional. Health status affects prescription drug use, but prescription drug use also may affect health status. For example, having depression may result in an antidepressant being used, but then using the antidepressant helps the depression and improves health status. Consequently, if you ask someone if they are depressed, they may report they are not, because they are not depressed when they are on the medication. In order to minimize this problem, respondents were asked if they ever had been diagnosed with any of the illnesses. This is the format used in the National Health Interview Survey. Another potential problem with health status is that insurance status and health status may be correlated. However, data from the Rand Health Insurance Experiment suggested that differences in health insurance coverage do not significantly affect self-reported health status (Brook et al. 1983).

Other control variables collected were demographic data on age, gender, education, race, income, and employment status. Age was collected as a continuous variable, but income and education were collected as categorical variables because they potentially are more sensitive types of information to collect from consumers. Consumers were asked to report the highest level of education they had completed: elementary school, some high school, graduated high school, some post high school, graduated from a four year college, and Masters, Ph.D., or professional degree. These categories were chosen to match the categories provided in census data. Race information was collected using five categories: Caucasian, Hispanic, African-American, American Indian, Asian, and other. These categories also were chosen to match census categories. This question was not on the pilot survey, but was added to the main survey because of its public policy relevance.

Respondents were asked to report their approximate annual household income, before taxes, in 1998. Categories provided were: less than $10,000, $10,000 to $14,999, $15,000 to $24,999, $25,000 to $34,000, $35,000 to $49,999, $50,000 to $64,000, $65,000 to $79,999 and $80,000 or more. These categories were chosen to be comparable with census data. The financial resources of the household also are based on household size, and to account for this, respondents were asked to report how many people regularly live in their household.

Data on employment status were collected because employed individuals may find it harder to get time off from work to see a physician. Respondents were asked to report their employment status using the following categories: working 35 or more hours per week, working 15 to 34 hours per week, working 1 to 14 hours per week, and not currently

employed (including retired). The categories were chosen based on census categories. Data on zip code were collected in order to determine geographic region. This allowed the sample to be compared with the population, and accounted for possible regional differences in prescribing.

There are both time costs and monetary costs involved in obtaining prescription drugs. Travel time costs were assessed by asking respondents to report the distance they had to travel, both to their physician and their pharmacy. It was thought that distance would be easier for respondents to estimate and less variable than travel time to the physician and pharmacy. Categories were provided: less than 1 mile, 1 to 5 miles, 6 to 10 miles, 11 to 20 miles and more than 20 miles. These items are relatively crude measures of time costs, but are an improvement on previous research on insurance effects on utilization, because most of those studies did not include any measure of time costs. Time costs may now be an even more important factor in prescription drug use, due to the decrease in monetary costs resulting from the expansion of insurance coverage.

Questionnaire Pre-Test:

A 39 item questionnaire was developed to capture the variables described above. The questionnaire was given to a convenience sample of 12 consumers and colleagues. Each person took the survey and then was interviewed to determine whether the questions were clear and answerable. Based on this pre-test, several changes were made to the questionnaire. Respondents were asked how much they typically had to pay for physician visits, but this question was found to be difficult for individuals with Medicare to answer because of the complexity of the payment system. This question was not a crucial part of

the analysis, so it was removed from the questionnaire. It also was suggested that it would be easier for respondents to list the prescriptions they used if a table format was provided. The section on type and amount of cost sharing was found to be difficult for respondents to answer, so it was modified and additional instructions were added.

Pilot Test of the Questionnaire:

A cover letter and the modified questionnaire (Appendix B) were pilot tested via mail survey. They also were submitted to the University's Health Sciences Human Subjects Review Committee. The goals of this pilot test were: 1) to further analyze and refine the preference measure, 2) to obtain an estimate of the overall response rate and undeliverable rate, 3) to determine whether item non-response was a problem, in particular for the item asking respondents to list the prescription drugs they were taking, and 4) to determine what percent of respondents had insurance coverage for prescription drugs or physician services and what percent of respondents had used any prescription drugs in the last thirty days.

Results pertaining to the first objective are discussed separately in the section describing how the preference measure was developed. The population for the pilot survey was adult Wisconsin consumers, 30 percent from the 18 to 49 age group and 70 percent from the 50 and over age group. The higher percentage from the older age group was chosen because older individuals are more frequent users of prescription drugs, and because this was the population of interest in the study. The younger individuals were included in the pilot because of the need to analyze and refine the new preference scale. A scale that was tested in a wide range of ages potentially is more useful for future research.

The sampling frame was a mailing list purchased from the mailing list company KM

Lists. This company maintains a file containing information on approximately 85 to 90 percent of the United States households. The exact number of available households depends on the type of information requested. For this study, the requested information was name, address, gender, age range, and income range. This information was used to compare characteristics of respondents and non-respondents. Unless otherwise requested, the name provided by the company is the head of household, which more often is male. In order to have a more even mix of male and female respondents, 50 percent male names and 50 percent female names were requested. The female names could be either a female head of household or the spouse of a male head of household. A specific mix of ages was requested: 70 percent from the 50 and older age group and 30 percent from the 18 to 49 age group.

A total of 6,000 names were requested, to provide enough names for both the pilot and main mailing, and to have extra names available in case over-sampling from a particular population was required, e.g. low income. The mailing list company selected these names from a file containing 2,180,260 households, using stratified random sampling. The households were stratified first by zip code, then alphabetically by street name, then by house number. Next, a random starting point was picked and every nth name was selected, with n depending on the number needed for each population, e.g. males head of households age 50 and over. Three sets of mailing labels and a galley sheet listing name, address, age range, gender, and income for all of the selected households were purchased. The age was provided in 5 year increments except for the first category, which was 0 to 24, and the last category, which was 75 and over. There were some names where the only age information provided was that they were 65 or older. Income information was provided in $5,000

increments, except for the first category, which was less than $10,000, and incomes over $60,000, which were in increments of $10,000. The highest income category was $150,000 and over.

For the pilot survey, 300 names were chosen from this mailing list by randomly selecting two names from each page. The age, gender, and income of the pilot sample is provided in Table 3.1, with some categories collapsed to simplify reporting. The sample size was determined based on requirements for reliability analysis and factor analysis for the preference scale. These types of analyses require 10 responses per item (Peter 1979), so for 10 items, 100 responses were required. Based on a projected response rate of 33 percent, 300 surveys were mailed. The surveys were administered via mail using Dillman's (1978) methodology for mail surveys. Pre-notification postcards were mailed on September 9, 1998, surveys were mailed on September 19, 1998 and reminder postcards were mailed one week after the surveys.

As specified by Dillman (1978), the cover letters were hand signed and stamps were used for the postcards and outgoing surveys. A postage paid envelope was included to encourage response. Using stamps on the return envelopes is more expensive than business reply envelopes, especially if a low response rate is anticipated. However, there may better response rate with stamps (Dillman 1978). To determine whether using stamps on the return envelope increased response rate enough to justify the extra cost, half the pilot surveys were mailed with stamped return envelopes and half were mailed with business reply envelopes. The questionnaire was a 12 page booklet, printed on light blue, cream, buff, or grey 20# paper. Four different colors were used to determine the response rate from specific age

Table 3.1 Demographic Characteristics for the Pilot Sample and Respondents

	Pilot Sample[1]		Pilot Respondents[2]	
	N	%	N	%[3]
Gender				
Male	155	51.7	51	48.1
Female	145	48.3	55	51.9
Age[4]				
18 to 34	44	14.7	15	14.3
35 to 49	47	15.7	14	13.3
50 to 64	104	34.7	40	38.1
65 or older	105	35.0	36	34.3
			mean = 56.2 range = 24 to 90	
Income[5]				
less than $15,000	65	21.7	20	19.8
$15,000 to $34,999	105	35.0	31	30.7
$35,000 to $64,999	54	18.0	31	30.7
$65,000 or more	76	25.3	19	18.8

1. N = 300
2. N = 106
3. Percent of those who provided information.
4. Missing data, n = 1
5. Missing data, n = 5. Categories provided by the mailing list company did not exactly match the categories on the survey. For example, the mailing list range was $16,000 to $35,999 and the corresponding survey range was $15,000 to $34,999.

groups: buff was 18 to 34, grey was 35 to 49, blue was 50 to 64, and cream was age 65 or older. This also was used to check whether a survey sent to someone in a particular age group actually was completed by someone in that age group.

Pilot Survey Results:

Results pertaining to the first goal of the pilot survey, analysis and refinement of the preference scale, are reported in the section on preference scale development. The second goal of the pilot survey was to determine the undeliverable rate and response rates, both overall and for subgroups of interest. Of the 300 surveys mailed, 12 surveys were undeliverable and 106 usable surveys were returned, yielding an undeliverable rate of 4.0 percent and a usable response rate of 36.8 percent. Response was poorest for males, individuals age 35 to 49, and individuals in the $15,000 to $34,000 and the $65,000 and over income groups. Response generally was good in the 50 and over age group and the $15,000 or less income group, which were subgroups of interest for the study. For surveys with stamped return envelopes, the response rate was 39.1 percent, and for surveys with business reply envelopes the response rate was 34.5 percent.

The third goal of the pilot survey was to assess item non-response rates for critical items. The item where there was the most concern about non-response was the item asking respondents to list the names, directions, and quantity used for all the prescription drugs they used in the last 30 days. Of the respondents who reported using at least one prescription drug in the last 30 days, 90 percent were willing to list the requested information about the drugs. This was better than expected, and considered to be a reasonable response rate for a potentially time consuming question. Item non-response did not appear to be a significant

problem for any of the other items. Even income, which typically has a high item non-response rate, had only 4.7 percent non-response. Item non-response rates were less than one percent for items pertaining to insurance coverage and the number of prescriptions used. Some of the items had "don't know" choices. The only item where a high percentage of respondents (19.8 percent) reported that they did not know the answer, was the question asking whether all the health insurance plans they had to choose from covered prescription drugs. However, it was anticipated that this question would be difficult for respondents to answer and it was included merely as a descriptive item.

The final goal of the pilot survey was to obtain an estimate of the percent of respondents who were uninsured, and the percent of respondents who had not used any prescriptions in the last 30 days. A large number of prescription drug users were required for the analyses and a reasonable number of uninsured were required for comparative purposes. The majority of respondents, 87.7 percent, had insurance for physician visits but only 69.8 percent had insurance coverage for prescription drugs. Only 24.5 percent of respondents reported using no prescription drugs in the last 30 days. The 50 and older age group was the population of interest for the study, and in this age group 61.8 percent had prescription drug insurance coverage and 22.4 percent reported no prescription drug use in the last 30 days.

Questionnaire Modifications Based on Pilot Results:

The results of the pilot survey revealed no major problems with the questionnaire. However, a few minor problems were discovered and the questionnaire was modified accordingly. One problem was that a few respondents apparently did not understand that

insurance included insurance coverage provided through a government program, for example the Veterans' Administration. These respondents reported that they did not have insurance for prescription drugs, but it was apparent from their responses to other questions that they actually did have insurance. The questions on insurance were modified to read "Is there a private insurance plan or other program that pays for your prescription drugs/physician visits, and example of "other programs" were provided in the instructions. Some respondents also did not understand that "not currently employed" included retired, so this was clarified. It also was decided to ask respondents who answered yes to the question "Was there any time in the last year when you did not have insurance for prescription drugs?" to explain why this happened. A question on race also was added.

The population surveyed changed from all adults in the pilot survey to individuals age 50 and older in the main survey, and this necessitated a few changes on the questionnaire. There was a question on the pilot survey about whether there were children in the household under the age of five, and this question was not included on the main survey because of the lower probability of older individuals having small children in the household. Two questions about Medicare were added because many of the study population were Medicare eligible. Respondents were asked whether they had Medicare, parts A and B, and whether they had a supplemental Medicare (Medigap) insurance plan. The modified questionnaire is provided in Appendix C, along with a copy of the modified cover letter. The changes in the cover letter were specified by the Human Subjects Review Committee, who approved the project under HSC Protocol #98-720-344 (Appendix D). Items listed on the questionnaire, but not described in the text, were included for future analyses.

Development and Refinement of the Consumer Medical Care Preference Scale:

The literature review of previous research on consumer health beliefs and medical care preferences revealed no scale that was acceptable for use in this study. Consequently, a new scale was developed to measure consumer medical care preferences. The scale was grounded in economic utility theory, and thus was designed to determine what responses to health problems were preferred, or valued more highly by consumers. The scale was intended to capture preferences for using or not using physician services, and preferences for using or not using prescription drugs. Both types of preferences may affect prescription drug use because prescription drugs orders typically are obtained from physicians. However, it was not known a priori if the two types of preferences would form separate dimensions of the medical care preference scale.

The characteristics of the preference scale were determined somewhat by its intended use. This study was a multivariate study of prescription drug use, and data were collected via mail survey. In order to have an acceptable response rate, the length of the questionnaire needed to be reasonable. This, in combination with the large number of variables that were collected, dictated a somewhat parsimonious preference scale. As a result of the space constraints, the preference scale was limited to one page in length, including instructions and the preference items. This study examined general prescription drug use, not prescription drug use in a specific therapeutic class. Consequently, the preference scale also was intended to be general and not disease specific. As a result, no reference to specific symptoms, or specific diseases was made in the scale. All items were phrased in terms of preferences for treating a "health problem." Health problem was used

because it was thought to be a more general term than "illness."

Ten items for the scale were generated by the researcher based on items used in previous health belief studies and by recalling comments made by consumers about their use of physician services or prescription drugs. The comments were made by pharmacy customers (the researcher was a practicing pharmacist) and by friends and relatives. The items are listed in Table 3.2. Items 4 and 6 were adapted from the health locus of control scale (Wallston and Wallston 1978) and item 7 was adapted from Wirick (1966). The remainder of the items were new items generated by the researcher. All items were measured on five point Likert scales (strongly disagree, disagree, neither agree nor disagree, agree, and strongly agree). This type of scale was used because it is easy for consumers to use, and because a summated score can be constructed from it (Churchill 1991).

The items were designed to capture consumer preferences for using physician services and prescription drugs. The items pertaining to physician services reflected preferences for self-treating versus seeking physician help for a health problem. The items pertaining to prescription drugs reflected preferences for using or not using prescription drugs. Some of these items explicitly compared prescription drugs, either to home remedies or to over-the-counter (OTC) drugs. Most of the items were worded so that agreeing with the statement showed preferences for using self-care instead of physician services and not using prescription drugs. However, to avoid scale response bias, items 3, 7, and 8 were worded so that agreeing with statement showed preferences for using physician services and prescription drugs. These items subsequently were reverse coded.

Analyzing and refining the preference measure was critical, because it was a new

Table 3.2 Medical Care Preference Items

Item #	Item Description	Mean[1]	S.D.
1	If I have a health problem, I would rather treat myself than go to the doctor.	3.42	1.22
2	Taking prescription drugs to treat a health problem is the last thing I would do.	4.02	0.99
3*	I like to talk to my doctor whenever I have a health problem.	3.76	0.98
4	I know my health better than most doctors do.	2.88	1.10
5	When I have a health problem, I usually wait and see if I get better on my own before going to see a doctor.	2.24	1.02
6	I believe home remedies often work better than prescription drugs.	3.21	1.03
7*	When I have a health problem, I contact a doctor right away.	2.68	0.90
8*	When I have a health problem, my first thought is to use a prescription drug.	2.27	0.87
9	When I have a health problem, it is hard to convince me to see a doctor.	3.36	1.12
10	When I have a health problem, I prefer to try an over-the-counter (OTC) product before taking a prescription drug.	3.02	1.07

* Reverse coded

1. Likert scale: 1 = strongly agree through 5 = strongly disagree

measure. Methods for the pilot test of the preference measure were described earlier. Of the 106 pilot surveys returned, six had missing data on one or more of the preference items, so 100 surveys were used in the analyses. Means and standard deviations were calculated for all of the items, and internal consistency of the entire scale was assessed using coefficient alpha.

Exploratory factor analysis, with principal components extraction, was used to determine whether the scale was unidimensional or multidimensional. It was hypothesized that even if the scale was multidimensional, the dimensions still would be correlated, because they all would relate to some aspect of medical care preferences. Therefore, Promax, an oblique

rotation method that allows the dimensions to correlate, was used. Means and standard deviations for each of the items are reported in Table 3.2. Means ranged from 2.24 to 4.02 and most standard deviations were close to 1. The coefficient alpha for the overall scale was .874, which is very good reliability for a new scale (Nunnally and Bernstein 1994). Table 3.3 reports item-total statistics for individual items and factor analysis results. Item-total correlations were above .50, except for items 4 and 8, which had item-total correlations of .486 and .459 respectively. Items 4 and 8 also were items that could be removed from the scale with little effect on the coefficient alpha. Item 5 had the highest item-total correlation, 0.739.

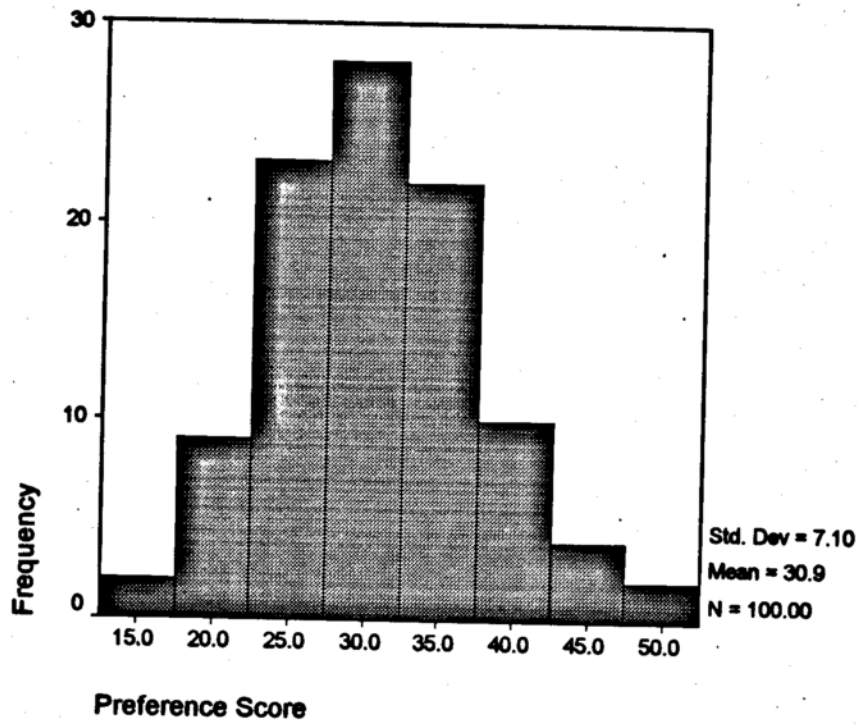
Table 3.3 Item-Total Statistics and Factor Analysis Results[1]

Item #	Item-Total Correlation	Alpha if Item Deleted	Pattern Matrix		Structure Matrix	
			Factor 1	Factor 2	Factor 1	Factor 2
1	.697	.854	0.922	-0.006	.887	.459
2	.577	.864	0.821	-0.008	.777	.387
3	.583	.863	0.379	0.381	.594	.595
4	.486	.871	0.791	-0.154	.704	.294
5	.739	.851	0.225	0.706	.624	.833
6	.684	.855	0.634	0.223	.760	.582
7	.644	.859	-0.161	1.010	.410	.919
8	.459	.872	-0.140	0.785	.304	.706
9	.578	.864	0.463	0.291	.628	.553
10	.529	.868	0.007	0.644	.432	.682

N = 100

1. Principal Components Extraction and Promax Rotation were used. Correlation between factors was 0.566 and 59.9 percent of variance was explained.

Figure 3.1 Distribution of Medical Care Preference Scores - Pilot Survey



Factor analysis results are reported both as a pattern matrix and a structure matrix because an oblique rotation method was used. The pattern matrix represents the change in an item per unit change in a factor, holding all other factors constant, and values greater than 1 are possible (Nunnally and Bernstein 1994). The structure matrix reflects the correlation between an item and a component, and values are less than or equal to 1. Two factors were extracted, although the correlation between them was 0.566, suggesting that the factors could be related enough to be in one scale (Nunnally and Bernstein 1994). One factor appeared to be related to preferences for the timing in seeking medical care (items 5,7,8,10) and the other was preferences for using versus not using medical care (items 1,2,4,6,9). However, the structure matrix shows that several items dual loaded, also suggesting that the

factors were not distinct. Items 3,5, and 9 especially were problematic in terms of dual loading.

The correlation between factors suggests the items could be summed to create one scale, and this was done to assess the distribution of the summed scale (Figure 3.1). The resulting preference measure had a mean of 30.88 and a standard deviation of 7.10. Scores ranged from 14 to 50, out of a possible 10 to 50, and the scores had a distribution that was close to normal. Higher scores signified individuals that prefer to seek formal medical care when they have a health problem. The wide range of scores suggested that the scale captured different preferences for using medical care.

The initial results for the preference measure were encouraging. The scale had good internal consistency and there was a wide range of scores. However, there also was some dual loading and a two of the items had relatively low item to total correlations. Based on this, and some comments made by the respondents, some items were modified. Table 3.4 lists the modified preference scale that was used in the study. A priori, there was some thought that item 4 did not fit with the rest of the scale, and this was supported by the results. This item was dropped from the scale, although it was retained in the questionnaire for possible use as a comparative item in future analyses. Item 8 also had a low item to total correlation. However, it was thought to be desirable to include at least one positive item about prescription drugs, so the following item was substituted, "For most health problems, I would rather take a prescription drug than a non-prescription drug." To improve face validity, item 6 was changed from a belief statement to a preference statement. The new

item was, "When I have a health problem, I often prefer to use home remedies instead of prescription drugs."

Table 3.4 Modified Medical Care Preference Measure

For most health problems, I would rather treat myself than go to the doctor.
For most health problems, I prefer to avoid taking prescription drugs.
I usually like to talk to a doctor when I have a health problem.
For most health problems, I wait and see if I get better on my own before going to see a doctor.
For most health problems, I wait and see if I get better on my own before taking a prescription drug.
When I have a health problem, I often prefer to use home remedies instead of prescription drugs.
When I have a health problem, I usually contact a doctor right away.
For most health problems, I would rather take a prescription drug than a non-prescription drug.
When I have a health problem, it is sometimes hard to convince me to see a doctor.

Another problem mentioned by a few respondents was that they had difficulty answering some of the items because their answers would vary depending on the type of health problem. Changing the items to specify "minor" or "serious" health problems was considered, but information on both types of health problems would have been desired, and asking about both types of health problems for each item would have made the scale too long. There also may have been differences in how respondents interpreted minor and serious. Consequently it was decided to add the phrase "When answering the questions, try to think about your general preferences for using health care," to the instructions. It also

was noticed that some items were qualified with "most" or "often" and that item non-response was lower for these items. Where possible, the items were modified to include "most", "usually", or "often." It was thought that this also might help get the respondents' focus away from a particular health problem.

A global preference item, worded "I prefer to treat most health problems without help from doctors or prescription drugs," was added to the questionnaire. This item was not included in the preference scale with the rest of the items, but was used to provide a measure of convergent validity for the preference scale.

II. Data Collection

Study Population and Sample:

The population for the study was Wisconsin residents age 50 and older. This population was chosen for a variety of reasons. The analyses required adequate numbers of prescription drug users and enough uninsured individuals. Individuals age 65 and older are more likely to be prescription drug users and a higher percentage of them do not have prescription drug insurance. Davis et al. (1999) estimated that 34.8 percent of these individuals do not have insurance coverage for prescription drugs. They also are of interest from a public policy perspective. Most are eligible for Medicare, and there is discussion of adding some type of prescription drug coverage to the Medicare benefits.

Individuals age 50 and older were included because they also are likely to be prescription drug users, and because it would have been difficult to measure the effect of

physician insurance coverage on prescription drug use in a 65 and older population. Most Medicare eligibles have coverage for physician visits, and including only this population would create problems measuring cross price effects. Furthermore, many researchers have examined prescription drug use in individuals age 65 and older, but individuals age 50 to 64 generally have been ignored. This lack of research belies the importance of this group. These individuals are the next cohort that will become eligible for Medicare, and therefore they should be of interest to policymakers. They also will be the first cohort becoming eligible for Medicare that is accustomed to having insurance coverage for prescription drugs.

The sampling frame was a mailing list purchased from KM Lists, described previously in the section describing the pilot survey. The sample was selected randomly from the mailing list by selecting 3 out of every 4 names. Subsequently, some males were deleted and some females were added to the sample so that the percentages of males and females would match the population percentages, 45 and 55 percent respectively. The population percentages were based on 1997 estimates of the age 50 and older population in Wisconsin, extrapolated from 1990 Census data (Census.gov 1998).

Sample Size:

Sample size was determined based on: 1) the desired precision for examining differences in the estimated number of prescriptions, 2) to account for the large number of independent variables in the model, and 3) to account for the interaction term being analyzed. The desired precision level was to be able to detect a 0.2 difference in the mean number of prescriptions used in the last thirty days, with a 95 percent confidence interval. Using the estimated standard deviation of 2.94 prescription drugs (from the pilot survey),

the resulting sample size was approximately 830. The general rule of thumb pertaining to the sample size requirements for independent variables is that approximately 10 observations are required for each variable. The sample size of 830 was more than enough to cover this requirement. There were no set guidelines to determine the sample size required to examine the interaction effect. However, a statistician was consulted, and he felt that a sample size of 1,000 would be advisable to have adequate power to examine the interaction effect (Douglas 1998).

A two part model was used for the analysis, and because only prescription drug users were included in the second part of the model, 1,000 prescription users were required. Based on 77.6 percent prescription drug users in the 50 and older age group of the pilot survey respondents, approximately 1,300 respondents were necessary. Based on the 38.6 percent response rate for individuals age 50 and older from the pilot survey, approximately 3,500 surveys needed to be mailed.

Data Collection:

Data were collected using the modified questionnaire, administered via mail survey. Data collection methods were based on Dillman's (1978) methodology for mail surveys. Pre-notification postcards, 5 ½" by 4 1/4" and printed on ivory cover stock, were mailed on 2/4/99. There were two reasons for using pre-notification postcards. First, they have been shown to increase response rate by an average of 8 percent (Churchill 1991). Second, the mailing list was purchased several months before the main survey, for use in the pilot survey. As a result, a higher than usual undeliverable rate was anticipated, and using pre-notification postcards allowed old addresses to be updated. Addressed were updated where possible for

undeliverable postcards that were returned prior to the questionnaire mailing. New names were selected randomly to replace names whose pre-notification postcards were returned without a new address.

The questionnaires mailed on 2/13/99 were 12 page booklets. A cover letter printed on University of Wisconsin School of Pharmacy stationary was included with each questionnaire. Half of the cover letters were hand signed, and response rates for the hand signed versus preprinted signatures were tracked using two different color survey booklets. Blue survey booklets were used for hand signed cover letters and ivory survey booklets were used for cover letters with preprinted signatures. The mailing labels were ordered by zip code, so to avoid confounding of response rate by geographic region, the hand signed cover letters were mailed to every other individual. The surveys were mailed in stamped 9 ½ by 6 ½ inch envelopes. Business reply envelopes were used instead of stamped return envelopes, because although the response rate for the pilot survey was somewhat higher for stamped return envelopes, the difference was not enough to justify the extra labor and expense of using stamped return envelopes.

To increase response rate, a new one dollar bill was included with each survey. The response rate from the pilot survey was somewhat low, and dollar incentives have worked well in previous research to increase response rate. Monetary incentives have been shown to increase response rate by an average of 15 percent (Churchill 1991), and in a previous mail survey in a Wisconsin population the use of a dollar token increased response rate by over 20 percent. Per protocol (Appendix E), a random selection of the outgoing surveys were

audited to make sure they contained dollar bills. Reminder postcards, 5 ½" by 4 1/4" and printed on ivory cover stock, were mailed one week after the survey mailing.

III. Data Entry and Analysis

Data Entry:

Returned surveys were assigned an identification number, dated, and examined to see if the majority of the survey had been completed. The zip code item on the survey also was examined. If respondents had not completed the zip code item and the envelope was postmarked, the zip code was taken from the postmark. Any name or address information on the returned surveys was removed. When undeliverable surveys were received, the individuals were marked off on the sample list, and the dollar bills were removed from the surveys and returned to the fund they were paid out of. A coding scheme was developed (Appendix F) and the completed surveys were coded and entered into a database using Foxpro.

During the process of data entry, several decision were made about coding. The reported number of prescriptions used in the last 30 days (item 6) sometimes was different from the number of prescription drug names listed in item 12. There were a couple of possible reasons for this difference. The respondents may have had difficulty recalling or counting the number of prescriptions used and having to list them cued their memory. Alternatively, they may not have been willing to list the drug names for some of the prescriptions they used. However, there did not seem to be any pattern to whether the

number of listed prescriptions was greater or less than the number given in item 6, suggesting that the difference probably was due to recall difficulties. If there was a discrepancy between item 6 and item 12, the number of prescriptions listed in question 12 was used because having to list the names of the drugs probably prompted the respondents' memory.

There were some discrepancies between answers to items 1 and 2 (whether there was a private insurance plan or other program that paid for all or part of their doctor visits and prescription drug costs) and information reported in other parts of the survey. For example, some individuals reported that all of their prescription drug costs were paid for, but then reported that they had a copayment or coinsurance for prescription drugs. Another example was that some individuals reported that none of their doctor visit costs were paid for, but then reported later in the survey that they had Medicare Part B which does provide some coverage for physician visits. Respondents were asked to report the name of their health insurance plan, so where information about the plan was available, this was used to verify the information provided in items 1 and 2.

There appeared to be two distinct problems with these questions. One was that some respondents were not sure how to distinguish between all and part of the costs. It may be that respondents who paid only a small percentage of their prescription drug costs felt that this was closer to all of the costs than part of the costs. If there was clear evidence that they paid any part of their costs, the responses were coded as part of costs paid for, even if they had marked all of their costs were paid. Also, because of the possible confusion, no

distinction was made between people with part coverage and complete coverage in the analyses.

Another problem was that some respondents reported in items 1 and 2 that they had no prescription drug coverage or physician coverage, but then answered subsequent questions as if they had insurance. There appeared to be to two typical reasons for this problem. A few respondents with insurance through Medicaid or the Veterans Administration did not appear to understand that "private insurance or other program" applied to them, in spite of the fact that examples of other programs that might pay for the cost of doctor visits or prescription drugs were listed. A more common problem was individuals who did not use any prescription drugs answering item 2 as if they did not have insurance, but then reporting later in the survey that they had insurance (e.g. then had $4/$8 copayments for generic/brand name drugs). It is unclear why this occurred, unless they interpreted the question to be whether or not the insurance company actually had paid any prescription drug costs. If they did not use any prescription drugs, then the insurance company did not pay any of their drug costs.

If there was clear evidence from answers to other questions that the respondents had some coverage for prescription drugs or doctors visits, the coding for questions 1 and/or 2 was changed to reflect this (n =52). If the responses to other questions were unclear or contradictory, then question 1 and/or question 2 was coded as "don't know" (n=6). All six of these individuals reported in question 2 that they had no prescription drug insurance coverage, and then had confusing answers in Part D, (e.g. reported that their pharmacies sent in their claims for them), but then had out-of-pocket costs. In all of these cases,

insurance type could not be determined from the reported out-of-pocket prescription drug expenses. Respondents also had a difficult time answering the question about whether they had supplemental Medicare insurance, and as a result, this question was not used in any analysis.

There also were some decisions made about how to code different types of insurance. Approximately 44 individuals reported "discount card" plans where they received a variable discount off the prices they paid for prescriptions. The discount amount, where known, was usually less than 10 percent. These plans really are not insurance plans, and individuals who reported that their only "insurance" coverage was from this type of plan were classified as having no prescription drug insurance. There also were a number of individuals whose prescription drug coverage was in the form of catastrophic coverage. For example, in Wisconsin, all Medigap plans must include a minimum level of catastrophic drug coverage (80 percent of drug costs are paid after a deductible of $6,250). Individuals who reported having a prescription drug deductible of at least $5,000 were classified as having catastrophic coverage (n=16).

Data Preparation:

After the data were entered, they were inspected for out of range, unusually large or small values, or missing values. Items left blank by respondents were coded as 9 or 99, so missing values indicated an entry error. Any data that were in any of those categories were double checked and corrected if necessary. If any item was entered incorrectly, the data for the entire section of the survey were double checked. This database of raw data was maintained, and a separate database was created for the purposes of data analysis.

The original database contained 182 individuals (9.4 percent) who reported an age of under 50. This may have occurred because individuals who received the survey passed it along to a spouse, relative, or friend. Alternatively, the mailing list may have had incorrect ages listed for some individuals. There is evidence that this occurred. Two of the surveys returned by individuals under the age of 50 had address labels on the return envelope. These individuals were found in the mailing list, and supposedly were in their fifties. However, the age of one of the individuals was in the 20s and the other was in the 30s. Regardless of the reason, respondents under the age of 50 were not in the study population and were excluded from the analysis.

Missing Data:

Missing data were handled either by replacing the missing data or by omitting the individual from the analyses. Respondents with missing data on items considered to be critical were removed from the database. This included item 2 (insurance for prescription drugs), item 7 (the number of prescriptions used) and item 42 (health status). Respondents also were removed from the database if they were missing more than two of the preference scale items. Respondents with missing data on multiple demographic items also were removed from the database (e.g. some respondents appeared to have missed an entire page). The number of respondents missing data for each of these items is provided in Table 3.5. A total of 102 individuals were removed from the database because of missing data.

After these individuals were removed from the database, the rest of the missing data were replaced. Missing age was replaced with the mean age. Missing data for gender, education, employment status, number of individuals living in the household, travel distance

to the doctors office and pharmacy, preference items, and HMO membership were replaced with the median values for each of the respective items, rounded to the nearest integer. The item with the highest non-response rate was income. Income was correlated with education, gender, and employment status so instead of replacing missing income data with the overall

Table 3.5 Missing Data on Critical Items

Item	Number Missing Data[1]
Number of Prescriptions	6
Prescription Drug Insurance	
missing	2
"don't know"	10
Medical Care Preferences (more than 2 missing items in scale)	50
Health Status	25
Missing Multiple Demographic Items	16

1. The numbers do not sum to 102 because some individuals were in multiple categories.

median income, the following methods were used. For individuals living by themselves, income was replaced by the median income within the same gender, employment, and education categories. For individuals with more than one individual living in the household, income was replaced by the median income within the same employment and education categories. In this case, gender differences were not accounted for because both spouses probably were present in the household, and income was reported at the household level.

The numbers of replacements for these items are provided in the descriptive portion of the results chapter.

Preliminary Data Analysis:

Frequencies, means and standard deviations were examined for all variables, using the software package SPSS 8.0. To examine frequencies for zip code, respondents were categorized into 9 geographic regions, based on the first three digits of the zip code. Composition of the respondents across age category, gender, income category, and geographic region was compared to the sample, and to the population where possible. Statistical significance of the differences were assessed using Chi-Square tests at an alpha level of 0.05 . For the comparison, the respondents' age and income were combined into the same categories used for the sample (taken from the mailing list).

Respondents who omitted any of the medical care preference items were excluded from the analysis of the preference scale, but respondents under the age of 50 were included. A few respondents qualified their responses, e.g. with "except for serious medical conditions," and these responses were classified as missing responses. To analyze the medical care preference scale, first items 15, 20, and 21 were reverse coded. Then the internal consistency of the medical care preference scale was assessed using coefficient alpha. Bivariate correlations and item to total statistics also were calculated for all items in the scale. The Kaiser-Meyer-Olkin Measure of Sampling Adequacy and Bartlett's Test of Sphericity were used to determine if factor analysis was an appropriate technique for analyzing the scale, and then exploratory factor analysis, with principal components

extraction, was used to determine whether the scale was unidimensional or multidimensional. A value of 1 was used as the cutoff eigenvalue.

It was hypothesized that even if the scale was multidimensional, the dimensions still would be correlated, because they all would relate to some aspect of medical care preferences. Therefore had the scale been multidimensional, an oblique rotation method would have been used. However, the scale was unidimensional, so no rotation was needed. The nine medical care preference items were summed to create a medical care preference score. A high score on this scale signified strong self-treating preferences, although the scale subsequently was reversed so that high scores indicated stronger help-seeking preferences. The correlation between the medical care preference score and the global medical care preference item (item 23) was examined as a measure of convergent validity. The correlation was expected to be positive and strong.

Prescription Drug Costs:

It was necessary to calculate the total cost of prescription drugs used by respondents from the list of drugs they reported using in the last 30 days. Drug name and strength, and the quantity used in the last thirty days were entered into a database using a Foxpro data entry program. The data entry program linked the drug name and strength with the national drug code (ndc), therapeutic class, and a generic/brand name identifier from a Medispan database. If the quantity used in the last month was not given by the respondent, but directions for use were listed, then the quantity was imputed from the directions (e.g. directions of one tablet twice a day resulted in an imputed quantity of 60). Some assumptions about the quantity used were made in order to simplify the data entry

procedure. For eye drops, it was assumed that one of the smallest size bottles was used. For inhalers, it was assumed that one inhaler was used, unless the directions indicated that more than one would have been required. For topical products, it was assumed that one of the smallest size tube or bottle were used, unless the respondent indicated a larger quantity.

There were 145 respondents who listed the drug names but not the drug strengths. A protocol for entering these drugs was developed. If there was a frequently prescribed strength for the drug product, determined by researcher judgement, then that strength was used. Otherwise, if there were only two strengths available then the lower strength was used. If there were more than two strengths available, then the middle strength was entered.

The Medispan database did not contain recent cost information, so this information had to be entered separately. There were 906 unique drug products in the database, and cost information for these products was obtained from the 1999 Redbook and the Wisconsin maximum allowable cost (MAC) list. For brand name drug products (n = 532), the direct manufacturer price listed in the Redbook was used if available (n =161). If there was no direct price listed, then average wholesaler price (AWP) from the Redbook, less 13.34 percent was used (Kreling 1991).[4]

For generic drug products (n =374), the Wisconsin MAC was used if the drug was included in the MAC list (n = 259). If the drug was not included in the Wisconsin MAC list, then AWP less 42.5 percent was used as the cost (OIG 1997). Even though the brand name

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4. There was a more recent estimate available from an Office of the Inspector general (OIG) study, but their cost estimate of AWP less 18.3 percent seemed low. The direct manufacturer price for brand name products in my sample was an average of AWP less 17 percent, thus, it seems unlikely that pharmacies would be able to purchase products at a price less than the direct manufacturer's price.

cost estimates from this study were somewhat questionable, it was the only available cost estimate for generic prescription drug products. Costs were based on the most common package size purchased, usually 100 for tablets and capsules, and 480 ml for liquids.

A per unit cost (e.g per tablet or per ml) was calculated by dividing the cost per package by the number of units in the package. Then the cost per prescription was calculated by multiplying the unit cost by the quantity used in the last 30 days. The total cost of all prescription drugs used by each respondent was obtained by summing all of the per prescription drug costs for each individual. No total cost could be calculated for the 103 respondents (6.2 percent) who reported using at least one prescription drug, but who failed to list the drug name(s).

Hypothesis Testing:

For the hypothesis testing, some variables were recoded and several sets of dummy variables were created. The variables used in the analyses are listed and defined in Table 3.6. A new variable, PROBRX was created to distinguish between users and non-users of prescription drugs. The number of prescriptions used in the last 30 days, NUMRX, was taken directly from the survey, but the cost of the prescriptions used in the last 30 days, COSTRX, was calculated from the list of drug names and quantities reported by respondents as described in the previous section.

A dummy variable, RXINS was created to capture the effects of insurance coverage for prescription drugs. A value of 0 was assigned for individuals who reported having no insurance, or only a catastrophic coverage plan. Individuals with the catastrophic coverage plan had such large deductibles ($5,000 or more) that it was unlikely their prescription drug

costs would exceed the deductible. Consequently, their decision making about prescription drugs was thought to be closer to uninsured individuals than insured individuals. A value of 1 was assigned for individuals who had all or part of their prescription drug costs covered by a public or private insurance plan. Individuals with public and private insurance were put in the same category because there were not enough individuals with public insurance to warrant a separate category. Similarly, there were not enough individuals who had insurance that paid all of their prescription drug costs to justify separate categories for insurance that paid all costs and insurance that paid only part of the costs.

Information on physician insurance was collected with the intention of measuring the cross-price effects of physician insurance coverage. However, there were not enough respondents who did not have insurance for physician visits to justify including physician insurance in the model. Including a measure of the extent of insurance coverage for physician visits (all versus part of costs paid) was considered, but accuracy of responses for this item were questionable.

The summated medical care preference score (MEDPREF) was created by summing the nine medical care preference items. Although the high scores on the scale originally signified stronger self-treating preferences, for easier interpretation, the scale was reversed so that high scores signified individuals with strong help-seeking preferences. The MEDPREF scale score was used for all of the analyses except the model examining the interaction between insurance and medical care preferences. In that model, medical care preferences were converted from a continuous to a dichotomous variable (CATPREF) by splitting MEDPREF at the median. Individuals with a preference score of 25 or less were

classified as self-treaters and individuals with a preference score of 26 or more were classified as help-seekers. This conversion was necessary because if a product term with a continuous variable and a dichotomous is used, the interaction effect measured is the moderating effect of the continuous variable on the dichotomous variable (Jaccard et al. 1990). This would measure whether there was a different preference effect in insured and uninsured individuals. However, what I wanted to examine was whether there was a different insurance effect in individuals with help-seeking and self-treating preferences.

Six dummy variables were created to assess the effect of income, because the income categories were not equal intervals. Income of less than $10,000 was used as the reference category. The two highest income categories were combined into one dummy variable because of the small number of individuals in the second highest category. The natural logarithm of the number of individuals in the household was included as a separate variable to control for the effects of household size on income (Grootendorst 1997). The natural logarithm was used because the distribution of number of individuals in the household was skewed. Information on employment status was collected, but not included in the analyses because of strong correlations with age and income, -0.59 and 0.46 respectively. Three dummy variables were created to measure the effect of education. The three dummy variables were high school degree, some post high school, a college degree or higher. Less than a high school degree was used as the reference category.

Three dummy variables were created to capture the effect of self-reported health status. Dummy variables were used because it is doubtful that the five categories provided were perceived as equal interval by respondents. For example, the difference between

excellent and very good health may be perceived differently than the difference between good and fair health. Excellent health was used as the reference category. The third dummy variable included individuals who reported fair and poor health, because there were not enough individuals with poor health to justify a separate category.

NUMCOND was obtained by counting the number of medical conditions that the respondents reported having. Entering each medical condition separately as a dummy variable was considered, but that would have added 16 or more variables to a model that was already large. It was decided that self-reported health status and the number of medical conditions would provide adequate control of health status.

Respondents originally were classified into nine geographic regions using the first three digits of their reported zip code, but for the hypothesis testing those categories were collapsed into 5 dummy variables. The reason for including these variables was to control for possible differences in prescribing patterns or access to medical services across geographic region. A list of the zip codes in each geographic region and a map of the state showing the regions are given in Appendix G. The most urban area, Southeast Wisconsin, was used as the reference category. The rest of the state was divided into a Southcentral/Southwest region, a West region, an East region, and a North region. The regions were determined using the post office's divisions as a starting point, and then modifying based on knowledge of different areas of the state. The intent was to group areas together that were similar in terms of population density and HMO penetration.

A dichotomous variable was created to capture the level of adverse selection risk (ASRISK). Individuals were classified either as high or low adverse selection risks. It is

important to clarify that being at high or low risk for adverse selection is not the same as being at high or low risk for prescription drug use. Adverse selection behavior can be exhibited by individuals who expect low or high prescription drug use. Individuals who expect to use very few prescriptions may be more likely to decline prescription drug insurance coverage, whereas individuals who expect to use many prescription drugs may be more likely to purchase prescription drug insurance. The purpose of the adverse selection risk variable was to identify individuals who were likely to exhibit either of these types of adverse selection behavior.

Individuals who have insurance coverage from a large employer are considered to be at very low risk for adverse selection (Browne 1992). A large part of the price for insurance coverage typically is paid by the employer as part of the employee's compensation package, and that portion of their compensation is forfeited if they do not take the coverage. Also, because the insurance rate is based on a large group, one individual's high medical expenses should not have much impact on the insurance group rate.

Individuals whose insurance is through a small employer, or who purchased an individual policy directly from the insurance company are at much higher risk for adverse selection. Individuals who do not have insurance through an employer have to purchase an individual policy directly from an insurance company. In this case, individuals who expect to have very low medical expenses may choose not to purchase insurance. Individuals who expect to have very high medical expenses should be more likely to purchase insurance coverage. Individuals who have insurance through a small employer also are at higher risk for adverse selection. If any individuals in their employment group have high medical

expenses, the rate for the entire group may increase, causing individuals who expect low medical expenses to refuse the insurance. Consequently, all individual who received insurance through employers with 100 or fewer employees were classified as being at high risk for adverse selection.

Individuals who did not have insurance coverage also needed to be categorized as high or low adverse selection risks. In the uninsured group, high adverse selection risks were individuals who chose not to purchase prescription drug insurance coverage because they expected not to use many prescription drugs. Uninsured individuals were asked to give the reason why they did not have insurance coverage for prescription drugs. Individuals who reported that they did not think they needed prescription drug insurance were classified as high adverse selection risks. The other uninsured individuals were classified as low adverse selection risks because most of them reported they were uninsured because prescription drug insurance cost too much, or because the insurance coverage that they had access to did not cover prescription drugs.

Table 3.6 Definition of Variables

Dependent Variables	Definition
PROBRX	1 if used at least 1 prescription in the last 30 days, 0 otherwise
NUMRX	number of prescriptions used in the last 30 days
COSTRX	cost of prescriptions used in the last 30 days
Independent Variables	
RXINS	1 if all or part of prescription drug costs are paid for by public or private insurance, 0 otherwise

MEDPREF	summated medical care preference score, range = 9 to 45 with higher scores representing stronger help-seeking preferences
CATPREF	1 if Medpref = 26 or more, 0 otherwise
INSXPREF	interaction effect between prescription insurance and medical care preferences (Rxins*Catpref)
VERYGDHLTH	1 if self-reported health status = very good, 0 otherwise
GOODHLTH	1 if self-reported health status = good, 0 otherwise
FAIRPOORHLTH	1 if self-reported health status = fair or poor, 0 otherwise
NUMCOND	number of self-reported medical conditions
AGE	age in years, continuous variable
AGE^2	age in years, squared
FEMALE	1 if female, 0 otherwise
HSCHGRAD	1 if high school degree, 0 otherwise
POSTHSCH	1 if some post high school education, 0 otherwise
COLLGRAD	1 if college degree, 0 otherwise
INC10to14	1 if income = $10,000 to $14,999
INC15to24	1 if income = $15,000 to $24,999
INC25to34	1 if income = $25,000 to $34,999
INC35to49	1 if income = $35,000 to $49,999
INC50to64	1 if income = $50,000 to $64,999
INC>64	1 if income = $65,000 or more
LNHOUSE	the natural logarithm of the number of individuals in the household
MEMBHMO	1 if Health Maintenance Organization member
SWESTCENT	1 if resides in Southwest or Southcentral region, 0 otherwise
WEST	1 if resides in West region of Wisconsin, 0 otherwise
EAST	1 if resides in East region of Wisconsin, 0 otherwise
NORTH	1 if resides in North region of Wisconsin, 0 otherwise

TRAVMD	1 to 5, with 1 being the shortest distance
TRAVPH	1 to 5, with 1 being the shortest distance
ASRISK	1 if high risk of adverse selection, 0 otherwise

Econometric Model:

The hypotheses were tested using a two part econometric model used in previous research examining prescription or health care utilization (Duan et al. 1983; Leibowitz et al. 1985; Coulson and Stuart 1995; Grootendorst 1995). In part I of the model, the probability of any use is estimated, and in Part II, the extent of use, conditional on any use is examined. Grootendorst (1995) compared the two part model, the Poisson model, the negative binomial model, and zero-altered negative binomial model as estimators for prescription drug utilization, and found that the two part model was the best fitting model based on the mean squared error and Vuong non-nested model selection criteria. In his two part model, he used a probit model for part I and a negative binomial model for part II.

Part I:

Although Grootendorst (1995) used a probit model in part I of the model, past studies have used either probit or logit models. A logit model, logistic regression, was used because of the added flexibility of interpretation given by the odds ratios. The model is described in equation 3.1.

Coefficients were estimated using SPSS 8.0 software and Maximum Likelihood estimation. Goodness of fit for the model was assessed using the Model Chi-Square test, and the Nagelkerke measure of Pseudo R^2.

Equation 3.1:

$$P(PROBRX = 1|X) = \exp(\beta iXi) / (1 + \exp(\beta iXi)) + e_i \text{ where } e_i \sim (0, \pi^2/3)$$

$$\begin{aligned}\beta_i X_i = {} & \beta_0 + \beta_1 Insrx + \beta_2 Medpref + \beta_3 Insxpref + \beta_4 Age + \beta_5 Age^2 + \beta_6 Female + \\ & \beta_7 Inc10to14 + \beta_8 Inc15to24 + \beta_9 Inc25to34 + \beta_{10} Inc35to49 + \beta_{11} Inc50to64 + \\ & \beta_{12} Inc{>}64 + \beta_{13} Lnhouse + \beta_{14} Hschgrad + \beta_{15} Posthsch + \beta_{16} Collgrad + \\ & \beta_{17} Verygdhlth + \beta_{18} Goodhlth + \beta_{19} Fairpoorhlth + \beta_{20} Numcond + \\ & \beta_{21} Membhmo + \beta_{22} Travmd + \beta_{23} Swestcent + \beta_{24} East + \beta_{25} West + \beta_{26} North\end{aligned}$$

Part II:

Two different dependent variables were used in Part II of the model, the number of prescription drugs used in the last 30 days and the total cost of the prescription drugs used in the last 30 days. Numbers of prescriptions are count data, and consequently, coefficients estimated using ordinary least squares (OLS) regression may be inefficient, inconsistent, and biased (Long 1997). Another problem with OLS is that the assumption of homoscedasticity often is violated in count data models, resulting in estimated standard errors that are smaller than their true values (Gardner et al. 1995). This results in artificially inflated t test values. Consequently, a Poisson regression model was used to predict the number of prescription drugs, conditional on any prescription drug use (equation 3.2). This model accounts for the unique characteristics of count data, and is a non-linear model. The Poisson model was estimated using Intercooled Stata 6.0 software and maximum likelihood techniques.

There is one important assumption in the Poisson model, that the conditional mean is equal to the conditional variance. Count distributions often are over-dispersed (conditional variance greater then the conditional mean), in which case a negative binomial model is a better fitting model (Gardner et al. 1995; Long 1997). Overdispersion was tested for using

two methods. First, the Poisson model was estimated and the goodness of fit of the model was assessed using a Chi-square test. Then a negative binomial model was estimated to get an estimate of alpha, the measure of dispersion. The significance of alpha was determined using a likelihood ratio test. Standard errors in Poisson may be inaccurate, usually less than their value, and as a result, the Poisson models were estimated using regular variance estimates and robust variance estimates.

Equation 3.2:

$$P(Ni|Xi) = \exp(-\mu_i)\mu_i^{\,yi} / N_i! \quad \text{where Ni = number of prescription drugs and}$$

$$\mu_i = \exp(\beta_i X_i)$$

$$\begin{aligned}\beta_i X_i = {} & \beta_0 + \beta_1 Insrx + \beta_2 Medpref + \beta_3 Insxpref + \beta_4 Age + \beta_5 Age^2 + \beta_6 Female + \\ & \beta_7 Inc10to14 + \beta_8 Inc15to24 + \beta_9 Inc25to34 + \beta_{10} Inc35to49 + \beta_{11} Inc50to64 + \\ & \beta_{12} Inc{>}64 + \beta_{13} Lnhouse + \beta_{14} Hschgrad + \beta_{15} Posthsch + \beta_{16} Collgrad + \\ & \beta_{17} Verygdhlth + \beta_{18} Goodhlth + \beta_{19} Fairpoorhlth + \beta_{20} Numcond + \\ & \beta_{21} Membhmo + \beta_{22} Travmd + \beta_{23} Travph + \beta_{24} Swestcent + \beta_{25} East + \beta_{26} West \\ & + \beta_{27} North\end{aligned}$$

An ordinary least squares (OLS) regression model was used to predict the cost of prescription drugs (equation 3.3). This variable was the summed cost of all the prescription drug products used in the last 30 days. This is not the same as total prescription drug expenditures, which include both drug product costs and dispensing costs. The prescription drug cost distribution typically is skewed, resulting in non-normality of errors, so a logarithmic transformation of the cost was used in the model. Total costs less than one dollar were rounded up to one dollar to avoid negative values after the logarithmic transformation. There are many assumptions that need to be met in order to have unbiased and consistent coefficients estimates in an OLS regression model. These include lack of

perfect multicollinearity, homoscedasticity, normally distributed error terms, independent observations, and linearity.

Multicollinearity was assessed by examining bivariate correlations between the independent variables. Variance Inflation Factors (VIFs) also were calculated. Homoscedasticity was tested by examining a plot of the residuals against the fitted values, and using the Cook-Weisberg test for heteroscedasticity. Normality of the error term was determined by examining the histogram plot of the standardized residuals. Autocorrelation and independence of observations were not considered to be problems because the data were cross-sectional, and collected from a random sample of individuals. Linearity was assessed by examining scatter plots for each of the independent variables against the dependent variable.

Equation 3.3

$$\ln(\text{Rxcost}_i) = \beta_i X_i + e_i \text{ where } e_i \sim N(0, \delta i)$$

$$\begin{aligned}\beta_i X_i = {} & \beta_0 + \beta_1\text{Insrx} + \beta_2\text{Medpref} + \beta_3\text{Insxpref} + \beta_4\text{Age} + \beta_5\text{Age}^2 + \beta_6\text{Female} + \\ & \beta_7\text{Inc10to14} + \beta_8\text{Inc15to24} + \beta_9\text{Inc25to34} + \beta_{10}\text{Inc35to49} + \beta_{11}\text{Inc50to64} + \\ & \beta_{12}\text{Inc>64} + \beta_{13}\text{Lnhouse} + \beta_{14}\text{Hschgrad} + \beta_{15}\text{Posthsch} + \beta_{16}\text{Collgrad} + \\ & \beta_{17}\text{Verygdhlth} + \beta_{18}\text{Goodhlth} + \beta_{19}\text{Fairpoorhlth} + \beta_{20}\text{Numcond} + \\ & \beta_{21}\text{Membhmo} + \beta_{22}\text{Travmd} + \beta_{23}\text{Travph} + \beta_{24}\text{Swestcent} + \beta_{25}\text{East} + \beta_{26}\text{West} \\ & + \beta_{27}\text{North}\end{aligned}$$

Model Building:

Hypothesis testing was accomplished using a model building approach. An alpha of 0.05 was used in all of the models. To be conservative, two-tailed hypothesis tests were used in all of the models even though some of the hypotheses were directional. All of the

models were analyzed both in Part I (the probability of any prescription drug use) and in Part II (number and cost of prescription drugs used by prescription drug users) of the analyses. In the first model, only RXINS and the control variables were entered into the regression equation. This allowed the insurance coefficients to be compared to previous research. In the second model, RXINS, the control variables, and MEDPREF were included. This allowed the incremental effect of the preference measure to be examined, and the insurance coefficients with and without the preferences measure to be compared. The third model was used to examine the interaction effect. In this model RXINS, CATPREF, INSXPREF, and the control variables were included.

The final model controlled for possible selection bias. The model with RXINS, MEDPREF, and the control variables was re-estimated controlling for adverse selection. This was accomplished by including a dummy variable representing adverse selection risk group and an interaction term for insurance and the adverse selection risk group. A significant interaction effect meant that the insurance effect was different for individuals at high and low risk for adverse selection, suggesting that there was adverse selection bias. The prescription drug insurance coefficient in this model is the insurance effect in the low adverse selection risk group, and is a relatively pure estimate of the moral hazard insurance effect. The insurance coefficients in the low adverse selection risk group also were compared to the insurance coefficients in the original model to determine the amount of adverse selection bias in the original estimates.

CHAPTER 4

RESULTS

This chapter is organized into four main sections. The first section reports results from the data collection process and includes response rate, a description of phone calls received about the surveys, and a possible history effect. The second section reports descriptive information and data analyses for the medical care preference scale. The third section reports descriptive data for the other items in the survey, and is divided into five subsections: 1) demographic data, 2) insurance data, 3) data from health related items, 4) prescription drug use for different levels of insurance and medical care preferences, and 5) bivariate correlations for variables included in subsequent regression models. The subsection on demographic data includes comparisons between respondents and the sample or population where data were available. The fourth section reports the results of hypothesis testing, including the model without the preference measure, the model with the medical care preference measure, the model with the interaction between insurance and the preference measure, and the model controlling for adverse selection.

I. Results from the Data Collection Process

Response Rate:

Ninety-eight pre-notification postcards were returned because of incorrect addresses prior to mailing the surveys. Of these postcards, addresses were updated for the 5 that listed a forwarding address, and new addresses were selected for the remainder. A total of 1,943

completed surveys were returned. In addition,1 incomplete survey and 20 blank surveys were returned, 18 surveys were returned because the individual was deceased, and 68 surveys were returned because the address was incorrect. An additional 13 reminder postcards were returned because of incorrect addresses, and it was assumed that these individuals also did not receive the survey booklet. A phone number was provided in the cover letter, and 25 individuals called with questions or comments about the survey. The types of calls are reported in Table 4.1. The individuals who did not receive the survey, or who lost the survey were sent a replacement, and the persons who called to report that the survey addressee was deceased or too ill to complete the survey were told to discard the survey.

Table 4.1 Telephone Calls from Respondents

Type of Call	N
received postcard(s) but no survey form	11
relative called to report that the addressee was deceased	6
relative called to report that the addressee was too ill to complete survey	3
lost form, please send another	2
question on preference items	1
question about what the survey will be used for	1
threw out survey (did not want to complete)	1

The response rate for the survey, 57.2 percent, was calculated by dividing the number of responses (n = 1,943) by the number of surveys mailed minus the number of

undeliverables (n= 3,395). Undeliverables included surveys with incorrect addresses and surveys sent to deceased individuals (total undeliverable rate = 3.0 percent). The number of deceased individuals was determined based on surveys returned marked deceased, and phone calls from relatives of the deceased individuals. Although the overall response rate for the survey was 57.2 percent, some of the respondents were under the age of 50, or were omitted critical items. A total of 183 respondents (9.4 percent) under the age of 50 were deleted from the database and another 102 respondents (5.2 percent) were removed because of missing data on critical items. This left 1,658 individuals for subsequent data analyses, a usable response rate of 48.8 percent.

Half of the surveys included hand signed cover letters and half had cover letters with preprinted signatures. Slightly more surveys were returned by individuals who were sent hand signed cover letters (50.7 percent of returned surveys), but the difference was not significantly significant (Chi-square =0.347, $P < 0.05$).

Non-Response Bias:

The surveys were anonymous, so it was not possible to know definitively whether or not there was non-response bias. However, comparison of early and late responders provides some insights into the problem because late responders may be similar to non-responders. Selected characteristics were compared for the first 200 respondents and the last 200 respondents. It was thought that uninsured individuals would be more likely to respond to the survey, because they would be concerned about the issue of insurance coverage for prescription drugs. There was some evidence that this occurred, because 32.7 percent of the early responders were uninsured and only 28.6 percent of the late responders

were uninsured. However, the percents of uninsured for both early and late responders were less than percent uninsured for all of the respondents.

Even if more uninsured responded, this does not necessarily create problems for the data analyses. The purpose of the study was to compare prescription drug utilization in uninsured and insured individuals, not to determine the percent of uninsured individuals in Wisconsin. Non-response bias would be a problem only if uninsured responders were somehow different from uninsured non-responders, or insured responders were different from insured non-respondents. To assess this issue, item means for self-reported health status, the global preference measure, and number of prescription drugs used were compared for uninsured and insured early responders and late responders. These comparisons are summarized in Appendix H, but the groups were quite similar. The one difference was that insured and uninsured early responders both used less prescriptions than insured and uninsured late responders. However, the difference in number of prescriptions between insured and uninsured individuals was similar for both groups.

History Effect:

An incident that may have affected response rate occurred during the data collection period. One week prior to my survey, another survey containing a one dollar bill to increase response rate was mailed out to Wisconsin residents by colleagues in the same department. One of the surveys was mailed to the office of a state representative, who issued a press release expressing his opinion that the use of dollar tokens in surveys by researchers at a state funded University was "a waste of taxpayer dollars." The story was picked up by National Public Radio, three newspapers, and a local television station (one of the

newspaper articles is provided in Appendix I). Unfortunately, the majority of the stories in the mass media aired the same day that most individuals would have received my survey. Although the two surveys were on different topics, both surveys were from the School of Pharmacy and one professor's name appeared on both surveys, so people who heard the story may have assumed that it pertained to my survey. It is not known what, if any, affect the publicity had on my response rate.

II. Medical Care Preference Scale Results

For reference purposes, the medical care preference scale items are listed in Figure 4.1. Frequencies, means, and standard deviations for all nine preference scale items and the global medical care preference item are reported in Table 4.2. These results were from respondents of all ages who answered at least one of the preference scale items. Responses were distributed across all of the response categories for all of the items. Means ranged from 2.31 to 3.77 (after reverse coding items 15, 20, and 21), while standard deviations ranged from 0.92 to 1.21. Bivariate correlations for all of the preference items are listed in Table 4.3, and were between 0.139 and 0.665. The alpha coefficient for the overall scale was 0.879, which was very good reliability for a new measure (Nunnally and Bernstein 1994). Item to total correlations (Table 4.4) were between 0.493 and 0.711, and the coefficient alpha values with each item deleted all were less than the coefficient alpha for the entire scale.

Two tests were performed to test whether the data were appropriate for factor analysis. The Kaiser-Meyer-Olkin Measure of Sampling Adequacy was 0.901, and Bartlett's

Figure 4.1 List of Preference Items:

Item 13: For most health problems, I would rather treat myself than go to the doctor.

Item 14: For most health problems, I prefer to avoid taking prescription drugs.

Item 15: I usually like to talk to a doctor when I have a health problem.

Item 17: For most health problems, I wait and see if I get better on my own before going to see a doctor.

Item 18: For most health problems, I wait and see if I get better on my own before taking a prescription drug.

Item 19: When I have a health problem, I often prefer to use home remedies instead of prescription drugs.

Item 20: When I have a health problem, I usually contact a doctor right away.

Item 21: For most health problems, I would rather take a prescription drug than a non-prescription drug.

Item 22: When I have a health problem, it is sometimes hard to convince me to see a doctor.

Item 23: I prefer to treat most health problems without help from doctors or prescription drugs. (global item, not part of scale)

Table 4.2 Distributions of the Medical Care Preference Items

	Percent of Responses[1]							
Item #	SD	D	N	A	SA	Missing	Mean	S.D.
13	11.2	25.7	18.0	32.5	9.9	2.7	3.04	1.21
14	7.4	20.5	15.7	42.0	12.0	2.4	3.31	1.16
15[2]	16.2	49.4	20.4	9.7	2.2	2.1	2.31	0.94
17	2.9	8.7	12.0	58.4	15.6	2.3	3.77	0.92
18	5.4	19.3	10.9	48.9	13.2	2.3	3.46	1.12
19	7.4	29.7	21.5	32.4	6.6	2.4	3.01	1.10
20[2]	3.9	18.7	22.6	43.7	8.4	2.8	3.35	1.01
21[2]	5.2	28.7	26.9	29.7	6.9	2.6	3.05	1.05
22	5.4	31.0	16.9	37.6	6.9	2.3	3.00	1.09
23	9.1	31.8	18.0	31.9	6.6	2.7	2.98	1.14

SD = strongly disagree, D = disagree, N = neutral, A = agree, SA = strongly agree

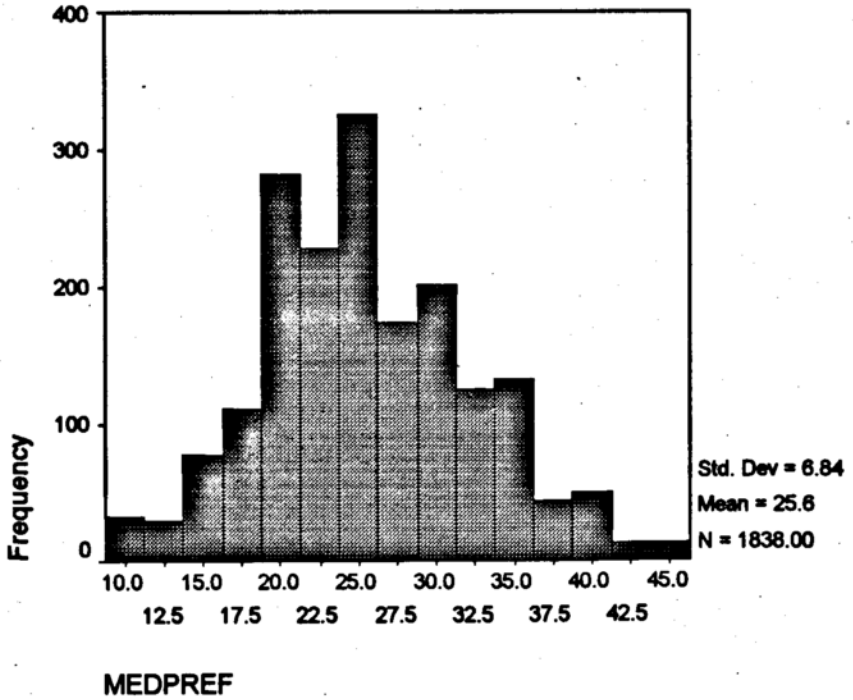
1. All respondents who answered at least one of the preference items (N = 1,933)
2. Calculated after items were reverse coded.

Table 4.3 Bivariate Spearman Correlations for the Preference Items

Item	13	14	15	17	18	19	20	21
13	1.00							
14	.638	1.00						
15	.374	.273	1.00					
17	.550	.496	.225	1.00				
18	.509	.510	.214	.665	1.00			
19	.542	.529	.258	.508	.542	1.00		
20	.360	.333	.480	.399	.330	.362	1.00	
21	.273	.320	.374	.212	.215	.331	.470	1.00
22	.499	.396	.275	.483	.470	.457	.328	.139

N = 1,871 to 1,901

Figure 4.2 Medical Care Preference Scale Distribution[1]



1. Higher scores signify stronger help-seeking preferences.

Test of Sphericity was rejected at $p < 0.05$. Both of these results indicate that using factor analysis to analyze the data was appropriate. One factor that explained 51.0 percent of the variance in the measure was extracted, and factor loadings for that factor are given in Table 4.4. Since the scale was unidimensional, a single summed medical care preference score was created (MEDPREF) by adding the scores from all nine preference items. For ease of interpretation, the scale was reversed so that higher scores on the scale indicated stronger self-treating preferences. The resulting scale had a mean of 25.56, a median of 25.0 and a standard deviation of 6.82. Scores on the scale ranged from 9 to 45, out of a possible 9 to 45, and had a distribution that was close to normal (Figure 4.2). The number of observations in Figure 4.2 reflects respondents of all ages who answered all of the preference scale items.

A global medical care preference item (item 23) was included on the survey as one measure of convergent validity. This item had a mean of 2.98, a standard deviation of 1.14, and a somewhat bimodal distribution (see Table 4.2). The correlation between the score on the global item and MEDPREF was 0.756, signifying a strong positive relationship between the two scores. Correlations between MEDPREF and various demographic and health variables also were examined (see Table 4.5). Correlations between MEDPREF and the health variables were moderate and positive, 0.179 and 0.201 respectively for health status and number of medical conditions. The correlation between MEDPREF and age was 0.211, but the correlations between MEDPREF and gender, education, and income all were less than 0.100. This suggested that the preference scale measured a construct not captured by demographic and health variables, and provided some evidence of divergent validity.

Table 4.4 Item-Total Statistics and Factor Analysis Results for the Preference Scale[1]

	Item-Total Statistics				Factor Analysis
Item #	Mean IID	S.D. IID	I-T Correlation	Alpha IID	Factor Loadings
13	22.60	5.93	.711	.857	.791
14	22.87	6.01	.675	.861	.758
15[2]	21.88	6.30	.523	874	.613
17	23.34	6.19	.675	.862	.762
18	23.02	6.07	.644	.864	.740
19	22.57	6.05	.673	.861	.756
20[2]	22.92	6.14	.654	.863	.740
21[2]	22.62	6.26	.493	.877	.586
22	22.66	6.16	.564	.871	.662
Overall Scale	25.56	6.82		.879	

IID = if item deleted, I-T = item to total

1. Respondents of any age who answered all of the preference items (N = 1,838). Higher scores signify stronger help-seeking preferences.
2. Reverse coded.

The relationship between medical care preferences and health status was examined in more depth because of the moderate correlation (Table 4.6). The mean for MEDPREF increased somewhat (more help-seeking) as health status worsened, from 23.25 for individuals reporting excellent health to 28.41 for individuals reporting poor health. However, there still was considerable variability in MEDPREF across all of the five health status categories. Some individuals reporting excellent health had preference scores at the top of the scale, while individuals reporting fair and poor health status had preference scores as low as 10 and 15 respectively. The standard deviation was somewhat greater for individuals reporting poor health, probably because of the smaller number of observations in this category.

Table 4.5 Correlations Between the Medical Care Preference Scale and Demographic Variables

Variable	Correlation with Preference Scale[1]
Age[2]	.211
Gender	-.063
Education	-.071
Income	-.048
Health Status	.179
Number of Medical Conditions[2]	.201

1. High score on the preference scale signify stronger help-seeking preferences. Spearman correlations unless otherwise indicated.
2. Pearson correlations

Table 4.6 Distribution of the Medical Care Preference Scale by Health Status

	MEDPREF Scale[1]			
Health Status	Mean	S.D.	Range	N[2]
Excellent	23.25	7.01	9 - 45	272
Very Good	24.78	6.48	9 - 45	623
Good	26.29	6.63	9 - 45	629
Fair	27.41	6.78	10 - 45	240
Poor	28.41	8.12	15 - 45	51

1. Higher scores signify stronger help-seeking preferences.
2. Excludes individuals who did not report health status.

III. Descriptive Results

Demographic Items:

Demographic characteristics of respondents are listed, and where possible compared to characteristics of the sample and the population in Table 4.7. Information about the sample was obtained from the mailing list company, and needs to be interpreted with caution, given that the data may be inaccurate or outdated. Information about the population was obtained from 1997 estimates extrapolated from 1990 census data. The population comparisons were limited to age and gender, because extrapolated estimates only were available for these variables, and original census data were too old to be useful. All descriptive results are reported prior to replacing missing data.

The percentage of female respondents, 60.2 percent, was significantly greater than the percentage of females in the sample or the population. The sample and population

Table 4.7 Descriptive Results for Demographic Items

Variable	Respondents N	Respondents %	Sample[1] %	Population[2] %
Gender[3]				
Male	659	39.7	45.6	45.3
Female	998	60.2	54.4	54.7
missing data	1	0.1		
Age[4]				
50 to 54	299	18.0	18.9	20.7
55 to 59	264	15.9	14.1	16.2
60 to 64	226	13.6	10.4	14.1
65 and older	869	52.2	56.5	49.0
65 to 69	247	14.9		13.5
70 to 74	235	14.2		12.0
75 to 79	172	10.4		10.0
80 to 84	135	8.1		7.3
85 and older	76	4.6		6.2
missing data	4	0.3		
Mean = 65.8, Std Dev = 10.6, Range = 50 to 95				
Education				
elementary or some high school	242	14.6		
graduated high school	543	32.8		
some post high school	479	28.9		
graduated 4 year college	241	14.5		
Masters, Ph.D. or Prof. Degree	151	9.1		
missing data	2	0.1		

Table 4.7 cont.

Variable	Respondents N	Respondents %	Sample[1] %
Household Income[5]			
less than $10,000	172	10.4	31.1
$10,000 to $14,999	226	13.6	
$15,000 to $24,999	320	19.3	16.6
$25,000 to $34,999	267	16.1	13.9
$35,000 to $49,999	216	13.0	15.9
$50,000 to $64,999	133	8.0	15.1
$65,000 to $79,999	75	4.5	
$80,000 or more	142	8.6	7.4
missing data	107	6.5	
Number in Household			
1	654	39.4	
2	756	45.6	
more than 2	234	14.2	
missing data	14	0.8	
Mean = 1.81, S.D. = 0.86, Max = 7			
Employment			
not currently working	961	58.0	
working 1 to 14 hrs/wk	53	3.2	
working 15 to 34 hrs/wk	122	7.4	
working 35 or more hrs/wk	520	31.3	
missing data	2	0.1	

Table 4.7 cont.

	Respondents		Sample[1]
Variable	N	%	%
Race			
White, Non-Hispanic	1592	96.0	
Black	34	2.1	
Hispanic	7	0.4	
American Indian	5	0.6	
Asian	3	0.2	
Other	7	0.4	
Missing	5	0.3	
Geographic Region of Residence[6]			
Southeast	442	26.7	28.1
Southcentral/Southwest	267	16.1	14.8
East	407	24.5	22.7
West	232	14.0	16.3
North	272	16.4	18.1
Missing or out of state	38	2.3	

N = 1,658

1. Based on information from the mailing list, excluding known undeliverables
2. Based on 1997 population estimates for the State of Wisconsin (Census.gov 1999).
3. Respondents significantly different from sample (Chi-square = 22.9, p = 0.000).
4. Respondents significantly different from sample (Chi-square = 26.1, p = 0.000).
5. Respondents significantly different from sample (Chi-square = 55.2, p= 0.000). Categories provided by the mailing list company did not match the categories on the survey exactly. For example, the mailing list range was $16,000 to $35,999 and the corresponding survey range was $15,000 to $34,999.
6. Respondents significantly different from sample (Chi-square = 13.1, p = 0.011).

percentages were equal by design, because the percentage of females in the sample was chosen to match the population percent. The higher percentage of female respondents may have occurred for several reasons. It is possible that women were more willing to complete and return the survey than men. It also is possible that surveys addressed to a male were completed by the female spouse, either at the request of the husband, or because the husband was ill or deceased. For whatever reason, higher percentages of female respondents have been reported in previous pharmacy related research (Carroll and Jowdy 1987; Wiederholt 1987).

The mean age for respondents age 50 and older was 65.8, with a range of 50 to 95. As discussed in the previous section, respondents under the age of 50 were excluded from the data analyses. There was good distribution across all age categories, with 52.2 of the sample reporting ages of 65 or older. The age distribution differed significantly from the sample and the population, but the differences for each category typically were not more than 1 or 2 percent. The comparison with the sample may be somewhat misleading, because the mailing list data were about 6 months old. For some individuals, the mailing list only specified that they were age 65 or older, and thus, comparisons within smaller age categories could not be made. One difference between respondents and the population was that there were fewer respondents age 85 and older. It is possible that some of these individuals were not able to return the survey due to illness, or difficulty completing the survey.

There also was good distribution of respondents across the different education levels. One concern prior to mailing the survey was that lower education individuals would be unable or unwilling to complete the somewhat lengthy survey, but this did not appear to be a

problem. About 15 percent of respondents had not completed high school and 32.8 percent had a high school degree but no further education. Another 29 percent of respondents had gone to college, but did not have a four year degree. This group included individuals with two year associates degrees. About 15 percent of respondents had degrees from a four year college and 9 percent of respondents had advanced degrees. Recent population or sample information on education was not available for comparison purposes.

About 10 and 14 percent of respondents reported household incomes of less than $10,000 and $10,000 to $14,999, respectively. Almost 20 percent of respondents had household incomes in the $15,000 to $24,000 range, and another 16 percent were in the $25,000 to $34,000 range. There was not a large percentage of high income respondents, only 8.6 percent reported household incomes of $80,000 or more. There were 6.5 percent of respondents who refused to give their household income. The income of respondents differed significantly from the income of the sample, although some of the differences may have been due to methodological reasons. The income categories given by the mailing list company were slightly different than the income categories on the survey. For example, the category on the survey was $15,000 to $24,999 while the corresponding category on the mailing list was $16,000 to 25,999. Another possible reason for the difference is that the income reported on the mailing list may have been outdated. The mailing list was purchased in August, and the income information may have been even older. This may explain the higher percentage of respondents in the $80,000 and over category.

The mean number of individuals living in the household was 1.81. Almost 40 percent of respondents lived alone, and only 14 percent reported more than 2 individuals were living

in the household. The most individuals living in any household was 7. About 60 percent of respondents were not currently employed. This included retired individuals. About one third of the respondents were employed full time (defined as 35 or more hours per week) and only about 10 percent were employed part time. The respondents were not very racially diverse (96 percent white), but neither was the population from which sample was drawn.

The largest percentage of respondents resided in the Southeast area of the state, which is the most densely populated. The geographic region of residence was significantly different for the sample and respondents. Respondents were slightly more likely to reside in the South-central/Southwest area and the East, and were slightly less likely to reside in the Southeast, West and North. However, the differences were only about two percentage points, and may not have been of practical significance. Differences also could have been a function of the dividing line chosen. There were about two percentage points more respondents in the East and about two percentage points fewer respondents in the West, relative to the sample. These individuals may have been living close to one another, and they may have been in the other region had the dividing line been drawn slightly differently.

Items Related to Health Insurance Coverage:

Descriptive results for all of the items pertaining to health insurance coverage are reported in Table 4.8. The vast majority of respondents (93.9 percent) had at least some coverage for physician visits, but only 29.1 percent had insurance that paid for all of their physician visit costs. Fewer respondents (64.6 percent) had coverage for prescription drugs, and only 3.9 percent had all of their prescription drug costs covered. Over 75 percent of the insurance coverage for prescription drugs was through an employer or former employer, and

Table 4.8 Descriptive Results for Health Insurance Related Items

Variable	N	Percent
Insurance for Prescription Drugs (n = 1,658)		
all costs covered	65	3.9
part of costs covered	1007	60.7
large deductible plan	13	0.8
no insurance	573	34.6
Insurance for Doctor Visits (n = 1,658)		
all costs covered	482	29.1
part of costs covered	1074	64.8
large deductible plan	9	0.5
no insurance	93	5.6
Source of Prescription Insurance[1] (n = 1,072)		
employer/former employer	822	76.7
government(e.g. Medicaid/VA)	54	5.0
purchased directly from insurance Co.	82	7.6
other	50	4.7
missing data	64	6.0
Number of Employees[2] (n = 822)		
25 or less	43	5.2
26 to 100	81	9.9
101 to 500	193	23.5
more than 500	482	58.6
missing data	23	2.8

1. Individuals with prescription drug insurance (does not include large deductible plan).
2. Individuals with prescription drug insurance through employer.

Table 4.8 cont.

Variable	N	Percent
Number of Plans Available[3] (n = 1,072)		
1	419	39.1
2 or 3	294	27.4
more than 3	171	15.9
do not know	81	7.6
missing data	107	10.0
All Plans Covered Prescriptions[3] (n = 1,072)		
yes	684	63.8
no	129	12.0
don't know	162	15.1
missing data	97	9.1
Changed Plans in Last Year[3] (n = 1,072)		
yes	137	12.8
no	879	82.0
don't know	7	0.7
missing data	49	4.5
Gap in Prescription Drug Coverage[3] (n = 1,072)		
yes	41	3.8
no	966	90.1
don't know	14	1.3
missing data	51	4.8

3. Individuals with prescription drug insurance.

Table 4.8 cont.

Variable	N	Percent
Why No Prescription Drug Coverage[4] (n = 586)		
employer did not offer	66	11.3
available, but cost too much	157	26.8
do not need	80	13.7
refused by insurance company	22	3.8
can not afford	41	7.0
other	149	25.4
missing data	71	12.1
HMO Member (n = 1,658)		
yes	435	26.2
no	1134	68.4
don't know	61	3.7
missing data	28	1.7
Medicare Coverage (n = 1,658)		
yes, Part A only	139	8.4
yes, Parts A & B	736	44.6
no	750	45.4
missing data	26	1.6
Supplemental Medicare Plan[5] (n = 875)		
yes	580	66.3
no	217	24.8
don't know	40	4.6
missing data	38	4.3

4. Individuals with no prescription drug insurance or large deductible plan.
5. Individuals who reported having Medicare coverage

the majority of these employers had more than 100 employees. Only 7.6 percent of the respondents who had coverage purchased the policy directly from an insurance company and even fewer individuals had prescription drug insurance coverage from the government, via Medicaid or the Veterans Administration. A possible explanation for the low number of Medicaid individuals is that many of the elderly individuals on Medicaid are nursing home residents, and either were not in the sampling frame or could not complete the survey.

Over one third of individuals with prescription drug insurance coverage had no choice of plans and only 15.9 percent of respondents had a choice of more than three plans. Very few individuals (12.0 percent) were offered a plan without prescription drug coverage. However, these results should be interpreted cautiously, because there were many individuals who had difficulty answering these two questions. About 18 percent of respondents either reported they did not know the number of plans available or left it blank. Even more respondents (24.2 percent) did the same for the question about whether all plans covered prescription drugs. A possible explanation for this problem is that a spouse may have chosen the insurance plan. These questions were problematic for older individuals, possibly because individuals purchasing supplemental Medicare policies were unaware of all the coverage choices.

About 13 percent of respondents reported changing insurance plans but only 3.8 percent of respondents with prescription drug coverage reported any gaps in the prescription drug coverage in the last year. This indicates that most of the insurance plan changes were between plans with drug coverage and not between a plan with drug coverage and a plan without drug coverage. If there were gaps in prescription drug coverage, respondents were

asked to describe why it happened. Many of these respondents had a gap in health insurance coverage in general, for example, they had switched jobs, lost their jobs, or had a waiting period before their insurance coverage took effect. Some individuals had a gap specifically in drug coverage, for example because they had exceeded their benefit limits, or because their plans only recently added drug coverage.

Individuals who did not have prescription drug insurance were asked to check the reason that best described why they did not have drug coverage. The most frequent response (26.8 percent) was that the insurance was available, but that they thought it cost too much. A number of individuals (7.0 percent) indicated that they simply could not afford the coverage, so this response was categorized separately. Almost 14 percent thought they did not need prescription drug coverage and only 3.8 percent were denied coverage by an insurance company. About one fourth of respondents gave some other reason. Some examples of these responses are: 1) "I am on Medicare and it does not cover drugs", 2) "My Medigap plan doesn't cover drugs", 3) "I don't have any insurance", and 4) "I wasn't aware you could get insurance for prescriptions." Most of the "other" responses were similar to the first two examples.

In addition to the items on prescription drug insurance coverage, respondents also were asked a few questions about their general health insurance coverage. About one forth of respondents belonged to an HMO. As expected, the percent of respondents with Medicare coverage (53 percent) was close to the percent of individuals age 65 and older. Of the respondents with Medicare coverage, 84.1 percent had both Parts A and B. It appeared that many respondents did not understand the meaning of a supplemental Medicare, or

Medigap plan. Some respondents answered this question even though they did not have Medicare coverage. Also, some respondents who appeared to have a Medicare supplemental plan (based on their answers to other questions) reported they did not have such a plan. As a result, the responses to this item should be viewed with caution.

Table 4.9 shows the percentage of individuals without prescription drug insurance coverage in different age groups. The percentage of uninsured was relatively low, approximately 14 percent, in the 50 to 54 and 55 to 59 age categories. The percentage of uninsured increased slightly in the 60 to 64 age group, probably as a result of these individuals beginning to retire. More individuals likely retired between ages 65 to 69, and this was reflected in the percent of uninsured individuals in this age group, almost 50 percent. There was a slightly higher percentage of uninsured individuals in the 70 to 74 age group, about 54 percent, but the uninsured percentage did not increase further in the last two age groups. When prescription drug insurance coverage was examined by employment status, 46.6 percent of unemployed individuals were uninsured while only 12.5 percent of full time workers had no prescription drug coverage. The percentage of part time workers with no prescription drug coverage (41.1 percent) was similar to the percentage of uninsured unemployed individuals.

The percentage of uninsured individuals across different levels of self-reported health status is reported in Table 4.10. Individuals in excellent or very good health were the most likely to have prescription drug insurance coverage. Only 33.6 percent and 28.8 percent respectively were uninsured. In contrast, 44.5 percent of respondents reporting fair health and 42.9 percent of respondents reporting poor health lacked prescription drug insurance

Table 4.9 Prescription Drug Insurance Coverage by Age

		No Prescription Drug Insurance	
Age	Total N	N	%
50 to 54	299	44	14.7
55 to 59	264	36	13.6
60 to 64	226	50	22.1
65 to 69	251	125	49.8
70 to 74	235	126	53.6
75 to 79	172	92	53.5
80 and older	211	113	53.6

N = 1,658

Table 4.10 Prescription Drug Insurance Coverage by Health Status

		No Prescription Drug Insurance	
Health Status	Total N	N	%
Excellent	250	84	33.6
Very Good	548	158	28.8
Good	584	222	38.0
Fair	227	101	44.5
Poor	49	21	42.9

N = 1,658

coverage. This pattern is not consistent with the presence of adverse selection, because with adverse selection, individuals in good health should be more likely to opt out of insurance and individuals in poor health should be more likely to be insured. A likely explanation is that individuals who are less likely to have the financial resources to obtain insurance are more likely to be in poor health.

Items Related to Health Care Utilization or Health Status:

Descriptive results for items related to health care utilization or health status are summarized in Table 4.11. The mean number of prescriptions used in the last 30 days was 2.62, with a standard deviation of 2.42. Only 20.1 percent of respondents reported using no prescription drugs. About 18 percent of respondents had used one prescription drug and another 17.7 percent used two prescription drugs. Only 4.5 percent of respondents reported using more than 7 different prescription drugs, and the greatest number of drugs any individual used was 19. The mean per person cost of prescription drugs used in the last 30 days was $71.91, with a standard deviation of $130. Approximately one third of respondents used less than $20.00 of prescription drugs. There were eight individuals who used more than $500 of prescription drugs in the last month, and one of these individuals used $3,377 of prescription drugs. This individual used 19 different prescription drugs, but the majority of the cost resulted from two cancer medications. The mean out-of-pocket expenditures for prescription drugs used in the last 30 days was $56.0, with a standard deviation of $71.6. Over half of the respondents had out-of-pocket expenditures for prescription drugs that were less than $50.

Table 4.11 Descriptive Results for Health Care Variables and Health Status Variables

Variable	N	Percent
Number of Prescription Drugs Used in Last 30 Days		
0	334	20.1
1	307	18.5
2	293	17.7
3 to 4	420	25.3
5 to 7	230	13.9
more than 7	74	4.5
Mean = 2.62, S.D. = 2.42, Max = 19		
Total Cost of Prescription Drugs Used in Last 30 Days		
$0 to $19.99	593	35.7
$20 to $49.99	269	16.2
$50 to $99.99	309	18.6
$100 to $199.99	270	16.3
$200 to $499.99	107	6.5
$500 or more	8	0.5
Missing	102	6.2
Mean = $71.91, S.D. = $130, Max = $3,377		
Out-of-Pocket Prescription Expenditures in Last 30 Days		
$0 to $24	564	42.0
$25 to $49	230	17.1
$50 to $99	216	16.1
$100 to $149	104	7.7
$150 or more	132	9.9
missing data	96	7.2
Mean = $56.0, S.D = $71.6, Max = $650		

Table 4.11 cont.

Variable	N	Percent
Distance to Doctors Office		
less than 1 mile	206	12.4
1 to 5 miles	683	41.2
6 to 10 miles	303	18.3
11 to 20 miles	254	15.3
more than 20 miles	191	11.5
missing data	21	1.3
Distance to Pharmacy[1]		
less than 1 mile (includes mail order)	407	30.4
1 to 5 miles	518	38.7
6 to 10 miles	145	10.8
11 to 20 miles	145	10.8
more than 20 miles	60	4.5
missing data	64	4.8
Health Status		
Excellent	250	15.1
Very Good	548	33.1
Good	584	35.2
Fair	227	13.7
Poor	49	3.0

1. For those who reported using at least one prescription in the last 30 days (n=1,339).

Table 4.11 cont.

Variable	N	Percent
Number of Reported Medical Conditions		
0	160	9.7
1	322	19.4
2	397	23.9
3	316	19.1
4	221	13.3
more than 4	242	14.6
Mean = 2.62, S.D. = 1.79, Max = 12		
Type of Medical Condition[2]		
Allergies	322	19.4
Anxiety	92	5.5
Arthritis	689	41.6
Asthma/COPD	142	8.6
Back Pain (severe)	348	21.0
Cancer	85	5.1
Depression	165	10.0
Diabetes	173	10.4
Epilepsy	13	0.8
Glaucoma	99	6.0
Gout	81	4.9
Heart Problem	324	19.5
High Blood Pressure	686	41.4
High Cholesterol/Triglycerides	498	30.0

Table 4.11 cont

Variable	N	Percent
Number of Reported Medical Conditions (cont.)[2]		
Migraine Headaches	110	6.6
Stomach Ulcer/GERD	132	8.0
Thyroid	184	11.1
Other condition (1)	172	12.7
Other condition (2)	43	2.6

2. Individuals reporting they have the medical condition.

As expected, the distance traveled to a pharmacy generally was less than the distance traveled to a doctors office. Only 4.5 percent of respondents had to travel more than 20 miles to their pharmacies, while 11.5 percent of respondents had to travel more than 20 miles to their physicians' offices. Almost a third of respondents traveled less than one mile to get to their pharmacies, but only 12 percent of respondents traveled less than one mile to get to their physicians' offices. However, for pharmacies, the less than one mile travel distance included respondents who had prescriptions delivered to them, either by a local pharmacy or by a mail order service. More individuals left the pharmacy travel distance question blank than the doctor travel distance question

Self-reported health status was somewhat skewed toward better health. About 15 percent of respondents reported they were in excellent health relative to others their age, while only 3 percent reported that they were in poor health. Approximately one third of respondents reported being in very good health, while only 13.7 percent reported being in fair health. Although there may have been some ceiling effects, this was less of a problem than it would have been in a younger population. Missing data were not reported for any respondents because this was considered a critical question, and respondents who omitted this item were not included in the database. Typically, this was not an item non-response problem, but resulted from cases where respondents omitted the entire last page.

The mean number of medical conditions reported was 2.62, with a standard deviation of 1.79. The greatest number of medical conditions reported by a respondent was 12. On the extremes of the distribution, 9.7 percent of respondents reported having no medical conditions and 14.6 percent of respondents reported having more than 4 medical conditions.

Most respondents reported having 1, 2, or 3 medical conditions. The most frequent types of medical conditions reported were arthritis and high blood pressure (41.6 and 41.1 percent respectively). High cholesterol or high triglycerides were the next most frequent (30.0 percent), and allergies, severe back pain, and heart problems also were relatively common (approximately 20 percent each). About 13 percent of respondents reported having at least one medical condition that was not listed, but none of these conditions were mentioned by more than 12 individuals.

Cross Tabulations for Prescription Drug Use:

For descriptive purposes, the univariate relationships between prescription drug insurance coverage and prescription drug use, and medical care preferences and prescription drug use were examined prior to the multivariate hypothesis testing. Table 4.12[5] reports prescription drug use in individuals with different levels of insurance. Individuals with no prescription drug insurance had somewhat lower levels of prescription drug use than insured individuals. The number of prescription drugs used was 2.45 for uninsured individuals and 2.71 for insured individuals. The average total cost of prescription drugs used in the last 30 days was $59.95 for uninsured individuals and $78.43 for insured individuals. For individuals who used at least one prescription drug, and who reported the drug names, the average cost per prescription was $24.49 for uninsured individuals and $29.03 for insured individuals. If the individual with $3,377 in drug costs was removed, the average cost per prescription for uninsured individuals decreased to $22.31.

5. Tables 4.12 and 4.13 should be viewed as descriptive, and interpreted with caution. They show raw data that are not adjusted for other variables affecting prescription drug utilization (e.g. health status).

To examine the effect of preferences, individuals were categorized into two preference levels, based on the median preference score. As shown in Table 4.12, individuals with lower preference scores (self-treaters) had considerably lower levels of prescription drug use than individuals with higher preference scores (help-seekers). The cost of prescription drugs used in the last 30 days averaged $51.86 for self-treaters and $92.81 for help-seekers. The univariate effect of preferences on prescription drug use also was examined using the single item preference measure (Table 4.13). The average number of prescription drugs used by individuals who strongly disagreed with the item was 4.03. An average of only 1.66 prescription drugs was used by individuals who strongly agreed with the statement on preferences. The pattern was similar for the percent of individuals with any prescription drug use. The average cost of prescription drugs was $109.17 for individuals who strongly disagreed with the item and only $56.23 for individuals who strongly agreed with the item.

Bivariate Correlations for Variables in the Regression Models:

Bivariate correlations for the variables included in the regression models were examined to assess potential multicollinearity problems (Table 4.14). All but one of the correlations were less than 0.500, and most were less than 0.300. Income was the most problematic, with a 0.515 correlation with education, a -0.459 correlation with age, a 0.398 correlation with prescription drug insurance coverage, and a -0.300 correlation with gender. Some of the predictors of prescription drug use potentially are predictors of insurance coverage, so the correlations between insurance coverage and the other variables were of

Table 4.12 Prescription Drug Use by Insurance Type and Medical Care Preference Score

		Prescription Drug Use In Last 30 Days		
	N	Any Use (%)	Number of Prescriptions	Cost of Prescriptions
No prescription insurance	586	79	2.45	$59.95
Prescription insurance	1072	81	2.71	$78.43
Self-treating preferences[1]	851	71	1.95	$51.86
Help-seeking preferences[2]	807	89	3.33	$92.81

1. Medical care preference score = 9 to 25
2. Medical care preference score = 26 to 45

Table 4.13 Prescription Drug Use by Single Item Medical Care Preference Measure

		Prescription Drug Use In Last 30 Days		
Preference Item[1] Score	N	Any Use (%)	Number of Prescriptions	Cost of Prescriptions
Strongly Disagree	153	95	4.03	$109.17
Disagree	546	87	3.17	$91.54
Neutral	302	80	2.50	$61.23
Agree	545	73	1.90	$49.60
Strongly Agree	105	53	1.66	$56.23

1. I prefer to treat most health problems without help from doctors or prescription drugs.

Table 4.13 *Bivariate Correlations for Variables in the Regression Model*[1]

	Regn	Trvrx	Trvmd	Hmo	Numcnd	Health	Lnhous	Inc	Educ	Gender	Age	Mdprf
Rxins	-.066	-.051	.018	.223	-.010	-.096	.169	.398	.198	-.154	-.348	.056
Medpref	-.057	-.066	-.030	-.020	.201	.179	-.011	-.048	-.071	-.063	.211[2]	1.00
Age	-.016	-.081	-.123	-.214	.149	.145	-.326	-.459	-.286	.090	1.00	
Gender	.005	-.016	-.031	-.059	.138	.020	-.373	-.300	-.022	1.00		
Educ	-.079	-.086	-.007	.122	-.051	-.213	.058	.515	1.00			
Income	-.088	-.012	.023	.168	-.143	-.254	.377	1.00				
Lnhouse	.026	.096	.100	.094	-.089	.027	1.00					
Health	.024	.053	.087	-.046	.432	1.00						
Numcnd	-.003	.006	.015	.014	1.00							
Hmo	-.129	-.037	-.012	1.00								
Travmd	.187	.485	1.00									
Travrx	.221	1.00										
Region	1.00											

1. Spearman correlations unless otherwise indicated.
2. Pearson correlation.

special interest. Income and age were moderately correlated with insurance coverage, but both correlations were less than 0.40. The correlations of health status and number of conditions with insurance coverage were low, -0.100 and -0.096 respectively. These correlations are consistent with previous research that suggests that the relationship between income and insurance coverage is stronger than the relationship between health status and insurance coverage.

The correlation between health status and the number of medical conditions was 0.432. These variables were expected to be somewhat related, but they still may reflect different aspects of health. The number of medical conditions is more of a quantity measure, in that it does not account for differences in severity between different medical conditions. For example, someone could have several medical conditions, but if they all are minor, then the individual may feel that they are in excellent health. The health status variable should capture more of the severity effect. In order to control for quantity and severity of health problems, both health variables were kept in the database in spite of the relatively strong correlation. The correlation between the distance traveled to a doctors office and the distance traveled to the pharmacy was 0.485.

IV. Hypotheses Testing

The hypothses were tested using a two part model of prescription drug, where Part I predicted the probability of any prescription drug use, and Part II predicts the number or cost of prescription drugs used by individuals who had used at least one prescription drug. A model building approach was used in both Part I and Part II of the analyses, resulting in an

extensive number of models. Figure 4.3 provides an overview of all of the models, the hypotheses that they were used to test, and the number of observations used in each set of models.

Figure 4.3 Overview of Models Used for Hypotheses Testing

Part I: Probability of any Prescription Drug Use:

Model I: Insurance and Control Variables - H1

Model II: Insurance, Medical Care Preferences, and Control Variables - H1 and H7

Model III: Insurance, Preferences, Control Variables, and Interaction Effect - H10

Model IV: Model II, re-estimated controlling for adverse selection risk - H6

N = 1,658

Part II: Number of Prescription Drugs Used

Model V: Insurance and Control Variables - H2

Model VI: Insurance, Medical Care Preferences, and Control Variables - H2 and H8

Model VII: Insurance, Preferences, Control Variables, Interaction Effect - H11

Model VIII: Model VI re-estimated controlling for adverse selection risk - H5

N = 1,324 (only prescription drug users)

Part II: Cost of Prescription Drugs Used

Model IX: Insurance and Control Variables - H3

Model X: Insurance, Medical Care Preferences, and Control Variables - H3 and H9

Model XI: Insurance, Preferences, Control Variables, Interaction Effect - H12

Model XII: Model X re-estimated controlling for adverse selection risk - H6

N = 1,222 (only prescription drug users who listed drug names)

Probability of Prescription Drug Use:

Logistic regression results from Part I, the probability of any prescription drug use, are reported in tables 4.15 through 4.18. Table 4.19 summarizes the odds ratios for all four

of the logistic regression models. Coefficients from a logistic regression model can be interpreted as the change in the log odds, holding all other variables constant. However, odds ratios (e^{β}) also are reported because the change in log odds is not intuitively easy to understand. Odds ratios can be interpreted as the relative likelihood of an event, where odds ratios greater than one indicate that the event was more likely to occur and odds ratios less than one indicate that the event was less likely to occur. The goodness of fit of the logistic regression models was assessed using Nagelkerke pseudo R^2, based on the change in the -2log likelihood.

Table 4.15 lists results from the model containing insurance and the control variables, but not the medical care preference measure. The insurance odds ratio of 1.92 indicates that individuals with prescription drug insurance were 1.92 times more likely to have used at least one prescription in the last 30 days than uninsured individuals. The insurance coefficient was significant, as were all of the health status variables. Individuals reporting very good health were 1.7 times more likely than individuals in excellent health to have used at least one prescription drug in the last 30 days. In comparison, individuals reporting good health and fair/poor health were 3.0 and 2.7 times more likely, respectively, to have used at least one prescription. It was interesting that the effect of good health relative to excellent health was greater than the effect of fair/poor health relative to excellent health. The number of reported medical conditions also had a significant effect on prescription drug use. For each additional medical condition, the odds of using at least one prescription drug increased by a factor of 2.1.

Table 4.15 Logistic Regression Results - Probability of Any Prescription Drug Use: Insurance Only Model

Variable	β	S.E.	Odds Ratio (e^{β})	Wald	p
Rxinsurance[1]	0.6507	0.1780	1.9169	13.3625	0.003
Verygdhlth[2]	0.5293	0.1882	1.6977	7.9067	0.005
Goodhlth[2]	1.1100	0.2153	3.0344	26.5877	0.000
Fairpoorhlth[2]	1.0101	0.3079	2.7458	10.7634	0.001
Numcond[3]	0.7590	0.0660	2.1362	132.3265	0.000
Age[4]	0.1812	0.0923	1.1986	3.8518	0.050
Agesquared	-0.0010	0.0007	0.9990	1.9607	0.161
Female	0.6982	0.1632	2.0102	18.315	0.000
Inc10to14[5]	1.1358	0.3045	3.1136	13.9084	0.000
Inc15to24[5]	1.2475	0.2867	3.4817	18.9353	0.000
Inc25to34[5]	1.2205	0.3078	3.3890	15.7197	0.000
Inc35to49[5]	0.9770	0.3222	2.6564	9.1960	0.002
Inc50to64[5]	1.0097	0.3733	2.7448	7.3174	0.007
Inc>64[5]	1.1327	0.3630	3.1041	9.7359	0.002
Ln(numhouse)	0.1158	0.1867	1.1228	0.3849	0.535
Highschgrad[7]	-0.2902	0.2464	0.7481	1.3874	0.239
Posthighsch[7]	-0.1947	0.2624	0.8230	0.5508	0.458
Collegegrad[7]	0.0851	0.2908	1.0888	0.0857	0.770
Memberhmo[8]	0.0298	0.1734	1.0302	0.0295	0.864
Travelmd[9]	0.1169	0.0640	1.1240	3.3316	0.068
Swestcentral[10]	0.1881	0.2280	1.2069	0.6806	0.409
East[10]	0.0044	0.2022	1.0044	0.0005	0.983
West[10]	-0.1597	0.2315	0.8524	0.4762	0.490
North[10]	-0.1427	0.2289	0.8670	0.3885	0.533
Constant	-10.3614	3.1095		11.1035	0.0009

N = 1,658

Nagelkerke Pseudo R^2 = .231

Footnotes listed on p. 173

Table 4.16 Logistic Regression Results - Probability of Any Prescription Drug Use: Insurance and Preferences Model

Variable	β	S.E.	Odds Ratio (e^{β})	Wald	p
Rxinsurance[1]	0.5193	0.1848	1.6809	7.8969	0.005
Medpref[11]	0.0948	0.0124	1.0994	58.1023	0.000
Verygdhlth[2]	0.5094	0.1928	1.6642	6.9813	0.008
Goodhlth[2]	1.0544	0.2201	2.8701	22.9494	0.000
Fairpoorhlth[2]	0.8983	0.3178	2.4555	7.9907	0.005
Numcond[3]	0.7403	0.0676	2.0967	119.8600	0.000
Age[4]	0.1724	0.0958	1.1881	3.2349	0.072
Agesquared	-0.0010	0.0007	0.9990	1.8425	0.175
Female	0.8480	0.1693	2.3349	25.0834	0.000
Inc10to14[5]	1.1495	0.3157	3.1567	13.2615	0.000
Inc15to24[5]	1.2463	0.2971	3.4774	17.6013	0.000
Inc25to34[5]	1.1899	0.3203	3.2867	13.8002	0.000
Inc35to49[5]	1.0238	0.3344	2.7837	9.3715	0.002
Inc50to64[5]	0.9872	0.3838	2.6838	6.6165	0.010
Inc>64[5]	1.1645	0.3734	3.2044	9.7255	0.002
Ln(numhouse)	0.0542	0.1910	1.0556	0.0804	0.777
Highschgrad[7]	-0.3679	0.2566	0.6922	2.0550	0.152
Posthighsch[7]	-0.2545	0.2716	0.7753	0.8776	0.349
Collegegrad[7]	0.0629	0.2991	1.0650	0.0443	0.833
Memberhmo[8]	0.0122	0.1767	1.0123	0.0048	0.945
Travelmd[9]	0.1286	0.0664	1.1372	3.7449	0.053
Swestcentral[10]	0.0972	0.2332	1.1021	0.1738	0.677
East[10]	0.0519	0.2083	1.0533	0.622	0.803
West[10]	-0.1664	0.2391	0.8467	0.4846	0.4863
North[10]	-0.1189	0.2373	0.8879	0.2512	0.616
Constant	-11.9292	13.5974		13.5974	0.0002

N = 1,658

Nagelkerke Pseudo R^2 = .261

Footnotes listed on p. 173

Table 4.17 Logistic Regression Results - Probability of Any Prescription Drug Use: Interaction Model

Variable	β	S.E.	Odds Ratio (e^{β})	Wald	p
Rxinsurance[1]	0.6768	0.2114	1.9675	10.2505	0.001
Catpref[12]	1.2217	0.2736	3.3930	19.9463	0.000
Insxcatpref[13]	-0.3351	0.3351	0.7043	1.0941	0.296
Verygdhlth[2]	0.5571	0.1912	1.7456	8.4898	0.004
Goodhlth[2]	1.0983	0.2188	2.9991	25.1913	0.000
Fairpoorhlth[2]	1.0187	0.3144	2.7696	10.4992	0.001
Numcond[3]	0.7431	0.0671	2.1025	122.7665	0.000
Age[4]	0.1688	0.0946	1.1839	3.1835	0.074
Agesquared	-0.0009	0.0007	0.9991	1.6909	0.194
Female	0.8141	0.1678	2.2572	23.5481	0.000
Inc10to14[5]	1.1990	0.3142	3.3169	14.5645	0.000
Inc15to24[5]	1.2416	0.2950	3.4613	17.7151	0.000
Inc25to34[5]	1.1745	0.3171	3.2366	13.7226	0.000
Inc35to49[5]	0.9912	0.3316	2.6945	8.9376	0.003
Inc50to64[5]	0.9921	0.3800	2.6970	6.8160	0.009
Inc>64[5]	1.1407	0.3704	3.1288	9.4832	0.002
Ln(numhouse)	0.1546	0.1900	1.1672	0.6624	0.416
Highschgrad[7]	-0.3455	0.2552	0.7079	1.8321	0.176
Posthighsch[7]	-0.2219	0.2695	0.8010	0.6780	0.410
Collegegrad[7]	0.0601	0.2975	1.0620	0.0409	0.840
Memberhmo[8]	0.0657	0.1757	1.0679	0.1398	0.708
Travelmd[9]	0.1105	0.0659	1.1168	2.8097	0.094
Swestcent[10]	0.1467	0.2307	1.1580	0.4042	0.525
East[10]	0.0589	0.2062	1.0606	0.0816	0.775
West[10]	-0.1571	0.2366	0.8547	0.4406	0.5068
North[10]	-0.1482	0.2349	0.8623	0.3979	0.528
Constant	-10.1773	3.1768		10.2630	0.0014

N = 1,658

Nagelkerke Pseudo $R^2 = 0.251$

Footnotes listed on p. 173

Table 4.18 Logistic Regression Results - Probability of Any Prescription Drug Use: Adverse Selection Model

Variable	β	S.E.	Odds Ratio (e^{β})	Wald	p
Rxinsurance[1]	0.4607	0.2028	1.5852	5.1630	0.023
Medpref[11]	0.0942	0.0124	1.0988	57.5196	0.000
Verygdhlth[2]	0.4940	0.1931	1.6389	6.5469	0.011
Goodhlth[2]	1.0235	0.2217	2.7828	21.3027	0.000
Fairpoorhlth[2]	0.8657	0.3190	2.3767	7.3654	0.007
Numcond[3]	0.7400	0.0678	2.0959	119.4350	0.000
Age[4]	0.1682	0.0960	1.1832	3.0679	0.080
Agesquared	-0.0009	0.0007	0.9991	1.6727	0.196
Female	0.8538	0.1697	2.3486	25.3160	0.000
Inc10to14[5]	1.1525	0.3174	3.1659	13.1855	0.000
Inc15to24[5]	1.2686	0.2992	3.5560	17.9791	0.000
Inc25to34[5]	1.2049	0.3213	3.3364	14.0606	0.000
Inc35to49[5]	1.0492	0.3361	2.8555	9.7431	0.002
Inc50to64[5]	1.0177	0.3854	2.7668	6.9721	0.008
Inc>64[5]	1.1939	0.3751	3.2998	10.1278	0.001
Ln(numhouse)	0.0527	0.1914	1.0541	0.0758	0.783
Highschgrad[7]	-0.3644	0.2582	0.6946	1.9919	0.158
Posthighsch[7]	-0.2372	0.2735	0.7888	0.7523	0.386
Collegegrad[7]	0.0570	0.3002	1.0587	0.0361	0.849
Memberhmo[8]	0.0059	0.1769	1.0059	0.0011	0.973
Travelmd[9]	0.1248	0.0666	1.1329	3.5093	0.061
Swestcent[10]	0.1136	0.2338	1.1203	0.2361	0.627
East[10]	0.0590	0.2084	1.0608	0.0801	0.777
West[10]	-0.1476	0.2399	0.8628	0.3786	0.538
North[10]	-0.1039	0.2376	0.9013	0.1911	0.662
Constant	-11.7550	3.2408		13.1560	0.000
Asrisk[14]	-0.3888	0.3011	0.6779	1.6665	0.197
Insxasrisk[15]	0.2977	0.3754	1.3468	0.6289	0.428

N = 1,658

Nagelkerke Pseudo $R^2 = 0.261$

Footnotes listed on p. 173

Table 4.19 Summary of Odds Ratios for the Logistic Regression Models

Variable	Model I	Model II	Model III	Model IV
Rxinsurance[1]	1.9169*	1.6809*	1.9675*	1.5852*
Medpref[11]	-	1.0994*		1.0988*
Catpref	-	-	3.3930*	
Insxcatpref	-	-	0.7043	
Verygdhlth[2]	1.6977*	1.6642*	1.7456*	1.6389*
Goodhlth[2]	3.0344*	2.8701*	2.9991*	2.7828*
Fairpoorhlth[2]	2.7458*	2.4555*	2.7696*	2.3767*
Numcond[3]	2.1362*	2.0967*	2.1025*	2.0959*
Age[4]	1.1986*	1.1881	1.1839	1.1832
Agesquared	0.9990	0.9990	0.9991	0.9991
Female	2.0102*	2.3349*	2.2572*	2.3486*
Inc10to14[5]	3.1136*	3.1567*	3.3169*	3.1659*
Inc15to24[5]	3.4817*	3.4774*	3.4613*	3.5560*
Inc25to34[5]	3.3890*	3.2867*	3.2366*	3.3364*
Inc35to49[5]	2.6564*	2.7837*	2.6945*	2.8555*
Inc50to64[5]	2.7448*	2.6838*	2.6970*	2.7668*
Inc>64[5]	3.1041*	3.2044*	3.1288*	3.2998*
Ln(numhouse)[6]	1.1228	1.0556	1.1672	1.0541
Highschgrad[7]	0.7481	0.6922	0.7079	0.6946
Posthighsch[7]	0.8230	0.7753	0.8010	0.7888
Collegegrad[7]	1.0888	1.0650	1.0620	1.0587
Memberhmo[8]	1.0302	1.0123	1.0679	1.0059
Travelmd[9]	1.1240	1.1372	1.1168	1.1329
Swestcent[10]	1.2069	1.1021	1.1580	1.1203
East[10]	1.0044	1.0533	1.0606	1.0608
West[10]	0.8524	0.8467	0.8547	0.8628
North[10]	0.8670	0.8879	0.8623	0.9013

* Significant at $p < 0.05$

Model I: Insurance and Control Variables (N = 1,658)

Model II: Insurance, Medical Care Preferences, and Control Variables (N = 1,658)

Model III: Insurance, Preferences, Control Variables, and Interaction Effect (N = 1,658)

Model IV: Model II re-estimated controlling for adverse selection risk (N = 1,658)

Footnotes listed on p. 173

Several of the demographic variables also were significant. Females were twice as likely as males to have used at least one prescription drug. Older individuals were significantly more likely to have used at least one prescription drug, and because the age squared term was not significant, the relation appeared to be linear. For each additional year of age, individuals were 1.2 times more likely to have used a prescription. All of the income dummy variables were significant, for example, individuals with a household income of $10,000 to $14,999 were 3.1 times more likely to have used a prescription drug than individuals with a household income of less than $10,000. It appeared that once a threshold level of income was achieved ($10,000), the effect of income was stable. For example, the effect of income of $65,000 or more approximately was the same as the effect of income of $10,000 to $14,000. Education level and geographic region of residence did not have significant effects on the probability of prescription drug use. HMO membership and distance to the physicians office also did not have significant effects.

Table 4.16 shows the results of the model including medical care preferences. When medical care preferences were included in the model, the odds ratio for prescription drug insurance decreased from 1.9 to 1.7, but still was significant. Medical care preferences also had a significant effect on the probability of any prescription drug use. For each increase of one point in preference score (more help-seeking), the odds of using at least one prescription drug increased by a factor of 1.1. A one point increase in the preference score is not a very large or meaningful increase, so it also is useful to look at the effect of a standard deviation increase in preference score. To obtain the odds ratio for a standard deviation increase, the β coefficient was multiplied by 7 (approximately one standard deviation), and then the

inverse natural log of the new β was calculated (Hoesmer and Lemeshow 1989). For each 7 point increase in preference score, the odds of using at least one prescription drug increased by a factor of 1.94. This was slightly greater than the effect of prescription drug insurance coverage.

Including the medical care preference measure did not have a large effect on most of the other variables. The odds ratio for age decreased slightly and became non-significant ($p>0.05$). The odds ratio for gender decreased slightly, but the significance level did not change. The odds ratios for the health status variables also changed minimally, and the significance levels did not change. Adding the medical care preference measure improved the fit of the model, from pseudo $R^2 = 0.231$ to pseudo $R^2 = 0.261$.

Table 4.17 reports the results from the model that included the interaction between insurance coverage for prescription drugs and medical care preferences. In order to measure whether the insurance effect was different in individuals with different preferences, the preference measure had to be converted to a dichotomous variable. If the interaction was the product of a continuous variable (preferences) and a dichotomous variables (insurance), the effect being measured would have been whether the preferences effect differed across insurance type. The preference measure was converted to a dichotomous variable by splitting scores at the median (CATPREF: 0 = self-treaters, 1 = help-seekers). In Table 4.17, the insurance coefficient is interpreted as the effect of insurance in individuals with preference scores in the bottom half of the range (self-treaters). Insured self-treaters were about 2 times more likely to use at least one prescription drug than uninsured self-treaters. The insurance effect in help-seekers is the sum of the insurance coefficient and the

interaction coefficient ($\beta = 0.3417$). This meant that insured help-seekers were about 1.4 times more likely to have used at least one prescription drug. The CATPREF coefficient is the effect of preferences in uninsured individuals, so uninsured help-seekers were 3.4 times more likely to use at least one prescription drug than uninsured self-treaters. The interaction coefficient measured the incremental effect of being both insured and a help-seeker, and was negative, but not significant.

The final logistic regression model (Model IV) accounted for possible adverse selection bias. Respondents were classified as low and high adverse selection risk (see Appendix J for a comparison of the characteristics of high and low risks), and Model II was re-estimated including the adverse selection risk variable (ASRISK) and the product of ASRISK and RXINSURANCE in the model. The insurance coefficient in Model IV is the insurance effect in individuals classified as low adverse selection risks. The insurance effect for these individuals should be a relatively pure estimate of the moral hazard effect. The interaction effect between adverse selection risk and insurance determines whether the insurance effect is different in high and low adverse selection risks. The insurance coefficent in Model IV also was compared to the insurance coefficient in Model II. If there is adverse selection bias, the insurance coefficient in Model IV should be less than the insurance coefficient in Model II.

The results for Model IV are summarized in Table 4.18. In this model, insured low adverse selection risks were 1.59 times more likely than uninsured low adverse selection risks to have used at least one prescription drug in the last 30 days. The interaction between ASRISK and RXINSURANCE was positive, indicating that the insurance effect was greater

in high adverse selection risks than in low adverse selection risks, but the effect was not significant. The insurance coefficient in Model IV was 11.3 percent less than the insurance coefficient in Model II (0.4607 versus 0.5193). The insurance coefficient in low adverse selection risks (Model IV) should be relatively free of adverse selection bias, so the difference suggests that the Model II insurance coefficient was biased slightly upwards by adverse selection.

The self-reported health status coefficients were slightly less in Model IV than in Model II, although they still were significant. The coefficients for number of medical conditions almost were identical in the two models. The change in the self-reported health status variables may have occurred because they are more subjective measures of health. Insurers may be able to assess the number of medical conditions and adjust rates accordingly, but they probably do not collect information on self-reported health status (Browne 1995). If insurers and purchasers of insurance have the same information about the purchasers health status, adverse selection is less likely to occur.

Number of Prescription Drugs:

Tables 4.20 through 4.24 report Poisson regression results for Part II of the model, the expected number of prescription drugs used by individuals who had used at least one prescription drug in the last 30 days (n = 1,324). Table 4.24 provides a summary of $e^{\beta} - 1$ values for all four of the Poisson regression models. In a Poisson regression, $e^{\beta} - 1$ can be interpreted as the relative, or percent change in the expected number of prescriptions, holding all other variables constant (Long 1997). The Poisson model is a non-linear model, and thus the absolute change in the expected number of prescriptions differs, depending on

the level of the other independent variables. The absolute changes in the expected number of prescriptions were determined by changing the levels of variables of interest and holding all other variables at their means. Goodness of fit for the Poisson models was tested using chi-square tests, where significant chi-square values indicate that the Poisson model is a poor fit. For all of the Poisson models, the chi-square tests were non-significant. A negative binomial model also was fitted, however, the dispersion coefficient was non-significant, indicating that the model was not over dispersed, and a Poisson model was appropriate. Robust standard errors were calculated and compared to the regular standard errors, but no appreciable differences were seen, so the regular standard errors are reported.

The first Poisson model included only insurance and the control variables (Table 4.20). Having insurance coverage for prescription drugs resulted in a 15.6 percent increase in the expected number of different prescriptions drugs used by individuals using at least one prescription drug. All of the health variables were significant. Being in very good health increased the expected number of prescription drugs by 17 percent and being in fair or poor health increased the expected number of prescriptions by 60 percent, both relative to excellent health. Each additional medical condition increased the expected number of prescription drugs by about 15 percent. Female gender increased the expected number of prescriptions by about 7 percent, but this was not significant at the 0.05 alpha level. None of the other independent variables, including the income dummy variables, significantly increased the expected number of prescription drugs. The non-significant income effect differs from Part I of the model, where income significantly increased the probability of any prescription drug use. The pseudo R^2 for the model was 0.103.

Table 4.20 Poisson Regression Model - Number of Prescription Drugs Used: Insurance Only Model

Variable	β	S.E.	$e^{\beta} - 1$	z	p< |z|
Rxinsurance[1]	0.1448	0.0359	0.1558	4.038	0.000
Verygdhlth[2]	0.1582	0.0670	0.1714	2.360	0.018
Goodhlth[2]	0.2943	0.0664	0.3422	4.434	0.000
Fairpoorhlth[2]	0.4728	0.0713	0.6045	6.636	0.000
Numcond[3]	0.1430	0.0086	0.1537	16.714	0.000
Age[4]	0.0065	0.0191	0.0065	0.340	0.734
Agesquared	0.0000	0.0001	0.0000	-0.010	0.992
Female	0.0667	0.0362	0.0690	1.845	0.065
Inc10to14[5]	-0.0245	0.0588	-0.0242	-0.416	0.677
Inc15to24[5]	-0.0164	0.0577	-0.0163	-0.283	0.777
Inc25to34[5]	-0.0097	0.0630	-0.0097	-0.154	0.878
Inc35to49[5]	0.0865	0.0695	0.0904	1.244	0.213
Inc50to64[5]	-0.0599	0.0837	-0.0581	-0.716	0.474
Inc>64[5]	-0.0457	0.0816	-0.0447	-0.560	0.576
Ln(numhouse)[6]	0.0131	0.0415	0.0312	0.315	0.753
Highschgrad[7]	-0.0526	0.0670	-0.0512	-1.102	0.271
Posthighsch[7]	-0.0273	0.0664	-0.0269	-0.534	0.593
Collegegrad[7]	-0.0405	0.0713	-0.0397	-0.693	0.488
Memberhmo[8]	-0.0066	0.0690	-0.0066	-0.179	0.858
Travelmd[9]	0.0084	0.0144	0.0084	0.579	0.562
Travelph[16]	-0.0197	0.0148	-0.0195	-1.327	0.185
Swestcentral[10]	-0.0556	0.0482	-0.0541	-1.155	0.248
East[10]	-0.0662	0.0420	-0.0641	-1.575	0.115
West[10]	-0.0658	0.0513	-0.0637	-1.282	0.200
North[10]	-0.0380	0.0485	-0.0373	-0.783	0.434
Constant	-0.0197	0.6614		-0.030	0.976

N = 1,324
Pseudo R^2 = 0.103
Goodness of fit chi-2 = 1,264 (p = 0.743)
Footnotes listed on p. 173

Table 4.21 Poisson Regression Results - Number of Prescriptions Used: Insurance and Preferences Model

Variable	β	S.E.	$e^{\beta} - 1$	z	p< |z|
Rxinsurance[1]	0.1130	0.0361	0.1196	3.132	0.002
Medpref[11]	0.0174	0.0024	0.0176	7.189	0.000
Verygdhlth[2]	0.1322	0.0671	0.1413	1.969	0.049
Goodhlth[2]	0.2540	0.0666	0.2892	3.815	0.000
Fairpoorhlth[2]	0.4213	0.0715	0.5239	5.889	0.000
Numcond[3]	0.1390	0.0086	0.1491	16.172	0.000
Age[4]	0.0051	0.0190	0.0051	0.269	0.788
Agesquared	0.0000	0.0001	0.0000	-0.078	0.938
Female	0.0872	0.0363	0.0911	2.406	0.016
Inc10to14[5]	-0.0240	0.0588	-0.0237	-0.407	0.684
Inc15to24[5]	-0.0149	0.0577	-0.0148	-0.258	0.796
Inc25to34[5]	-0.0281	0.0604	-0.0277	-0.445	0.656
Inc35to49[5]	0.0963	0.0695	0.1011	1.386	0.166
Inc50to64[5]	-0.0782	0.0838	-0.0752	-0.933	0.351
Inc>64[5]	-0.0545	0.0816	-0.0530	-0.668	0.504
Ln(numhouse)[6]	0.0117	0.0415	0.0118	0.282	0.778
Highschgrad[7]	-0.1322	0.0476	-0.1238	-1.122	0.262
Posthighsch[7]	-0.2540	0.0510	-0.2243	-0.430	0.667
Collegegrad[7]	-0.4213	0.0584	-0.3438	-0.479	0.632
Memberhmo[8]	-0.0018	0.0370	-0.0018	-0.049	0.961
Travelmd[9]	0.0109	0.0144	0.0110	0.758	0.449
Travelph[16]	-0.0177	0.0147	-0.0175	-1.201	0.230
Swestcentral[10]	-0.0285	0.0484	-0.0281	-0.589	0.556
East[10]	-0.0461	0.0421	-0.0451	-1.093	0.274
West[10]	-0.0432	0.0513	-0.0423	-0.842	0.400
North[10]	-0.0280	0.0486	-0.0276	-0.469	0.639
Constant	-0.3315	0.6621		-0.501	0.617

N = 1,324
Pseudo $R^2 = 0.112$
Goodness of fit chi-2 = 1,213 (p = 0.953)
Footnotes listed on p. 173

Table 4.22 Poisson Regression Results - Number of Prescriptions Used: Interaction Model

Variable	β	S.E.	$e^{\beta} - 1$	z	$p < \|z\|$
Rxinsurance[1]	0.0385	0.0549	0.0393	0.720	0.472
Catpref[12]	0.1235	0.0546	0.1315	2.262	0.024
Insxcatpref[13]	0.1457	0.0672	0.1568	2.168	0.030
Verygdhlth[2]	0.1568	0.0672	0.1698	2.334	0.020
Goodhlth[2]	0.2784	0.0666	0.3210	4.180	0.000
Fairpoorhlth[2]	0.4607	0.0714	0.5852	6.455	0.000
Numcond[3]	0.1380	0.0086	0.1480	16.019	0.000
Age[4]	0.0043	0.0190	0.0043	0.227	0.821
Agesquared	0.0000	0.0001	0.0000	0.016	0.987
Female	0.0846	0.0362	0.0883	2.335	0.020
Inc10to14[5]	-0.0244	0.0588	-0.0241	-0.414	0.679
Inc15to24[5]	-0.0108	0.0577	-0.0107	-0.187	0.852
Inc25to34[5]	-0.0156	0.0603	-0.0155	-0.247	0.805
Inc35to49[5]	0.0997	0.0696	0.1048	1.433	0.152
Inc50to64[5]	-0.0700	0.0838	-0.0676	-0.835	0.404
Inc>64[5]	-0.0443	0.0817	-0.0433	-0.543	0.587
Ln(numhouse)[6]	0.0117	0.0415	0.0118	0.417	0.677
Highschgrad[7]	-0.0637	0.0477	-0.0617	-1.336	0.182
Posthighsch[7]	-0.0370	0.0512	-0.0363	-0.722	0.470
Collegegrad[7]	-0.0414	0.0583	-0.0406	-0.709	0.478
Memberhmo[8]	-0.0095	0.0371	-0.0095	0.256	0.798
Travelmd[9]	0.0067	0.0144	0.0067	-0.900	0.641
Travelph[16]	-0.0133	0.0148	-0.0132	-1.037	0.368
Swestcentral[10]	-0.0377	0.0483	-0.0370	-0.781	0.435
East[10]	-0.0438	0.0422	-0.0429	-1.037	0.300
West[10]	-0.0558	0.0512	-0.0543	-1.090	0.276
North[10]	-0.0287	0.0486	-0.0283	-0.590	0.555
Constant	-0.0428	0.6624		0.065	0.949

N = 1,324
Pseudo $R^2 = 0.112$
Goodness of fit chi-2 = 1,213 (p = 0.951)
Footnotes listed on p. 173

Table 4.23 Poisson Regression Results - Number of Prescriptions Used: Adverse Selection Model

Variable	β	S.E.	$e^{\beta} - 1$	z	p < |z|
Rxinsurance[1]	0.0922	0.0387	0.0966	2.383	0.017
Medpref[11]	0.0174	0.0024	0.0176	7.171	0.000
Verygdhlth[2]	0.1239	0.0191	0.1319	1.842	0.065
Goodhlth[2]	0.2452	0.0672	0.2779	3.675	0.000
Fairpoorhlth[2]	0.4115	0.0667	0.5091	5.736	0.000
Numcond[3]	0.1387	0.0717	0.1488	16.115	0.000
Age[4]	0.0041	0.0191	0.0041	0.213	0.831
Agesquared	0.00003	0.0001	0.00003	-0.022	0.982
Female	0.0888	0.0363	0.0929	2.450	0.014
Inc10to14[5]	-0.0199	0.0590	-0.0201	-0.338	0.736
Inc15to24[5]	-0.0091	0.0578	-0.0091	-0.157	0.875
Inc25to34[5]	-0.0193	0.0633	-0.0195	-0.305	0.760
Inc35to49[5]	0.1026	0.0696	0.1080	1.474	0.140
Inc50to64[5]	-0.0744	0.0838	-0.0772	-0.888	0.375
Inc>64[5]	-0.0458	0.0817	-0.0569	-0.561	0.575
Ln(numhouse)[6]	0.0088	0.0416	0.0088	0.211	0.833
Highschgrad[7]	-0.0503	0.0477	-0.0516	-1.055	0.291
Posthighsch[7]	-0.0209	0.0511	-0.0211	-0.408	0.683
Collegegrad[7]	-0.0291	0.0584	-0.0295	-0.0291	0.618
Memberhmo[8]	-0.0033	0.0370	-0.0033	-0.089	0.929
Travelmd[9]	0.0098	0.0144	0.0098	0.679	0.497
Travelph[16]	-0.0171	0.0148	-0.0172	-1.156	0.248
Swestcentral[10]	-0.0228	0.0486	-0.0231	-0.470	0.639
East[10]	-0.0453	0.0423	-0.0463	-1.070	0.285
West[10]	-0.0418	0.0514	-0.0427	-0.813	0.416
North[10]	-0.0196	0.0487	-0.0198	-0.402	0.688
Constant	-0.2728	0.6632	-0.3136	-0.411	0.681
Asrisk[14]	-0.1653	0.0848	-0.1797	-1.949	0.051
Insxasrisk[15]	0.1683	0.0965	0.1833	1.744	0.081

N = 1,324, Pseudo $R^2 = 0.110$

Goodness of fit chi-2 = 987 (p = 0.927)

Footnotes listed on p. 173

Table 4.24 Summary of $e^{\beta} - 1$ for Poisson Regression Models

Variable	Model V	Model VI	Model VII	Model VIII
Rxinsurance[1]	0.1558*	0.1196*	0.0393	0.0966*
Medpref[11]	-	0.0176*	-	0.0176*
Catpref	-	-	0.1315*	-
Insxcatpref	-	-	0.1568*	-
Verygdhlth[2]	0.1714*	0.1413*	0.1698*	0.1319*
Goodhlth[2]	0.3422*	0.2892*	0.3210*	0.2779*
Fairpoorhlth[2]	0.6045*	0.5239*	0.5852*	0.5091*
Numcond[3]	0.1537*	0.1491*	0.1480*	0.1488*
Age[4]	0.0065	0.0051	0.0043	0.0041
Agesquared	0.0000	0.0000	0.0000	0.00003
Female	0.0690	0.0911*	0.0883*	0.0929*
Inc10to14[5]	-0.0242	-0.0237	-0.0241	-0.0201
Inc15to24[5]	-0.0163	-0.0148	-0.0107	-0.0091
Inc25to34[5]	-0.0097	-0.0277	-0.0155	-0.0195
Inc35to49[5]	0.0904	0.1011	0.1048	0.1080
Inc50to64[5]	-0.0581	-0.0752	-0.0676	-0.0772
Inc>64[5]	-0.0447	-0.0530	-0.0433	-0.0569
Ln(numhouse)[6]	0.0312	0.0118	0.0118	0.0088
Highschgrad[7]	-0.0512	-0.1238	-0.0617	-0.0516
Posthighsch[7]	-0.0269	-0.2243	-0.0363	-0.0211
Collegegrad[7]	-0.0397	-0.3438	-0.0406	-0.0295
Memberhmo[8]	-0.0066	-0.0018	-0.0095	-0.0033
Travelmd[9]	0.0084	0.0110	0.0067	0.0098
Travelph[16]	-0.0195	-0.0175	-0.0132	-0.0172
Swestcentral[10]	-0.0541	-0.0281	-0.0370	-0.0231
East[10]	-0.0641	-0.0451	-0.0429	-0.0463
West[10]	-0.0637	-0.0423	-0.0543	-0.0427
North[10]	-0.0373	-0.0276	-0.0283	-0.0198

* Significant at $P < 0.05$

Model V: Insurance and Control Variables (N = 1,324)

Model VI: Insurance, Medical Care Preferences, and Control Variables (N = 1,324)

Model VII: Insurance, Preferences, Control Variables, Interaction Effect (N = 1,324)

Model VIII: Model VI re-estimated controlling for adverse selection (N = 1,324)

Footnotes listed on p. 173

Table 4.21 provides the results when medical care preferences are added to the model with insurance and the control variables. With preferences in the model, the effect of insurance coverage for prescription drugs is a 12.0 percent increase in the expected number of prescriptions. This is less than the 15.6 percent increase in the model without medical care preferences. The effect of medical care preferences is a 1.8 percent increase in the expected number of prescriptions for each one point increase in the preference score (more help-seeking). The effect of a 7 point increase (approximately one standard deviation) in the preference score is a 13 percent increase in the expected number of different prescription drugs. The insurance effect and the preference effect both were significant.

The health status variables still were significant, although the magnitude of the effect decreased somewhat for all of the variables. Being in fair or poor health resulted in a 52 percent increase in the expected number of different prescription drugs, compared to a 60 percent increase in the model without medical care preferences. The effect of female gender was slightly greater in this model, a 9 percent increase versus a 7 percent increase in the model without preferences, but this was enough to result in a significant gender effect. None of the coefficients for the other independent variables were significant. Adding the medical care preference score slightly improved the fit of the model, from a pseudo R^2 of 0.103 for the model without preferences, to a pseudo R^2 of 0.112.

Results for the model including the interaction between insurance and medical care preferences are reported in Table 4.22. In this model, the preference measure again was converted to a dichotomous variable by splitting scores at the median. The insurance coefficient in this model represents the effect of insurance in self-treaters, and the preference

coefficient represents the effect of preferences in uninsured individuals. Having insurance coverage for prescription drugs increased the expected number of prescription drugs used in self-treaters by 3.9 percent, and was not significant. The insurance effect in help-seekers is the sum of the insurance coefficient and the interaction coefficient (0.1842), and was a 20.2 percent increase in the expected number of prescription drugs. As the large difference between the insurance effect for self-treaters and the insurance effect for help-seekers suggests, the interaction between preferences and insurance was significant. Being a help-seeker increased the expected number of prescriptions in uninsured individuals by 13.2 percent, relative to self-treaters, and the effect was significant. The coefficients of the other independent variables were comparable to the coefficients in the model without the interaction effect.

Results from the model controlling for adverse selection are reported in Table 4.23. Insurance coverage for prescription drugs increased the expected number of prescription drugs by 9.7 percent for individuals at low risk for adverse selection, and the effect was significant. The interaction between ASRISK and RXINSURANCE was positive, and approached statistical significance ($p=0.08$). This indicated that the insurance effect on the expected number of prescription drugs was greater for high adverse selection risks than for low adverse selection risks, and provided some evidence of adverse selection. The ASRISK coefficient was negative and significant, indicating that high adverse selection risks used less prescription drugs than low adverse selection risks. This indicates that the adverse selection behavior in the high risk group likely was healthy individuals opting out of prescription drug insurance coverage. The insurance coefficient in this model was 18.4 percent less (0.0922 vs

0.1130) than the insurance coefficient in Table 4.21. This suggested that the insurance coefficient in Table 4.21 was biased upwards by adverse selection. Table 4.24 summarizes $e^{\beta} - 1$ for all four of the Poisson regression models.

Results from a Poisson regression also can be reported in terms of the absolute change in the expected number of prescription drugs. However, because the Poisson model is non-linear, absolute changes need to be reported for a specific level of each of the independent variables. The approach used was to set independent variables of interest at meaningful levels, and hold all other independent variables at their means. Table 4.25 reports the absolute change in the expected number of prescription drugs used in the last 30 days, using coefficients from the Poisson regression model including insurance and preferences (Table 4.21). Levels of insurance coverage for prescription drugs and medical care preferences were varied because they were the main variables of interest in the study. The effects of varying health status and gender also were examined for comparative purposes.

Holding all other independent variables at their means, uninsured individuals used an average of 2.60 different prescription drugs in the last 30 days. Insured individuals used an average of 2.92 different prescription drugs, an increase of 0.32 drugs per month compared to uninsured individuals. The average number of prescription drugs used when the medical preference score was at its mean was 2.80. Increasing the score by 7 points (approximately one standard deviation toward more help-seeking preferences) resulted in an increase of 0.36 prescription drugs per month. Decreasing the preference score by 7 points resulted in a decrease of 0.32 prescription drugs per month. Varying the preference scale over its full

Table 4.25 The Absolute Change in the Expected Number of Prescription Drugs: Poisson Regression Results from the Model Including Insurance and Medical Care Preferences

Independent Variable and Level	Number of Prescriptions[1]	Change
Prescription Drug Insurance		
= 0 (no insurance)	2.60	
= 1 (has insurance)	2.92	+0.32
Medical Care Preference Score		
MEDPREF = 18.9	2.48	-0.32
MEDPREF = 25.9 (mean)	2.80	
MEDPREF = 32.9	3.16	+0.36
MEDPREF = 9	2.09	
MEDPREF = 45	3.90	+1.81
Health Status[2]		
Excellent Health	2.29	
Very Good Health	2.61	+0.32
Good health	2.95	+0.66
Fair or Poor Health	3.48	+1.19
Gender		
= 0 (male)	2.66	
= 1 (female)	2.90	+0.24

1. The expected number of prescriptions used in the last 30 days: $E(y|x) = \sum\exp(B_0*X_1\beta_1*...*X_k\beta_k)$, where all independent variables, except the selected variable, were held at their means and βs were taken from Table 4.21.

2. The selected health status dummy variable was set to 1, all other health status dummy variables were held at 0 (For excellent health, all health status dummy variables were set to 0).

range (from 9 to 45), increased the number of prescription drugs used by 1.81 prescriptions.

The magnitude of the effect of varying insurance status and preference scores was compared to the effect of varying health status and gender. Individuals in excellent health used an average of 2.29 prescription drugs per month. Reporting very good health and good health increased the expected number of prescriptions by 0.32 and 0.66, respectively. Poor or fair health increased the expected number of prescriptions by 1.19 relative to individuals reporting excellent health. Gender had a relatively small effect on the expected number of prescriptions. Females used 0.24 more prescriptions over a 30 day period than males.

Total Cost of Prescription Drugs:

An ordinary least squares (OLS) regression model was used to predict the natural logarithm of the total cost of prescription drugs used in the last 30 days by individuals who had used at least one prescription drug. This total cost variable used in this study is different from total prescription drug expenditures, because it included only the cost of the prescription drug products whereas total prescription drug expenditures include both the drug product costs and dispensing costs. Expenditures can be patient out-of-pocket expenditures or they can be payments made by the patient's insurance company, and as a result, data on total prescription drug expenditures can not be obtained via patient self-report. Thus, the variable used in this stdy was the total cost of the prescription drug products used in the last 30 days.

OLS regression has a number of assumptions that need to be met in order for the coefficient estimates to be unbiased, consistent and efficient. The graphs, scatter plots, and other tests of the assumptions are provided in Appendix K. Using the natural logarithm of

the total cost of prescription drugs as the dependent variable, the residuals had a distribution that was sufficiently close to normal. Multicollinearity was assessed by examining the bivariate correlations between independent variables (discussed previously), and the variance inflation factors (VIFs). There is evidence of multicollinearity if the largest VIF is greater than 10, and the mean of all the VIFs is considerably larger than 1 (Chatterjee and Price 1991). The only two VIFs greater than 10 were age and agesquared. This was not considered to be problematic, because the value of agesquared was the square of age. The mean of all the other VIFs was about 2, which is acceptable.

Linearity was assessed by examining partial regression scatter plots of each of the independent variables against the dependent variable. No significant non-linearity was detected. Autocorrelation was not considered to be a problem, because the data were cross-sectional. Heteroscedasticity was tested by examining the scatter plot of residuals against predicted values, and using the Cook-Weisberg test for heteroscedasticity. Examination of the scatter plot revealed that the spread of the residuals decreased as the predicted values increased, a potential heteroscedasticity problem. Heteroscedasticity was confirmed by the Cook-Weisberg test. Further examination revealed that multiple independent variables appeared to be contributing to the problem. In the presence of heteroscedasticity, the coefficient estimates remain unbiased, but the standard errors are affected. Standard errors were calculated using the White-Huber robust method to account for the heteroscedasticity.

Results from the OLS equations predicting the total cost of the prescription drugs used in the last 30 days are reported in Tables 4.26 through 4.30. Table 4.30 summarizes the β coefficients for all four of the OLS regression models. The dependent variable for

these equations was the natural logarithm of the total cost of prescription drugs used in the last 30 days. The coefficients for continuous variables, multiplied by one hundred, can be interpreted as the percentage increase in the cost of prescription drugs for every one unit increase in the continuous variable. For dichotomous variables, the percentage increase in prescription drug costs associated with being in the group coded 1 is determined by equation 4.1 (Hardy 1993).

Equation 4.1 $$\text{Percentage change} = 100[\exp(\beta) - 1]$$

The first model estimated included prescription drug insurance and the control variables, but not medical care preferences (Table 4.26). Having insurance coverage for prescription drugs resulted in a 52.1 percent increase in the total cost of prescription drugs used in the last 30 days. Both the number of prescription drugs used and the per prescription cost of the drug products used contribute to total prescription cost. The insurance effect on the total cost of prescription drugs was 36.5 percentage points greater than the insurance effect in the comparable model predicting the number of prescription drugs (Table 4.20), suggesting that prescription drug insurance has a large effect on the per prescription cost. Of the health status variables, fair/poor health and number of medical conditions had significant effects on the cost of prescription drugs used. Self-reported fair or poor health increased the cost of prescriptions used by 65.0 percent, and each additional medical condition increased the cost of prescriptions by 24.0 percent.

Table 4.26 OLS Regression Results - Total Cost of Prescription Used: Insurance Only Model

Variable	β	Robust S.E.[17]	Std Beta	t	p
Rxinsurance[1]	0.4193	0.0855	0.150	4.902	0.000
Verygdhlth[2]	0.0487	0.1218	0.017	0.400	0.689
Goodhlth[2]	0.1789	0.1247	0.066	1.435	0.152
Fairpoorhlth[2]	0.5004	0.1478	0.147	3.385	0.001
Numcond[3]	0.2401	0.0207	0.314	11.625	0.000
Age[4]	0.0902	0.0464	0.718	1.944	0.052
Agesquared	-0.0006	0.0003	-0.675	-1.859	0.063
Female	0.1441	0.0852	0.052	1.692	0.091
Inc10to14[5]	-0.0367	0.1547	-0.010	-0.237	0.813
Inc15to24[5]	0.1147	0.1560	0.036	0.735	0.463
Inc25to34[5]	0.0825	0.1668	0.024	0.494	0.621
Inc35to49[5]	0.0269	0.1885	0.007	0.143	0.887
Inc50to64[5]	0.1794	0.2022	0.036	0.887	0.375
Inc>64[5]	0.1584	0.2053	0.040	0.772	0.440
Ln(numhouse)[6]	0.3848	0.0954	0.126	4.033	0.000
Highschgrad[7]	-0.1912	0.1163	-0.068	-1.645	0.100
Posthighsch[7]	-0.1246	0.1246	-0.042	-1.001	0.317
Collegegrad[7]	-0.1856	0.1362	-0.060	-1.362	0.173
Memberhmo[8]	-0.0214	0.0812	-0.007	-0.263	0.793
Travelmd[9]	-0.0106	0.0315	-0.010	-0.336	0.737
Travelph[16]	0.0302	0.0316	0.027	0.956	0.339
Swestcentral[10]	-0.2489	0.1104	-0.070	-2.256	0.024
East[10]	-0.1201	0.0958	-0.039	-1.254	0.210
West[10]	-0.2463	0.1181	-0.064	-2.085	0.037
North[10]	0.0178	0.1089	0.005	0.164	0.870
Constant	-0.6193	1.6320		-0.379	0.704

N = 1,222
Adjusted R^2 = 0.173
Footnotes listed on p. 173

Table 4.27 OLS Regression Results - Total Cost of Prescriptions Used: Insurance and Preference Model

Variable	β	Robust S.E.[17]	Std Beta	t	p
Rxinsurance[1]	0.3778	0.0852	0.136	4.437	0.000
Medpref[11]	0.0247	0.0059	0.123	4.192	0.000
Verygdhlth[2]	0.0185	0.1217	0.007	0.152	0.879
Goodhlth[2]	0.1358	0.1247	0.050	1.089	0.276
Fairpoorhlth[2]	0.4382	0.1479	0.129	2.962	0.003
Numcond[3]	0.2330	0.0210	0.305	11.072	0.000
Age[4]	0.0860	0.0459	0.684	1.874	0.061
Agesquared	-0.0006	0.0003	-0.671	-1.869	0.062
Female	0.1778	0.0844	0.065	2.106	0.035
Inc10to14[5]	-0.0372	0.1505	-0.010	-0.247	0.805
Inc15to24[5]	0.1140	0.1518	0.036	0.751	0.453
Inc25to34[5]	0.0585	0.1622	0.017	0.361	0.718
Inc35to49[5]	0.0337	0.1851	0.009	0.182	0.856
Inc50to64[5]	0.1559	0.1974	0.031	0.790	0.430
Inc>64[5]	0.1545	0.2013	0.039	0.767	0.443
Ln(numhouse)[6]	0.3690	0.0943	0.121	3.914	0.000
Highschgrad[7]	-0.1923	0.1161	-0.068	-1.656	0.098
Posthighsch[7]	-0.1183	0.1244	-0.040	-0.951	0.342
Collegegrad[7]	-0.1751	0.1352	-0.056	-1.295	0.196
Memberhmo[8]	-1.4321	0.0810	-0.005	-0.175	0.861
Travelmd[9]	-0.0703	0.0316	-0.006	-0.223	0.824
Travelph[16]	0.0312	0.0317	0.028	0.985	0.325
Swestcentral[10]	-0.2252	0.1104	-0.063	-2.041	0.042
East[10]	-0.0982	0.0949	-0.032	-1.034	0.301
West[10]	-0.2291	0.1166	-0.059	-1.965	0.050
North[10]	0.0418	0.1068	0.012	0.391	0.696
Constant	-0.9714	1.6162		-0.601	0.548

N = 1,222
Adjusted R^2 = 0.186
Footnotes listed on p. 173

Table 4.28 OLS Regression Results - Total Cost of Prescriptions Used: Interaction Model

Variable	β	Robust S.E.[17]	Std Beta	t	p
Rxinsurance[1]	0.3934	0.1288	0.141	3.053	0.002
Catpref[12]	0.3780	0.1255	0.142	3.012	0.003
Insxcatpref[13]	-0.0061	0.1526	-0.002	-0.040	0.968
Verygdhlth[2]	0.0433	0.1224	0.015	0.354	0.723
Goodhlth[2]	0.1481	0.1251	0.055	1.184	0.237
Fairpoorhlth[2]	0.4763	0.1478	0.140	3.223	0.001
Numcond[3]	0.2309	0.0208	0.302	11.079	0.000
Age[4]	0.0871	0.0458	0.693	1.904	0.057
Agesquared	-0.0006	0.0003	-0.675	-1.885	0.060
Female	0.1828	0.0838	0.066	2.181	0.029
Inc10to14[5]	-0.0250	0.1500	-0.007	-0.167	0.868
Inc15to24[5]	0.1258	0.1511	0.040	0.833	0.405
Inc25to34[5]	0.0627	0.1609	0.018	0.390	0.697
Inc35to49[5]	0.0365	0.1833	0.009	0.199	0.842
Inc50to64[5]	0.1773	0.1952	0.036	0.908	0.364
Inc>64[5]	0.1598	0.1994	0.040	0.801	0.423
Ln(numhouse)[6]	0.3852	0.0938	0.126	4.108	0.000
Highschgrad[7]	-0.2040	0.1145	-0.072	-1.781	0.075
Posthighsch[7]	-0.1266	0.1245	-0.043	-1.017	0.309
Collegegrad[7]	-0.1862	0.1343	-0.060	-1.386	0.166
Memberhmo[8]	-0.0019	0.0810	-0.001	-0.024	0.981
Travelmd[9]	-0.0151	0.0315	-0.014	-0.479	0.632
Travelph[16]	0.0359	0.0317	0.032	1.136	0.256
Swestcentral[10]	-0.2296	0.1097	-0.064	-2.092	0.037
East[10]	-0.0964	0.0955	-0.031	-1.010	0.313
West[10]	-0.2418	0.1155	-0.063	-2.094	0.036
North[10]	0.0366	0.1065	0.010	0.344	0.731
Constant	-0.5963	1.6122		-0.370	0.712

N = 1,222

Adjusted $R^2 = 0.190$

Footnotes listed on p. 173

Table 4.29 OLS Regression Results - Total Cost of Prescription Drug Used: Adverse Selection Model

Variable	β	Robust S.E.[17]	Std Beta	t	p
Rxinsurance[1]	0.2793	0.0910	0.100	3.069	0.002
Medpref[11]	0.0250	0.0059	0.125	4.262	0.000
Verygdhlth[2]	-0.0083	0.1222	-0.003	-0.068	0.946
Goodhlth[2]	0.1019	0.1250	0.038	0.815	0.415
Fairpoorhlth[2]	0.4056	0.1485	0.119	2.731	0.006
Numcond[3]	0.2314	0.0210	0.303	11.007	0.000
Age[4]	0.0819	0.0463	0.652	1.768	0.077
Agesquared	-0.0006	0.0003	-0.637	-1.758	0.079
Female	0.1871	0.0841	0.068	2.225	0.026
Inc10to14[5]	-0.0265	0.1492	-0.007	-0.177	0.859
Inc15to24[5]	0.1332	0.1518	0.042	0.877	0.380
Inc25to34[5]	0.0847	0.1621	0.025	0.522	0.602
Inc35to49[5]	0.0585	0.1852	0.015	0.316	0.752
Inc50to64[5]	0.1712	0.1971	0.034	0.869	0.385
Inc>64[5]	0.1844	0.2014	0.046	0.916	0.360
Ln(numhouse)[6]	0.3610	0.0946	0.118	3.818	0.000
Highschgrad[7]	-0.1819	0.1160	-0.064	-1.568	0.117
Posthighsch[7]	-0.1103	0.1238	-0.038	-0.891	0.373
Collegegrad[7]	-0.1799	0.1352	-0.058	-1.330	0.184
Memberhmo[8]	-0.0168	0.0805	-0.006	-0.209	0.834
Travelmd[9]	-0.0113	0.0316	-0.010	-0.358	0.720
Travelph[16]	0.0324	0.0317	0.029	1.021	0.308
Swestcentral[10]	-0.2050	0.1105	-0.057	-1.855	0.064
East[10]	-0.0961	0.0949	-0.031	-1.013	0.311
West[10]	-0.2232	0.1166	-0.058	-1.915	0.056
North[10]	0.0522	0.1061	0.015	0.491	0.623
Constant	-0.7620	1.4822		-0.541	0.607
Asrisk[14]	-0.5566	0.1826	-0.1638	-3.048	0.002
Insxasrisk[15]	0.6398	0.2062	0.1665	3.104	0.002

N = 1,222
Adjusted R^2 = 0.192
Footnotes listed on p. 173

Table 4.30 Summary of β Coefficients for the OLS Regression Models

Variable	Model IX	Model X	Model XI	Model XII
Rxinsurance[1]	0.4193*	0.3778*	0.3934*	0.2793*
Medpref[11]	-	0.0247*	-	0.0250*
Catpref	-	-	0.3780*	-
Insxcatpref	-	-	-0.0061	-
Verygdhlth[2]	0.0487	0.0185	0.0433	-0.0083
Goodhlth[2]	0.1789	0.1358	0.1481	0.1019
Fairpoorhlth[2]	0.5004*	0.4382*	0.4763*	0.4056*
Numcond[3]	0.2401*	0.2330*	0.2309*	0.2314*
Age[4]	0.0902	0.0860	0.0871	0.0819
Agesquared	-0.0006	-0.0006	-0.0006	-0.0006
Female	0.1441	0.1778*	0.1828*	0.1871*
Inc10to14[5]	-0.0367	-0.0372	-0.0250	-0.0265
Inc15to24[5]	0.1147	0.1140	0.1258	0.1332
Inc25to34[5]	0.0825	0.0585	0.0627	0.0847
Inc35to49[5]	0.0269	0.0337	0.0365	0.0585
Inc50to64[5]	0.1794	0.1559	0.1773	0.1712
Inc>64[5]	0.1584	0.1545	0.1598	0.1844
Ln(numhouse)[6]	0.3848*	0.3690*	0.3852*	0.3610*
Highschgrad[7]	-0.1912	-0.1923	-0.2040	-0.1819
Posthighsch[7]	-0.1246	-0.1183	-0.1266	-0.1103
Collegegrad[7]	-0.1856	-0.1751	-0.1862	-0.1799
Memberhmo[8]	-0.0214	-1.4321	-0.0019	-0.0168
Travelmd[9]	-0.0106	-0.0703	-0.0151	-0.0113
Travelph[16]	0.0302	0.0312	0.0359	0.0324
Swestcentral[10]	-0.2489*	-0.2252*	-0.2296*	-0.2050
East[10]	-0.1201	-0.0982	-0.0964	-0.0961
West[10]	-0.2463*	-0.2291*	-0.2418*	-0.2232
North[10]	0.0178	0.0418	0.0366	0.0522

* Significant at $P < 0.05$

Model IX: Insurance and Control Variables (N = 1,222)

Model X: Insurance, Medical Care Preferences, and Control Variables (N = 1,222)

Model XI: Insurance, Preferences, Control Variables, Interaction Effect (N = 1,222)

Model XII: Model X re-estimated controlling for adverse selection (N = 993)

Footnotes listed on p. 173

Footnotes for Tables 4.15 through 4.24 and 4.26 through 4.30:

1. 0 = no prescription drug insurance, 1 = prescription drug insurance

2. Set of dummy self-reported health status variables, relative to excellent health: very good health, good health, fair or poor health.

3. Self reported number of medical conditions, 0 to 12.

4. Age in years, 50 to 95.

5. Set of household income dummy variables, relative to annual household income less than $10,000: $10,000 - $14,999, $15,000 to $24,999, $25,000 to $34,999, $35,999 to $49,999, $50,000 to $64,999, $65,000 or more.

6. The natural logarithm of the number of individuals living in the household.

7. Set of education dummy variables, relative to less than a high school degree: high school degree, some college, 4 year college degree or more advanced degree.

8. 1 if reported being a Health Maintenance Organization (HMO) member, 0 otherwise

9. Distance usually traveled to physician's office: 1 = less than 1 mile, 2 = 1 to 5 miles, 3 = 6 to 10 miles, 4 = 11 to 20 miles, and 5 = more than 20 miles.

10. Set of geographic region dummy variables, relative to Southeast region of Wisconsin: Southwest/Southcentral region of Wisconsin, East region of Wisconsin, West region of Wisconsin, North region of Wisconsin.

11. Medical Care Preference Score, 9 to 45.

12. 0 = self-treater (MEDPREF = 9 to 25), 1 = help-seeker (MEDPREF = 26 to 45)

13. The product of CATPREF and RXINSURANCE.

14. 0 = low adverse selection risk, 1 = high adverse selection risk

15. The product of ASRISK and RXINSURANCE.

16. Distance usually traveled to pharmacy: 1 = less than 1 mile, 2 = 1 to 5 miles, 3 = 6 to 10 miles, 4 = 11 to 20 miles, 5 = more than 20 miles.

17. Standard errors were calculated using the White-Huber robust variance method because of heteroscedasticity in the model.

Some other variables were significant in this model that were not significant in the model predicting the number of prescriptions used, and vice versa. The coefficient for age and the coefficient for agesquared approached significance at the alpha level of 0.05. Each additional year of age increased the cost of prescriptions used by 9 percent, but the negative coefficient for agesquared suggests that the magnitude of the effect diminished as age increased. Females had prescription drug costs that were about 15 percent higher than males, but this was not significant at an alpha level of 0.05. The coefficients for the variables indicating residence in the Southwest/Southcentral region and the West region were negative and significant. Individuals residing in these regions had prescription drug costs that were about 28 percent less than costs for individuals residing in the Southeast region.

A completely unexpected finding was that the coefficient for logarithm of the number of individuals in the household was positive and significant. This indicated that the cost of prescription drugs used increased as the number of individuals in the household increased. The effect of number of individuals in the household was not significant in the model predicting the number of prescriptions used, suggesting that the significant effect on total cost was due to more expensive prescriptions being used, instead of more prescriptions being used. This finding was investigated further, to determine whether the effect primarily resulted from a difference in drug costs between one and more than one individuals in the household, or a difference in drug costs between one or two and more than two individuals in the household. The effect of number of individuals in the household appeared to result from a difference in per person drug costs for households with one person compared to per person drug costs for households with more than one person.

As mentioned previously, there was one individual who had substantially greater prescription drug costs than any other individuals ($3,377). When the survey information for this individual was re-examined, it appeared that approximately $2,000 of the drug costs were from two cancer medications. In addition to being an outlier, this individual was a potential problem because she only paid about $300 out-of-pocket for the drugs, even though she reported having no insurance coverage for prescription drugs. This seems to indicate that she actually may have some insurance coverage for prescription drugs, although all of her other survey answers were consistent with having no coverage. As a result of her extreme expenditures and the uncertainty about her insurance status, the model was re-estimated without her data to see how much the insurance coefficients were affected. Excluding her resulted in an insurance coefficient of 0.4336, a 3.4 percent increase over the original estimate.

Table 4.27 reports results with medical care preferences added to the model. With preferences in the model, having prescription insurance increased the cost of prescription drugs used by 45.9 percent. This was slightly less than the 52 percent insurance effect in the model without preferences. Without the outlier, the insurance coefficient was 3.8 percent larger ($\beta = 0.392$). The preference effect also was significant, as the cost of prescription drugs used increased by 2.5 percent for every one point increase in the medical care preference score (more help-seeking). A 7 point increase in preference score resulted in a 17.3 percent increase in drug costs. This is close to the 13 percent increase in the number of prescription drugs that resulted from an increase of 7 points in preference score, suggesting that the preference effect on total prescription costs mostly resulted from the preference

effect on the number of drugs used. Including preferences increased the adjusted R^2 about 1.5 percent.

The other significant variables in this model were similar to the significant variables in the model without preferences. Fair/poor health, number of medical conditions, age, age2, ln(number in household), Southwest/Southcentral region, and West region all had significant effects on the cost of prescription drugs used. The one change in significance from the model without preferences was that gender became significant. The total cost of prescription drugs used by females was about 19 percent higher than the cost of drugs used by males.

Table 4.28 reports results from the model with the interaction between insurance coverage and medical care preferences. To examine the interaction effect, the preference scale again was converted to a dichotomous variable (CATPREF). Including the interaction term changes the interpretation of the insurance and preference coefficients. The insurance coefficient is interpreted as the effect of insurance in self-treating individuals. Unlike the insurance effect on the number of prescriptions used by individuals with self-treating preferences (Table 4.22), the insurance effect on the cost of prescriptions used by self-treaters was significant. The insurance effect on the cost of prescription drugs used by self-treaters was 48.2 percent. This effect probably was due to the effect of insurance on the per prescription drug costs, because insurance did not significantly increase the number of prescription drugs used by self-treaters. The insurance effect on the cost of prescription drugs used by help-seekers was the sum of the insurance coefficient and the interaction coefficient ($\beta = 0.3873$), and was 47.3 percent. This insurance effect was less than the

insurance effect in self-treaters, but unlike the model predicting the number of prescription drugs used (Table 4.22), the interaction effect between prescription drug insurance coverage and medical care preferences was not significant.

The CATPREF coefficient can be interpreted as the effect of preferences in uninsured individuals. The cost of prescription drugs used by uninsured help-seekers was 45.9 percent more than the cost of prescription drugs used by uninsured self-treaters, and this difference was statistically significant. The other variables in the model had significance levels that were similar to the non-interaction model (Table 4.27).

The results from the model controlling for adverse selection are provided in Table 4.29. The insurance coefficient in this model was expected to be a relatively pure estimate of the moral hazard insurance effect, because it was the insurance effect in individuals at low risk for adverse selection. For low adverse selection risks, insurance increased the cost of prescriptions used in the last 30 days by 32.2 percent. The level of adverse selection risk (ASRISK) had a negative and significant effect on the cost of prescription drugs used, indicating that high adverse selection risks had lower prescription drug costs than low adverse selection risks. The interaction between adverse selection risk and insurance was positive and significant, indicating that the insurance effect was greater in high adverse selection risks. This finding is consistent with adverse selection.

When the insurance coefficient in this model was compared to the insurance coefficient in the model not controlling for adverse selection (Table 4.27), it was 26.1 percent less (0.2793 versus 0.3778). The preference coefficients in the two models were similar, but the significance levels of two of the control variables were different when

adverse selection was controlled. Southwest/Southcentral region, and West region no longer were significant at an alpha level of 0.05. The results from all four of the OLS regression models are summarized in Table 4.30.

CHAPTER 5

DISCUSSION

Discussion of the results is divided into four main sections. The first section provides a discussion of the advantages and disadvantages of collecting prescription drug utilization data via consumer survey versus using pharmacy data or insurance claims data. The second section is a discussion of the results of hypothesis testing. It is divided into subsections on the insurance effect on prescription drug utilization, medical care preferences, and control variables. Implications of the study, and future research ideas are discussed in the third section. The fourth section lists limitations of the study, and provides a discussion of the practical significance of the limitations.

I. Prescription Drug Data Collection

Data on prescription drug utilization were collected via consumer survey in this study. Many past studies on the effect of insurance have used pharmacy data or insurance claims data rather than survey data. Consequently, observations from this study of the advantages and disadvantages of survey data potentially are useful for future studies. One advantage of a consumer survey is that information typically not in pharmacy records or insurance databases can be collected. The most important variable in this study that would not have been available in a claims database or pharmacy records was the medical care preference measure. The preference measure was an important predictor of prescription

drug utilization. Claims databases and pharmacy records also may lack information on health status, and in any type of health care utilization study it is important to control for health status. In this study, both self-reported health status and the number of medical conditions were important, and significant, control variables. Although it may be possible to impute some health status measures from prescription data, this is less desirable than collecting the information directly.

How do self-reported survey data on prescription drug utilization compare to prescription drug utilization data from claims databases or from pharmacies? Some potential advantages and disadvantages were apparent from this study. One advantage of survey data is that they may be more complete than data from pharmacy records or from claims databases. Claims databases lack data on prescriptions that were purchased, but not submitted to the insurance company. For example, a claim will not be submitted to the insurance company if the cost of the prescription is less than the insurance copayment. Claims databases also are limited because there is no information on uninsured individuals. Pharmacy records contain information for both insured and uninsured individuals and they contain information on all prescriptions purchased at the pharmacy, but there are two problems with these data. One problem is that individuals may purchase prescriptions at multiple pharmacies, and unless you are able to obtain records from all of their pharmacies, including mail order, some data may be missing.

The other problem with pharmacy record data is that when patients use samples they were given at the doctor's office, their pharmacy records usually will not contain that information. Even though my survey did not ask patients to specify from whom they

received their prescription drugs, some respondents commented that they received samples from their physicians. This especially seemed to be the case for uninsured individuals, some of whom said their doctors regularly gave them samples because they could not afford to purchase the medication. If information on samples is unavailable, then it appears as if uninsured individuals are using fewer prescription drugs, and less expensive prescription drugs than they actually use. Data about the prevalence of sampling was not collected explicitly in my study, but it would be an interesting topic for future research.

There are other potential differences in the accuracy of the data. With data from pharmacy records, the researcher has to guess the amount that the individuals actually used from how often they purchase the medication. This especially is problematic for medication used "as needed." You also assume that the patient uses whatever drugs were purchased, but this may not be the case. They could share their medications with friends or relatives, or they could discontinue the medication. My survey asked respondents to list the drugs they used and it asked them to list the quantity they used. Some respondents did not list the quantity, so it had to be imputed from the directions, but this was not a common occurrence.

A potential problem with using self-reported survey data is a reliance on the respondents being willing and able to list accurately the prescription drugs they are taking. There was concern that respondents would refuse to list the prescription drugs they used, but this occurred only for about 6 percent of the respondents. There also was concern that respondents would omit some types of drugs (e.g. antidepressants). Although there was no way to verify whether this occurred, the number of drug names listed was compared with the number of drugs they reported in an earlier question on the survey. Although there

sometimes were discrepancies, the numbers of drug names listed were both larger and smaller than the numbers they said they were taking, suggesting that the problem was recall, and not respondents deliberately omitting individual drug names.

There was concern that respondents would not be able to list the drug names accurately, but this did not appear to be a problem. There only were a few cases where I was unable to identify the drug from the name they listed. However, one problem with the survey data was that about 11 percent of the respondents who reported taking at least one drug did not list the strengths of the drugs they were taking. This could have been because they were not aware of the strengths or they may not have noticed that they were supposed to list the strengths. It is possible that the question could be restructured to make it clearer that the strength should be listed.

II. Results of Hypotheses Testing

Insurance Effects on Prescription Drug Utilization:

There were three main sets of hypotheses that were determined based on the economic utility model. The first set of hypotheses predicted that insurance coverage would increase prescription drug utilization. The data did not permit examination of the effect of insurance coverage for physician services, but as predicted, having prescription drug insurance coverage significantly increased the probability of any prescription drug use, the number of prescription drugs used, and the total cost of prescription drugs used. Insured individuals were about 1.7 times more likely than uninsured individuals to have used at least

one prescription drug in the last 30 days. For prescription drug users, insured individuals used about 12 percent more prescriptions and had about 46 percent greater total prescription drug costs than uninsured individuals over a one month period. Total prescription drug costs are affected by the number of prescription drugs used and by the per prescription cost of the prescription drugs used. The difference between the insurance effect on the number of prescription drugs used and the insurance effect on the total cost of drugs used seems to indicate that insurance has an especially large effect on the per prescription cost of prescription drugs.

Another interesting finding was that including preferences in the model slightly decreased the insurance effect. When preferences were not included in the model, insured individuals were about 1.9 times more likely to have used at least one prescription drug, used about 17 percent more prescriptions than uninsured individuals, and had 52 percent greater prescription drug costs. These models did not control for selection bias, and it is possible that the differences were due to preferences having some effect on the choice of insurance. In addition to decreasing the insurance effect, adding preferences to the model somewhat improved the fit of the model.

How did the insurance effect in my study compare to the magnitude of insurance effect in other studies? Davis et al. (1999) reported that Medicare beneficiaries with prescription drug insurance used about 33 percent more prescriptions and had 60 percent greater prescription drug expenditures over a one year period. However, these estimates were unadjusted for differences in health status or demographic characteristics between the two groups. In my study, the effects of insurance coverage, unadjusted for health status and

demographic characteristics, were that insured individuals used about 11 percent more prescriptions and had about 31 percent greater prescription drug costs over a 30 day period.

Coulson et al. (1995) found that individuals with prescription insurance coverage used about 0.38 more prescriptions in a two week period than individuals with physician coverage only did. In my study, individuals with prescription drug insurance coverage used, on average, about 0.32 more prescription drugs per month than uninsured individuals. However, this was for individuals who had used at least one prescription drug, and the Coulson et al. study appeared to include all individuals in the model. Grootendorst (1995) reported that prescription drug insurance coverage increased the number of prescriptions used in a four week period by about 16 percent. This is very close to the estimated insurance effect in the model without preferences in my study. Neither the Coulson et al. study or the Grootendorst study reported differences in the total cost of prescription drugs used. The RAND Health Insurance Experiment included prescription drug expenditures, and in that study per capita prescription drug expenditures were about 60 percent greater in the group with 0 percent coinsurance then they were in the group with 95 percent coinsurance (Leibowitz et al. 1985).

One of the objectives of my study was to do examine the extent to which estimates of the insurance effect were biased upwards by adverse selection. This was an important question to address because there have been contradictory results in earlier studies examining the extent of the bias. In my study, insurance estimates in a group relatively free from adverse selection bias were compared to estimates of the insurance effect in the entire sample. In the model predicting the probability of any prescription drug use in the last 30

days, the insurance effect did not differ significantly between low and high adverse selection risks. The insurance effect in the low adverse selection group was about 11 percent less than the insurance effect in the full group, an odds ratio of 1.6 versus an odds ratio of 1.7. The lack of adverse selection bias in this model may be because it only compares non-users to users. It was hypothesized that individuals who expect high prescription drug expenditures would be more likely to purchase insurance. However, when users are compared to non-users, users could be individuals who used only one prescription drug or they could be individuals who used ten prescription drugs. Someone who only expects to use one prescription drug probably would not be more likely to purchase prescription drug insurance.

The adverse selection bias was greater in the models predicting the number of prescription drug used and the total cost of prescription drugs used by individuals who had used at least one prescription drug in the last 30 days. In the low adverse selection group, the insurance coefficients were about 18 percent less than the full group in the model predicting the number of prescription drugs used and about 26 percent less than the full group in the model predicting the total cost of prescription drugs used. In these models, the differences in the insurance effects between low and high adverse selection risks either were statistically significant or approached significance. From a practical standpoint, the insurance coefficients in the model with less adverse selection bias would be useful in a model trying to predict what the effect would be of extending prescription drug insurance coverage to an entire population (because there would not be adverse selection if everybody had coverage). The insurance coefficients from the full model probably are appropriate

when trying to predict the additional prescription drug use that would result from offering, but not requiring, prescription drug insurance.

Medical Care Preferences:

The second set of hypotheses predicted that medical care preferences would have a significant effect on prescription drug utilization. For each 7 point increase in preference score (more help-seeking), respondents were about 1.9 times more likely to have used at least one prescription drug in the last 30 days. The magnitude of this effect was comparable to the magnitude of the insurance effect. For individuals who had used at least one prescription drug, a 7 point increase in preference score increased the number of prescription drugs used by about 13 percent and the total cost of prescription drugs used by about 17 percent. The preference effect on number of prescriptions used was comparable to the insurance effect, but the preference effect on the cost of prescriptions used was less than the insurance effect.

The similar effect of medical care preferences on the number of prescriptions used and the cost of prescriptions used suggests that the effect of preferences on the unit cost of prescriptions used is minimal. If preferences affected cost independently of utilization, a much larger effect on total cost of prescriptions used would be expected. For example, the effect of insurance on the total cost of prescriptions was over 4 times as large as the insurance effect on the number of prescription drugs, whereas the preference effect on the cost of prescriptions only was about 1.3 times as large as the preference effect on the number of prescriptions. The apparent lack of a preference effect on per prescription cost may be because the preference scale was designed to measure preferences for using or not

using physician services and prescription drugs. It was not intended to capture preferences related to the cost of the drug product, for example preferences for using brand name prescription drugs or preferences for using new technology. It is possible that these preferences exist, and that a scale could be developed to measure them.

It is important to consider that the preference effects occurred in a model that controlled for demographic characteristics and health status. An argument sometimes made is that preferences are adequately captured by demographic characteristics, so there is no need to measure them explicitly. This study provided evidence that this was not the case. Preliminary analyses revealed low correlations between the preference scale and demographic variables. The highest correlation between a demographic variable and the preference score was 0.210, for age. Correlations for education, income and gender all were less than 0.10. In the multivariate model, preferences had strong, significant effects even after controlling for all of the demographic variables.

Another argument against including preferences was that preferences will be determined by health status, with sicker individuals being help-seekers and healthy individuals being self-treaters. The correlations of health status and number of medical conditions with preferences were 0.17 and 0.20 respectively, so although the direction of the effect was that sicker individuals had stronger help-seeking preferences, the relationship was not very strong. When preferences were examined by self-reported health status, there was considerable variability in preferences for each category of health status. For example, in the group reporting poor health there were individuals with strong self-treating preferences and in the group reporting excellent health there were individuals with strong help-seeking

preferences. The distribution did become slightly more skewed towards help-seeking as health status worsened. An interesting question is whether preferences are stable, or change in response to experiences. Sick individuals with strong self-treating preferences always may have had self-treating preferences, or they may have had a bad experience with the health care system that caused their preferences to become more self-treating.

Preferences were conceptualized based on an economic utility model, where preferences affect the shapes of individuals' indifference curves. In this model, preferences are considered to be immutable, and thus would be stable over time. Although this study was cross-sectional, and not designed to examine whether preferences change, the stability of preferences is an intriguing question to consider. It is my opinion that preferences likely are formed from a combination of health attitudes, health beliefs, and personality traits, and thus are more stable than a specific health attitude or health belief. As a result, while it may be possible for someone's preferences to change slightly in one direction or the other, it seems unlikely that someone with strong self-treating preferences would be converted into someone with strong help-seeking preferences and vice versa. However, a longitudinal study is needed for this question to be answered definitively.

The third set of hypotheses based on the economic utility model predicted that the insurance effects would be greater in individuals with help-seeking preferences. It seems logical that someone with strong self-treating preferences would be unlikely to increase their use of prescription drugs dramatically just because they have insurance. However, there was no interaction effect between preference and insurance in part I of the model, the probability of using at least one prescription drug. This may be because in this model there is no

distinction between using one versus two prescription drugs, and using one versus ten prescription drugs, for example. There was a significant interaction effect in the model predicting the number of prescription drugs used by individuals who had used at least one prescription drug. In this model, having insurance only increased the expected number of prescriptions by 3.9 percent in individuals with preferences score below the median (more self-treating), and the effect was not significant. In contrast, having insurance increased the expected number of prescriptions by 20.2 percent for individuals with help-seeking preferences.

In the model predicting the total cost of prescription drugs used by prescription drug users, the interaction effect between insurance and preferences was not significant and the insurance effect in individuals with self-treating preferences was significant. This likely was due to preferences not affecting the cost of the drug product used. Even though insurance did not increase the number of prescription drugs used by self-treaters, it may still have increased the cost of drug products used, thereby increasing the total cost of the prescription drugs.

In an economic utility model, preferences typically are assumed to be revealed by behavior, and are not measured explicitly. The results from this study show that measuring preferences is possible, and including preferences adds to the explanatory power of the model. This suggests that in studies where the purpose of the model is to explain or predict behavior, incorporating an explicit measure of preferences into the model may be useful. Including preferences in the model showed the strong effect that preferences have, and revealed the interaction between preferences and insurance in the model predicting the

number of prescription drugs used. Including preferences also improved the fit of the models, and for most models, the magnitude of the improvement in fit was similar to the improvement in fit from including insurance in the model.

Control Variables:

Although the main purpose of including demographic and health status variables in the model was to get an unconfounded measure of the insurance and preference effects, there were some interesting or unexpected findings relative to their effects on prescription drug utilization. One interesting effect was the income effect. Higher income levels were expected to increase prescription drug use for two reasons. First, the typical income effect for consumer goods is that the demand for normal goods increases as income increases. Second, individuals with low income may have difficulty accessing health care goods and services. The six dummy variables for income only were significant in the model predicting the probability of any prescription drug use. There were not significant income effects in the models predicting the number of prescription drugs used or the total cost of prescription drugs used by prescription drug users. Income effects in previous research on prescription drug utilization also have been mixed.

Another interesting finding relative to the income effect was that the magnitude of the effect was similar for all six of the income dummy variables. It appeared that individuals with incomes greater than or equal to $10,000 were more likely to have used at least one prescription drug than individuals with incomes less than $10,000. It did not appear to matter whether the income was, for example, $15,000 or $75,000. This suggests that the income effect is related to access, and is not a typical income effect where consumption of a

good increases as income increases. Income information often can be difficult to obtain, and the findings from this study suggest that it is sufficient to know whether individuals have income of greater or less than $10,000. Knowing the exact level of income for individuals with incomes greater than $10,000 may not be necessary.

The income used in the study was the household income, and thus the natural logarithm of the number of individuals in the household was included as a way to adjust the household income to the individual level. A completely unexpected finding was that the household size variable had a significant effect on the total cost of prescription drugs used by prescription drug users, with the cost increasing as household size increased. This effect did not occur in the model predicting the probability of using at least one prescription drug or the model predicting the number of prescription drugs used. Many of the obvious factors that this could be related to (e.g. gender, income, age) were controlled for in the model, so this finding was difficult to explain.

Further analysis revealed that the effect primarily was due to a difference in individual prescription drug costs between one individual in the household, and more than one individual in the household. This could result from differences between joint and individual decision making about prescription drug use. For example, individuals living alone may be reluctant to purchase an expensive prescription, but in households where both spouses are present, one spouse might encourage the other spouse to purchase the medication, regardless of cost. An alternative hypothesis is that there is an experience factor, for example, one spouse tries a less expensive blood pressure medication and than has to switch to a more expensive one. If the other spouse subsequently has to start taking a

high blood pressure medication, he or she might request the more expensive medication immediately.

The majority of the other demographic control variables were not significant, or had expected effects on prescription drug utilization. Being female significantly increased the probability of any prescription drug use, and the number and total cost of prescription drugs used. Older individuals using more prescriptions and had greater total prescription drug costs, but the effect technically was not statistically significant in most models, although it did approach significant levels. Education level was not significant in any of the models. Geographic region was included in the models to account for possible regional differences in prescribing or access to health care. The only significant finding was that individuals residing in the southwest/southcentral and West regions of the state had lower total prescription drug costs than individuals living in the southeast region of the state. Although HMO membership was controlled for separately and was not significant, it is possible that the regional difference somehow was related to the number or type of HMOs in the southwest/southcentral region.

The distances traveled to the pharmacy and physician's office were included as measures of the time costs of obtaining care. The only significant effect was that the probability of any prescription drug use increased as the travel distance to the physician's office increased. This effect was opposite of what was expected, because individuals who had longer distance to travel to the physician's office would be expected to visit the doctor less often, and therefore be less likely to use a prescription drug. It is possible that this

finding was a sample anomaly, or that travel distance to the physician's office was related to some unobserved variables that affected the probability of prescription drug use.

III. Implications and Future Research

Insurance:

This study examined the effect of insurance coverage for prescription drugs on prescription drug use in a population of older adults that typically have insurance coverage for physician visits. The results from this study are important from a policy perspective, because they are applicable to the current debate on whether to add prescription drug benefits to Medicare. It appears that insured individuals use not only more prescription drugs, but considerably more expensive prescription drugs, and this needs to be taken into consideration when calculating the cost of adding a prescription drug benefit to Medicare. The much greater effect of insurance on the total cost of prescription drugs used suggests that if there are concerns about the costs of the providing a drug benefit, efforts directed toward controlling the cost of prescription drugs used will have a greater effect than efforts directed toward trying to control the number of prescription drugs used. If cost containment is the objective, future research is needed to determine how prescription drug insurance benefits best can be structured to minimize the insurance effect on the total cost of prescription drugs used. For example, are consumer cost sharing mechanisms such as copayments or coinsurance effective at controlling the cost of the drug products used, or are supply side mechanisms such as formularies or capitation necessary?

Future research also is necessary to determine the mechanism of the insurance effect. Are insured individuals more likely to request prescription drugs and uninsured individuals more likely to refuse to take prescription drugs? Alternatively, do physicians tend to prescribe more expensive prescription drugs for insured individuals, independent of patient request? If the effect is not patient initiated, why do physicians prescribe more expensive drugs for insured individuals and how much influence does pharmaceutical marketing have on physicians' decisions? Also, is the insurance effect different for acute versus chronic medication, or for different therapeutic classes? It also would be interesting to measure the insurance effect over a longer period of time. The insurance effect may be greater when measured over longer periods, because there may be more illness episodes and therefore more opportunities for insurance to affect individuals' decisions about prescription drug use. The same might be true for the effect of medical care preferences.

Another important research question is whether the benefits of the increased utilization in insured individuals are worth the cost. Is there an "appropriate" level of use for prescription drugs, and if so, are insured individuals using too many prescription drugs or are uninsured individuals using too few prescription drugs? Although these questions are very difficult to answer, examining the insurance effect for different therapeutic classes of prescriptions drugs may provide some answers. For example, are insured individuals with hypertension more likely to be treated with an antihypertensive medication than uninsured individuals with hypertension? Or, are they equally likely to be treated with a prescription drug, but insured individuals are treated with more expensive prescription drugs than uninsured individuals. Research on how the increased prescription drug utilization affects

patient outcomes also is important. This type of research also is difficult, and may be accomplished best by examining utilization and outcomes within a particular disease state. However, given the effect of preferences on prescription drug utilization, it is important to consider that there may not be one "appropriate" level of use for everybody.

Medical Care Preferences:

The results pertaining to medical care preferences have implications for policy makers and health care providers. From a policy maker's perspective, individuals on both ends of the preference spectrum are of interest. Individuals who have strong self-treating preferences may be reluctant to seek necessary care for an illness, or they may avoid using preventive care. This ultimately may cost the health care system more, and result in poorer outcomes. For many disease states, the cost of care is lower, and outcomes are better if the disease is diagnosed sooner. On the other hand, individuals with strong help-seeking preferences are of concern because they may see a physician or use prescription drugs to treat health problems that would have resolved on their own or that could been treated with home remedies or over- the-counter (OTC) medications. The health care system may spend money on unnecessary services for these individuals.

The interaction effect between insurance and medical care preferences also may be of interest to policymakers. There is interest in expanding health insurance coverage to improve access to health care, but there also is concern that insurance coverage may be one factor contributing to rising health care costs. In this study, insurance significantly increased both the number and total cost of prescriptions. However, an interesting finding was that the insurance effect on the number of prescriptions used was not significant in individuals

with self-treating preferences. This suggests that "moral hazard" only may be a potential problem in individuals with stronger help-seeking preferences.

The results pertaining to medical care preferences also have implications for health care providers. Individuals with strong self-treating preferences may need more encouragement to seek care when they have a medical problem. They also may be reluctant to take prescription drugs, and if a prescription drug is the necessary treatment, physicians and pharmacists may need to take extra time explaining why taking the prescription drug is important. In contrast, individuals with strong help-seeking preferences may need to be educated about when it is appropriate to handle medical problems on their own. When appropriate, they also may need extra encouragement to try non-drug treatments instead of taking a prescription drug. Physicians also may want to consider patient preferences when deciding whether or not prescribe a drug. Individuals with strong self-treating preferences may be more receptive to non-drug therapy.

The results from this study suggest many future research ideas. One area of research is further scale development of the medical care preference measure. There were a number of respondents who omitted the preference items, and some respondents commented that they had trouble answering the questions because their answers would depend on the type of medical condition. Although they had been instructed to think in terms on general tendencies, this appeared difficult for some individuals. It is possible that the items could be modified to specify minor or serious medical conditions. Further scale validation in other populations also is necessary. Although the scale was pilot tested in a wide range of ages, the majority of the sample for the main survey was individuals age 50 and older. In the pilot

study, age did not seem to be a significant influence on preferences, but further testing of the scale in different age groups is necessary.

It also will be important to see if medical care preferences are as strong predictors of other types of health care utilization as they were for prescription drug utilization in this study. Past research on the effect of health attitudes on physician utilization has had mixed results. This could mean that preferences are more important predictors for prescription drug utilization then they are for other types of health care utilization, or it could mean that the preference scale captures something different than health attitude scales. Future research could measure the effect of medical care preferences on physician utilization. Future research also could compare the medical care preference scale developed in this study to other health attitude or personality scales, for example medical care skepticism scales or the health locus of control scale. This would provide some measure of divergent validity for the scale.

Another interesting research project would be to determine at what point(s) in the process of prescription drug use preferences exert their effect. It could be in the first stage of the process, the decision to visit the physician. Help-seekers may visit the physician more frequently than self-treaters. The preference effect also could be in the second stage of the process, the physician's decision to prescribe a drug. For example, help-seekers may be more likely to request that the physician prescribe a drug. This raises the question of whether help-seekers would be more responsive to direct-to-consumer advertising for prescription drugs. Preferences also may have an effect in the final stage of the prescription drug use process, the patient's decision to purchase and use a drug after it is prescribed.

For example, are self-treaters more likely to fail to purchase the prescription after it is prescribed? Or, are help-seekers more willing to continue taking a prescription medication over a long period of time?

Research also needs to be done to determine how preferences are formed. Is there a strong personality component to preferences, for example is there an "independence" trait that causes people to have stronger self-treating preferences. Or are preferences formed as a result of interactions with the health care system. If this is the case, strong help-seeking preferences may result from positive interactions with the health care system and self-treating preferences may result from negative experiences with the health care system, or a lack of experience with the health care system. This leads to another research question, discussed earlier in the discussion section. Do medical care preferences change, or are they relatively stable over time? In order to answer this question, medical care preferences need to be measured in a longitudinal study. If preferences do change, a related research question is to examine what factors cause them to change.

Given the potential impact of preferences on the use of health care, another important research question from a policy perspective is whether behavior can be changed, even if preferences cannot be changed. For example, would educating self-treaters about the importance of using preventive care or seeking early treatment cause them to use more health care? It is possible that behavior can be changed, even if the underlying preferences are stable. Help-seekers potentially could be educated about self-treatment options, or alternative therapies. There has been recent growth in the use of alternative medicines. It would be interesting to examine whether users of alternative therapies are more likely to be

self-treaters. From a policy perspective, another useful study would be to examine whether cost sharing provisions in insurance plan (e.g. copayments or coinsurance) have differential effects on individuals with help-seeking and self-treating preferences.

Control Variables:

The significance and non-significance of some of the control variables used in this study suggest some topics for future research. The pattern of significant income effects was interesting, and future research is necessary to validate these effects, and to examine why income was significant in the model predicting the probability of prescription drug use, but not in the models predicting the number or cost of prescription drugs used. Another interesting finding was that the number of individuals in the household significantly affected the cost of prescription drugs used, but not the number of prescription drugs used by individuals. In the previous section, some possible reasons for this effect were proposed, and future studies could examine if any of those explanations were correct.

This study focused on a selected group of variables, primarily patient related, but there are potentially important variables affecting prescription drug utilization that were not examined in the study. The three stage process model of prescription drug used described in the theoretical framework provides some insights into what other types of variables might be important to examine in future research. In the first stage of the model, the patient decision to seek care, the availability of providers may be an important issue to consider. Information on the number of health care providers in the area could be linked to patient data via zip code, to determine if the number or type of providers in the area affects patients' decisions to seek care. The health belief model suggests some other potentially important variables.

Patients' perceptions of their susceptibility to illnesses, and their perceptions of the costs and benefits of seeking care may affect their decisions.

In the second stage of the model, the decision of the physician to order a prescription drug, many physician variables may be important. For example, future research could examine whether the physician's specialty or experience level affects either the likelihood of prescribing a drug, or the type of drug prescribed. It also would be interesting to examine physicians' medical care preferences to see if their preferences influence their prescribing habits. It is possible that physicians with self-treating preferences may tend to suggest non-drug treatments before prescribing prescription drugs. More detailed information on the type of practice setting, e.g. type of HMO, also would be useful. Physicians' options for prescribing may be restricted in some settings because of drug formularies.

In the third stage of the model, the patient's decision to purchase and use the prescription drug, more patient variables potentially could be studied. If the study were disease specific, it would be useful to monitor how patients' experiences with the prescriptions drugs affected their decision to continue to use the drug. The health belief model also might be useful in this portion of the process model, for example, patients' perceptions of the costs and benefits of the drug, and their perceptions of the potential severity of the disease might affect their decision to use a prescription drug. These perceptions may change over the course of an illness, so longitudinal study might be necessary to examine these effects.

IV. Limitations

In order to draw accurate conclusions from the study, the results need to be considered together with the limitations of the study. As with any study involving survey data collection, response bias is a concern. Although every effort was made to maximize response rate, about 40 percent of the sample did not respond. These individuals may have been unable to respond (e.g. ill or deceased) or may have chosen not to respond. Non-response is a concern if non-respondents differ from respondents on key characteristics.

Some demographic information was available for the sample, so differences between respondents and the sample were assessed. The main difference was that there were about 15 percent more female respondents than there were in the entire sample. Females used significantly more prescription drugs than males, but it is unclear whether the insurance coefficients or the medical care preference coefficients were biased by the higher number of females. The differences in age, income and geographic region, although statistically significant, probably were not large enough to be of practical significance.

One key difference is that the percent uninsured in this study appears to be greater than other estimates. Of individuals aged 65 or more, 52.4 percent reported having no prescription drug insurance. This exceeds the 34.8 percent uninsured reported in a national study (Davis 1999). There are several possible explanations for the difference. There may have been response bias in my study, from uninsured individuals being more interested in the topic and thus more likely to respond. Alternatively, the level of insurance in this population may be lower in Wisconsin than in the nation, or the level of insurance may be decreasing

(the Davis study used data collected in 1995). In 1998, only two out of the 27 insurers who sold Medigap plans in Wisconsin offered prescription drug coverage other than the catastrophic coverage mandated by the state, and those two plans were not available in all areas. This suggests that it may be more difficult to obtain Medigap prescription drug coverage in Wisconsin than it is in states that have the ten standard Medigap policies.

It also may be possible that the definitions of prescription drug insurance differed between studies. The Davis study considered individuals to be insured if they reported drug coverage for any part of the year, or if an insurance company had made a prescription drug payment on their behalf at any time during the year. In my study, current insurance status was assessed. In an early study, Long (1994) estimated that in 1991 approximately 45 percent of the elderly had no prescription drug insurance coverage, which is closer to the percent of uninsured elderly in my study.

If uninsured individuals were more likely to respond, for the purposes of this study, the key question is whether the uninsured and insured individuals who responded were somehow different from the uninsured and insured individuals who did not respond. If they were different, then estimates from the study may be inaccurate. However, based on the comparison of insured and uninsured early and late responders, it seemed likely that the uninsured respondents were similar to the uninsured non-respondents. In this case, the estimated coefficients from the study should be accurate, but the percentages of uninsured and insured should not be generalized to the state. It would be inappropriate to conclude, based solely on this study, that 35 percent of Wisconsin residents aged 50 and over do not have prescription drug insurance coverage.

Another potential limitation of the data is that they were self-reported by respondents, and may be inaccurate. However, there were several checks built into the survey to try to address this problem. To determine insurance coverage, there was the main question about whether there was insurance coverage for prescription drugs, but there also were several items that asked respondents to describe the type and amount of cost sharing, the source of their insurance, the name of their insurance plan, and the amount they paid out of pocket for prescription drugs. Having this additional information allowed a more accurate assessment of whether or not they had insurance coverage. For example, it allowed individuals with a "discount card" plan and catastrophic coverage to be identified. The additional information also identified potential inconsistencies, for example, persons with Wisconsin Medicaid reporting that they did not have insurance coverage for prescription drugs. Having the respondents list the names of the prescription drugs they were using also provided a validity check for the item asking about the number of prescription drugs they used. Having to list the drug names may have cued their memory and thus improved the accuracy of the estimated number of prescription drugs used.

Another limitation is that the study population only included Wisconsin residents age 50 and older, and thus the results may not be generalizable to other states and younger populations. The state of Wisconsin was chosen because of my familiarity with insurance plans in the state and potentially higher response rates resulting from respondent familiarity with and good will towards the University of Wisconsin. A key limitation from using only Wisconsin residents was that there was a very low proportion of minorities in the population. This especially limits generalizability of the results to states with more racially diverse

populations. The older population used in the study limits the generalizability of the preference measure results to younger populations. It is possible that the medical care preference distribution and effects would be different in a younger population, although there was no evidence of this in the pilot survey.

A limitation pertaining to the preference measure is that it was a new scale. Although the scale had good reliability, and was unidimensional, some respondents omitted the preference items or reported having difficulty answering the items. There were a few respondents who commented that their answers would depend on how they interpreted "health problem," and differences in interpretation may have influenced their answers. As discussed previously, the results need to be validated in other populations, and more work needs to be done on scale development.

Another limitation was in how the insurance variable was measured. Prescription drug insurance was measured as a dichotomous variable, the presence or absence of prescription drug insurance coverage. No distinction was made between plans with generous coverage and plans with significant amounts of cost sharing. There also was no measure of whether the plans had any supply side cost containment mechanisms, such as formularies or capitated arrangements with providers. Although HMO membership was assessed, it is possible that some respondents could not accurately answer this question. The type and strictness of cost containment measures also may vary considerably between HMOs. Although I had intended to include a measure of physician insurance coverage in the study, this was not possible because most of the respondents had physician coverage. The prescription drug insurance effect may have been slightly confounded by the physician

insurance effect, because a small percentage of the individuals who had no prescription drug insurance also had no physician insurance.

A final limitation is that the method used to control for adverse selection was based on two key assumptions. One of these assumptions was that adverse selection is unlikely in individuals who receive their insurance coverage through a large employer. It is possible that some of these employees are required by their employers to pay a substantial portion of the cost of the health insurance. If this is the case, individuals who expect very low health care expenditures may be unwilling to pay their portion, and may choose to opt out of the coverage. The other assumption was that only those uninsured individuals who reported they "did not think they needed prescription drug insurance coverage," were at high risk for adverse selection. Potentially, ininsured individuals who reported that the "insurance cost too much" also were at some risk for adverse selection.

CHAPTER 6

CONCLUSIONS

In this study, an economic utility model was proposed as a theoretical framework to study prescription drug utilization. The premise of this model was that consumers seek to maximize their utility, subject to their budget constraints. The model predicts that utilization of medical care is determined by the point of tangency between consumers' indifference curves and their budget constraints. The focus of this study was on the effects of prescription drug insurance coverage and medical care preferences on prescription drug utilization. In the model, insurance coverage for prescription drugs is predicted to increase prescription drug utilization because it lowers the price of prescription drugs to the consumer, thereby changing the budget constraint. Preferences for using medical care also were predicted to affect prescription drug utilization, because preferences change the shapes of individuals' indifference curves.

To test the model, Wisconsin consumers were surveyed via mail to determine their insurance status, their medical care preferences, and their prescription drug utilization in the last 30 days. The predicted insurance effect was supported by the results of the study. Individuals with prescription drug insurance were 1.7 times more likely than uninsured individuals to use at least one prescription drug. Insured individuals who used at least one prescription drug used about 12 percent more prescription drugs and had about 46 percent greater prescription drug costs than uninsured individuals.

Although the utility model predicted that preferences would affect prescription drug utilization, it generally is assumed that preferences are revealed by behavior or are captured by demographic variables or health status, and thus are not measured explicitly. In this study, a scale was developed to measure consumers' preferences for using medical care, and this represents a departure from how this model typically is operationalized. Preferences were assessed along a continuum, with one end representing preferences for seeking medical care, defined as physician services and prescription drugs, and the other end representing preferences for treating health problems without help from physicians and prescription drugs. Results from this study suggest that preferences can be measured, and that they are not well captured by demographic variables or health status. The correlation between the preference scale and self-reported health status only was 0.17, and the correlations between the preference scale and demographic variables all were 0.21 or less.

The results also show that medical care preferences have a strong effect on prescription drug utilization. For each standard deviation increase in the preference scale (towards more help-seeking preferences), individuals were 1.9 times more likely to have used at least one prescription drug in the last 30 days. In individuals who had used at least one prescription drug, a standard deviation increase in the preference score increased the number of prescription drugs used by 13 percent and the total cost of prescription drugs used by 17 percent. For the probability of any prescription drug use and the number of prescription drugs used, the magnitude of the preference effect was the same as the magnitude of the insurance effect. For the cost of prescription drugs used, the preference effect was less than the insurance effect, probably because preferences have a minimal effect

on the cost of drug products used. Adding preferences to the models somewhat improved their fit.

The utility model also predicted that there would be an interaction effect between medical care preferences and insurance, with the insurance effect being smaller in individuals with stronger self-treating preferences. This interaction effect was significant in the model predicting the number of prescription drug used by individuals who had used at least one prescription drug. In this model, the insurance effect in individuals with self-treating preferences only was 3.9 percent, and was not significant. The insurance effect for individuals with help-seeking preferences was 20.2 percent. In the model predicting the cost of prescription drugs used, there was not a significant interaction effect and the insurance effect was significant even in individuals with self-treating preferences.

The strong effect of medical care preferences on prescription drug utilization and the significant interaction effect between insurance and preferences in the model predicting the number of prescription drugs, suggest that measuring preferences can provide important insights into consumer behavior. This should be taken into consideration in future studies that use a utility model as a framework. From a theoretical perspective, there is value in measuring preferences, not just in health care research, but potentially in any research based on the utility model. The significant preference effects also are important from a practical perspective. There is concern that insurance has a "moral hazard" effect, that because insurance decreases the price of prescription drugs to the consumer, it will increase prescription drug use. However, in individuals with self-treating preferences, there was no difference in the number of prescriptions used by insured and uninsured individuals. The

moral hazard effect appears to be more problematic in individuals with stronger help-seeking preferences, and for the cost of the drug products used.

Another objective of this study was to determine to the extent to which estimates of the insurance effect are biased by adverse selection. Individuals who expect to use a lot of prescription drugs may be more likely to purchase insurance and individuals who expect to use very few prescription drugs may be less likely to purchase insurance. This makes it difficult to determine if the difference in prescription drug utilization between insured and uninsured individuals is due to moral hazard or adverse selection. In this study a different approach was used to determine the extent of the bias from adverse selection. Past studies of the insurance effect on prescription drug utilization have relied on a variety of econometric techniques to control for adverse selection, but there was not a consensus on which technique was the best way to handle the problem. Consequently, the method used in this study was based on research on adverse selection in the health insurance market. The assumption made is that some individuals, depending on their source of insurance, are more at risk for adverse selection.

It was expected that controlling for adverse selection would result in smaller insurance coefficients, and this was what occurred. In individuals at low risk for adverse selection, the insurance coefficient was 11 percent less for the model predicting the probability of any prescription use, 18 percent less for the model predicting the number of prescription drugs used, and 26 percent less for the model predicting the cost of prescription drugs used, all relative to the models that included both low and high adverse selection risks. The difference in the insurance effects for high and low adverse selection risks was not

significant in the model predicting the probability of any prescription drug use, approached significance in the model predicting the number of prescriptions used, and was significant in the model predicting the cost of prescription drugs. These results suggest that adverse selection is a potential problem in the prescription drug insurance market.

The results of this study have important implications for policy makers, insurers, and providers of health care services. For policy makers and insurers, the results have implications for the way in which prescription drug benefits are designed. The exceptionally strong effect of insurance on the cost of prescription drugs used suggests that efforts directed toward controlling the cost of prescription drugs used may be more successful in decreasing overall prescription drug expenditures than efforts directed toward controlling the number of prescription drugs used. However, more research needs to be done to determine whether demand side or supply side cost control mechanisms are more likely to be successful in decreasing the cost of the drug products used. More research also needs to be done to determine whether the additional prescription drug use and costs in insured individuals results in improved health outcomes.

The potential adverse selection problem also needs to be taken into consideration when designing prescription drug insurance benefits. Many individuals use prescription drugs to treat chronic conditions, and thus have very good knowledge of their expected prescription drug expenses. If individuals are given the option of selecting or not selecting prescription drug coverage, it is expected that individuals who use a lot a prescription drugs will be more likely to select the insurance. This increases the cost of the insurance, which in turn may result in even more low risk individuals opting out of coverage. Bundling

prescription drug insurance coverage with other types of health care coverage may be one way to minimize this problem.

Policy makers and insurers also may be interested in the strong effect of preferences on prescription drug utilization. The individuals at both end of the preference continuum are of interest. Individuals with strong preferences for self-treating may use less preventive care and may postpone necessary treatment for health problems. This ultimately may result in poorer outcomes and greater costs for the health care system. Individuals with stronger help-seeking preferences may use physician services or prescription drugs to treat problems that could have been handled outside of the formal health care system. This also results in higher health care costs. Future research is necessary to determine whether preferences can be changed, or if education can change behavior, even if the underlying preferences are stable.

The results also have implications for health care providers. Having a better understanding of patient preferences for seeking medical care may help health care providers improve patient care. In some cases, they may be able to tailor treatment decisions based on patient preferences. For example, an individuals with self-treating preferences may be more willing to try a non-drug treatment. Understanding preferences also may help with patient education. Individuals with strong help-seeking preferences potentially could be educated about how to self-treat some health problems, and individuals with self-treating preferences could be educated about when they need to seek care from the formal health care system.

Aside from the direct implications of the results, it is hoped that this study accomplishes two things. First, to draw attention to the importance of expanding economic

research to include more consumer variables. Preferences potentially are important predictors of many types of consumer behaviors, and including them in other economic studies might provide valuable insights into consumer decisions. In research that tries to predict or explain consumer behavior, it seems that measuring preferences, rather than assuming that they are revealed by behavior, is a useful technique. The technique of measuring preferences and including them as a predictor of behavior could be used in areas other than health care.

The second desired accomplishment was to emphasize the importance of interdisciplinary research. This study drew on ideas, previous research, and methodologies from several different disciplines. The main framework of the study was an economic theory, and much of the hypothesis testing used methods developed in previous econometric research. The method used to test for adverse selection bias was based on research from the discipline of risk management and insurance, while measurement of medical care preferences drew heavily on previous work on construct measurement and scale development from the disciplines of psychology and marketing. Finally, most of the previous research on constructs related to medical care preferences was done by researchers in sociology or health services research. It is unlikely that this dissertation research would have been possible without exposure to methods and ideas from a wide range of disciplines. Interdisciplinary research provides an important opportunity to generate ideas and stretch boundaries.

BIBLIOGRAPHY

Anderson, RM (1968) Behavioral model of families' use of health services. Research Series No. 25 Chicago, IL: Center for Health Administration Studies, University of Chicago.

Anderson, RM (1975) Health services distribution and equity. In: Anderson RM., Kravits J. and Anderson OW. Eds. Equity in Health Services: Empirical Analyses in Social Policy. Cambridge; Bellinger Publishing: 9-32.

Anderson, RM. (1995). Revisiting the behavioral model and access to medical care: does it matter? *Journal of Health and Social Behavior*. 36(March): 1-10.

Akerlof, GA. (1970). The market for 'lemons': quality uncertainty and the market mechanism. *Quarterly Journal of Economics*. 84:488-500.

Bazargan, M., Bazargan S. and Baker, RS. (1998). Emergency department utilization, hospital admissions and physician visits among elderly African American persons. *The Gerontologist*, 38(1): 25-36.

Berk, ML., Schur, CL., and Mohr, P. (1990). Using survey data to estimate prescription drug costs. *Health Affairs*, 9(Fall): 146-156.

Bice, TW and White, KL (1969). Factors related to the use of health services: an international comparative study. *Medical Care*. 7(2):124-133.

Brook, RH., Ware, JE, Rogers WH, et al. (1983). Does free care improve adults' health? *New England Journal of Medicine*, 309:1426 - 1434.

Browne, M.J. (1992). Evidence of adverse selection in the individual health insurance market. *Journal of Risk and Insurance*, 59:13-33.

Browne, MJ. and Doerpinghaus, HI. (1993). Information asymmetries and adverse selection in the market for individual medical expense insurance. *Journal of Risk and Insurance*, 50:300-312.

Browne, MJ. and Doerpinghaus, HI. (1994). Asymmetric information and the demand for Medigap insurance. *Inquiry*, 31:445-450.

Carroll, NV. and Jowdy, AW (1987). Demographic and prescription patronage motive differences among segments in the community pharmacy market. *Journal of Pharmaceutical Marketing and management*, 1(4):19-34.

Chatterjee, S. and Hadi, A.S. (1991). Regression Analysis by Example. New York. John Wiley & Sons. Second Edition.

Chewning, B. (in press). Evaluation of a computerized contraceptive decision aid for adolescent patients. *Patient Education and Counseling*

Chewning, B. (1994). Clients' side effect expectations, experiences, and discontinuation of oral contraceptives. Proceedings of the 1994 U.S. Pharmacopeial Convention, U.S. Pharmacopeial Convention.

Chewning, B. and Sleath, B. (1996). Medication decision-making and management: a client-centered model. *Social Science and Medicine*, 42(3):389-398.

Churchill, GA. (1991). Marketing Research Methodological Foundations. Chicago. The Dryden Press. Fifth Edition. 425 - 426.

Copeland, C. (1999). Prescription drugs: issues of cost, coverage, and quality. *EBRI Issue Brief*, No. 208 (Employee Benefit Research Institute), April.

Coulson, NE. and Stuart, BC. (1995). Insurance choice and the demand for prescription drugs. *Southern Economic Journal*, 61(4):1146-1157.

Coulson, NE., Terza, JV., Neslusan, CA., and Stuart, BC. (1995). Estimating the moral-hazard effect of supplemental medical insurance in the demand for prescription drugs in the elderly. *American Economic Review*, 85(2):122-126.

Crichton, EF., Smith DL, and Demanuele F. (1978). Patient recall of medication information. *Drug Intelligence and Clinical Pharmacy*, 12:591.

Cummins, JD., Smith BD., Vance, NR., and VanDerhei, J. (1983). Risk Classification in Life Insurance. Boston. Kluwer, Nijhoff Publishing.

Davis, M., Poisal, J., Chulis, G., Zarabozo, C., and Cooper, B. (1999). Prescription drug coverage, utilization, and spending among Medicare beneficiaries. *Health Affairs*, 18(1):231-243.

Dillman, DA. (1978). Mail and Telephone Surveys: The Total Design Method. New York. Wiley Publishing.

Douglas, Jeffrey (1998). Personal communication, November, 1998.

Duan, N., Manning, WG., Morris, WG., and Newhouse, JP. (1983). A comparison of alternative models for the demand for medical care. *Journal of Business and Economic Statistics*, 1(April):115-126.

Eisenberg, JM (1979). Sociologic influences on decision-making by clinicians. *Annals of Internal Medicine*, 90: 957-964.

Eisenberg, JM (1985). Physician utilization: the state of research about physicians' practice patterns. *Medical Care*, 23(5): 461-483).

Feldstein, PJ. (1966). Research on the demand for health services. *Milbank Memorial Fund Quarterly*, 44:128-162.

Fiscella, K., Franks, P., and Clancy, CM. (1998). Skepticism toward medical care and health care utilization. *Medical Care*, 36(2): 180-189.

Folland, S., Goodman, AC. and Stano, M. (1993). The Economics of Health and Health Care. New York. Macmillan Publishing Company. 37-39.

Gardner, W., Mulvey, EP., and Shaw, EC. (1995). Regression analyses of counts and rates: Poisson, over-dispersed Poisson, and negative binomial models. *Psychological Bulletin*, 118(3): 392-404.

Gianfrancesco, FD., Baines, AP. And Richards, D. (1994). Utilization effects of prescription drug benefits in an aging population. *Health Care Financing Review*, 15(3): 113-126.

Goddeeris, J., and Weisbrod, BA. (1985). What we don't know about why health expenditures have soared: interaction of insurance and technology. *The Mount Sinai Journal of Medicine*, 52(9):685-691.

Greenlick, MR. and Darsky, BJ. (1968). A comparison of general drug utilization in a metropolitan community with utilization under a drug prepayment plan. *American Journal of Public Health*, 58(11):2121-2136.

Grootendorst, PV. (1995). A comparison of alternative models of prescription drug utilization. *Health Economics*, 4(3):183-198.

Grootendorst, PV., O'Brien, BJ., and Anderson, GM. (1997). On becoming 65 in Ontario: effects of drug plan eligibility on use of prescription medications. *Medical Care*, 35(4):386-398.

Grossman, M. (1972). The Demand for Health: A Theoretical and Empirical Investigation. New York. Columbia University Press.

Hardy, MA (1993). Regression With Dummy Variables. Series: Quantitative Applications in the Social Sciences. Newbury park. Sage Publications: 56-60.

Harris, BL., Stergachis, A., and Ried, LD. (1990). The effect of drug co-payments on utilization and cost of pharmaceuticals in a Health Maintenance Organization. *Medical Care*, 28(10):907-917.

Health Care Financing Administration (1998). National Health Care Expenditures 1960 -1996. Online. Http://www.hcfa.gov/stats/stats.htm [20May1998].

Hosmer, DW. and Lemeshow, S. (1989). Applied Logistic Regression. New York; John Wiley and Sons: 56-59.

Hurd, MD. and McGarry, K. (1997). Medical insurance and the use of health care services by the elderly. *Journal of Health Economics*, 16:129-154.

Jaccard, J., Turrisi, R., and Wan, CK. (1990). Interaction effects in multiple regression. Newbury Park; Sage Publications.

Jung, K. (1998). Influence of the introduction of a per-visit copayment on health care use and expenditures: the Korean experience. *The Journal of Risk and Insurance*:33-56.

Keeler, EB. and Rolph, JE. (1988). The demand for episodes of treatment in the health insurance experiment. *Journal of Health Economics*, 7:337-367.

Kraus, NA, Machlin, S, Kass, BL. (1999) Use of health care services, 1996. Rockville (MD): Agency for Health Care Policy and Research. MEPS Research Findings No. 7. AHCPR Pub. No. 99-0018.

Kravits, J.(1975). The relationship of attitudes to discretionary physician and dentist use by race and income. In: Anderson R., Kravits J. and Anderson OW. Eds. Equity in Health Services: Empirical Analyses in Social Policy. Cambridge; Bellinger Publishing: 73-94.

Kreling, DH. (1991). A comparison of pharmacists' acquisition costs and potential Medicaid prescription ingredient cost reimbursement in Wisconsin. *Journal of Research in Pharmaceutical Economics*, 3(3):25-53.

Langlie, JK. (1977). Social networks, health beliefs, and preventive health behavior. *Journal of Health and Social Behavior*, 18:244-260.

Lassila, HC., Stoehr, GP., Ganguli. M., Seaburg, EC., Gilby, JE, Belle, SH. and Echement, DA. (1996). Use of prescription medications in an elderly rural population: the MoVIES project. The Annals of Pharmacotherapy, 30: 589-95.

Lavers, RJ. (1989). Prescription charges, the demand for prescriptions and morbidity. *Applied Economics*, 21:1043-1052.

Leibowitz, A., Manning, WG., and Newhouse, JP. (1985). The demand for prescription drugs as a function of cost-sharing. *Social Science and Medicine*, 21(10):1063-1069.

Lilja, J. (1976). How physicians choose their drugs. *Social Science and Medicine*. 10 (7-8):363-365. Link, CR., Long, SH. And Settle, RF. (1980). Cost sharing, supplementary insurance, and health services utilization among the Medicare elderly. *Health Care Financing Review*. Fall: 25-31.

Long, SH. (1994). Prescription drugs and the elderly: issues and options. *Health Affairs*, Spring (II):157-174.

Long, JS. (1995). Regression Models for Categorical and Limited Dependent Variables. Thousand Oaks; Sage Publications: 217-250.

Maeland, JG and Havik, OE. (1989). Use of health services after a myocardial infarction. *Scandinavian Journal of Social Medicine*, 17: 93-102.

Manning, WG., Newhouse, JP., Duan, N., Keeler, EB., Leibowitz, A., and Marquis, MS. (1987). Health insurance and the demand for medical care: evidence from a randomized experiment. *American Economic Review*, 77(3):251-277.

Martin, DP., Diehr, P., Cheadle, A., Madden, CW., Patrick, DL., and Skillman, SM. (1997). Health care utilization for the "newly insured": results from the Washington basic health plan. *Inquiry*, 34(Summer):129-142.

Matthews, VL and Feather, J. (1976). Utilization of health services in Western Canada: basic Canadian data from the World Health Organization/International Collaborative Study of Medical Care Utilization. *Canadian Medical Association Journal*, 114(Feb. 21): 309-312.

McCaffrey, DJ., Smith, MC., Banahan, BF., Frate, DA. and Gilbert, FW. (1998). A continued look into the financial implications of initial noncompliance in community pharmacies: an unclaimed prescription audit pilot. *Journal of Research in Pharmaceutical Economics*, 9(2): 33-57.

McCall, N., Rice, T., Boismier, J., and West, R. (1991). Private health insurance and medical care utilization: evidence from the Medicare population. *Inquiry*, 28(Fall):276-287

Mechanic, D. (1979). Correlates of physician utilization: why do major multivariate studies of physician utilization find trivial psychosocial and organizational effects? *Journal of Health and Social Behavior*, 20(4):387-396.

Mott, DA. and Kreling, DH. (1998). The association of insurance type with costs of dispensed drugs. *Inquiry*, 35(Spring):23-35.

National Pharmaceutical Council (1998). Pharmaceutical Benefits Under State Medical Assistance Programs: National Pharmaceutical Council, Reston, VA.

Nelson, AA., Jr., Reeder, CE., and Dickson, WM. (1984). The effect of a medicaid drug copayment program on the utilization and cost of prescription services. *Medical Care*, 22(8):724-736.

Newhouse, JP. And Phelps, CE. (1976) New estimates of price and income elasticities of medical care services. In: The Role of Health Insurance in the Health Services Sector. ed. Richard N. Rosett, New York. National Bureau of Economic Research: 261 - 319.

Nicholson, W. (1994) Intermediate Microeconomics and Its Application. Fort Worth. The Dryden Press. 6th edition: 126-127.

Nunnally, JC, and Bernstein IH. (1994). Psychometric Theory. New York. McGraw-Hill Inc. 3rd Edition:491-508.

O'Brien, B. (1989). The effect of patient charges on the utilization of prescription medicines. *Journal of Health Economics*, 8:109-132.

Office of the Inspector General (OIG) (1997). Medicaid Pharmacy: actual acquisition cost of generic prescription drug products. HHS/OIG Audit Reports–Health Care Financing Administration. A-06-97-00011.

Pauly, MV. (1968). The economics of moral hazard: comment. *American Economic Review*, 58(3):531-537.

Peter, JP (1979). Reliability: a review of psychometric basics and recent marketing practices. *Journal of Marketing Research*. 16(Feb.):6-17.

Phelps, CE. and Newhouse, JP. (1974). Coinsurance, the price of time, and the demand for medical services. *Review of Economics and Statistics*, 56(3):334-342.

Phillips, C. (1992). Insurance program design and utilization of pharmaceutical benefits within therapeutic, medication source and demographic categories. Ph. D. Dissertation - University of Oklahoma.

Polit C. and Sharp H. (1983). Strategies in RDD Sampling. Madison, WI: Wisconsin Survey Research Laboratory, University of Wisconsin.

Price, JR and Mays, JW. (1985). Biased selection in the Federal employees health benefits program. *Inquiry*, 22 (Spring): 67-77.

Reeder, CE. and Nelson, AA. (1985). The differential impact of copayment on drug use in a Medicaid population. *Inquiry*, 22(4):396-403.

Ryan, M. and Birch, S. (1991). Charging for health care: evidence on the utilization of NHS prescribed drugs. *Social Science and Medicine*, 33(6):681-687.

Schwartz, RK., Soumerai, SB., and Avorn J. (1989). Physician motivations for nonscientific drug prescribing. *Social Science and Medicine*, 28(6): 577-582.

Scitovsky, AA. and Snyder, NN. (1972). Effect of coinsurance on the demand for physician services. *Social Security Bulletin*, 35(6):3-19.

Sharp K., Ross CE. and Cockerham WC. (1983). Symptoms, Beliefs and the Use of Physician Services Among the Disadvantaged. *Journal of Health and Social Behavior*. 24(Sept.):255-263.

Smith, DG. (1993). The effects of copayments and generic substitution on the use and costs of prescription drugs. *Inquiry*, 30:189-198.

Smith, MC. and Garner, DD. (1974). Effects of a Medicaid program on prescription drug availability and acquisition. *Medical Care*, 12:571-581.

Stoller, EP. (1982). Patterns of physician utilization by the elderly: a multivariate analysis. *Medical Care*, 20(11):1080-1089.

Strain LA. (1991). Use of Health Services in Later Life: The Influence of Health Beliefs. *Journal of Gerontology*. 46(3): S143-150.

United States Bureau of the Census (1998). Population Estimates Program. Population Division, Washington D.C. Online. Http://www.census.gov/population/www/estimates/statepop.html [December1998].

Vistnes, JP. and Banthin, JS. (1997). The demand for medicare supplemental insurance benefits: the role of attitudes toward medical care and risk. *Inquiry*, 34: 311-324.

Wallston, BS., Wallston KA., Kaplan GD., and Maides SA. (1976). Development and validation of the health locus of control (HLC) scale. *Journal of Consult Clinical Psych*, 44:580-585.

Wallston, KA. and Strudler Wallston, B. (1978). Development of the multidimensional health locus of control (MHLC) scales. *Health Education Monographs*, 6(2):160-170.

Weeks, HA. (1973). Changes in prescription drug utilization after the introduction of a prepaid drug insurance program. *Journal of the American Pharmaceutical Association*, NS13(4): 205-209.

Weiner, JP., Lyles, A., Steinwachs, DM., and Hall, KC. (1991). Impact of managed care on prescription drug use. *Health Affairs*, 10(1):140-154.

Welch, BL., Hay, JW, Miller, DS, Olsen, RJ, Rippey, RM and Welch, AS. (1987). The Rand health insurance study: a summary critique. *Medical Care*, 25(2): 148-156.

Wiederholt, JW (1987). Development of an instrument to measure evaluative criteria that patients use in selecting a pharmacy for obtaining prescription drugs. *Journal of Pharmaceutical Marketing and Management*, 1(4): 35-60.

Wirick GC. (1966). A multiple equation model of demand for health care. *Health Services Research*. Winter: 301-346.

Wolfe, JR. and Goddeeris, JH. (1991). Adverse selection. moral hazard, and wealth effects in the Medigap insurance market. *Journal of Health Economics*, 10: 433-459.

Wolinsky, FD. and Johnson, RJ. (1991). The use of health services by older adults. *Journal of Gerontology*, 46(6): S345-S357.

Zelnio, RN (1982). The interaction among the criteria physicians use when prescribing. *Medical Care*, 20(3): 277-285.

APPENDIX A

OVERVIEW OF THE MEDICARE PROGRAM

This appendix is intended to provide an overview of Medicare and Medicare supplemental insurance policies. All of the information was taken from the websites www.medicare.gov and www.xact.org/medicare, or brochures on Medicare supplemental insurance policies obtained from the Wisconsin Office of the Commissioner of Insurance (OCI). More detailed information can be obtained from the websites or OCI.

Medicare is a government sponsored insurance program that provides insurance coverage for 39 million elderly and disabled Americans. United States citizens are eligible for coverage at age 65, provided that they or their spouse have worked at least ten years in Medicare-covered employment. Coverage under the age of 65 is available for individuals with kidney disease or a chronic disability. Eligible individuals are encouraged to enroll at age 65, and although there are some exceptions, premiums typically are higher for individuals who choose to enroll later.

Medicare is divided into two parts, Medicare Part A and Medicare Part B. Part A helps cover hospital costs; including room charges, inpatient prescription drugs and equipment. It also pays part of skilled nursing home care, home health care, and hospice care costs. Generally, there are no premiums for Part A coverage, but there are significant cost sharing requirements. The cost sharing requirements are based on benefit periods, which start the first time the enrollee receives inpatient care, and end when the enrollee has been out of the hospital or skilled nursing facility for 60 days in a row. For 1999, the deductible is $768 per benefit period and the coinsurance is $0 for the first 60 days, $192 a day for days 61 through 90 and $384 a day for days 91 through 150.

Medicare Part B helps pay for physician services and some other outpatient services,

but it does not provide coverage for prescription drugs. There is a monthly premium for Part B coverage, $45.50 per month for 1999. In addition to the premium, enrolles pay a deductible of $100 per year and 20 percent of approved charges for physician and most other outpatient services. Enrollees can choose to see any provider that accepts Medicare, both participating and non-participating providers. A participating provider agrees to accept assignment, which means that they accept Medicare's approved payment amount as payment in full. If an enrollee sees a non-participating provider, the provider can bill the enrollee for charges up to 15 percent above the Medicare approved rate.

As a result of the significant cost sharing requirements in Medicare, many Medicare enrollees choose to purchase a private supplemental insurance policy, referred to as a "Medigap" plan. Although these policies are purchased from private insurers, the government regulates many of the policy terms. For example, if a Medigap policy is purchased within ten months of when Medicare Part B enrollment occurred, insurers can not charge higher premiums for the policy or refuse to sell a policy, even if the enrollee is in poor health. The federal government also has established ten standard types of Medigap plans, identified as plans A through J. Plan A is a core benefit package that covers the coinsurance for physician visits and the hospital coinsurance for days 61 through 90. All other Medigap policies include these core benefits and have some additional benefits. Generally, plans A through J progress from least comprehensive to most comprehensive. The only plans that provide prescription drug coverage are H, I, and J. Plans H and I have the same prescription drug benefits: a $250 deductible, 50 percent coinsurance, and a maximum yearly benefit of $1,250. Plan J also has the $250 deducible and 50 percent coinsurance, but has a maximum

yearly benefit of $3,000.

Some states, including Wisconsin, have a waiver from the federal government to establish their own Medigap policy regulations. In Wisconsin, all Medigap policies are required to include catastrophic drug coverage, which must pay at least 80 percent of outpatient prescription drug charges after a $6,250 yearly deductible is met. They may offer an optional prescription drug rider, which must pay at least 50 percent of prescription drugs costs, up to a maximum of $3,000 per year and may have up to a $250 yearly deductible. Most insurers do not offer the optional rider. In 1998, only 2 of the 27 insurers who sold individual Medigap policies in Wisconsin offered the additional prescription drug coverage.

Medicare traditionally has been a fee-for-service type of insurance, where enrollees are allowed to go to any provider that accepts Medicare, and Medicare reimburses the providers each time a service is provided . However, recently the government has been trying some alternative types of coverage. One alternative is a Medicare Managed Care plan, where a Medicare approved network of providers agrees to provide care to enrollees for a fixed monthly payment, regardless of the level of care provided. Enrollees are restricted to using providers in the network, however there may be less cost sharing and/or more benefits in the managed care plans. For example, some managed care plans cover prescription drugs and vision services. Medicare also is testing a Medical Savings Account Plan. This is a high deductible plan, where Medicare pays the premium and deposits money into a medical savings account established by the enrollee. The deposited money can be used to pay for medical expenses.

The number and type of alternatives to the original Medicare plan vary by location.

In Wisconsin, there are five alternative plans that provide coverage in some areas of the state. The plans are: PrimeCare Health Plan, Humana WI Health Organization, Medicare Blue, Network Health Plan of WI, and Medical Associates Clinic Health Plan. These plans provide different levels of prescription drug coverage. PrimeCare and Medicare Blue pay for 80 percent of prescription drug costs, Humana pays 100 percent of plan-approved prescription drugs, Network Health covers prescription drug costs up to $2,000 per year for an additional $40 monthly premium, and Medical Associates does not cover prescription drugs. It is unclear whether Medicare managed care plans will continue to provide coverage for prescription drugs, because the costs of this coverage have been high.

APPENDIX B

POSTCARDS, PILOT COVER LETTER, AND PILOT QUESTIONNAIRE

Dear Consumer:

In the next week, you will receive a survey about prescription drug insurance and prescription drug use in the mail from the University of Wisconsin School of Pharmacy

The survey is being sent to a small sample of Wisconsin consumers who were selected at random. Your response is very important to us, so please complete and return the survey when you receive it.

Thank you,

David Kreling, Ph.D., R.Ph.
University of Wisconsin
School of Pharmacy

Julie Ganther, M.S., R.Ph.
University of Wisconsin
School of Pharmacy

Dear Consumer:

Last week you received a survey about prescription drug insurance and prescription drug use.

If you have completed and returned the survey, **thank you very much for your help**. If not, please do so as soon as possible. Your response is very important to us because we sent the survey to only a small sample of Wisconsin consumers.

If you did not receive the survey, or need a replacement, please call us at (608) 262-3454 and we will send you another.

Thank you,

David Kreling, Ph.D., R.Ph.
UW School of Pharmacy

Julie Ganther, M.S., R.Ph.
UW School of Pharmacy

UNIVERSITY OF
WISCONSIN
MADISON

September 15, 1998

Dear Wisconsin Consumer:

The cost of medical care in the United States is increasing at a rapid rate. This especially is true for prescription drugs, which are becoming more and more expensive. This is of concern because many Wisconsin residents do not have any health insurance coverage, and many more do not have insurance coverage for prescription drugs.

We would like to invite you to participate in a survey. Your input is needed to learn more about whether people without insurance have the same access to doctors and prescription drugs as people with insurance. We are interested in responses both from people with health insurance and people without health insurance.

Any adult in the household can complete the survey. **Your information is important to us even if you do not use any prescription drugs or have not seen a doctor recently.**

Your name is one of a small number of Wisconsin consumers who were selected at random for the study so your response is very important to us. Please take about 15-25 minutes now to complete the form and return it in the postage paid envelope provided. Your responses are completely anonymous.

Thank you for taking time to share your information with us. If you have any questions concerning the survey, or need help answering any part of the survey please call us at (608) 262-3454.

Sincerely,

David H. Kreling, Ph.D., R.Ph.
Associate Professor
School of Pharmacy
University of Wisconsin - Madison

Julie M. Ganther, M.S., R.Ph.
Doctoral Candidate
School of Pharmacy
University of Wisconsin - Madison

Survey on Health Insurance and Medical Care Use

You can help us learn whether people without health insurance have the same access to doctors and prescription drugs as people with health insurance. Your information is important even if you do not use any prescription drugs or you have not seen a doctor recently.

All responses are very important to us!

Answering these survey questions will take 15 to 25 minutes. Please do not write your name anywhere on the form. If you wish, you can give us additional comments in the space provided at the end of the form. All responses are completely anonymous.

Part A: Health Insurance

First we would like to know about your insurance for doctor visits and prescription drugs

For each question please check one answer.

1. Do you have insurance that pays for all or part of the cost of doctor visits?

_____ yes
_____ no
_____ don't know

2. Do you have insurance that pays for all or part of prescription drug costs?

_____ yes
_____ no
_____ don't know

3. Do you belong to a health maintenance organization (HMO)?

_____ yes
_____ no
_____ don't know

Part B: Use and Cost of Medical Care

Next we would like to ask you some questions about your use of doctors and prescription drugs

4. How many times did you visit a doctor in the last 30 days?

_____

5. How many times did you visit a doctor in the last 6 months?

_____

6. How far do you usually have to travel to visit a doctor?

_____ less than 1 mile
_____ 1 to 5 miles
_____ 6 to 10 miles
_____ 11 to 20 miles
_____ more than 20 miles

7. How many different prescription drugs did you use in the last 30 days?

_____

8. How sure are you that you can get a prescription drug if you need one?

_____ totally sure
_____ very sure
_____ fairly sure
_____ only a little sure
_____ not at all sure

If you did not use any prescription drugs in the last month, skip to question 14

9. About how much did you spend for prescription drugs in the last 30 days?

$_____

10. How far do you usually have to travel to pick up a prescription?

_____ less than 1 mile
_____ 1 to 5 miles
_____ 6 to 10 miles
_____ 11 to 20 miles
_____ more than 20 miles

11. How many different pharmacies do you get prescription drugs from?

_____

12. What types of pharmacies do you get prescription from? (Check **ALL** that apply)

_____ chain pharmacy (for example Walgreens, Shopko, Kmart, Walmart, Osco)
_____ independent pharmacy (pharmacy that is locally owned)
_____ clinic pharmacy (pharmacy that is inside a medical clinic)
_____ mail order pharmacy
_____ other _____

Now, we need some information about the specific prescription drugs you use to determine whether the uninsured have access to the same types of drugs as the insured.

13. Please list the drug name and strength, the directions for use, and about how many you used for **each** prescription drug you took in the **last 30 days** (you may need to look at your prescription vials to get some of this information). If you need more room use the back of the survey.

OR

If it would be easier, you can get this information from your pharmacy. To do this: 1) ask your pharmacy to print out a report of the prescriptions you purchased in the last 3 months -we need 3 months because all of the prescription drugs you used in the last month may not have been purchased in the last month, 2) remove your name from the report, and 3) mail the report back with the survey. Most pharmacy print out this report for you free of charge.

Drug Name and Strength	**Directions (how you took it)**	**Quantity used in the last 30 days**
Example: Amoxicillin 500mg	1 capsule 3 times a day	21
Example: OrthoNovum 1/35	1 tablet once a day	about 30
Example: Tylenol with Codeine #3	1 or 2 tablets as needed	about 15

Part C: Medical Care Preferences

Now we want to know some of your feelings about doctors and prescription drugs

Please circle your level of agreement with each statement, using the scale below.

SA = Strongly Agree
A = Agree
N = Neither agree nor disagree
D = Disagree
SD = Strongly Disagree

14.	If I have a health problem, I would rather treat myself than go to the doctor.	SA	A	N	D	SD
15.	Taking prescription drugs to treat a health problem is the last thing I would do.	SA	A	N	D	SD
16.	I like to talk to my doctor whenever I have a health problem.	SA	A	N	D	SD
17.	I know my health better than most doctors do.	SA	A	N	D	SD
18.	When I have a health problem, I usually wait and see if I get better on my own before going to see a doctor.	SA	A	N	D	SD
19.	I believe home remedies often work better than prescription drugs.	SA	A	N	D	SD
20.	When I have a health problem, I contact a doctor right away.	SA	A	N	D	SD
21.	When I have a health problem, my first thought is to use a prescription drug.	SA	A	N	D	SD
22.	When I have a health problem, it is hard to convince me to see a doctor.	SA	A	N	D	SD
23.	When I have a health problem, I prefer to try an over-the-counter (OTC) product before taking a prescription drug.	SA	A	N	D	SD

Part D: Prescription Drug Insurance

If you have insurance for <u>prescription drugs</u> please answer questions 24 - 31.
If you do NOT have insurance for prescription drugs please skip to question 32.

24. Even people with prescription drug insurance may have to pay part of the cost for prescription drugs. Please check ANY of the types of cost sharing listed below that your prescription drug insurance plan uses (copayment, coinsurance, deductible, or other). For each type you checked fill in the cost that you have to pay. Sometimes the amount of cost sharing is different for brand name and generic prescriptions. If you are not sure about the amount you pay and you have a prescription drug card, the information may be on the card.

    If your insurance company pays **ALL** of your prescription drug costs please check the "no cost sharing" option.

    _____ COPAYMENT: **A fixed amount** that you pay each time you get a prescription. (For example $10 for brand name, $5 for generic)

    What is the amount you have to pay for each prescription?

    $_____ for brand name prescriptions $_____ for generic prescriptions

    _____ COINSURANCE: **A fixed percent** of the price that you pay each time you get a prescription. (For example 20%)

    What percent of the price do you have to pay for each prescription?

    _____% for brand name prescriptions _____% for generic prescriptions

    _____ DEDUCTIBLE: A fixed amount that you have to pay before your insurance company starts to pay for prescriptions. (For example $200)

    What is the amount of your deductible?

    $_____

    _____ OTHER: If you plan has any other type of cost sharing, please describe it below.

    _____

    _____

    _____

_____ NO COST SHARING: Insurance company pays **ALL** of my prescription drug costs.

25. Who sends in the claim to the insurance company when you get a prescription drug?

_____ my pharmacy sends in the claim
_____ I send in the claim
_____ other (please describe)_____

26. What is the source of your **prescription drug** insurance? (If you have more than one source of prescription drug insurance check all that apply.)

_____ employer, family member's employer, or former employer **(answer 26a)**
_____ the government (for example Medicaid or Veterans' Administration)
_____ you purchased it directly from an insurance company
_____ other (please describe)_____

26a. If your prescription drug insurance is from an employer, approximately how many employees does the employer have?

_____ 10 or less
_____ 11 to 25
_____ 26 to 50
_____ 51 to 100
_____ 101 to 500
_____ more than 500

27. How many health insurance plans did you have to choose from?

_____ 1
_____ 2 or 3
_____ more than 3
_____ don't know

28. Did all of the health insurance plans cover prescription drugs?

_____ yes
_____ no
_____ don't know

29. About how much do you have to pay **each** month for your health insurance plan that includes prescription drug coverage?

$_____

30. Is your health insurance an individual or family plan?

_____ Individual
_____ Family

31. Was there any time in the last year when you did **NOT** have insurance for prescription drugs?

_____ yes
_____ no
_____ don't know

Only answer question 32 if you presently do not have insurance coverage for prescription drugs. If you have prescription drug insurance please skip to Part E (question 33).

32. Please check the reason which **BEST** describes why you do not have prescription drug insurance.

_____ the insurance offered by my employer did not include prescription drug insurance
_____ I could have purchased prescription drug insurance but I decided it cost too much
_____ I do not think I need prescription drug insurance
_____ the insurance company refused to give me prescription drug insurance
_____ other (please describe)_____
_____
_____
_____

Part E: Information About Yourself

Finally, we would like some information about yourself to help us learn who does and does not have access to health insurance.

33. What is your age?

_____ years

34. What is your gender?

_____ female
_____ male

35 What is your level of education? (Please check the highest level that you completed)

_____ elementary school
_____ some high school
_____ graduated high school
_____ some post high school
_____ graduated 4 year college
_____ Masters, Ph.D., or professional degree

36. What is your zip code? _____

37. Are you currently employed?

_____ yes, working 35 or more hours per week
_____ yes, working 15 to 34 hours per week
_____ yes, working 1 to 14 hours per week
_____ no, not currently employed

38. How many people (including yourself and children) regularly live in your household?

_____

39. Do you have any children under the age of 5 who regularly live in your household?

_____ yes
_____ no

40. What was your approximate annual **household** income, before taxes in 1997? (Please check one.)

_____ less than $10,000
_____ $10,000 to $14,999
_____ $15,000 to $24,999
_____ $ 25,000 to $34,999
_____ $35,000 to $49,999
_____ $50,000 to $64,999
_____ $65,000 to $79,999
_____ $80,000 or more

41. How would you rate your health relative to others who are your age?

_____ Excellent
_____ Very Good
_____ Good
_____ Fair
_____ Poor

42. Please check **ANY** of the following medical conditions that a doctor has ever told you that you have.

_____ allergies/hayfever
_____ anxiety or panic attacks
_____ arthritis
_____ asthma
_____ back pain (severe and chronic)
_____ depression
_____ diabetes
_____ epilepsy/seizures
_____ glaucoma
_____ gout
_____ heart problem
_____ high blood pressure
_____ high cholesterol
_____ migraine headaches
_____ stomach ulcer
_____ thyroid problem
_____ other _____
_____ other _____

43. If you know the name of your health insurance plan please list it below. If you have more than one health insurance plan, list the plan(s) which cover(s) prescription drugs.

_____

We welcome any comments about health insurance, prescription drugs, or the survey

THANK YOU VERY MUCH FOR YOUR HELP!

APPENDIX C

POSTCARDS, COVER LETTER, AND QUESTIONNAIRE

Dear Wisconsin Consumer:

In the next week, you will receive a survey in the mail from the University of Wisconsin School of Pharmacy about health insurance and access to prescription drugs.

The survey is being sent to a randomly selected sample of Wisconsin consumers. Your response is very important, so please complete and return the survey when you receive it.

Thank you,

David Kreling, Ph.D., R.Ph.
University of Wisconsin
School of Pharmacy

Julie Ganther, M.S., R.Ph.
University of Wisconsin
School of Pharmacy

Dear Wisconsin Consumer:

Last week you received a survey from the University of Wisconsin about health insurance and access to prescription drugs.

If you have completed and returned the survey, **thank you very much for your help**. If not, please do so as soon as possible, because your response is very important to us.

If you did not receive the survey, or need a replacement, please call us at (608) 262-3454 and we will send you another.

Thank you,

David Kreling, Ph.D., R.Ph.
UW School of Pharmacy

Julie Ganther, M.S., R.Ph.
UW School of Pharmacy

UNIVERSITY OF
WISCONSIN
MADISON

February, 1999

Dear Wisconsin Consumer,

The cost of medical care in the United States is increasing at a rapid rate. This especially is true for prescription drugs, which are becoming more and more expensive. This is of concern because many Wisconsin residents do not have any health insurance coverage, and many more do not have insurance coverage for prescription drugs. Your input is needed to learn more about whether people without insurance have the same access to doctors and prescription drugs as people with insurance.

We would like to invite you to participate in a research survey. We are interested in responses both from people with health insurance and people without health insurance. Your information also is important to us even if you do not use any prescription drugs. Although there is no direct benefit to you for participating, we hope that the results will be used to improve access to health care, and this may help consumers in the future.

Your name was selected at random for the study and your participation is voluntary. Your response is important, so please take about 15-25 minutes now to complete the survey and return it in the postage paid envelope provided. Your responses will be compiled with those of other Wisconsin consumers and are completely anonymous.

Thank you for taking time to share your information with us. If you have any questions concerning the survey, or need help answering any part of the survey, please call us at (608) 262-3454.

Sincerely,

David H. Kreling

David H. Kreling, Ph.D., R.Ph.
Associate Professor
School of Pharmacy
University of Wisconsin - Madison

Julie Ganther

Julie M. Ganther, M.S., R.Ph.
Doctoral Candidate
School of Pharmacy
University of Wisconsin - Madison

P.S. The one dollar bill is yours to keep. Thank you for your help!

Survey on Health Insurance and Access to Prescription Drugs

You can help us learn whether people without health insurance have the same access to prescription drugs as people with health insurance. We are interested in responses both from people with insurance and people without health insurance. Your information also is important even if you do not use any prescription drugs.

<u>All responses are very important to us!</u>

Answering these survey questions will take 15 to 25 minutes. To preserve the anonymity of your responses, please do not write your name anywhere on the form or put your address on the return envelope. If you wish, you can give us additional comments in the space provided at the end of the form.

Part A: Health Insurance

Some people have all or part of their health care costs paid for by a private insurance plan or other program, for example Medicare, Medicaid, or Veterans Administration. We would like to know about your coverage for doctor visits and prescription drugs

For each question please check one answer.

1. Is there a private insurance plan or other program that pays for your doctor visits?

_____ yes, **ALL** of my doctor visit costs are paid for
_____ yes, **PART** of my doctor visit costs are paid for
_____ no
_____ don't know

2. Is there a private insurance plan or other program that pays for your prescription drugs?

_____ yes, **ALL** of my prescription drug costs are paid for
_____ yes, **PART** of my prescription drug costs are paid for
_____ no
_____ don't know

Part B: Use and Cost of Medical Care

Next we would like to ask you some questions about your use of doctors and prescription drugs

3. How many times did you visit a doctor in the last 30 days?

_____

4. About how many times did you visit a doctor in the last 6 months?

_____

5. How far do you usually travel to visit a doctor?

_____ less than 1 mile
_____ 1 to 5 miles
_____ 6 to 10 miles
_____ 11 to 20 miles
_____ more than 20 miles

6. How many different prescription drugs did you use in the last 30 days?

_____

7. How sure are you that you can get a prescription drug if you need one?

_____ totally sure
_____ very sure
_____ fairly sure
_____ only a little sure
_____ not at all sure

If you did not use any prescription drugs in the last month, skip to question 13.

8. About how much did you spend for prescription drugs in the last 30 days?

$_____

9. How far do you usually travel to pick up a prescription?

_____ less than 1 mile
_____ 1 to 5 miles
_____ 6 to 10 miles
_____ 11 to 20 miles
_____ more than 20 miles

10. How many different pharmacies do you get prescription drugs from?

_____

11. What types of pharmacies do you get prescription from? (Check **ALL** that apply)

_____ chain pharmacy (for example Walgreens, Shopko, Kmart, Walmart, Osco)
_____ independent pharmacy (pharmacy that is locally owned)
_____ clinic pharmacy (pharmacy that is inside a medical clinic)
_____ mail order pharmacy
_____ other (please describe)_____

Now, we need some information about the specific prescription drugs you use, to determine whether the uninsured have access to the same types of drugs as the insured.

12. Please list the drug name and strength, the directions for use, and about how many you used for **each** prescription drug you took in the **last 30 days** (you may need to look at your prescription vials to get some of this information). If you need more room use the back of the survey.

OR

If it would be easier, you can get this information from your pharmacy. To do this: 1) ask your pharmacy to print out a report of the prescriptions you purchased in the last 3 months -we need 3 months because all of the prescription drugs you used in the last month may not have been purchased in the last month, 2) remove your name from the report, and 3) mail the report back with the survey. Most pharmacies print out this report for you free of charge.

Drug Name and Strength	**Directions (how you took it)**	**Quantity used in the last 30 days**
Example: Amoxicillin 500mg	1 capsule 3 times a day	21
Example: OrthoNovum 1/35	1 tablet once a day	about 30
Example: Tylenol with Codeine #3	1 or 2 tablets as needed	about 15

Part C: Medical Care Preferences

Now we want to know some of your feelings about doctors and prescription drugs. When answering the questions, try to think about your general preferences for using

Please circle your level of agreement with each statement, using the scale provided.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
13. For most health problems, I would rather treat myself than go to the doctor.	SD	D	N	A	SA
14. For most health problems, I prefer to avoid taking prescription drugs.	SD	D	N	A	SA
15. I usually like to talk to a doctor when I have a health problem.	SD	D	N	A	SA
16. I know my health better than most doctors do.	SD	D	N	A	SA
17. For most health problems, I wait and see if I get better on my own before going to see a doctor.	SD	D	N	A	SA
18. For most health problems, I wait and see if I get better on my own before taking a prescription drug.	SD	D	N	A	SA
19. When I have a health problem, I often prefer to use home remedies instead of prescription drugs.	SD	D	N	A	SA
20. When I have a health problem, I usually contact a doctor right away.	SD	D	N	A	SA
21. For most health problems, I would rather take a prescription drug than a non-prescription drug.	SD	D	N	A	SA
22. When I have a health problem, it is sometimes hard to convince me to see a doctor.	SD	D	N	A	SA
23. I prefer to treat most health problems without help from doctors or prescription drugs.	SD	D	N	A	SA

Part D: Prescription Drug Insurance

Now we would like some information about your prescription drug insurance. If you have insurance or another program that pays for prescription drugs please answer items 24 - 32. If you do **NOT** have insurance for prescription drugs please skip to item 33.

24. Even people with prescription drug insurance may have to pay part of the cost for prescription drugs. Please check **ANY** of the types of cost sharing listed below that your prescription drug insurance plan uses (copayment, coinsurance, deductible, or other). For each type you check, fill in the cost that you have to pay. Sometimes the amount of cost sharing is different for brand name and generic prescriptions. If you are not sure about the amount you pay and you have a prescription drug card, the information may be on the card.

If an insurance company or other program pays **ALL** of your prescription drug costs please check here _____ and skip the rest of this question.

_____ COPAYMENT: A **fixed amount** that you pay each time you get a prescription. (For example $10 for brand name, $5 for generic)

What is the amount you have to pay for each prescription?

$_____ for brand name prescriptions
$_____ for generic prescriptions

_____ COINSURANCE: A **fixed percent** of the price that you pay each time you get a prescription. (For example 20%)

What percent of the price do you have to pay for each prescription?

_____% for brand name prescriptions
_____% for generic prescriptions

_____ DEDUCTIBLE: A fixed amount that you have to pay before your insurance company starts to pay for prescriptions. (For example $200)

What is the amount of your deductible?
$_____

_____ OTHER: If your plan has any other type of cost sharing, please describe it below.

_____

_____

25. Who sends in the claim to the insurance company when you get a prescription drug?

_____ my pharmacy sends in the claim
_____ I send in the claim
_____ other (please describe)_____

26. What is the source of your **prescription drug** insurance? (If you have more than one source of prescription drug insurance check all that apply.)

_____ my employer, a family member's employer, or former employer (**answer 26a**)
_____ the government (for example Medicaid or Veterans Administration)
_____ I purchased it directly from an insurance company
_____ other (please describe)_____

26a. If your prescription drug insurance is from an employer, approximately how many employees does the employer have?

_____ 10 or less
_____ 11 to 25
_____ 26 to 50
_____ 51 to 100
_____ 101 to 500
_____ more than 500

27. How many health insurance plans did you have to choose from?
_____ 1
_____ 2 or 3
_____ more than 3
_____ don't know

28. Did all of the health insurance plans cover prescription drugs?

_____ yes
_____ no
_____ don't know

29. About how much do you have to pay **each** month for your health insurance plan that includes prescription drug coverage?

$_____

30. Is your health insurance an individual or family plan?

_____ Individual
_____ Family

31. Have you changed health insurance plans in the last year?

_____ yes
_____ no
_____ don't know

32. Was there any time in the last year when you did **NOT** have insurance for prescription drugs?

_____ yes (on the lines below, please describe what happened)
_____ no
_____ don't know

If there was some time in the last year when you did **NOT** have insurance for prescription drugs, please describe what happened.

_____
_____
_____
_____

Only answer question 33 if you do <u>NOT</u> have insurance coverage for prescription drugs. If you have prescription drug insurance please skip to Part E (question 34).

33. Please check the reason which **BEST** describes why you do **NOT** have prescription drug insurance.

_____ the insurance offered by my employer did not include prescription drug insurance
_____ I could have purchased prescription drug insurance but I decided it cost too much
_____ I do not think I need prescription drug insurance
_____ the insurance company refused to give me prescription drug insurance
_____ other (please describe)_____
_____

Part E: Information About Yourself

Finally, we would like some information about yourself to help us learn who does and does not have access to health insurance.

34. What is your age?

_____ years

35. What is your gender?

_____ female

_____ male

36. What is your level of education? (Please check the highest level that you completed)

_____ elementary school or some high school

_____ graduated high school

_____ some post high school

_____ graduated 4 year college

_____ Masters, Ph.D., or professional degree

37. What is your zip code?

_____

38. Are you currently employed?

_____ yes, working 35 or more hours per week

_____ yes, working 15 to 34 hours per week

_____ yes, working 1 to 14 hours per week

_____ no, not currently employed (includes retired)

39. How do you describe yourself?

_____ White/Caucasian

_____ Hispanic/Latino

_____ Black/African-American

_____ Asian

_____ American Indian

_____ other (please describe)_____

40. What was your approximate annual **household** income, before taxes in 1998? (Please check one.)

_____ less than $10,000
_____ $10,000 to $14,999
_____ $15,000 to $24,999
_____ $ 25,000 to $34,999
_____ $35,000 to $49,999
_____ $50,000 to $64,999
_____ $65,000 to $79,999
_____ $80,000 or more

41. How many people (including yourself and children) regularly live in your household?

_____

42. How would you rate your health relative to others who are your age?

_____ Excellent
_____ Very Good
_____ Good
_____ Fair
_____ Poor

43. Please check **ANY** of the following medical conditions that a doctor has ever told you that you have.

_____ allergies/hayfever
_____ anxiety or panic attacks
_____ arthritis
_____ asthma
_____ back pain (severe and chronic)
_____ depression
_____ diabetes
_____ epilepsy/seizures
_____ glaucoma
_____ gout
_____ heart problem
_____ high blood pressure
_____ high cholesterol
_____ migraine headaches
_____ stomach ulcer
_____ thyroid problem
_____ other _____
_____ other _____

44. Do you belong to a health maintenance organization (HMO)?

_____ yes
_____ no
_____ don't know

45. Are you enrolled in Medicare?

____ yes, Part A only (answer question 45a.)
____ yes, Parts A and B (answer question 45a)
____ no (skip to question 46)

45a. Do have a supplemental Medicare insurance (Medigap) plan?
_____ yes
_____ no
_____ don't know

46. If you know the name of your health insurance plan please list it below. If you have more than one health insurance plan, list the plan(s) which cover(s) prescription drugs.

_____

We welcome any comments about health insurance, prescription drugs, or the survey.

_____
_____
_____
_____
_____
_____
_____
_____
_____

THANK YOU VERY MUCH FOR YOUR HELP!

Please fold the survey and return it in the enclosed postage paid envelope. Do not put your name or address anywhere on the survey or the envelope.

APPENDIX D

HUMAN SUBJECTS REVIEW COMMITTEE APPROVAL

UNIVERSITY OF
WISCONSIN
MADISON

Human Subjects Committee
Approval Notice

January 12, 1999

David Kreling, R.Ph, Ph.D
Associate Professor
3152 Chamberlin Hall

RE: HSC Protocol #98-720-344, "Consumer Demand for Prescription Drugs: An Investigation of Moral Hazard, Adverse Selection and the Role of Medical Care Preferences"

Dear Dr. Krehling:

The Health Sciences Human Subjects Committee (HSC) initially reviewed your research protocol during its August 24, 1998 meeting and requested modifications. Your letter of 23 December 1998 has addressed its concerns. Your research (protocol dated 8/10/98) is now approved.

Your HSC research protocol number is listed above. Please use this number on any documents or correspondence with us concerning your research protocol. This will help us process any future requests about your research. Please keep a copy of this approval letter with your research files. The HSC approval for your research will expire **August 18, 1999.**

The HSC reviewed your research to ensure that federal and other requirements for protecting human subjects involved in research (45 CFR 46), which are contained in the University of Wisconsin- Madison's Multiple Project Assurance (M-1285), are met. The MPA is a written pledge to follow the guidelines in protecting human research subjects. The HSC ensures that the federal regulations under 21 CFR 50 & 56 are also met. Under the MPA investigators. the HSC, and the HSC office staff all work together to comply with those guidelines.

We are available to assist you; however please note that investigators have responsibilities when conducting research involving human subjects. Some of these are:

1. Continuing Review. The HSC must review and approve all research protocols at intervals appropriate to the degree of risk but not less than once per year. There is **no grace period beyond one year from the last HSC approval date.** About two months before the approval for your research expires, the HSC will send you a reminder to submit a Continuing Review Report. You will also receive a second reminder about a month before your research approval expires. Please ensure that your continuing review is submitted to avoid lapses in approval of your research and the potential suspension of subject enrollment until your research can be reapproved. Although the HSC sends reminders, **it is ultimately your responsibility to**

submit your research protocol for continuing review and approval by the HSC. This letter and the approval and expiration date stamp on your consent forms are helpful reminders.

2. Changes. If you wish to change any aspect of your research (research design, interventions or procedures, subject population, consent form, instruments, surveys or advertisements, to name a few), please submit the changes using the "Change of Protocol" form. Please be aware that you **may not initiate** any changes to your research without first obtaining HSC review and approval. The **only exception** is when it is necessary to eliminate apparent immediate hazards to subjects.

3. Adverse or unanticipated events. Please report any adverse or unanticipated problems which involved risks to subjects or others, as well as any research related injuries and deaths, to the HSC within 10 days. You must also report any instances of serious or continuing problems, or non-compliance with the HSC's requirements for protecting human research subjects.

4. Final reports. When you have completed your research or have stopped work on your research, please submit a final report to the HSC promptly.

If you need further help, please contact the HSC office staff at 263-2362.

Sincerely,

Judith Van Kirk

Judith Van Kirk, Acting Director
Health Sciences Human Subjects Committee Office

Enclosure: OPRR Reports: Protection of Human Subjects

APPENDIX E

PROTOCOL FOR USING MONETARY TOKENS

SOCIAL AND ADMINISTRATIVE SCIENCES
UW SCHOOL OF PHARMACY
TOKEN PROTOCOL
FOR
PAYMENT OF SUBJECTS
MAIL SURVEYS

Overview:

The protocol establishes procedures to be followed for payments to subjects. If the subject either chooses to participate and return the survey or does not participate, the subject will be paid the $1 token. The survey is anonymous, and a subject's identity cannot be determined if he/she chooses to participate and return the survey. Therefore from the mailing list we will not know who participated and who did not participate.

Procedures:

1. Prepare a list of subjects' names and addresses who will receive payment.
2. Obtain cash advance for total payment amount; see pharmacy business office for forms and details.
3. Obtain funds from local bank (M & I). e.g. $1 token bills for total amount of subject payment.
4. Affix or insert payment in cover letter.
5. Insert questionnaire and cover letter into envelope. DO NOT SEAL THE ENVELOPE.
6. Take unsealed envelopes to pharmacy business office where designated staff will conduct a random audit per general audit policy and procedures to verify that a payment token is in each envelope.
7. Seal envelopes in presence of assigned personnel and have business office person sign audit statement.
8. Mail surveys.
9. Maintain Record File:
   - Address list of subjects with a notation that each subject on the attached mailing list received payment.
   - Req. Order Form for payment of subjects and file forms.
   - Completed Audit Form
10. Any undeliverable surveys must be marked as undeliverable on the mailing list, and the $1 tokens returned to the account from which the funds were drawn.

APPENDIX F

QUESTIONNAIRE CODE BOOK

Field Name	Item	Coding Scheme
IDNUM	-	identification number assigned sequentially by date received.
DATE	-	date received
FORM	-	0 = ivory questionnaire, 1 = blue questionnaire
MDINS	1	0 = no physician insurance, 1 = part of physician costs covered, 2 = all of physician costs covered, 3 = don't know, 5 = catastrophic physician insurance plan ($5,000 deductible or more), 9 = missing
RXINS	2	0 = no prescription drug insurance, 1 = part of prescription costs covered, 2 = all of prescription costs covered, 3 = don't know, 5 = catastrophic prescription plan ($5,000 deductible or more), 9 = missing
TRAVMD	5	1 = less than 1 mile, 2 = 1 to 5 miles, 3 = 6 to 10 miles, 4 = 11 to 20 miles, 5 = more than 20 miles, 9 = missing
NUMRX	6	number listed, 99 = missing
RXEXP	8	amount listed, 9999 = missing
TRAVRX	9	1 = less than 1 mile, 2 = 1 to 5 miles, 3 = 6 to 10 miles, 4 = 11 to 20 miles, 5 = more than 20 miles, 9 = missing
QUES13	13	1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree, 9 = missing
QUES14	14	1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree, 9 = missing
QUES15	15	1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree, 9 = missing
QUES17	17	1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree, 9 = missing
QUES18	18	1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree, 9 = missing

QUES19	19	1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree, 9 = missing
QUES20	20	1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree, 9 = missing
QUES21	21	1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree, 9 = missing
QUES22	22	1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree, 9 = missing
PREFRXMD	23	1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree, 9 = missing
SOURCE	26	1 = employer, 2 = government, 3 = individual purchase, 4 = other, 9 = missing
NUMEMP	26a	1 = 10 or less, 2 = 11 to 25, 4 = 51 to 100, 5 = 101 to 500, 6 = more than 500, 9 = missing
NUMPLAN	27	1 = 1, 2 = 2 or 3, 3 = more than 3, 4 = don't know, 9 = missing
PLANRX	28	0 = no, 1 = yes, 2 = don't know, 9 = missing
PLANEXP	29	amount listed, 999 = missing
NEWPLAN	31	0 = no, 1 = yes, 2 = don't know, 9 = missing
INSGAP	32	0 = no, 1 = yes, 2 = don't know, 9 = missing
NOINS	33	1 = employer insurance did not include, 2 = available but cost too much, 3 = don't need insurance, 4 = refused by insurance company, 5 = other, 6 = can't afford
AGE	34	number listed, 999 = missing
GENDER	35	0 = male, 1 = female, 9 = missing
EDU	36	1 = elementary or some high school, 2 = graduated high school, 3 = some post high school, 4 = graduated 4 year college, 5 = Masters, Ph.D., or professional degree, 9 = missing
ZIP	37	number listed, 99999 = missing

EMPLOY	38	0 = not currently employed, 1 = working 35 or more hours per week, 2 = working 15 to 34 hours per week, 3 = working 1 to 14 hours per week, 4 = self-employed, 9 = missing
RACE	39	1 = White/Caucasian, 2 = Hispanic/Latino, 3 = Black/African-American, 4 = Asian, 5 = American Indian, 6 = other, 9=missing
INCOME	40	1 = less than $10,000, 2 = $10,000 to $14,999, 3 = $15,000 to $24,999, 4 = $25,000 to $34,999, 5 = $35,000 to $49,999, 6 = $50,000 to $ $64,999, 7 = $65,000 to $79,999, 8 = $80,000, 9=missing
NUMHOUSE	41	number listed, 99 = missing
HEALTH	42	1 = excellent, 2 = very good, 3 = good, 4 = fair, 5 = poor, 9=missing
NUMCOND	43	number of medical conditions checked, 99 = missing
ALLERGIES	43	0 = no, 1 = yes, 9 = missing
ANXIETY	43	0 = no, 1 = yes, 9 = missing
ARTHRITIS	43	0 = no, 1 = yes, 9 = missing
ASTHMA	43	0 = no, 1 = yes, 9 = missing
BACK	43	0 = no, 1 = yes, 9 = missing
DEPRES	43	0 = no, 1 = yes, 9 = missing
DIABETES	43	0 = no, 1 = yes, 9 = missing
EPILEPSY	43	0 = no, 1 = yes, 9 = missing
GLAUCOMA	43	0 = no, 1 = yes, 9 = missing
GOUT	43	0 = no, 1 = yes, 9 = missing
HEART	43	0 = no, 1 = yes, 9 = missing
HIGHBP	43	0 = no, 1 = yes, 9 = missing
HICHCHOL	43	0 = no, 1 = yes, 9 = missing
MIGRAINE	43	0 = no, 1 = yes, 9 = missing

STOMACH	43	0 = no, 1 = yes, 9 = missing
THYROID	43	0 = no, 1 = yes, 9 = missing
OTHCOND1	43	see list of codes
OTHCOND2	43	see list of codes
HMO	44	0 = no, 1 = yes, 2 = don't know, 9 = missing
MEDICARE	45	0 = no, 1 = Part A only, 2 = Parts A and B, 9 = missing
MEDIGAP	45a	0 = no, 1 = yes, 2 = don't know, 9 = missing
PLANNAME	46	name listed
COMMENT	-	0 = no comment, 1 = comment

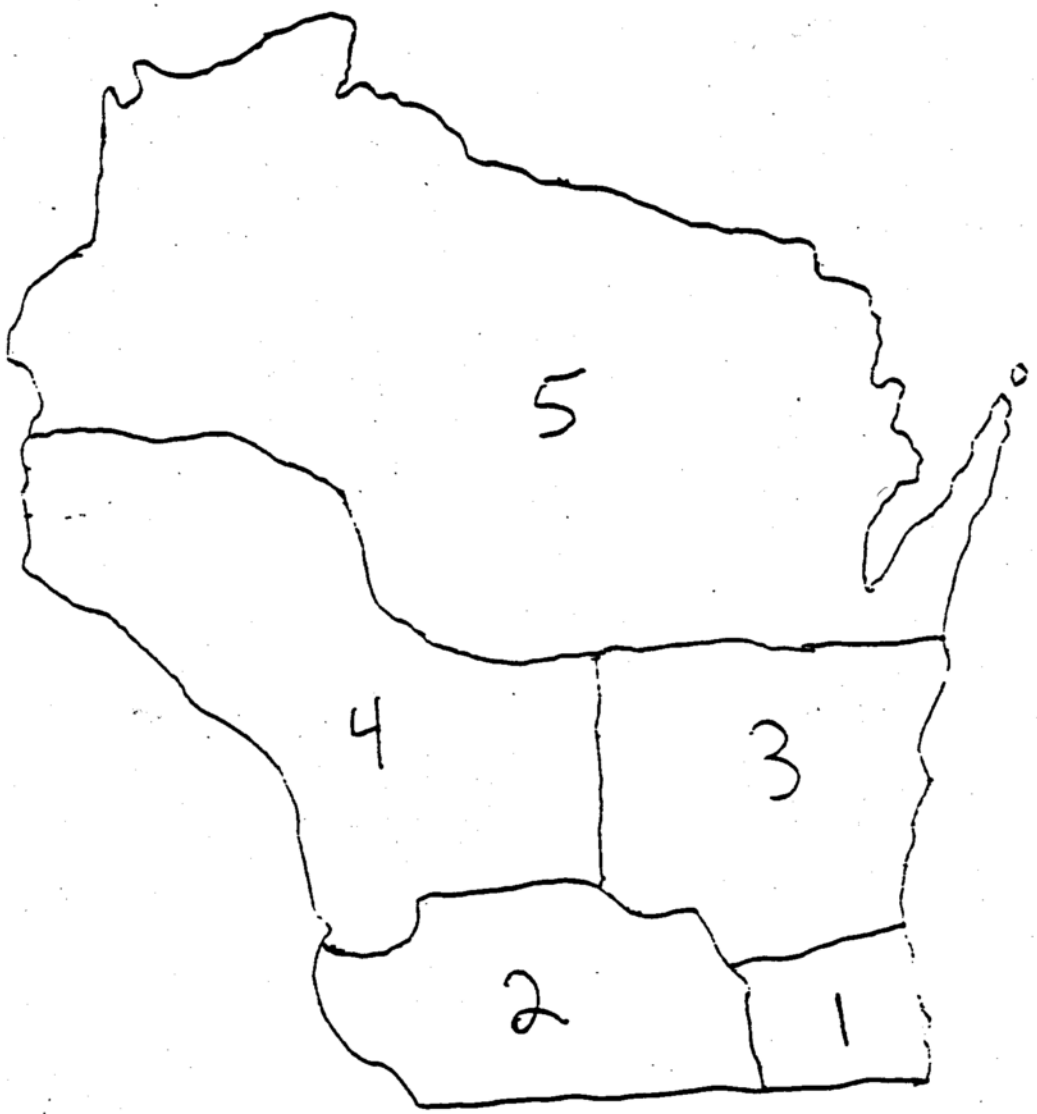
LIST OF CODES FOR OTHER CONDITIONS:

1. cancer
2. Lymes Disease
3. prostate problem
4. fibramyalgia
5. irritable bowel syndrome/Crohn's disease/ulcerative colitis
6. osteoporosis
7. hernia
8. miscellaneous
9. anemia or other blood disorder (except blood clots)
10. kidney failure/other kidney problem
11. gallstones or other gallbladder problem
12. cataracts or other eye problem
13. blood clots
14. psoriasis or other skin disease
15. hepatitis or other liver problem
16. post-stroke
17. diverticulitis
18. multiple sclerosis
19. bladder problem
20. schizophrenia
21. Parkinsons

APPENDIX G

GEOGRAPHIC REGION DEFINITION

GEOGRAPHIC REGION	CODE	ZIP CODES (first three digits)
SOUTHEAST	1	531 to 534
SOUTHCENTRAL/SOUTHWEST	2	535 to 538
EAST	3	530, 542, 543, 549
WEST	4	539, 540, 546, 547
NORTH	5	541, 544, 545, 548



APPENDIX H

COMPARISON OF EARLY AND LATE RESPONDERS

Mean (Standard Deviation) for Uninsured Individuals

Variable	Early Responders[1]	Late Responders[2]
Health Status	2.52 (0.97)	2.62 (1.10)
Global Preference Item	3.00 (1.11)	3.16 (1.10)
Number of Prescriptions	2.14 (2.10)	2.30 (2.32)

1. First 200 respondents
2. Last 200 respondents

Mean (Standard Deviation) for Insured Individuals

Variable	Early Responders[1]	Late Responders[2]
Health Status	2.43 (1.06)	2.43 (1.03)
Global Preference Item	2.81 (1.12)	2.83 (1.06)
Number of Prescriptions	2.40 (2.28)	2.64 (2.42)

1. First 200 respondents
2. Last 200 respondents

APPENDIX I

NEWSPAPER ARTICLE ON DOLLAR TOKENS

Lawmaker attacks UW survey with dollar for 'beverage'

By Mac Jones
of the Journal Sentinel staff

A survey two University of Wisconsin-Madison pharmacy administration professors sent to 1,000 randomly selected people included a dollar bill with the suggestion that they spend it on the beverage of their choice.

A state legislator Monday questioned the wisdom of using taxpayer money to encourage people to drink, particularly since many would probably choose a beverage that offers more of a kick than coffee or soda.

State Rep. Scott Suder (R-Abbotsford) was also critical of giving away university funds at a time when UW is asking for money.

"The surveys, from what I've been told, have only 50% to 60% return rate, so it's like throwing money away. It adds insult to injury to tell people to have a beverage of their choice," Suder said in a phone interview Monday.

"I don't think anyone can argue that sending free money in the mail to randomly selected people is good tax policy."

It is common to send a dollar or a token gift in surveys to encourage people to fill them out, said Joseph Wiederholt, a pharmacist and professor of pharmacy administration at UW-Madison. Wiederholt and David Kreling, an associate professor of pharmacy administration, sent the surveys to pharmacy consumers, throughout the state but mostly in Dane County, on Feb. 8.

The token payment "is an incentive to increase response rates," Wiederholt said. "If we don't have adequate response rates, it's difficult to use and analyze the data."

A survey was sent to Suder's office. He said he hopes "to send the dollar back to the taxpayers in some way."

Wiederholt said he didn't intend the suggestion to use the dollar on a beverage to encourage consumption of alcohol.

"When you look at the beverages you can buy with $1, what can you buy? A cup of coffee or a pop," he said.

The goal of the surveys was to come up with ways for pharmacists to improve service, Wiederholt added. The surveys questioned people about the importance of prescription medicine benefits when selecting health insurance carriers and the criteria needed to evaluate the service of pharmacists and pharmacies.

Wiederholt hopes to get a response rate of 50% to 70%. The $1,000 sent in the surveys came from a fund set up by a UW alumnus for this type of research.

But Suder, who was recently appointed chairman of the Assembly Wastecutters Task Force, said he doubts people who donate money to the university for research would want "it given away to do surveys."

APPENDIX J

COMPARISON OF LOW AND HIGH ADVERSE SELECTION RISKS

Comparison of High and Low Adverse Selection Risk Groups

Variable	Adverse Selection Risk (%) Low Risk[1]	High Risk[2]
Age		
50 to 64	47.1	49.7
65 and older	52.9	50.3
Gender		
male	40.2	37.8
female	59.8	62.2
Household Income		
less than $15,000	25.6	22.5
$15,000 to $49,999	52.9	56.3
$50,000 or more	21.5	21.2
Employment Status		
unemployed	59.3	52.8
employed part time	9.8	16.5
employed full time	30.9	30.7
Prescription Drug Insurance		
yes	63.5	69.7
no	36.5	30.3
Self-Reported Health Status		
excellent	14.1	19.4
very good	32.1	37.2
good	36.3	30.6
fair or poor	17.5	12.8

1. N = 1,338
2. N = 320

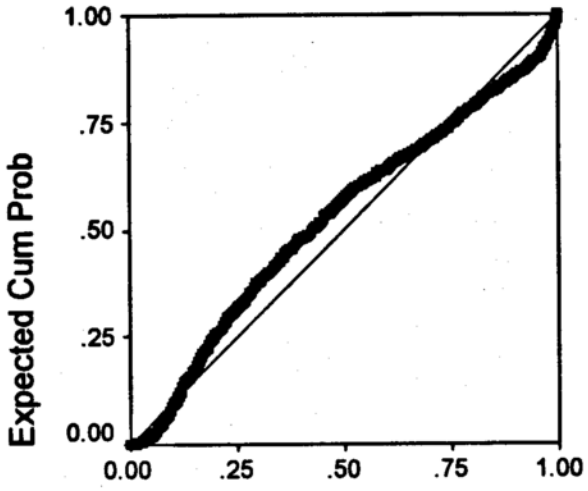
APPENDIX K

REGRESSION DIAGNOSTICS

Normal P-P Plot of Regression

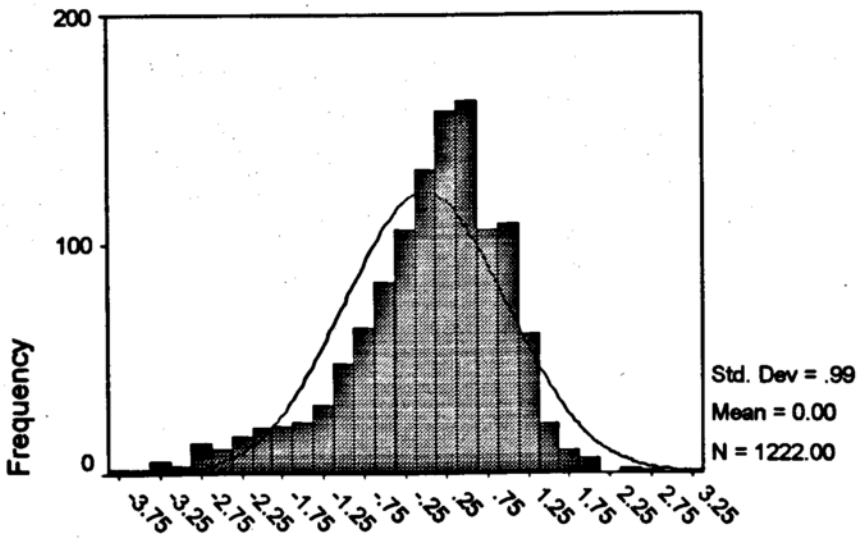
Standardized Residual

Dependent Variable: lnrxcost



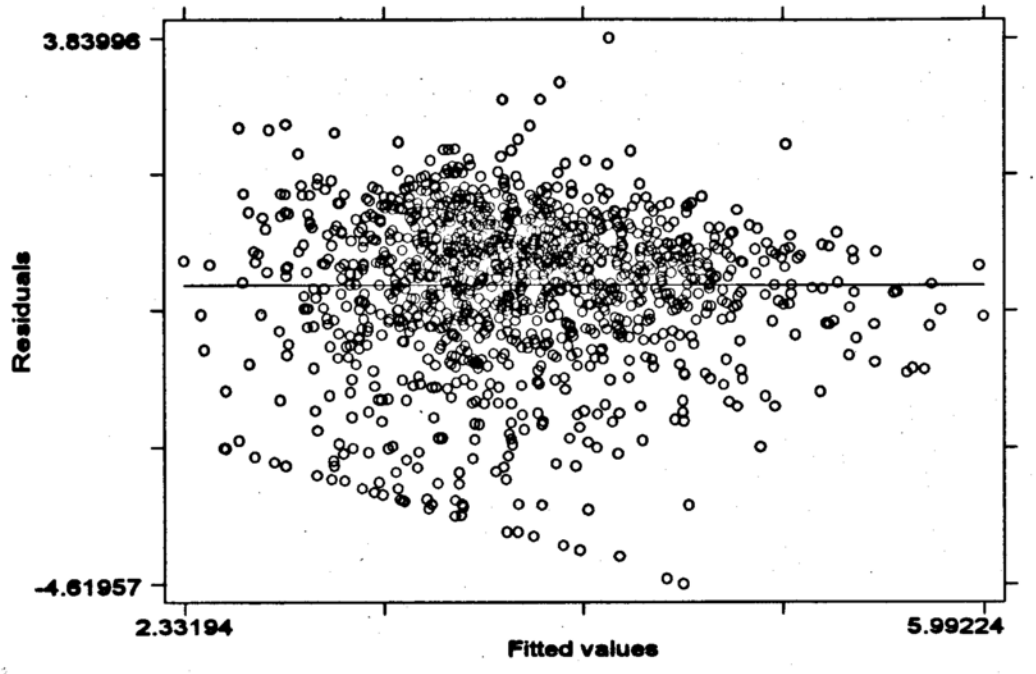
Histogram

Dependent Variable: LNRXCOST



Tests for Heteroscedasticity

Plot of residuals vs fitted values for OLS regression model:



Cook-Weisberg test for heteroscedasticity using fitted values of lnrxcost

Ho: Constant variance

$chi^2(1) = 32.72$

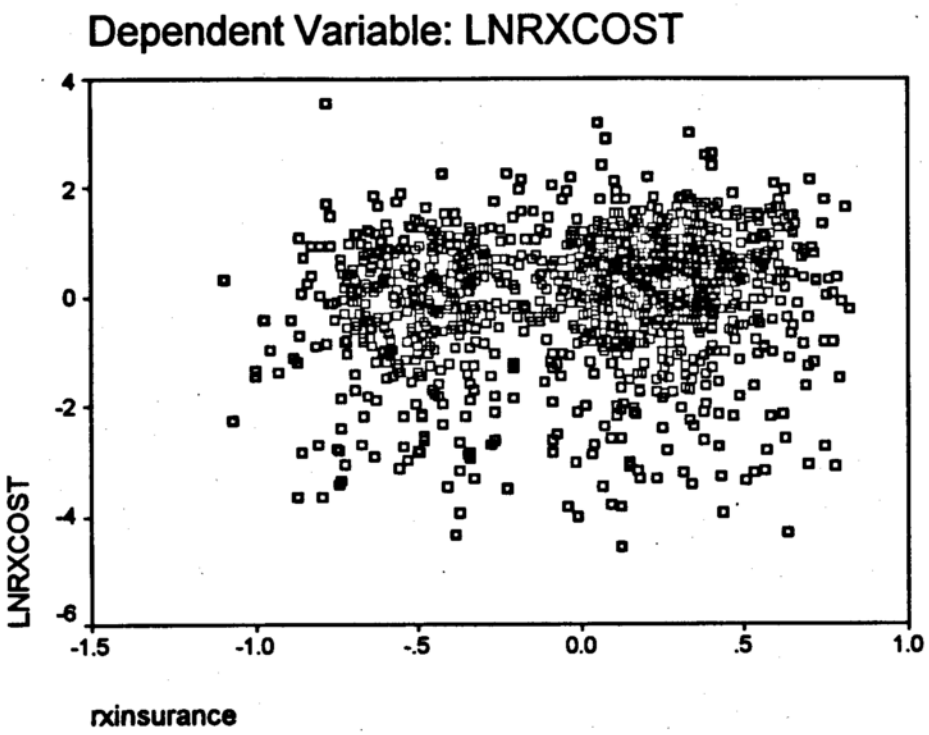
Prob > chi2 = 0.0000

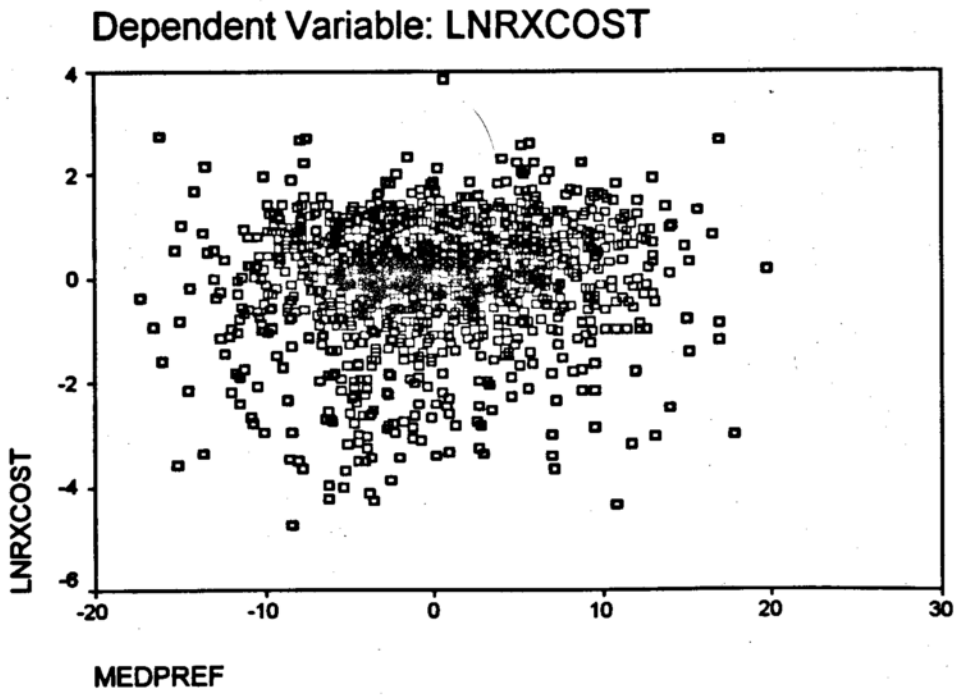
Tests for Multicollinearity

Variable	VIF	1/VIF
age	176.82	0.0057
agesquared	174.20	0.0057
goodhlth	3.28	0.3046
inc>64	3.15	0.3175
verygdhlth	2.86	0.3500
fairpoorhlth	2.81	0.3554
inc15to24	2.81	0.3562
inc25to34	2.79	0.3589
collegegrad	2.74	0.3655
inc35to49	2.68	0.3734
posthighsch	2.44	0.4099
highschgrad	2.29	0.4358
inc10to14	2.25	0.4445
inc50to64	2.10	0.4753
east	1.43	0.6986
ln(numhouse)	1.42	0.7037
north	1.42	0.7063
travmd	1.38	0.7263
swestcentral	1.37	0.7296
travph	1.36	0.7334
west	1.35	0.7421
rxinsurance	1.30	0.7700
female	1.28	0.7789
numcond	1.21	0.8240
memberhmo	1.13	0.8840
medpref	1.12	0.8896

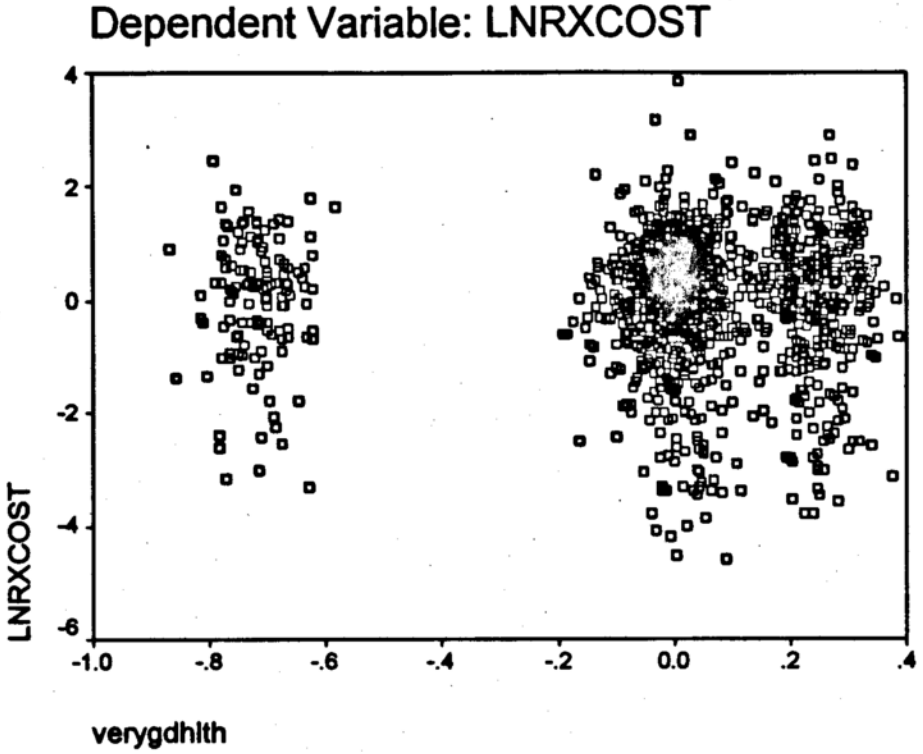
Mean VIF = 15.35
Mean VIF w/o agesquared in the model = 1.98

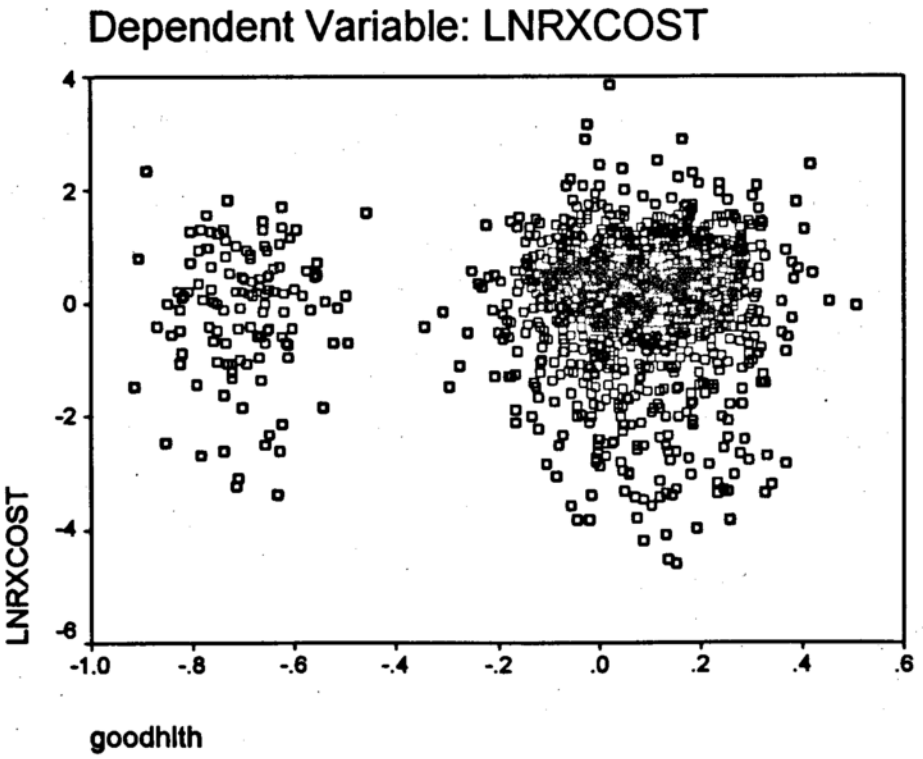
Partial Regression Plots for OLS Regression Model[1]

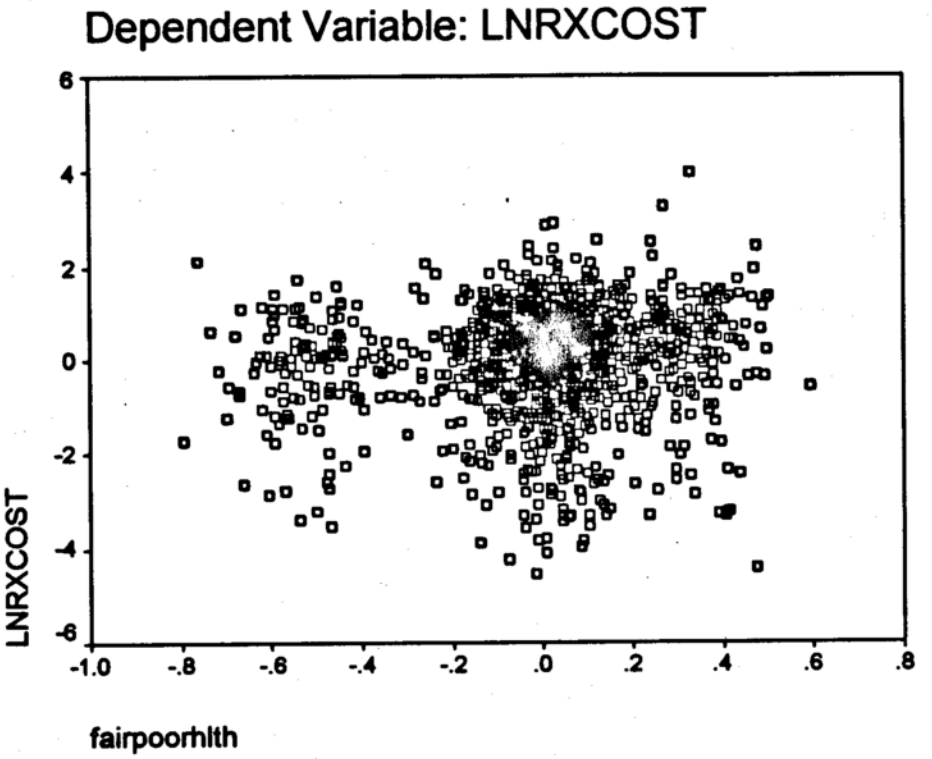


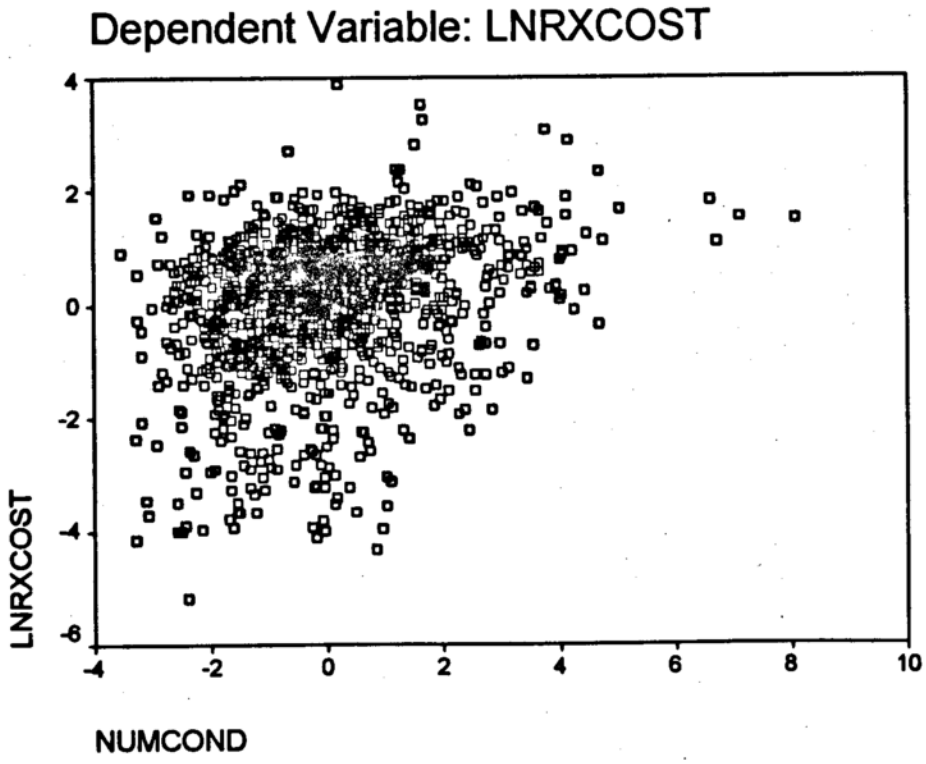


1. For OLS regression model with RXINSURANCE, MEDPREF, and control variables.

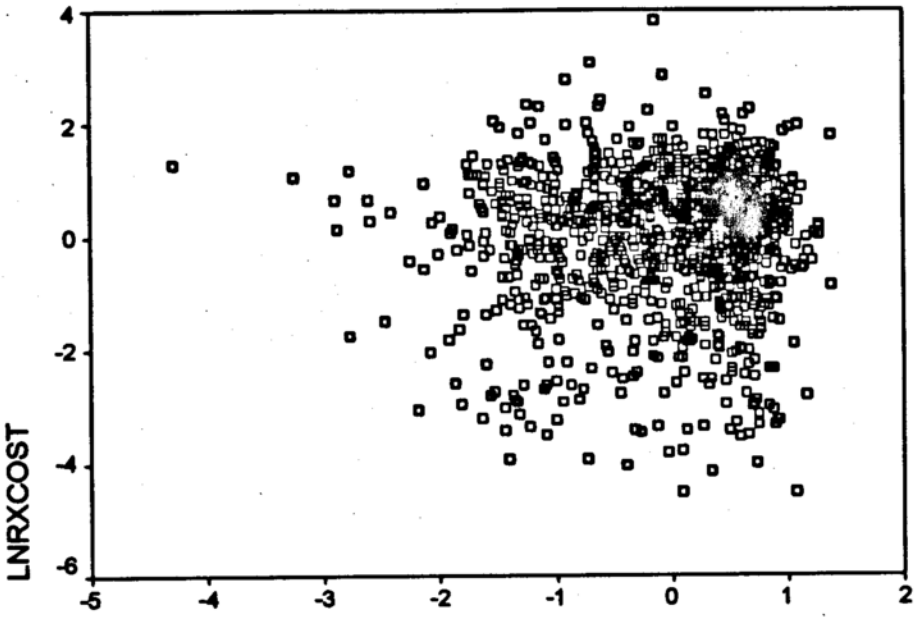

Dependent Variable: LNRXCOST
LNRXCOST
4
2
0
-2
-4
-6
-1.0
-.8
-.6
-.4
-.2
0.0
.2
.4
verygdhlth


Dependent Variable: LNRXCOST
LNRXCOST
4
2
0
-2
-4
-6
-1.0
-.8
-.6
-.4
-.2
.0
.2
.4
.6
goodhlth

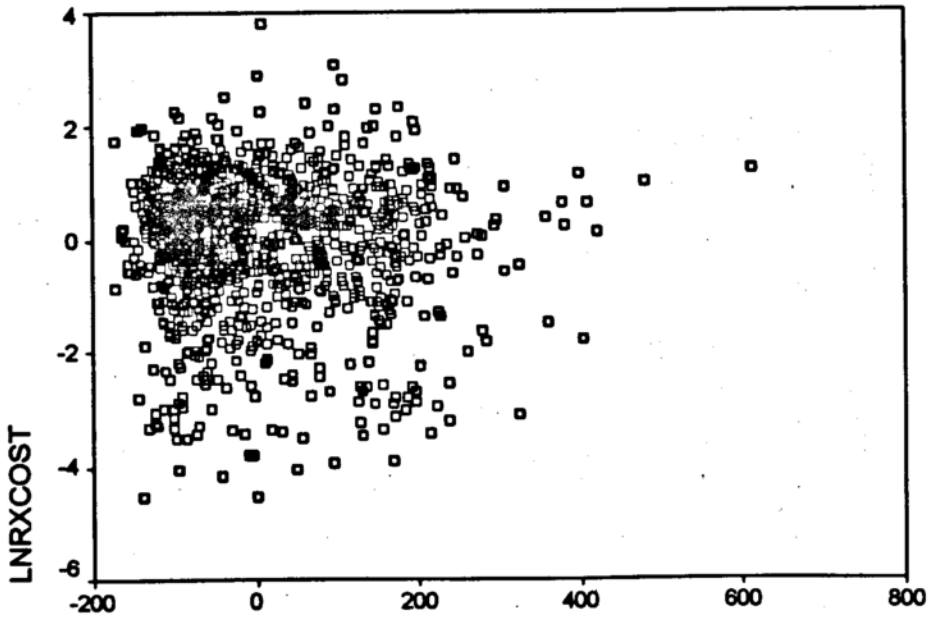

Dependent Variable: LNRXCOST
LNRXCOST
6
4
2
0
-2
-4
-6
-1.0
-.8
-.6
-.4
-.2
.0
.2
.4
.6
.8
fairpoorhlth

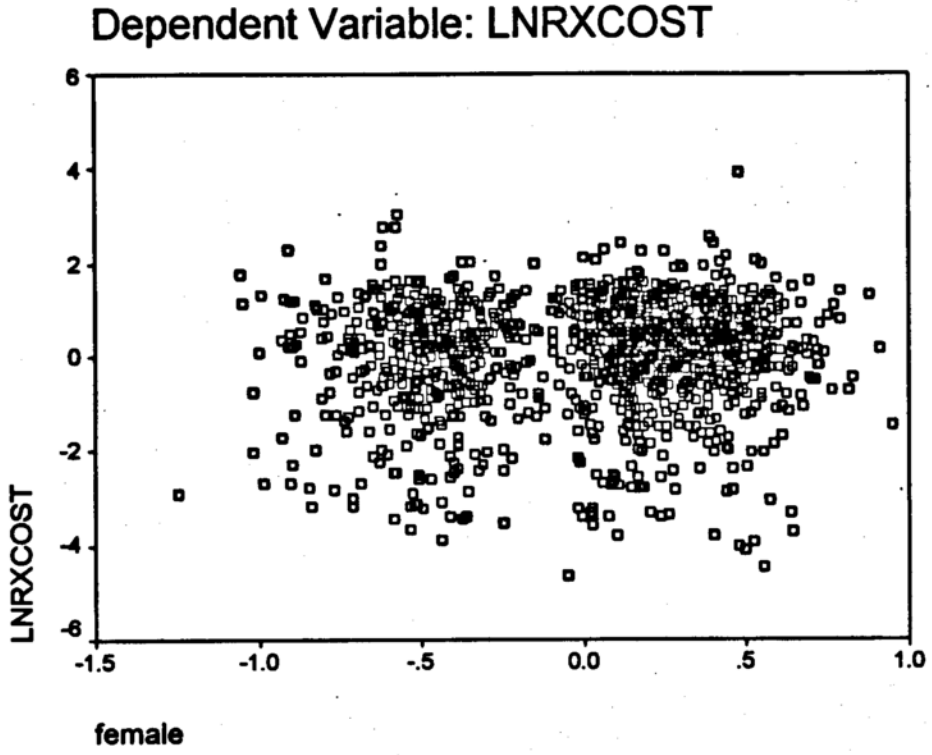

Dependent Variable: LNRXCOST
LNRXCOST
4
2
0
-2
-4
-6
-4
-2
0
2
4
6
8
10
NUMCOND

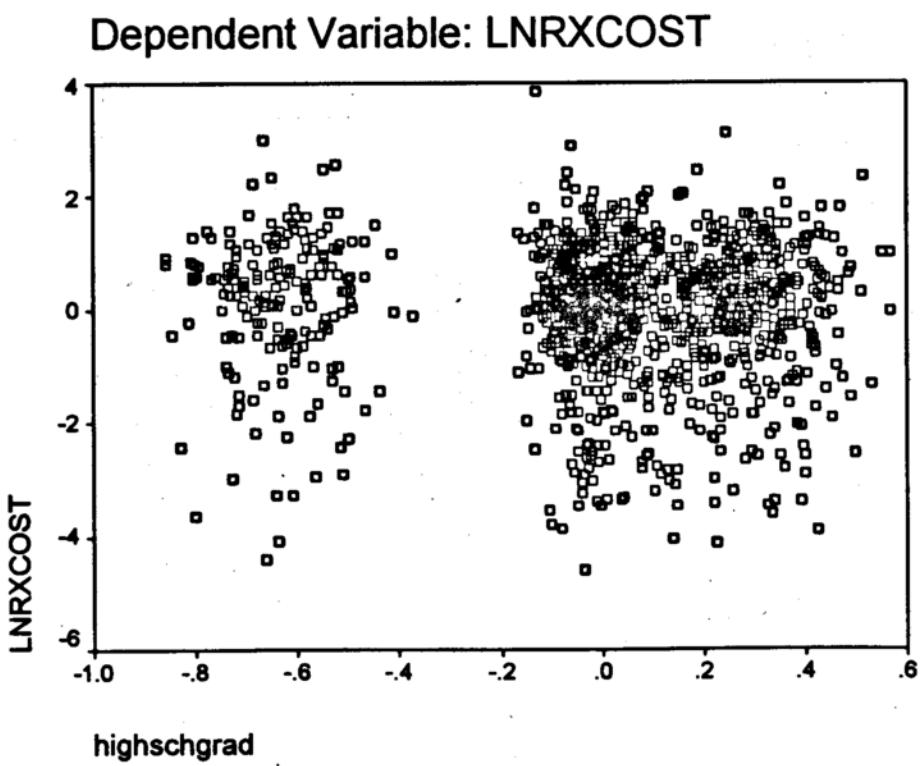
Dependent Variable: LNRXCOST

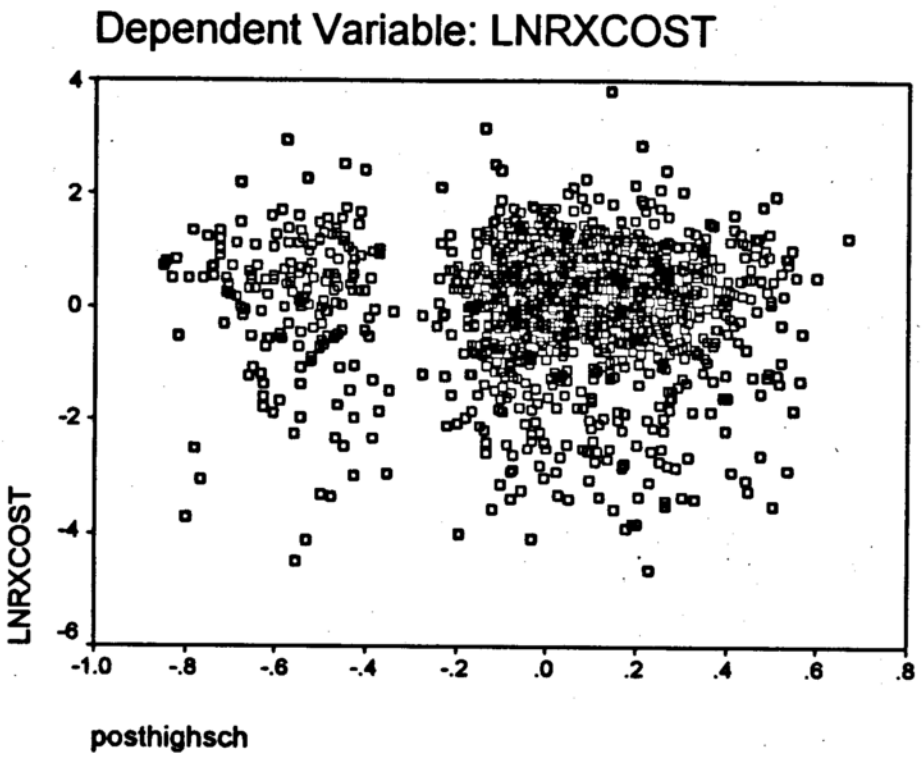


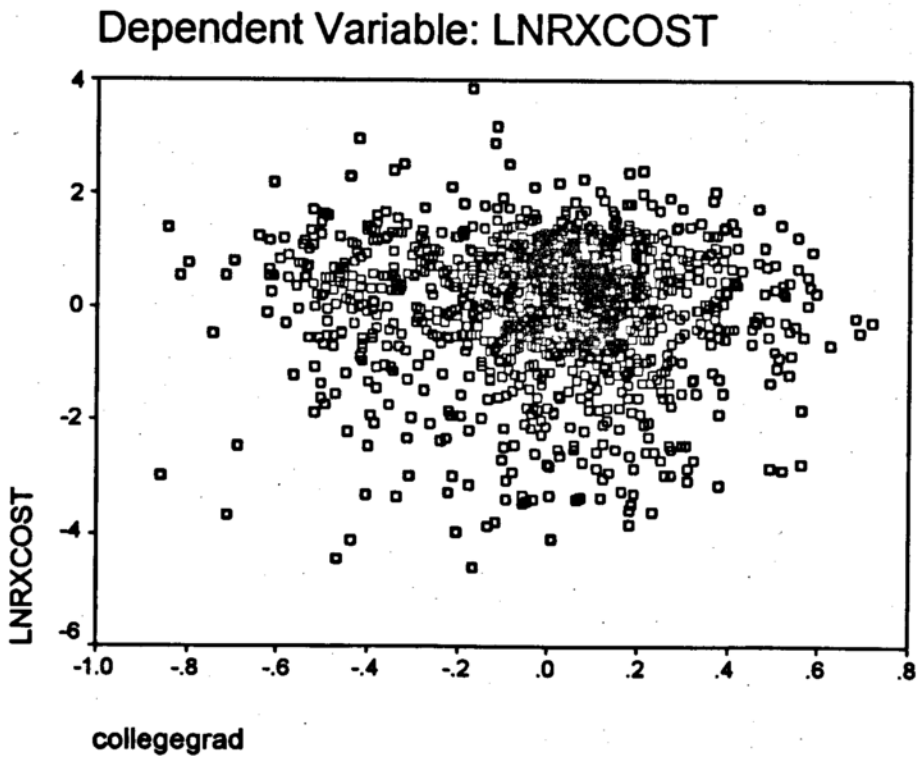
Dependent Variable: LNRXCOST

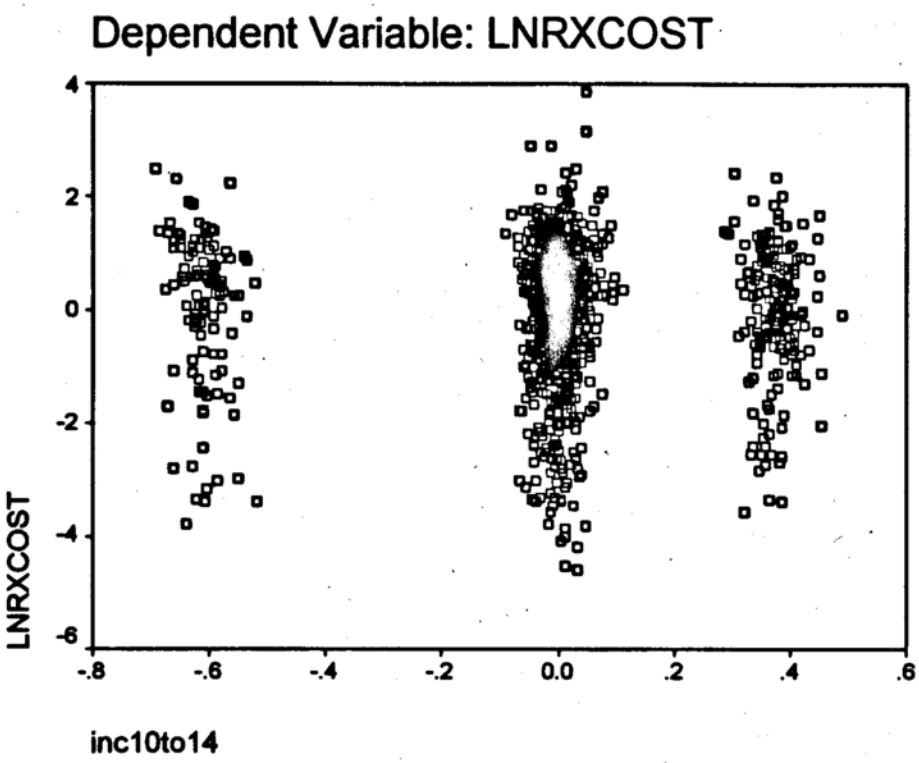


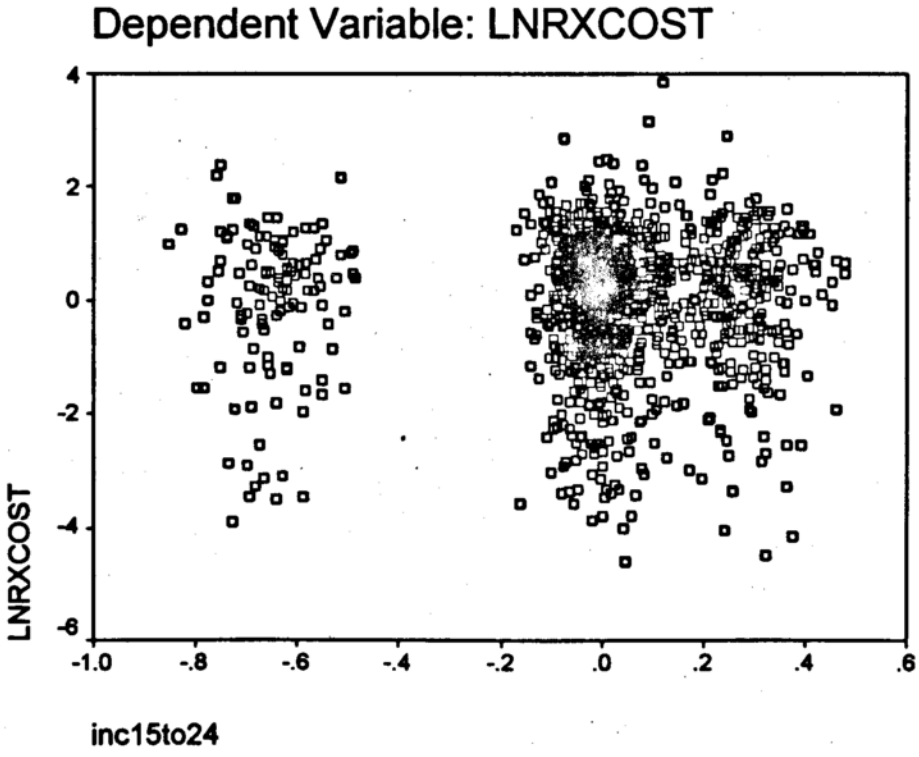

Dependent Variable: LNRXCOST
LNRXCOST
6
4
2
0
-2
-4
-6
-1.5
-1.0
-.5
0.0
.5
1.0
female


Dependent Variable: LNRXCOST
LNRXCOST
4
2
0
-2
-4
-6
-1.0
-.8
-.6
-.4
-.2
.0
.2
.4
.6
highschgrad

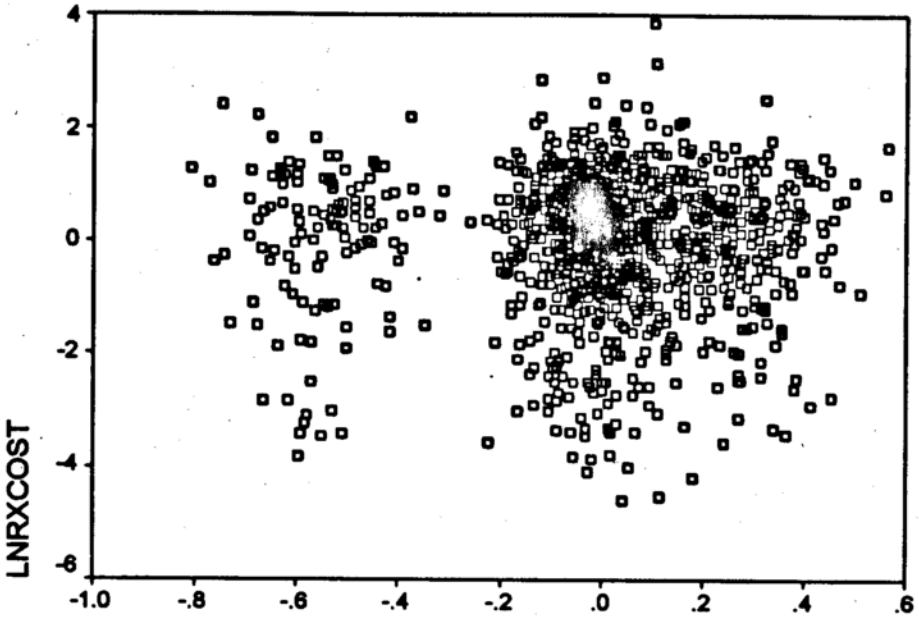

Dependent Variable: LNRXCOST
LNRXCOST
4
2
0
-2
-4
-6
-1.0
-.8
-.6
-.4
-.2
.0
.2
.4
.6
.8
posthighsch


Dependent Variable: LNRXCOST
LNRXCOST
4
2
0
-2
-4
-6
-1.0
-.8
-.6
-.4
-.2
.0
.2
.4
.6
.8
collegegrad

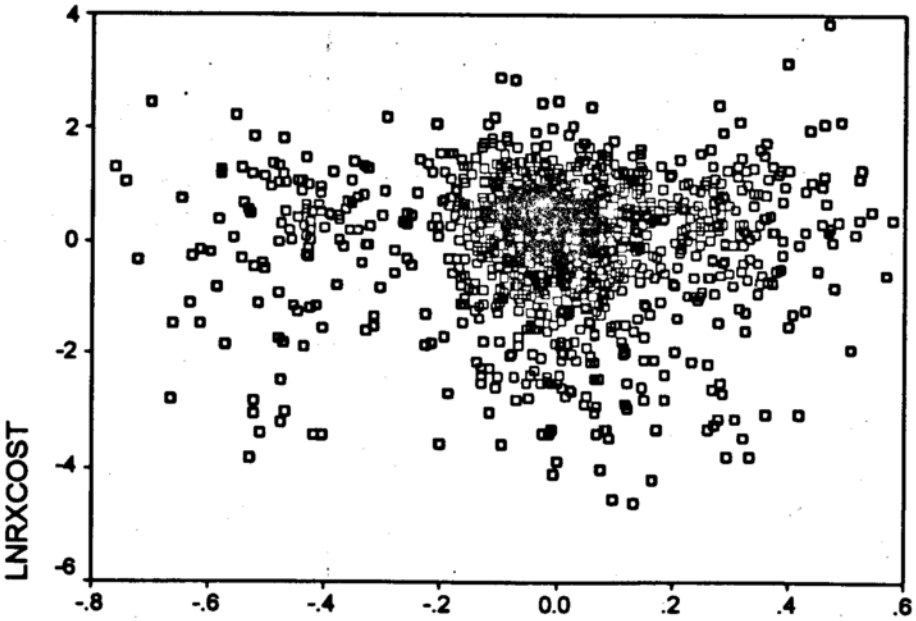

Dependent Variable: LNRXCOST
LNRXCOST
4
2
0
-2
-4
-6
-.8
-.6
-.4
-.2
0.0
.2
.4
.6
inc10to14


Dependent Variable: LNRXCOST
LNRXCOST
4
2
0
-2
-4
-6
-1.0
-.8
-.6
-.4
-.2
.0
.2
.4
.6
inc15to24

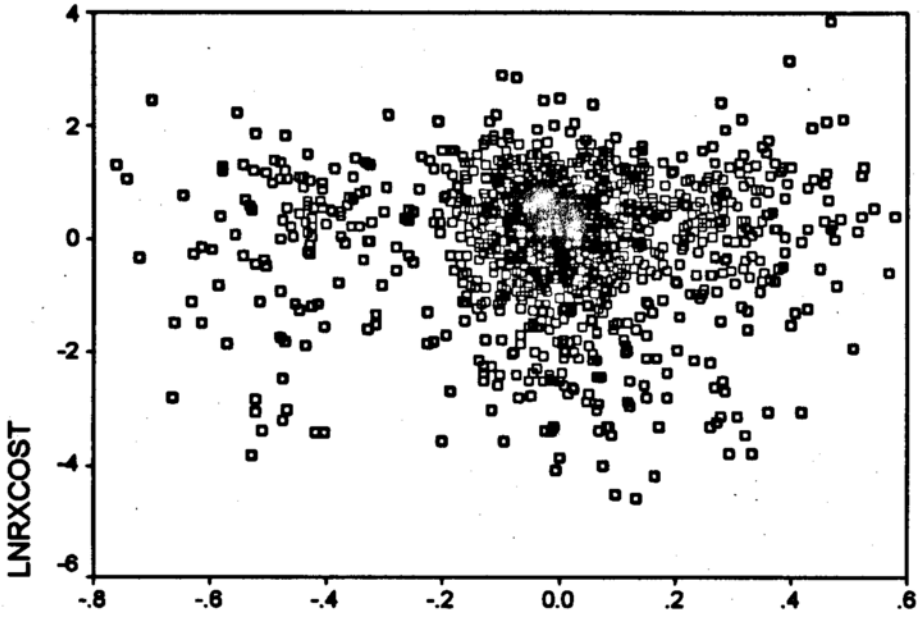
Dependent Variable: LNRXCOST



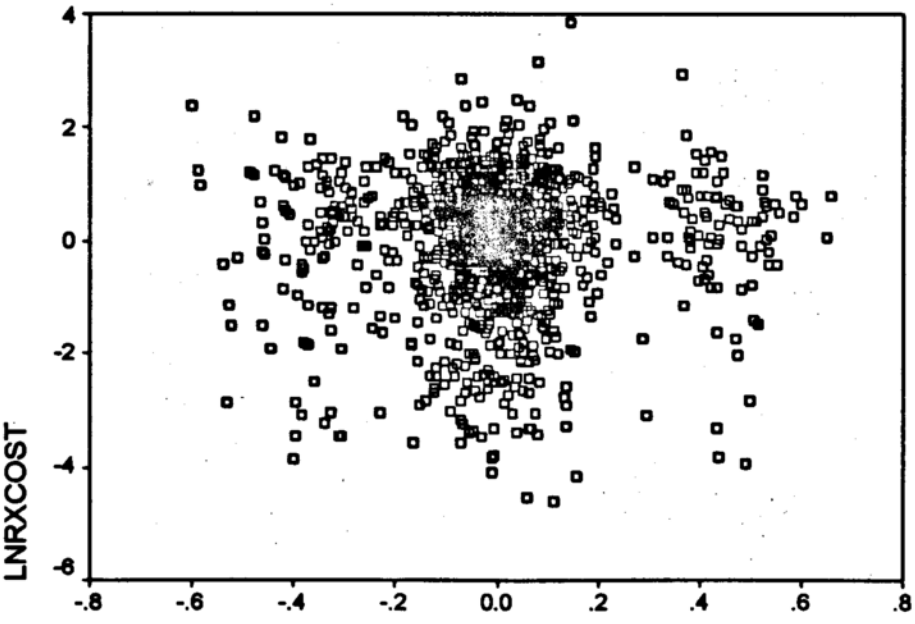
Dependent Variable: LNRXCOST

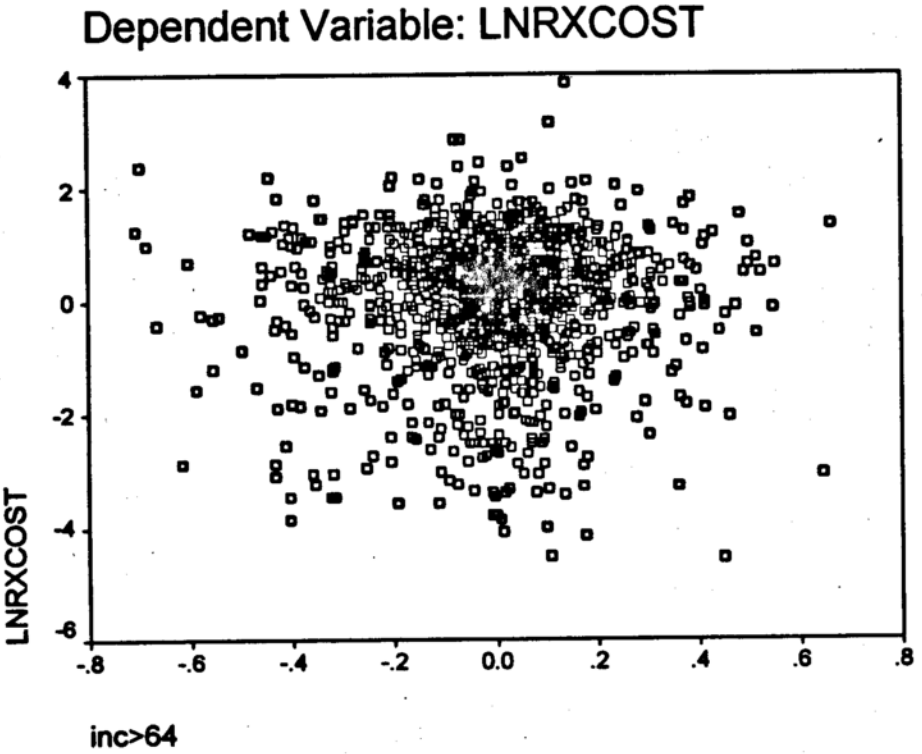


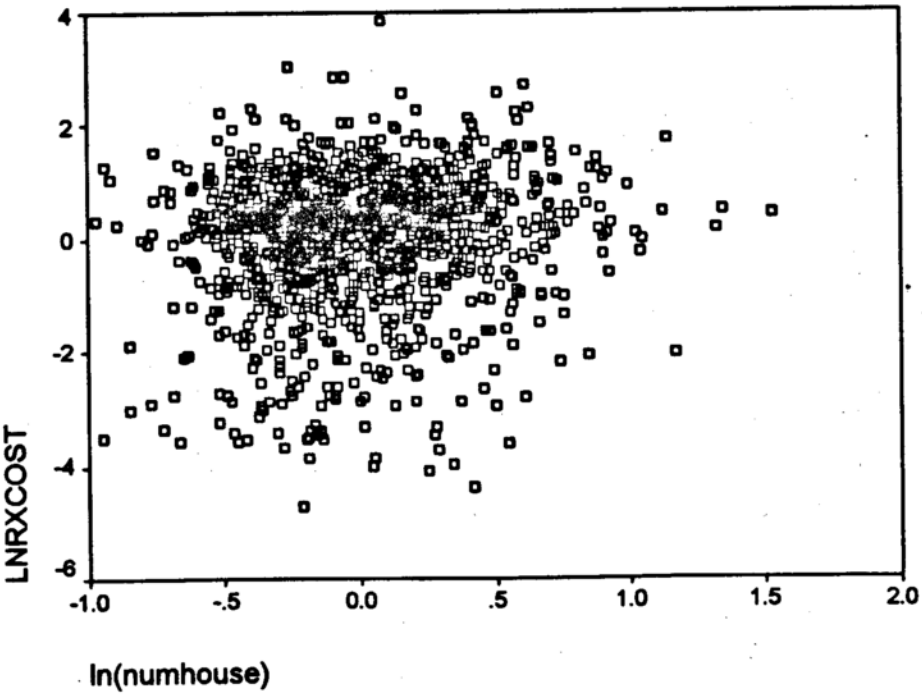
Dependent Variable: LNRXCOST

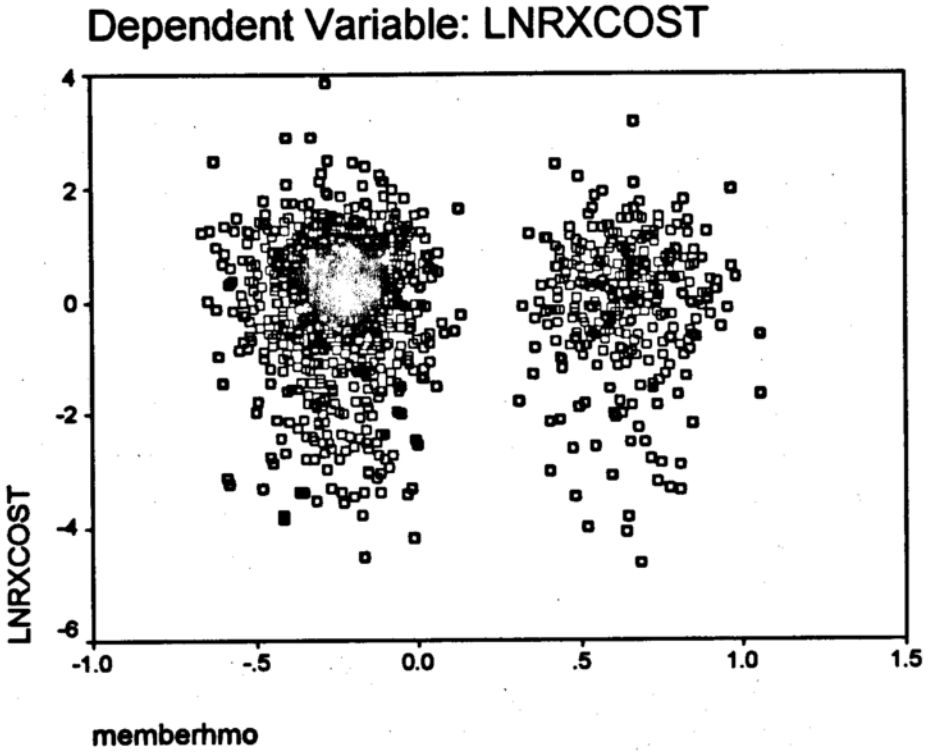


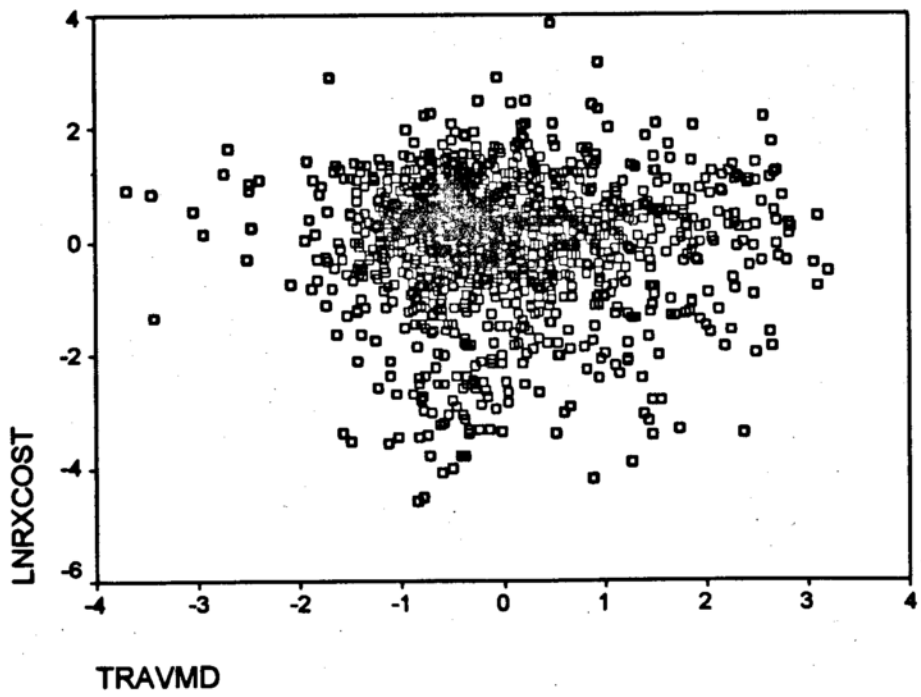
Dependent Variable: LNRXCOST

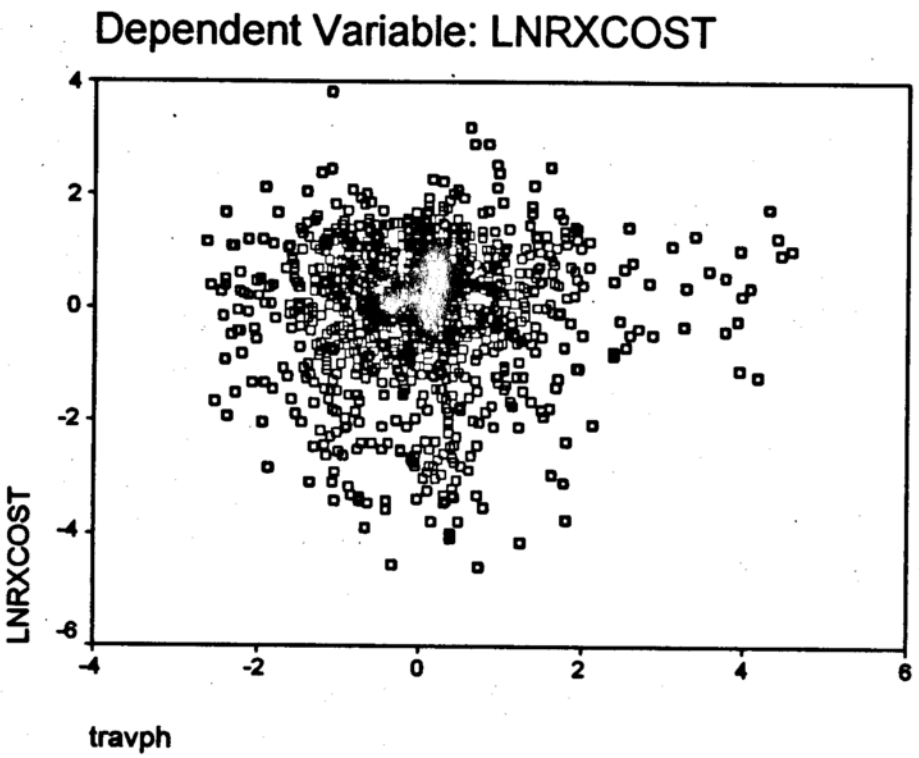


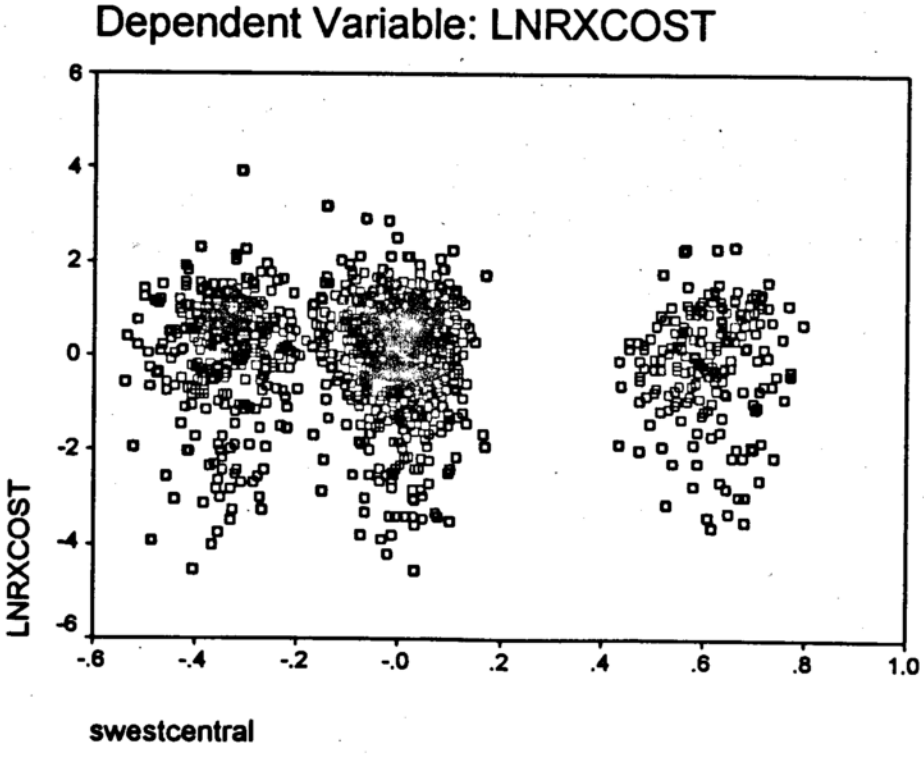

Dependent Variable: LNRXCOST
LNRXCOST
4
2
0
-2
-4
-6
-.8
-.6
-.4
-.2
0.0
.2
.4
.6
.8
inc>64

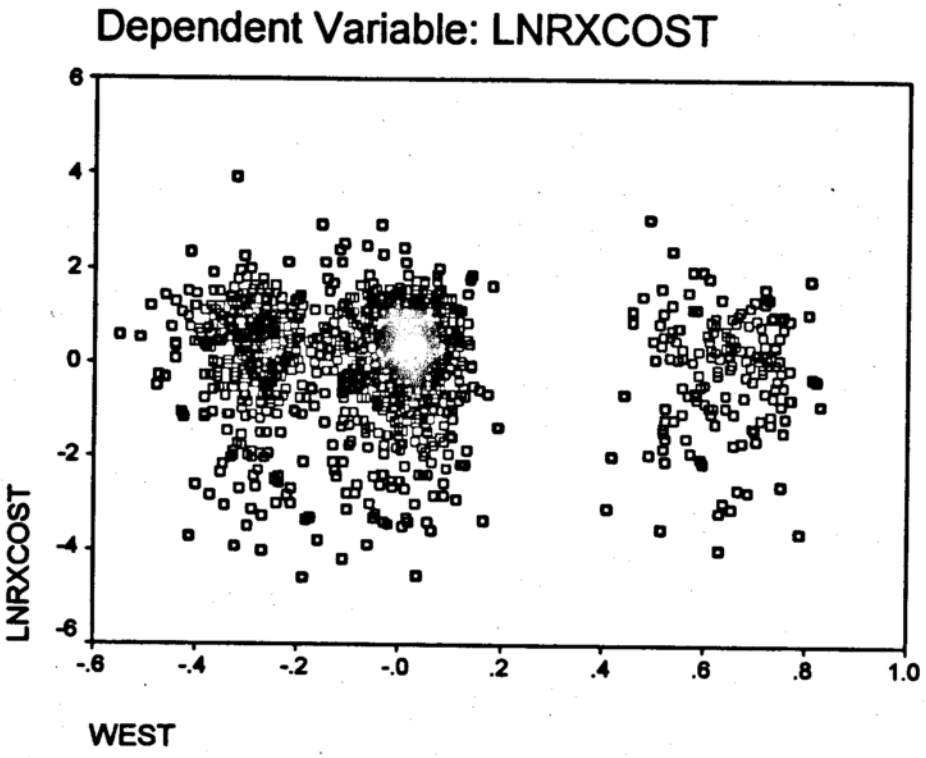

Dependent Variable: LNRXCOST
LNRXCOST
4
2
0
-2
-4
-6
-1.0
-.5
0.0
.5
1.0
1.5
2.0
ln(numhouse)

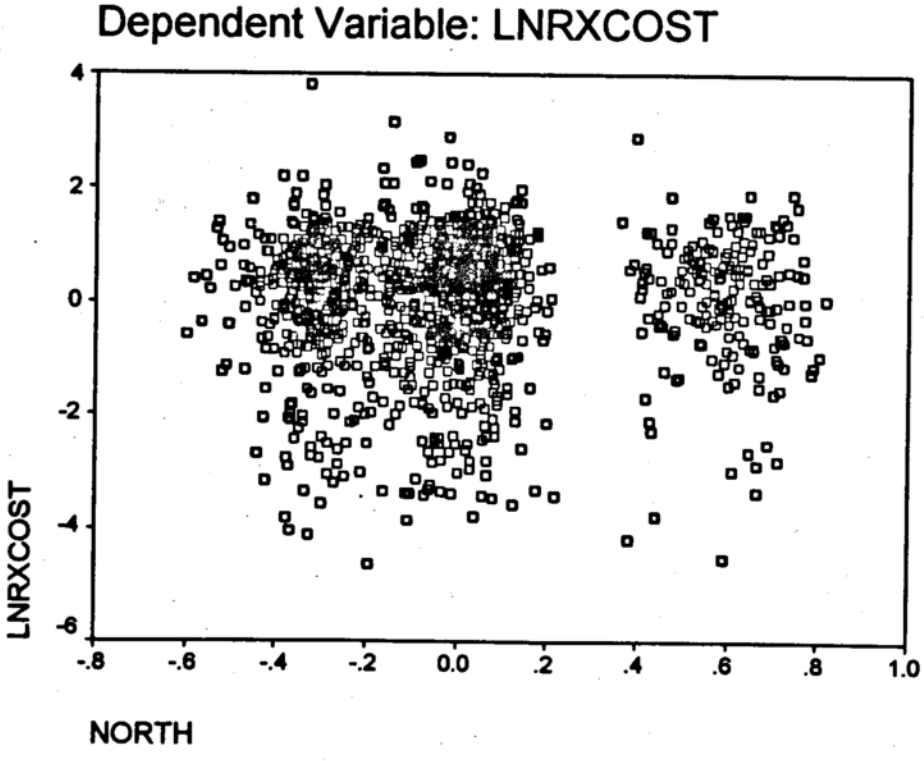

Dependent Variable: LNRXCOST
LNRXCOST
4
2
0
-2
-4
-6
-1.0
-.5
0.0
.5
1.0
1.5
memberhmo

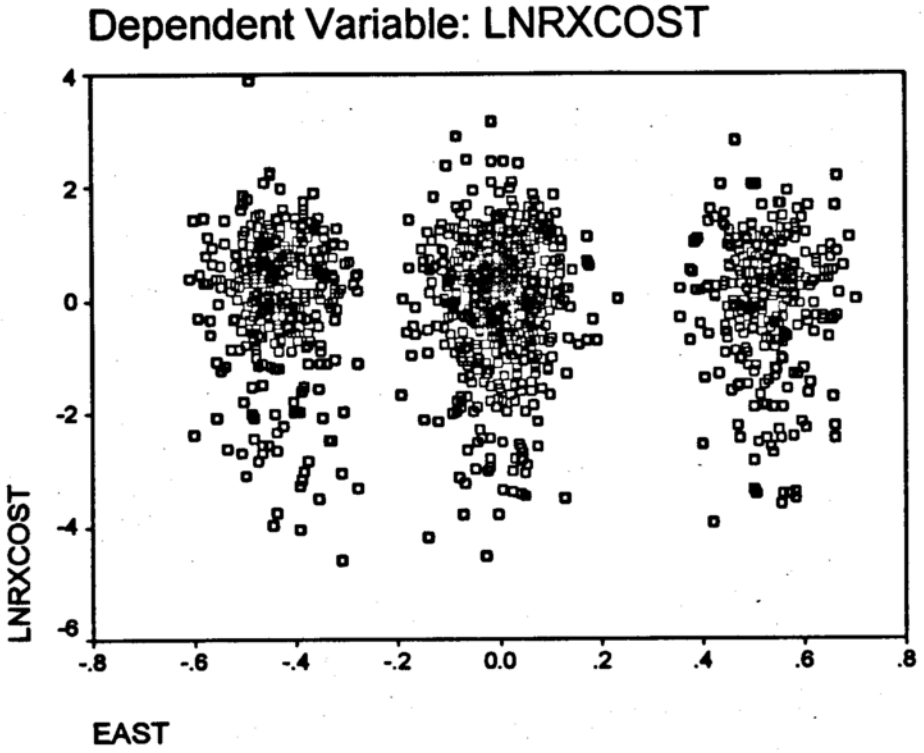

Dependent Variable: LNRXCOST
LNRXCOST
4
2
0
-2
-4
-6
-4
-3
-2
-1
0
1
2
3
4
TRAVMD


Dependent Variable: LNRXCOST
LNRXCOST
4
2
0
-2
-4
-6
-4
-2
0
2
4
6
travph


Dependent Variable: LNRXCOST
LNRXCOST
6
4
2
0
-2
-4
-6
-.6
-.4
-.2
-.0
.2
.4
.6
.8
1.0
swestcentral


Dependent Variable: LNRXCOST
LNRXCOST
6
4
2
0
-2
-4
-6
-.6
-.4
-.2
-.0
.2
.4
.6
.8
1.0
WEST


Dependent Variable: LNRXCOST
LNRXCOST
4
2
0
-2
-4
-6
-.8
-.6
-.4
-.2
0.0
.2
.4
.6
.8
1.0
NORTH


Dependent Variable: LNRXCOST
LNRXCOST
4
2
0
-2
-4
-6
-.8
-.6
-.4
-.2
0.0
.2
.4
.6
.8
EAST