ABSTRACT

LARI, NASIM. The Impact of Diabetes Patients' Trust in Their Physicians on Medical Care & Health-Producing Activities. (Under the direction of Alvin E. Headen, Jr.)

This research evaluates how a diabetic's trust in his physician and his travel costs influence his decision to obtain medical care and spend time on health-producing activities such as diet and exercise. One of the ways in which trust is built between a patient and his physician is through communication. In this context, communication is evaluated by whether the physician listens to the patient, whether the physician explains available options to the patient, and whether the patient is comfortable with speaking English. Travel costs are measured by travel time and difficulty of travel. The results suggest that the communication between a patient and his physician plays an important part in determining whether the patient obtains medical care and engages in health-producing activities. The results further suggest that lower travel costs result in increased probabilities of obtaining A1C tests and foot checks. This research helps identify factors that prevent patients from properly managing their diabetes. Through the identification of such factors, certain policy measures can be implemented (e.g. providing transportation, funds for transportation, translators, etc.) to encourage proper disease management. Further, with an increase in group practices, it would be interesting to evaluate how the effectiveness of these programs is influenced by better patient-provider relationships.

The Impact of Diabetes Patients' Trust in Their Physicians
on Medical Care & Health-Producing Activities

by
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DEDICATION

To

My Father, Mother and Sister -

Thank you.

BIOGRAPHY

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Chapter 1

INTRODUCTION

Approximately 23.6 million Americans - 8% of the population – are reported to have diabetes, and with an estimated 57 million pre-diabetics, the problem is only growing. The American Diabetes Association reports that in 2007, the annual direct medical costs of diabetes totaled $85 billion and were comprised of $27 billion for diabetes care and $58 billion for chronic diabetes-related complications. Diabetes and its complications also resulted in indirect costs associated with increased absenteeism, reduced productivity, disease-related unemployment disability, and loss of productive capacity due to early mortality, which totaled $58 billion.

Diabetes can lead to serious complications such as retinopathy, renalopathy, nephropathy, neuropathy, cardiovascular disease and infections. In 2005, diabetes was the leading cause of kidney failure, accounting for 44% of all new cases, and responsible for 60% of non-traumatic lower-limb amputations. Approximately 73% of diabetics had high blood pressure, 60-70% experienced mild to severe nerve damage, and 65% of deaths among diabetes patients were due to heart disease and stroke. However, proper management of the disease can help prevent or delay the occurrence of such serious complications. Thus, it is important to identify reasons why diabetics may not be properly managing their diabetes and how they can be encouraged to do so.

This research evaluates how a diabetic's trust in his physician, as measured through the area of communication between the patient and physician, and his travel costs influence his decision to obtain medical care and spend time on health-producing activities such as diet and exercise. Communication is evaluated by whether the physician listens to the patient, whether the physician explains available options to the patient, and whether the patient is comfortable with speaking English. By identifying the factors that may prevent the patient from properly managing his diabetes, certain policy measures can be implemented (e.g. providing transportation, funds for transportation, translators, etc.) to encourage proper disease management. Further, with an increase in group practices, it would be interesting to evaluate how the effectiveness of these programs is influenced by better patient-provider relationships.

Chapter 2

LITERATURE REVIEW

This research evaluates how a diabetic's trust in his physician and his travel costs influence his decision to obtain medical care and spend time on health-producing activities such as diet and exercise. The literature review presented here aims to provide an understanding of the importance of this research. The review begins with a brief description of diabetes and diabetes management, providing information on the science of the disease as it pertains to this research as well as the economic implications of diabetes, and is followed by a review of the models and variables used in this research.

2.1 Diabetes

Diabetes is a common chronic condition that can lead to serious complications if left untreated. Approximately 23.6 million Americans - 8% of the population - are reported to have diabetes, but it is difficult to find the exact figure as a national diabetes registry does not exist. With an estimated 57 million pre-diabetics, the problem is only growing (ADA 2009a). Diabetes has received much national and international attention. The United Nations (UN) General Assembly passed a resolution in late December 2006 recognizing diabetes as a global health threat and announcing November 14th as UN World Diabetes Day. The resolution encourages the development of policies for diabetes prevention, treatment and care by the UN member states (Ruder 2007).

The American Diabetes Association (ADA) reports that in 2007, the annual direct medical costs of diabetes totaled $85 billion and were comprised of $27 billion for diabetes care and $58 billion for chronic diabetes-related complications. Diabetes and its complications also resulted in indirect costs from increased absenteeism, reduced productivity, disease-related unemployment disability, and loss of productive capacity due to early mortality, which totaled $58 billion (ADA 2009b).

Diabetes can lead to serious complications such as retinopathy (eye disease), nephropathy (kidney disease), neuropathy (nerve disease), cardiovascular disease and infections. According to the ADA, in 2005, diabetes was the leading cause of kidney failure, accounting for 44% of all new cases, and responsible for 60% of non-traumatic lower-limb amputations. Approximately 73% of diabetics had high blood pressure, 60-70% experienced mild to severe nerve damage, and 65% of deaths among diabetes patients were due to heart disease and stroke (ADA 2009c). However, proper management of the disease can help prevent or delay the occurrence of such serious complications (Touchette 2005). Therefore, diabetes management is significant.

There are three main types of diabetes: type 1, type 2 and gestational diabetes. Type 1 and type 2 are the most common, while gestational diabetes occurs during some pregnancies. All types of diabetes result in too much glucose in the blood. Glucose is removed from the bloodstream with the help of insulin, a hormone made by the pancreas. People with type 1 diabetes make very little or no insulin. While people with type 2 and gestational diabetes make insulin, but their cells are resistant to the actions of insulin or not enough insulin is made (Touchette 2005).

Type 1 diabetes is more common among Caucasians under the age of 20 years. Its management includes regular insulin injections, while close attention is also paid to the patient's diet and exercise plan (Touchette 2005).

Type 2 makes up 90 to 95 percent of all diabetes cases. Most people with type 2 diabetes are over the age of 30 years; however today, with an increase in weight problems, an increasing number of children and teenagers are developing type 2 diabetes. Type 2 diabetes is more common among African Americans, Asian Americans, Hispanic Americans (except Cuban Americans) and Native Americans. Its management includes a balance of diet and exercise (Touchette 2005, Fackelmann 1991); some patients may acquire additional help in lowering blood glucose levels through pills and, of course, insulin injections as a last resort (Touchette 2005).

According to the ADA, the typical diabetes care schedule includes regular visits to the diabetes care provider once every three months for an A1C (HbA1c or glycated hemoglobin) test, weight measurement, blood pressure and foot checks. This care schedule further includes yearly HDL, LDL, triglycerides, and total cholesterol checks, as well as checking feet for sores, kidney function, and eyes for retinopathy (Touchette 2005).

Given that proper diabetes management can help prevent or delay the occurrence of serious complications, it is important for the patient to follow the diabetes care schedule. Early detection of problems can help the patient reevaluate his or her care schedule. For example, patients with diabetes are prone to poor blood circulation and nerve disease, which may lead to infections in the feet; detecting such problems via routine foot checks may help prevent amputations of extremities. Regular eye exams can help detect diabetic retinopathy, which untreated, can lead to blindness. As abnormal lipid profiles are common among diabetes patients, detecting abnormalities at earlier stages can help prevent serious complications such as heart disease and stroke. Finally, A1C tests, by providing an average blood glucose level for the past 2 to 3 months, can give useful information on how well the patient's treatment program is working (Touchette 2005). Thus, it is important to understand why patients do or do not seek treatment for their diabetes.

2.2 Grossman's Health Production Function

This research makes use of the Grossman (1972) health production function and the idea that the demand for medical care is in fact a derived demand that stems from the demand for good health. In Grossman's model, the individual gains utility not from health services, but from the commodity: healthy time.

In a landmark paper, Grossman constructs a model of the demand for "good health." He proposes that health is a durable capital good that produces an output of healthy time. Grossman uses two justifications for his model: the first, that health capital differs from other forms of human capital as it can actually determine the total amount of time an individual can spend on market and non-market activities, and the second, that consumers demand "good health" rather than medical services, and the demand for medical services is considered to be a derived demand.

Individuals maximize their utility subject to three constraints: the health production function, time constraint and budget constraint. Using Grossman's notation, the individual gains utility from a composite consumption good which is produced with market and non-market goods, and the flow of healthy days:

$$U = U(\varphi_0 H_0, \ldots, \varphi_n H_n, Z_0, \ldots, Z_n),$$

where H_0 is the initial stock of health, H_i is the stock of health in the i^{th} time period ($i = 0, \ldots, n$), φ_i depicts the service flow per unit stock, $h_i = \varphi_i H_i$ is the flow of healthy days, and Z_i is the composite consumption good in the i^{th} period.

Within the health production function, individuals inherit an initial stock of health that depreciates over time and increases with investments in market and non-market goods; these include medical care and time spent on health-producing activities. The depreciation rate is considered to be exogenous and may vary with time. The level of health depends on the resources allocated to its production and is not exogenous:

$$H_{i+1} - H_i = I_i - \delta_i H_i ,$$

where $I_i = I_i(M_i, TH_i; E_i)$ is gross investment and homogeneous of degree 1. δ_i is the depreciation rate in the i^{th} period, which Grossman predicts increases as individuals age beyond a certain point of the life cycle. M_i is medical care, TH_i represents the time spent on health-producing activities, and E_i is the stock of human capital, which influences production efficiency for non-market activities. Individuals produce the composite consumption good according to the following function:

$$Z_i = Z_i(X_i, T_i; E_i),$$

where X_i is the goods inputs and T_i is the time input.

The time constraint requires that the total amount of time available in each period (Ω) be exhausted by the time spent on health-producing activities, time spent in the labor market (TW_i), leisure time, and time lost (TL_i) from both market and non-market activities due to illness, thus:

$$\Omega = TH_i + TW_i + T_i + TL_i .$$

The budget constraint sets the present value of purchases of goods equal to the present value of earnings over the life cycle plus initial assets (A_0):

$$\sum \frac{P_i M_i + V_i X_i}{(1+r)^i} = \sum \frac{W_i TW_i}{(1+r)^i} + A_0 ,$$

where P_i is the price of M_i, V_i is the price of X_i, W_i is the wage rate and r is the interest rate.

The full wealth constraint is then obtained by substituting the time constraint in the budget constraint:

$$\sum \frac{P_i M_i + V_i X_i + W_i (TL_i + TH_i + T_i)}{(1+r)^i} = \sum \frac{W_i \Omega}{(1+r)^i} + A_0 = R.$$

To determine the optimal amount of health capital, Grossman takes the derivative of the Lagrangian with respect to I_{t-1} and finds:

$$G_i \left[W_i + \left(\frac{Uh_i}{\lambda} \right) (1+r)^i \right] = \pi_{i-1} \left(r - \tilde{\pi}_{i-1} + \delta_i \right),$$

where G_i is the marginal product of health capital, Uh_i is the marginal utility of healthy days, λ is the marginal utility of wealth, π_{i-1} is the marginal cost of gross investment in health, and $\tilde{\pi}_{i-1}$ is the percentage rate of change in marginal cost between two consecutive periods. This equation indicates that the undiscounted value of the marginal product of the optimal stock of health capital in any period must equal the supply price of capital.

Grossman also investigates the role of human capital in the productivity of the non-market sector. He argues that just as technology and entrepreneurial capacity can shift production functions for firms, there also exist certain forces that influence productivity in the non-market sector. He considers these forces to be environmental variables such as race, sex, stock of human capital, and other variables that can be associated with particular individuals and alter the marginal products of the direct inputs in household production functions. Grossman predicts that if education can improve non-market productivity by shifting human capital, the demand for the optimal stock of health should be larger for more educated individuals.

2.3 Health Insurance

Health economics literature provides a large body of research on the impact of health insurance on the demand for medical services. My research aims to expand on existing insurance models to include other variables such as trust and travel costs as determinants of the demand for medical care among diabetes patients.

In the 1970s, the federal government initiated the Rand Health Insurance Experiment (HIE) aiming, among other things, to decrease uncertainty about how demand responds to changes in price brought about by health insurance, and how these changes are publicly and privately quantified. Researchers randomly assigned participating families to different fee-for-service insurance plans or a prepaid group practice. The fee-for-service insurance plans varied in coinsurance rates (0, 5, 50, or 95 percent) and upper limits on annual out-of-pocket expenses (5, 10, or 15 percent of family income). The participants' consumption of medical care was recorded for three to five years. In their paper, Manning et al. (1987) estimate how cost-sharing affects the demand for medical care.

The authors focus primarily on how the use of medical care, other than outpatient psychotherapy and dental services, are affected by health plans, site, health status, sociodemographic and economic variables. They estimate two types of models; a simple means (ANOVA) and a four-equation model detailed in Duan et al. (1983). The participants are divided into three groups: nonusers, users of only outpatient services, and users of any inpatient services. The first two equations are probit equations: the first is for the probability that a person will receive any medical care during the year – this will separate the users from the nonusers – and the second equation is for the conditional probability that a user will have at least one inpatient stay, given he has some medical use – this will separate the two groups of users. The third equation is a linear regression for the logarithm of total annual medical expenses of the outpatient-only users, and the fourth equation is a linear regression for the logarithm of total annual medical expenses for the users of any inpatient service.

Studies based on the data from the RAND HIE claim that since insurance can be considered exogenous this will allow them to obtain unbiased estimates of price and income elasticities for the demand for medical care. In terms of utilization of medical services, Manning et al. find that increased cost-sharing, reduces the likelihood of any use of medical care, however once the service is used the quantity does not vary much with differences in insurance coverage. The study further finds that adults in the lowest 20 percent of the income distribution who began the experiment with high blood pressure displayed a clinically significant decrease in blood pressure in the free fee-for-service plan compared to the plans with cost sharing. Similarly, for adults within this income range who began the experiment with correctable vision problems, the authors find a modest improvement in corrected vision. Thus, it may be said that programs targeting chronic problems that are relatively inexpensive to diagnose and treat would be much more cost-effective in obtaining health gains than free care for all services.

Dor and Encinosa (2004) investigate the effects of cost-sharing on prescription compliance for diabetes patients. They define compliance as "the adherence to refilling of prescriptions of preventive care drugs without interruption." The authors distinguish between fixed copayments and variable coinsurance, and find that patient compliance is lower under coinsurance due to uncertainty in cost sharing.

Dor and Encinosa state that the patient will comply and fill his prescription only if his expected utility from compliance is larger than his expected reservation utility of not complying:

$$\int U(y + V(Q) - X(p))dG(p) > \int U(y - \varepsilon)dF(\varepsilon),$$

where y is the patient's income, ε is a random loss in health if the patient does not refill her medication, p is the random price of the next prescription, $X(p)$ is the out-of-pocket payment that the patient must make for a drug and is equal to c under copayments and equal to rp under coinsurance, $V(Q)$ is the value that the patient places on the drug, Q is the number of days supplied in the next prescription. The authors approximate the general utility function with mean-variance utility: $U(.) \approx u_1 E(.) - u_2 Var[.]$. Therefore, the patient will comply if:

$$u_1 E(y + V(Q) - X(p)) - u_2 Var[y + V(Q) - X(p)] > u_1(y + \overline{\varepsilon}) - u_2 Var[\varepsilon].$$

Using this framework, compliance will occur under copayments if:

$$D + Bc + MQ > K,$$

and compliance will occur under coinsurance if:

$$D + Br\overline{p} + Gr^2 + MQ > K,$$

where $D = u_1 d > 0; B = -u_1; G = -u_2\sigma^2 < 0; M = u_1 m > 0; K = u_1\overline{\varepsilon} - u_2 \operatorname{var}[\varepsilon]$.

By comparing the two equations we can see that compliance occurs more often under copayment than coinsurance.

Dor and Encinosa use claims data from nine large firms ($n = 27{,}057$) to estimate how an increase in coinsurance from 20% to 75% effects compliance among diabetes patients. The authors track individuals with at least one purchase of an anti-diabetic prescription with a 30-35 day drug supply. They sort individuals into three categories of non-compliers or individuals who did not buy another anti-diabetic prescription within 90 days after the first prescription ran out, partially compliant individuals or those who buy one or more prescriptions within 90 days, but those prescriptions do not cover the full 90 days, and fully compliant individuals or individuals who buy one or more prescriptions within 90 days that cover all 90 days. Dor and Encinosa then estimate compliance among these three groups as an ordered logit model, with outcomes ranked 0, 1, and 2 respectively. They also run simulations to demonstrate the effect of increases in copayments and coinsurance rates on the distribution of compliance. Dor and Ensinosa find that an increase in the coinsurance rate from 20% to 75% results in a 9.9% increase in non-compliant patients and a 24.6% decrease in the fully compliant patients. In the copayment model, an increase from $6 to $10 (an increase from the 25th to 75th percentile) results in a 6.2% increase in non-compliant patients and a 9% decrease in the share of fully compliant patients. The authors also estimate that while increasing the copayment from $6 to $10 reduces national drug spending for diabetes by $125 million, the treatment costs for diabetes-related complications due to poor glycemic control increases by $360 million.

Tao (2007) examines the impact of health insurance coverage on diabetics' decisions to treat and manage their condition, and on their health outcomes. She uses the Medical Expenditure Panel Survey (MEPS) and focuses on the adult non-elderly population (i.e., individuals aged 25 to 65) to jointly estimate demand equations for health insurance, medical care, lifestyle decisions and health, controlling for common unobserved determinants. She finds that health insurance with drug coverage leads to better adherence to diabetes care guidelines and lowers the probabilities of eye and kidney problems among the non-elderly adult population.

2.4 Language and Trust

In the 1960s, the television series *Marcus Welby, M.D.* followed the life of an intelligent, well-liked and trusted primary care physician (PCP). He represented what some seem to remember their PCPs having been in the good old days and what others wish their PCPs were today. He was the ideal physician; well-educated and well-trained in medicine, and willing to spend long hours with his patients, building a relationship with each one and gaining the patient's trust. What we have seen over recent decades is a great departure from this form of healthcare, and a movement toward a less personal form of healthcare (Dranove 2000). So, how does this phenomenon influence patients' treatment and health outcomes?

In a seminal paper, Arrow (1963) compares health care markets with other markets and discusses the role of the PCP. One distinguishing characteristic of an individual's demand for medical care is that it is not steady; rather it is unpredictable and irregular. In other words, aside from preventive services the demand for health care arises with an illness – a departure from the normal state of affairs. Another distinguishing characteristic is that apart from the cost of medical care, illness is a costly risk; the demand for medical care is associated with a probability of loss of full function, loss or reduction of earning ability, and even death. Finally, patients are idiosyncratic in their needs. Such characteristics of medical care demand lead individuals away from their traditional sources of information such as brand names and consumer reports, and more toward their PCP for information.

Arrow continues that the behavior expected from physicians is different from that of businessmen; as the patient cannot test the product before consumption, there is an element of trust between the patient and the physician. The patient expects the physician's behavior to be governed by concern for the patient, not self-interest.

The definition of trust within medical settings has long been an issue of debate, and much effort has been placed in defining and measuring trust. Mayer et al. (1995) define trust as "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party." Baier (1986) defines trust as "accepted vulnerability to another's possible but not expected ill will (or lack of good will)."

There are two main categories of trust: interpersonal trust and general trust. Interpersonal trust is built through repeated interactions by which an individual's trustworthiness can be tested over time (Mechanic 1996), such as the relationship a patient builds with his or her PCP. General trust, however, refers to trust in collective institutions, such as managed care organizations and hospitals, and is influenced by general social opinion of these institutions (Pearson and Raeke 2000). General trust has greater influence on interpersonal trust during the early stages of a treatment relationship (Hall et al. 2002).

Competence, compassion, privacy and confidentiality, reliability and dependability, and communication are common physician behaviors on which patients are believed to base their trust. Examples of common measures of patient trust include 1) the Trust in Physician Scale which is an 11-item interviewer administered questionnaire that assesses the patient's trust in the physician through questions about dependability, confidence and confidentiality; 2) the Primary Care Assessment Survey (PCAS), which measures seven elements of primary care performance, including trust domains such as integrity and competence; 3) the Patient Trust Scale, a 10-item scale dominated by questions on the impact of cost-consciousness on physician agency for patients (Pearson and Raeke 2000).

Safran et al. (1998) use the PCAS to assess how the seven elements of primary care performance – accessibility, continuity, comprehensiveness, integration, clinical interaction, interpersonal treatment, and trust – influence three factors: self-reported adherence to the physician's advice, patient satisfaction in the physician, and improved health status. Data was derived from a cross-sectional observational study of adults employed by the Commonwealth of Massachusetts (N=7204).

Adherence to physicians' advice was assessed for seven behavioral risks – smoking, alcohol use, seat belt use, diet, exercise, stress, and safe sex practices –

recommended by the US Preventive Services Task Force for PCPs to address with every adult patient. Patients were asked whether their PCP had ever discussed each topic with them, and whether they had ever attempted to modify their behavior as a result of this discussion. Adherence was then scored as the percentage of behaviors that the patient attempted to modify based on the PCP's advice. Satisfaction with the PCP was assessed with a single question: "All things considered, how satisfied are you with your regular doctor?" Seven response choices ranged from "completely satisfied, could not be better" to "completely dissatisfied, could not be worse." Health status was studied using an item that asked patients to compare their current general health status with that of 4 years ago, with 5 response choices ranging from "much better now" to "much worse now."

For the analysis, the authors use a two-stage analytic approach: in the first stage (adjusted bivariate regressions), they regress each outcome variable on each primary care variable individually, controlling for the patient characteristics; in the second stage (multivariable regressions), they regress each outcome variable on all primary care scales for which a statistically significant bivariate relationship was observed. The authors use linear regression for adherence (continuous variable), logistic regression for satisfaction (binary variable) and ordered logistic regression for health outcomes (categorical variable with 5 interval responses). The models control for patients' demographic characteristics, type of health plan, and other variables.

Safran et al. find that the physicians' whole-person knowledge of their patients and patients' trust in their physician are the variables most strongly associated with adherence, and that trust is the variable most strongly associated with patients' satisfaction with their physician. The authors show that adherence rates are 2.6 times higher among patients with whole-person knowledge scores in the 95th percentile compared with the 5th percentile. Further, the likelihood of complete satisfaction was 87.5% for those with 95th percentile trust scores compared with 0.4% for patients with 5th percentile trust scores. The authors note that these results are of particular interest today, considering the extensive changes in our nation's health care system that are believed to be threatening to physician-patient relationships.

Thus, the relationship created between a physician and his patient is an important one; one which the Institute of Medicine outlines as a “continuous healing relationship” and a desired characteristic of today’s health care delivery system (Willson 2005).

Another factor that plays an important part in the formation of the relationship between a patient and his physician is language. In 2000, the U.S. Census Bureau projected that by 2010, approximately 35% of the U.S. population will be a member of a racial or ethnic minority group, and that the number will increase to nearly 40% in 2020 (U.S. Census Bureau 2004). This projection is becoming a reality. In 2007 the U.S. population was estimated at 301.6 million people of whom 15% were Hispanic and overall, 34% were categorized as members of a minority group (U.S. Census Bureau 2008).

Weech-Maldonado et al. (2004) examine the impact of race/ethnicity and language on consumer reports and ratings of care in Medicaid managed care. With the ever increasing racial and ethnic minority groups, it is becoming increasingly important to pay close attention to the racial/ethnic disparities in access to care and health status.

The authors use the National Consumer Assessment of Health Plans Study (CAHPS®) Benchmarking Database 3.0 (NCBD 3.0) Adult Medicaid Surveys, which consists of survey responses from 49,327 adults in 156 Medicaid managed care plans across the 14 states of Arizona, California, Colorado, Hawaii, Kansas, Michigan, New York, Ohio, Oklahoma, Pennsylvania, Texas, Utah, Vermont and Washington in 2000. The telephone and mail surveys were administered in both Spanish and English; the response rate was 38%. The state Medicaid managed care programs represent approximately 44% of the total Medicaid managed care enrollees in the United States.

Weech-Maldonado et al. use an ordinary least squares approach. The dependent variables are the CAHPS 2.0 global rating items, which include ratings of the respondent's personal doctor or nurse, specialist, overall health care, and health plan, and multi-item reports of care, which include getting needed care (access to care), timeliness of care (getting care promptly), and provider communication (provider's communication with patients). The main independent variables include race/ethnicity, language spoken at home (Spanish, English, or other), and survey language (English or Spanish). The respondents are divided into the following nine categories: White, Hispanic/Latino, Black/African American, Asian/Pacific Islanders, American Indian/Alaskan native, American Indian/White, Other Multiracial, and Other Race/Ethnicity. Other independent variables include sex, age, education and self-rated health.

The authors find that in general, racial/ethnic and linguistic minorities had more negative experiences with care than white-English speakers. Asian-other have worse reports of care in terms of getting needed care, getting care promptly, provider communication, and staff helpfulness; however, Asian-English speakers didn't differ greatly from white-English speakers in these categories. Hispanic-Spanish have more negative reports in terms of timeliness of care, provider communication, and staff helpfulness. Finally, white-other languages have worse experiences in terms of getting needed care, timeliness of care, and staff helpfulness. Based on their results, Weech-Maldonado et al. express the necessity of looking past financial barriers and focusing on resolving existing non-financial problems within the health care system. One of their suggestions for addressing these existing problems is to recruit, retain and manage a more diverse workforce within the health care system.

As diabetes is a chronic condition which allows for the establishment of trust in the physician through repeated interactions, interpersonal trust is the focus of my conceptual model. Trust will be assessed through the area of communication, which I consider to consist of the following factors: whether the provider listens to the patient and seeks advice when choosing between treatments (listening), whether the physician explains options to the person (explaining), and whether the physician speaks the person's language (language).

2.5 Travel Time and Distance to Physician's Office

In her book, *Mama Might Be Better Off Dead*, investigative reporter Laurie Abraham (1993) details the experiences of four generations of one family with obtaining medical care, and physician reactions to the situation. One physician recounts problems that many patients face when trying to obtain medical care as what he calls "sociomas" or social problems such as not having a ride to the physician's office. Given that the amount of time that a patient spends traveling to his physician's office and sitting in the waiting room is time that he could have spent elsewhere (i.e. at work or at leisure), I also consider social problems, such as time and difficulty of travel, in my research.

In determining factors that influence women's decision to have breast cancer screening tests, Gerard et al. (2003) find that increased travel time negatively impacts future attendance. The breast screening process involves screening, assessment, notification of results, referral for treatment, and regular re-invitation and re-screening. The authors explore the feasibility of applying state preference discrete choice modeling (SPDCM), which is derived from the random utility theory (RUT) and Lancaster's economic theory of value, in developing breast cancer screening participation enhancement strategies; they quantify individuals' preferences for breast cancer screening services by analyzing how these individuals would have behaved in hypothetical situations. The individuals' choices reveal their preferences for a given option, which can be used to estimate the influence of each factor on the choice and also, the marginal rates of substitutions between the factors.

The individuals are asked a series of binary choices, i.e. whether or not they would present for re-screening in the future if the service was as described. Each decision is then modeled as a bivariate probit model with random effects, where 'yes' indicates that the respondent would accept screening and 'no' indicates that the respondent would not accept screening. The estimated model is:

$$Y_{it} = \beta' X + \gamma' Z + \varepsilon_{it},$$

where Y_{it} is the probability of respondent t accepting screening choice i; X is a matrix of attributes and their levels pertaining to the breast screening service; Z is the matrix of covariates; $\varepsilon_{it} = v_{it} + u_i$, where u_i is random error of i^{th} choice, constant over each subject's choices, and v_{it} is the difference among subjects with both components assumed to be normally distributed with zero means and independent of each other.

The authors take the correlation between the choices into account by estimating the serial correlation.

The authors choose 10 attributes; 9 related to the different aspects of the screening process and 1 related to screening outcome. The attributes related to different aspects of the screening process include method of invitation for screening and accompanying material and information, time waiting for an appointment, choice of appointment times available, travel time, procedure time, manner of staff, private changing areas, and time lapse before obtaining results. The attribute related to screening considers the accuracy of screening results. As all possible combinations of the attribute levels prove too many for an empirical study, the authors used an orthogonal main effects design with selected two-factor interactions such that the main effects of each attribute can be estimated independently of each other and three two-factor interactions could be estimated; however, reducing the possible combinations in this way results in the assumption that all unobserved effects are insignificant. Their design results in 32 breast screening options blocked into two sets of 16 options, labeled versions A and B; each version was placed in a self-complete postal questionnaire. Personal characteristics were also collected based on relationships with screening behavior.

The study was conducted in Sydney, Australia at a metropolitan breast screening and assessment service. A total of 180 questionnaires (90 versions of A and 90 versions of B) were randomly distributed between June and August 1999. Women who attended with an interpreter were excluded from the study. The overall response rate was 48%. The authors find that although accuracy of screening is the most important attribute of service to influence the probability of future attendance, travel time and screening time also play an important part; as travel time and screening time increase, respondents are less likely to screen in the future. Thus, in terms of policy implications, the service provider can assess which action is most cost effective and relevant – increasing accuracy or decreasing screening time.

Lourenço and Ferreira (2005) study the impact of time costs on the number of visits to the general practitioners (GPs) in Portuguese health centers. They consider two different time costs: physical waiting and appointment delay. Physical waiting refers to the total time the patient spends in seeing the physician – travel time and time spent in the physician's office – and appointment delay refers to the time spent waiting for an appointment (e.g. time spent on a waiting list), which is common in health systems, such as that of Portugal, that provide free care at the point of delivery.

The Portuguese health system is financed by public and private sources: 1) the National Health Service (NHS), which finances the majority of medical care, 2) public and private occupational health insurance coverage, which covers 20-25% of the population who are mostly individuals considered to be "better-off" and 3) voluntary health insurance. Visits to private GPs require full payment of the visit for individuals who do not have voluntary or occupational health insurance. On the other hand, visits to public GPs have low monetary costs; however, patients must be registered with a GP in their geographical area and should have a visit to their GP for referrals to specialists. Within this structure, approximately 30% of individuals who go to a health center without a previous appointment are able to see a GP on the same day. There is, however, an uneven distribution of medical resources across Portugal, leaving individuals in poorer and isolated geographic areas with limited access to health care and private alternatives, and those in regions with high NHS supply with greater private provision.

Lourenço and Ferreira use data from the 2003/2004 Europep Survey, which is representative of public health center users. From this data set, the authors selected individuals who visited health centers within the past 3 months, deleted multiple records, chose a random sample of individuals, and mailed questionnaires to these users. The response rate was 17%. They then deleted the records with missing values on variables of interest and obtained a final sample of 6,791 adults. The authors use a two-component negative binomial II finite mixture model (FMM) specification for two identified categories of users: low users who comprise 88% of the population, with an average of 4.3 visits to the GP annually, and frequent users, with an average of 11.2 visits. In their empirical estimation, the dependent variable is the number of visits to the GP and the independent variables include certain socioeconomic variables, health status, time costs, consultation, supply of health care, and some interactions.

Among their results, Lourenço and Ferreira find that less education is a factor that increases the utilization of health centers for both groups of users. The elasticity of utilization relative to time travel is positive and statistically significant for both groups; however, the magnitude is smaller among the low users. This unexpected result may have to do with the distribution of health centers across the country, leaving those who live in rural areas with less possibilities for substituting primary care. The elasticity of utilization relative to appointment delay is, however, negative and large in both classes.

The residents of the United Kingdom are also required to register with a general practitioner in order to receive general medical services under the NHS. Haynes et al. (2003) evaluate how the distance that patients have to travel to a GP isn't necessarily the closest distance because in making the decision to visit a GP, each patient is considering factors other than distance as well. Thus, in making his decision, the patient tends to occasionally substitute these other factors for the convenience of a shorter travel distance. The authors consider potential accessibility, travel time, and consumer choice.

Potential accessibility is an index of geographical accessibility. Haynes et al. calculate potential accessibility using a negative exponential decay function:

$$P_i = \sum_{j=1}^{N} a_j \exp[-b(T_{ij})],$$

where a_j is the attractiveness of service j, b is a constant rate of decay identified from the data, T_{ij} is the travel time from zone i to service j. Due to data limitations, all GP group practices were assumed to be equally attractive and every location was assigned an attractiveness value of 1. Haynes et al. used Arc/Info geographical information system software to calculate car travel times to the nearest group practice location and to the nearest group practice of the GP with which the patient was registered. The authors also consider public transportation, and divide the availability of public transportation into three categories of "good," "limited," and "no bus." Good availability of public transportation is considered walking access to a bus service with four or more daytime return trips to the GP location every weekday. Finally, to measure the range of choice, the authors use the number of GP practices with which the residents of each area were registered as an indicator.

Haynes et al. use data for over 2 million inhabitants of the three counties of Cambridgeshire, Norfolk, and Suffolk, obtained from four health authorities. The records contained information on patient postal codes and GPs. The authors excluded records with missing postal codes and GP registration information, and were left with 2,107,007 patients.

The authors find that while travel times to the patients' own registered GPs were short, they were not as short as they would have been had the patients gone to the nearest practice. For example, 47% of individuals traveled less than 5 minutes to reach their registered GP, whereas actually 67% of individuals would need to travel less than 5 minutes to reach the nearest GP. The proportion of residents registered with the nearest practice was least in the larger, urban areas. Thus, the effect of patient choice can be seen in increased car journey times. Further, they find that 29% of individuals in rural areas had "no bus" access, and the longest car journey times to the nearest GP group practices were found in these rural areas.

Overall, registrations with GPs exponentially decrease as travel times increase as defined by the following equation:

$$P = 167711 \exp(-0.289T),$$

which indicates that the number of patients registered with a practice decreased at a constant rate of 28.9% per minute of additional travel time. In terms of patient choices, the areas exercising most choice coincide with the places with a high density of group practices. Finally, potential accessibility is highest in the larger urban areas and lowest in rural areas with no group practice within walking distance. Thus, travel times and distances are an important factor to keep in mind when modeling patient decisions to choose physicians, visit their physicians, and obtain medical care.

2.6 Conclusion

My research contributes to existing literature by evaluating the impact of variables such as trust in the physician and travel costs on the use of medical care and health-producing activities by diabetes patients. This paper further evaluates the effects of such variables on health outcomes.

In assessing trust, I focus on the area of communication. I consider trust to comprise of how well the physician listens to the patient and explains existing options, and whether the patient is comfortable with speaking English. I also evaluate the effects of travel costs on the demand for medical care and health outcomes.

Incorporating the above-mentioned variables in existing insurance models allows for a more general picture of the patient's decision-making process. If the factors that prevent patients from properly managing their diabetes are identified, certain policy measures (e.g. providing transportation, funds for transportation, translators, etc.) may be implemented to encourage proper disease management.

Chapter 3

THEORETICAL FRAMEWORK

The primary focus of this research is to show how a diabetic's trust in his physician and his travel costs influence his demand for diagnostic medical care, medication and health-producing activities. Diagnostic medical care includes physician visits, A1C tests, foot checks, dilated eye exams, cholesterol and blood pressure checks; medication includes oral medications and insulin; health-producing activities include diet and exercise.

A dynamic stochastic model is utilized to explain the sequential decision-making behavior of individuals. Figure 3.1 depicts the timing of the individual's decisions regarding the purchase of health insurance, diagnostic medical care, medications, and health producing activities, and his related health outcomes. This timeline is detailed below.

The objective is for the individual to choose an insurance plan, a level of diagnostic medical care, medication, and health-producing activities TH_t to maximize his discounted lifetime expected utility subject to his time constraint, budget constraint and health production function.

3.1 The Individual's Per-Period Choices

The individual enters each period with health status H_{it} and prior to observing a health shock s_t, he chooses his health insurance plan I_{it}^{j}, where:

$$j = \begin{cases} 0 & \text{uninsured} \\ 1 & \text{insured without drug coverage} \\ 2 & \text{insured with drug coverage} \end{cases}$$

and $\sum_{j=0}^{2} I_{it}^{j} = 1$.

Upon observing a health shock s_t, the individual chooses the level of diagnostic medical care, medication, and health-producing activities. The amount of diagnostic medical care is represented as $D_{it} = d$, medication as $M_{it} = m$, and health producing activities as $TH_{it} = th$. Based on his choices, the individual's health status is then updated to H_{t+1} through the health production function. For simplicity, I have dropped the i subscript through the remainder of this work.

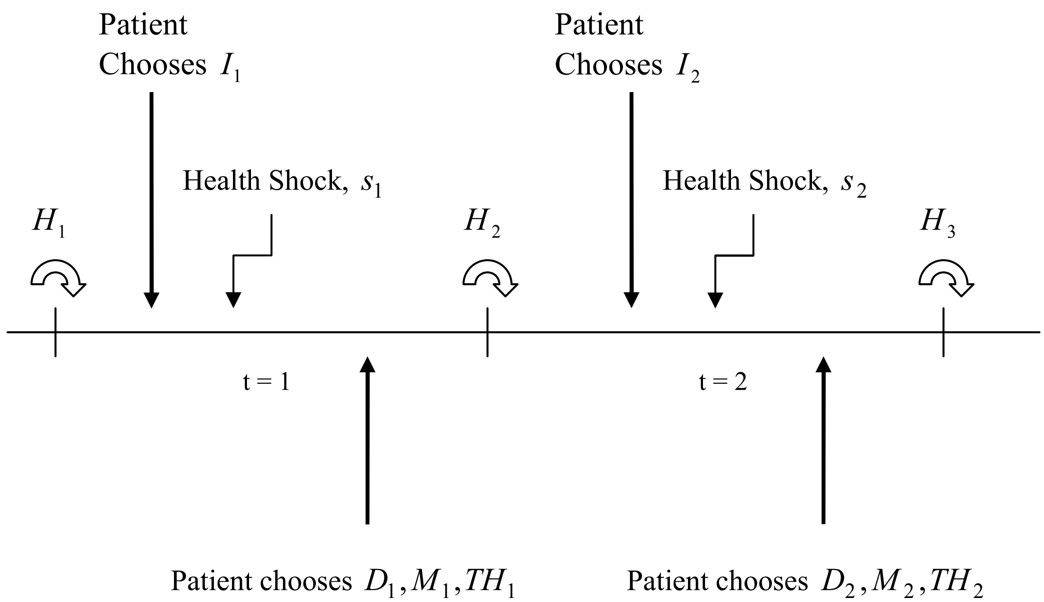

Figure 3.1 Timing of Decisions and Health Outcomes

3.2 Utility Function

In each period, t, the individual gains utility from a composite consumption good (C_t), good health (H_t), and leisure (L_t); thus the individual's utility function is defined as:

$$U_t = U_t(C_t, H_t, L_t), \tag{3.1}$$

where $U_C > 0, U_H > 0$, $U_L > 0$, and $U_{cc} < 0, U_{HH} < 0$, $U_{LL} < 0$.

3.3 Time & Budget Constraints

In each period, the individual's total time (Ω_t) is exhausted by time spent on leisure (L_t), work (ℓ_t), health-producing activities (TH_t), and diagnostic medical care and medication (TV_t); thus, the time constraint is defined as:

$$\Omega_t = L_t + \ell_t + TH_t + TV_t.(D_t + M_t).$$

As work decisions are not evaluated in this context, the time constraint may be rewritten such that the time spent on leisure, health-producing activities, and diagnostic medical care exhaust total time, which is now defined as the time in each period minus hours spent at work ($\overline{\Omega}_t$); thus, the time constraint is now defined as:

$$\overline{\Omega}_t = \Omega_t - \ell_t = L_t + TH_t + TV_t.(D_t + M_t). \tag{3.2}$$

The individual's budget constraint is:

$$Y_t = C_t + P^j_{D_t} D_t + P^j_{M_t} M_t + P_{TH} TH_t + P_{TV_t} TV_t.(D_t + M_t) + P^j_{I_t} I^j_t \tag{3.3}$$

Y_t is the individual's total income in time t. The individual distributes his income among the purchase of a composite consumption good (C_t), diagnostic medical care (D_t), medications (M_t), health-producing activities (TH_t), health insurance (I^j_t), and transportation to the physician's office for visits and diagnostic medical care

(TV_t). C_t is the composite consumption good and its price is normalized to 1, $P_{D_t}^j$ is the out-of-pocket price of diagnostic medical care, $P_{M_t}^j$ is the out-of-pocket price of medication (i.e., prescription drugs and insulin), P_{TH_t} is the price of health-producing activities, P_{TV_t} is the price of traveling to the physician's office and obtaining diagnostic medical care, and $P_{I_t}^j$ is the premium associated with the purchased health insurance. As the out-of-pocket price of diagnostic medical care and medication, and the premium associated with the purchased health insurance vary with the type of health insurance, I have included the superscript j to indicate the type of health insurance or lack thereof; $j = 0$ is uninsured, $j = 1$ is insured without drug coverage, and $j = 2$ is insured with drug coverage. If the individual is uninsured, then $P_{I_t}^0 = 0$, $P_{D_t}^0 = 1$, and $P_{M_t}^0 = 1$. I define $P_t = (P_{D_t}^j, P_{M_t}^j, P_{TH_t}, P_{TV_t}, P_{I_t}^j)$ as a vector of exogenous prices.

3.4 Health Production Function

The individual will maximize his utility subject to the health production function, time constraint and budget constraint. In determining health, I make use of Grossman's 1972 landmark work on the demand for medical care and the production of health. Based on Grossman's model the demand for medical care is a derived demand, which stems from the demand for good health, and the individual gains utility not from medical care, but from the commodity: healthy time. Within the Grossman health production function individuals inherit an initial stock of health that depreciates over time and increases with investments in the form of time spent on health producing activities and medical care. The individual's health production function is as follows:

$$P(H_{t+1} = h) = f(H_t, D_t(R_t), M_t(R_t), TH_t(R_t), Q_t, s_t), \tag{3.4}$$

where $f_H > 0, f_D > 0, f_M > 0, f_{TH} > 0$ and $f_{HH} < 0, f_{DD} < 0, f_{MM} < 0, f_{THTH} < 0$.

This equation indicates that health in the next period is determined by health and health inputs (i.e. medical care and time spent on health-producing activities) in the current period; health inputs are in turn functions of R_t, a vector of trust determinants, among other factors. As diabetes is a chronic disease, it allows for interpersonal trust to be built and tested over time. There are several common physician behaviors on which patients base their trust in their physician; some of these include competence, compassion, confidentiality, and communication. I assess trust through the area of communication, and define it through the following factors: whether the provider listens to the patient and seeks advice when choosing between treatments, whether the physician explains options to the person, and whether the physician speaks the person's language Q_t is a set of exogenous individual characteristics such as age, sex, race, marital status, and education, and s_t represents a health shock.

3.5 The Bellman Equation

The individual's objective is to choose an insurance plan I_t^j, a level of diagnostic medical care D_t, medication M_t, and health-producing activities TH_t to maximize his discounted lifetime expected utility subject to his budget constraint, time constraint and health production function. The individual chooses his health insurance plan at the beginning of each period, prior to a health shock, and his level of diagnostic medical care and health producing activities upon the realization of the health shock. State variables include H_t, which evolves through the health production function described above, P_t, R_t, Q_t, and s_t. Thus, the individual's value function, at time t, where $t < T$, using the Bellman equation and substituting the time and budget constraints into the utility function, conditional on a particular health insurance plan and with s_t known, is defined as:

$$
\begin{aligned}
&V_t^d(H_t, R_t, P_t, Q_t \mid I_t^j, s_t) = \\
&U_t(Y_t - P_{D_t}^j D_t - P_{M_t}^j M_t - P_{TH_t} TH_t - P_{TV_t} TV_t(D_t + M_t) - P_{I_t}^j I_t^j, H_t, \overline{\Omega}_t - TH_t - TV_t(D_t + M_t)) \\
&+ \beta[\sum_{h=0}^{H} \pi_{t+1}^h W_{t+1}(H_{t+1}, R_{t+1}, P_{t+1}, Q_{t+1})],
\end{aligned}
\tag{3.5}
$$

where d represents alternative demand behaviors, π_{t+1}^h is the probability of the individual being in health state *h* in period *t + 1*, given his stock of health H_t, level of diagnostic medical care D_t, medication M_t, and health-producing activities TH_t, individual characteristics Q_t, trust R_t, prices P_t, and health shock s_t.

At the beginning of each period s_t is unknown. The maximum expected value of lifetime utility conditional on the type of health insurance purchased is:

$$V_t^d(H_t, R_t, P_t, Q_t \mid I_t^j) = E_t[\max_{D_t, M_t, TH_t} V_t^d(H_t, R_t, P_t, Q_t, s_t \mid I_t^j)]. \tag{3.6}$$

The maximum expected value of lifetime utility unconditional on the type of health insurance is:

$$W_t(H_t, R_t, P_t, Q_t) = \max_{I_t^j}\left\{V_t^0(H_t, R_t, P_t, Q_t), V_t^1(H_t, R_t, P_t, Q_t), V_t^2(H_t, R_t, P_t, Q_t)\right\} \tag{3.7}$$

where $I_t^j \in \{0,1\}$, $\sum_{j=0}^{2} I_t^j = 1$.

I assume that individuals begin at time t = 1 until t = T + 1, at which time they will die. At t = T, the individual knows that he will die in the next period and will therefore not purchase any health insurance, diagnostic medical care or medication, and will not spend time on health-producing activities. Therefore, the value of lifetime utility at time T is:

$$V_T = U_T(Y_T, H_T = h, \overline{\Omega}_T). \tag{3.8}$$

Finding the demand functions for diagnostic medical care, medication, health-producing activities, and health insurance requires functional forms for both the utility and health production functions. The demand equations will be functions of the individual's health state, trust, travel costs, health insurance, prices and individual characteristics. For a description of dynamic programming and the Bellman equation please see Appendix A.

Chapter 4

DATA

This chapter provides a detailed description of the sample selection process and the Medical Expenditure Panel Survey (AHRQ 2007) variables used in this research. The chapter concludes with several informative summary statistics tables.

4.1 General Description of the Data Set

The Medical Expenditure Panel Survey (MEPS) – cosponsored by the Agency for Healthcare Research and Quality (AHRQ) and the National Center for Health Statistics (NCHS) – is a family of three surveys, which together provide nationally representative estimates of healthcare uses and expenditures, sources of payment, and insurance coverage for the United States civilian non-institutionalized population. MEPS consists of: 1) the Household Component (HC), which is the core survey, 2) the Medical Provider Component (MPC), and 3) the Insurance Component (IC).

AHRQ conducted the National Medical Care Expenditure Survey (NMCES or NMES-1) in 1977 and the National Medical Expenditure Survey (NMES-2) in 1987, making MEPS, which began in 1996, the third in a series of national probability surveys on the financing and use of medical care in the U.S. MEPS continues this series with design enhancements and efficiencies that provide a more current data resource that capture the changing dynamics of the healthcare delivery and insurance system.

The HC component of MEPS is drawn from the National Health Interview Survey (NHIS). The first stage of NHIS sample selection is an area sample of primary sampling units (PSUs), which generally consist of one or more counties. Within PSUs, density strata are defined and reflect the density of minority populations for blocks assigned to the strata. MEPS collects additional data on the NHIS subsample's healthcare expenditures, and links these data with additional information collected from the respondents' medical providers, employers, and insurance providers. While the NHIS, administered by the Centers for Disease Control and Prevention (CDC), is a nationally representative data set, it interviews individuals only once, which makes its use difficult in the context of my research. Another potential data set considered was the Behavioral Risk Factor Surveillance System (BRFSS), also administered by the CDC. Studies have found that the BRFSS provides national estimates comparable to those of the NHIS. One study compares national estimates from the NHIS and the BRFSS on smoking, height, weight, BMI, diabetes, hypertension, immunization, lack of insurance coverage, cost as a barrier to medical care, and health status. Overall the national estimates were similar; however, small differences according to demographic characteristics were found for height and BMI, with larger differences for health status (Nelson et al. 2003). The BRFSS also interviews individuals once, which is not ideal in the context of my analysis. Thus, I have chosen the MEPS data set, which uses an overlapping panel design, surveying individuals multiple times over a period of two-and-a-half years.

The Household Component collects medical expenditure data at both the person and household levels; and consists of detailed data on demographic characteristics, health conditions, health status, use of medical care services, charges and payments, access to care, satisfaction with care, health insurance coverage, income and employment.

The HC collects data through a preliminary contact followed by a series of five rounds of interviews. Using computer-assisted personal interviewing (CAPI) technology, data on medical expenditures and use for two calendar years are collected from each household. This series of data collection rounds is launched each subsequent year on a new sample of households to provide overlapping panels of survey data (Table 4.1).

Table 4.1 MEPS-HC Panel Design[1]

	1999	2000	2001	2002	2003	2004	2005	2006
Panel 4								
Panel 5								
Panel 6								
Panel 7								
Panel 8								
Panel 9								
Panel 10								
Sample Size Household	9,345	9,515	12,852	14,828	12,680	13,018	12,810	---
Sample Size Persons	23,565	23,839	32,122	37,418	32,681	32,737	32,320	---

The MEPS Medical Provider Component supplements and/or replaces information on medical care events reported in the MEPS HC by contacting medical providers and pharmacies identified by household respondents. The MPC sample includes all home health agencies and pharmacies reported by HC respondents; office-based physicians, hospitals and hospital physicians are also included in the MPC. Data are collected on medical and financial characteristics of medical and pharmacy events reported by HC respondents. The MPC is conducted through telephone interviews and record abstraction.

[1] Table extracted from Table: MEPS-HC Panel Design: Data Reference Periods. Available at http://meps.ahrq.gov/mepsweb/survey_comp/hc_data_collection.jsp

The MEPS Insurance Component collects data on health insurance plans obtained through private and public-sector employers. Data obtained in the IC include the number and types of private insurance plans offered, benefits associated with these plans, premiums, contributions by employers and employees, eligibility requirements, and employer characteristics.

Establishments participating in the IC are selected through: 1) a list of employers or other insurance providers identified by HC respondents who report having private health insurance at the Round 1 interview; 2) a Bureau of the Census list frame of private sector business establishments; 3) the Census of Governments from the Bureau of the Census.

To provide an integrated picture of health insurance, data collected from the first sampling frame (employers and insurance providers identified by MEPS HC respondents) are linked back to data provided by those respondents. Data from the two Census Bureau sampling frames are used to produce annual national and state estimates of the supply and cost of private health insurance available to American workers and to evaluate policy issues pertaining to health insurance. The IC is an annual survey. Data are collected from the selected organizations through a prescreening telephone interview, a mailed questionnaire, and a telephone follow-up for non-respondents (AHRQ 2007).

4.2 Diabetes-Specific Diagnostic Medical Care Variables

The typical diabetes care schedule, as recommended by the ADA, includes regular visits to the health care provider once every three months for an A1C (HbA1c or glycated hemoglobin) test, blood pressure and foot checks, and annual cholesterol checks and dilated eye exams. Physician visits, A1C tests, foot checks, dilated eye exams, cholesterol and blood pressure tests can be used to measure the use of diabetes-specific diagnostic medical care.

The variable pertaining to physician visits can be found in the Self-Administered Questionnaire (SAQ), which is a survey designed to collect a variety of health quality measures and the health status of adults. All adults age 18 and older in MEPS households were asked to complete this survey. SAQ asks the individual about the number of times he went to a doctor's office or clinic to get medical care.

Variables regarding cholesterol and blood pressure checks are available through the core survey. All adult respondents are asked how long it has been since their last blood pressure check and last blood cholesterol check by a doctor, nurse, or other health care professional.

The variables regarding A1C tests, foot checks, and dilated eye exams may be found in the Diabetes Care Survey (DCS). The DCS is a self-administered paper-and-pencil questionnaire, which was first administered in 2000 with round 5 of Panel 4. The DCS is administered once a year; thus providing two observations for each individual who receives the survey. Households receive a DCS based on their response to a question in the core survey, which asks the respondent whether he has ever been told by a health professional that he has had diabetes; this excludes gestational diabetes. The DCS repeats the question to confirm that the respondent has ever been told by a health professional that he has had diabetes. The DCS surveys the adult population.

The DCS asks questions regarding the number of times the respondent reported having an A1C blood test and his feet checked for sores or irritations in the previous year, and the last time the respondent reported having an eye exam in which the pupils were dilated. The DCS diabetes-specific medical care variables include: the number of times the respondent reported having a hemoglobin A1C test in [previous year]; the number of times the respondent reported having his/her feet checked for sores or irritations in [previous year]; the last time [year] the respondent reported having an eye exam in which the pupils were dilated.

4.3 Diabetes-Specific Medication Variables

In addition to specific diet and exercise needs, Type I diabetes management includes regular insulin injections and Type II management may require oral medications and, on occasion, insulin injections. The DCS asks whether the respondent is being treated for his diabetes by oral medications and/or insulin. The two variables of interest are: whether the respondent reported being treated for his/her diabetes by oral medications and whether the respondent reported being treated for his/her diabetes by insulin.

4.4 Diabetes-Specific Health Outcomes Variables

Diabetes can lead to serious complications such as retinopathy and nephropathy. In 2005, diabetes was the leading cause of kidney failure, accounting for 44% of all new cases. However, kidney failure and blindness due to diabetic retinopathy may be avoided through proper diabetes management. I measure diabetes-specific health outcomes using three variables: perceived health status, eye disease and kidney disease.

The core survey asks individuals about their perceived health status. Each individual can rank his health as good, fair or poor. The next two variables come from the DCS, which asks whether diabetes has caused kidney or eye problems.

4.5 Diabetes-Specific Input Behaviors Variables

Type 1 and Type 2 diabetes management involves special attention to diet and exercise regiments. Here, I consider variables in the data set that address health-producing activities such as diet and exercise. The DCS asks whether the respondent reported being treated for his/her diabetes by diet.

The core survey asks the adult respondent whether he currently spends half an hour or more in moderate to vigorous physical activity at least three times a week.

4.6 Trust and Language Variables

Competence, compassion, confidentiality, reliability, and communication are common physician behaviors on which patients are believed to base their trust. I will assess trust through the communication between the patient and his physician. I use variables from the Access to Care (AC) section of the MEPS HC.

The AC section gathers information on five main topic areas: family members' origins and preferred languages, family members' usual source of health care, characteristics of usual source of health care providers, satisfaction with and access to the usual source of health care provider, and access to medical treatment, dental treatment, and prescription medicines. For each individual family member, the AC section ascertains whether there is a particular doctor's office, clinic, health center, or other place that the individual usually goes if he/she is sick or needs advice about his/her health. The AC section collects information regarding the person's ability to access the Usual Source of Care (USC) provider as well as the person's satisfaction with the USC provider.

The following set of variables evaluates the level of satisfaction with the USC[2] provider. As these variables are indicative of the level of communication between the patient and the physician, and communication is one factor patients use to base their

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[2] The following variables can be used to help determine whether the USC is the physician providing diabetes care: Is the provider the person or place the family members would go to for preventive health care; is the provider the person or place the family members would go to for ongoing health problems.

trust on their physician, I use the variables to determine the individual's level of trust in his physician. The variables evaluate how well the physician listens to the patient, how well the physician explains the options to the patient, and whether the individual speaks English at home. The first two variables regarding the physician's listening and explaining are more subjective, while the final question is objective. Using objective variables is ideal; however, the nature of the dataset limits me to the use of the above-mentioned variables.

An alternative to using the AC variables was using the SAQ variables pertaining to communication. However, I chose the AC variables as they were directed toward the USC, a physician with which an individual has repeated interactions and can form interpersonal trust, rather than the SAQ variables which were geared toward providers in general and therefore dealt more with general trust or trust pertaining to the overall healthcare system.

4.7 Travel Cost Variables

In order to evaluate the individual's travel costs to the USC, I the following variables from the AC that can help describe these costs: how the person travels to the USC provider; how long it takes the person to travel to the USC provider; how difficult it is for the person the travel to the USC.

4.8 Health Insurance Variables

Health insurance plays an important part in the patient's decision-making process. The MEPS Insurance Component collects data on the number and types of private insurance plans offered, benefits associated with these plans, premiums, contributions by employers and employees, eligibility requirements, and employer characteristics. However, the amount of publicly available information from this component is limited. Thus, individuals are categorized into three groups of uninsured, insured without drug coverage and insured with drug coverage.

In order to separate uninsured individuals from insured individuals, I use a variable, which identifies individuals who were uninsured for the entire year. To separate the insured individuals without drug coverage from those with drug coverage, in each year, I make use of three variables that determine whether the individual had drug coverage in each of three rounds of interviews. Individuals with drug coverage for at least two of three rounds are considered to have had drug coverage for that year. Those individuals with Medicaid coverage are considered insured with drug coverage.

4.9 Other Variables of Interest

Other variables taken into account pertain to the individual's personal characteristics. These variables include age, sex, race, marital status and education (i.e., the highest degree obtained).

4.10 Using MEPS

Currently, panels 1 through 10 of MEPS are available through AHRQ. The DCS was first administered in 2000 with round 5 of Panel 4 and has been administered in two rounds (rounds 3 and 5) for all panels since; thus the panels of interest include panels 4 through 10. However, data on round 5 of Panel 10 is not yet available, providing only one DCS interview per individual in this panel; therefore, I exclude panel 10 from my analysis. Further, several Access to Care variables of interest in the context of this research, were first asked in 2002; thus, making panels 7, 8 and 9 appropriate for analysis. Pooling together these three panels, which span across four years, allows for a larger sample size and more reliable estimates. Table 4.2 shows the number of individuals in each panel.

Table 4.2 MEPS-HC: Panels[3]

	2002	2003	2004	2005	Respondents
Panel 7					16,234
Panel 8					16,338
Panel 9					16,194
Total					48,766

In my analysis, I use individuals who respond positively to the two diabetes diagnosis questions and the USC question. The USC question asks whether the respondent has a USC provider. Table 4.3 shows the number of individuals who

[3] Table extracted from Table: MEPS-HC Panel Design: Data Reference Periods (available at http://meps.ahrq.gov/mepsweb/survey_comp/hc_data_collection.jsp) and 2000 through 2005 consolidated yearly HC data.

answered the DCS in each of these panels. Among diabetic individuals, 94.1% reported having a USC provider. Approximately 99.2% of these individuals visited the USC provider for ongoing or preventive care. Those who did not have a USC sited problems such as having recently moved and not knowing where to go, wanting to treat themselves, seldom getting sick, etc.

Table 4.3 MEPS-HC: DCS Respondents

	2002	2003	2004	2005	Respondents
Panel 7					868
Panel 8					945
Panel 9					984
Total					2,797

Each respondent is observed for two time periods; thus the final sample size, upon ensuring the presence of key variables, is found by multiplying 1288 by 2, which is equal to 2,578 person-years.

4.11 Descriptive Statistics

Table 4.4 shows the summary statistics of socio-demographic variables for the diabetes dataset. The average age of the sample is approximately 51 years; the lowest age within the sample is 18 years and the highest age is 64 years. The sample consists of 42.5% males and 57.5% females, with a 70.1% majority of white individuals. Approximately 59% of the population is married and the average family size is 2.8 persons.

Table 4.4 Summary Statistics: Socio-Demographic Variables

Variable	Mean	S.D.
Age	51.0	9.7
Family Size	2.8	1.6
Income Logged	$24,450	$23,069
Sex		
Female	57.5	
Race		
White	70.1	
Marital Status		
Married	54.53	
Highest Degree Earned		
No Degree	30.8	
High School of GED	49.7	
Bachelor's Degree	15.7	
Master's or Doctorate Degree	3.9	
Poverty Status		
Poor/Near Poor	29.3	
Low Income	16.7	
Middle Income	27.0	
High Income	27.1	

The summary statistics are reported for all person-years. All values are percentages except Age, Family Size, and Income.

The average individual income is $24,450, with 29.3% of the sample defined as poor or near poor. According to the U.S. Census Bureau, between 2002 and 2005, the average individual income ranged from $22,794 to $25,036 (2008). The definitions of income and poverty categories are taken from the 2005 poverty statistics developed by the Current Population Survey (CPS), a result of the joint effort between the Bureau of Labor Statistic and the U.S. Census Bureau. Family income includes annual salary, wages, tips, bonuses, unemployment, child support, interest and dividends, etc. and excludes tax refunds and capital gains. Poverty status reports family income as a percentage of poverty (2008). Close to 70% of the sample holds a high school diploma or higher.

Table 4.5 presents the summary statistics of diagnostic medical care. Diagnostic medical care refers to regular visits to the health care provider for A1C tests, foot checks, blood pressure checks, and annual cholesterol and dilated eye exams. The ADA highly recommends 2 or more A1C tests per year.

For each diagnostic measure, individuals are considered compliant if they have 2 or more visits with their USC each year, 2 or more A1C tests, 2 or more foot checks, and one annual cholesterol check, blood pressure check and eye exam. Individuals with one or no visits, A1C tests, and foot checks, are considered noncompliant, as are those with no blood pressure checks, cholesterol checks, or dilated eye exams.

Nearly 80% of individuals are compliant with medical visits and A1C tests. Only half of the individuals are compliant with foot checks, receiving less than 2 checks within a year. A large number of individuals are compliant with blood pressure, cholesterol, and eye checks.

Table 4.5 Summary Statistics: Diagnostic Medical Care

Variable	Percent
Visits	
None or one visit	18.0
2 or more visits	82.0
A1C	
None or one test	20.7
2 or more tests	79.3
Foot Check	
None or one check	46.6
2 or more checks	53.4
Blood Pressure Check	
Yes	97.0
Cholesterol Check	
Yes	88.5
Dilated Eye Exam	
Yes	84.7

Table 4.6 displays the summary statistics of input behaviors and health outcomes. The table shows different combinations of input behaviors – exercise, diet, oral medications, and insulin. The majority of individuals opt to manage their diabetes through diet and oral medications. A small minority (less than 2%) opt not to use any of the listed input behaviors in managing their diabetes.

I use body mass index (BMI) to classify levels of overweight and obesity. According to the American Heart Association a BMI between 18.5 and 25 is considered ideal, while a BMI between 25 and 29.9 is considered overweight; a BMI of 30 or more indicates obesity (2007). The sample population proves to be heavily overweight, with approximately 25.9% classified as solely overweight, 62.7% solely obese and approximately 88% either overweight or obese. While these numbers appear large, they are in fact consistent with values reported by the Centers for Disease Control and Prevention (CDC); the prevalence of overweight or obesity among adults was 82-85% and the prevalence of obesity was 44-55% (Eberhardt 2004). The prevalence of overweight and obesity is higher among the diabetic population as compared to one-third prevalence in the general population (Ogden 2007).

Table 4.6 Summary Statistics: Input Behaviors and Health Outcomes

Variable	Percent
Input Behavior	
No input behaviors	1.4
Exercise only	0.8
Diet only	6.4
Oral medication only	6.1
Insulin only	2.8
Exercise and diet	4.6
Exercise and oral medication	3.5
Exercise and insulin	1.7
Diet and oral medication	28.4
Diet and insulin	4.5
Oral medication and insulin	2.0
Exercise, oral medication, and diet	20.7
Exercise, diet, and insulin	3.4
Exercise, oral medication, and insulin	0.5
Diet, oral medication, and insulin	8.2
Exercise, diet, oral medication, and insulin	5.1
Body Mass Index	
Overweight	62.7
Obese	25.9
Health Outcomes	
Retinopathy	26.4
Renalopathy	12.3
Self-perceived health status	
Good	16.6
Fair	64.1
Poor	19.4

Health outcomes are presented in Table 4.6 using 3 separate measures. The first two are diabetes-specific complications. Approximately 26% of the sample report having diabetes-related eye disease and 12% report having diabetes-related kidney disease. The third health outcome measure is a self-reported health status, which individuals report as good, fair, or poor.

Table 4.7 presents the summary statistics of the comorbidities. Diabetes may come with complications such as heart disease, stroke, and high blood pressure. This table provides a look at the occurrence of these complications, or comorbidities, among the sample of diabetes patients. As the table shows, there is a large (approximately 65%) incidence of high blood pressure among diabetes patients. In 2005, the ADA reported that approximately 73% of diabetics suffer from high blood pressure.

Table 4.7 Summary Statistics: Comorbidities

Variable	Percent
High Blood Pressure	64.4
Heart Disease & Stroke	
Coronary heart disease	10.1
Angina	6.6
Heart attack	9.1
Stroke	7.0
Other heart disease	10.5

Table 4.8 shows the summary statistics of the trust variables. The trust variables include whether the physician listens to the patient and asks about other treatments, explains options to the patient, and the patient is comfortable with English. Travel variables consist of travel time and difficulty of getting to the physician's office; approximately 15% travel over 30 minutes to see their USC provider.

Table 4.8 Summary Statistics: Trust & Travel

Variable	Percent
Trust	
Physician listens to patient	80.0
Physician explains options to the patient	93.8
Patient is comfortable with English	83.6
Travel	
Mode	
Drives	74.2
Is driven	17.0
Public transportation	6.8
Walks	2.0
Time	
Less than 15 minutes	45.3
15 to 30 minutes	39.4
More than 30 minutes	15.3
Difficulty	
Not too difficult	88.9
Somewhat difficult	8.7
Very difficult	2.5

Table 4.9 provides the summary statistics for employment and health insurance. Health insurance coverage is determined using a variable in MEPS which determines whether the individual was publicly or privately insured or uninsured in a given year. Prescription drug coverage was determined by examining each of three rounds in a given year; if the individual was covered for two rounds, he was considered to have prescription drug coverage. Approximately 87% of individuals have some type of coverage, which may or may not include prescription drug coverage.

Table 4.9 Summary Statistics: Employment & Health Insurance

Variable	Percent
Employment Status	
Employed	55.4
Health Insurance	
Insurance with drug coverage	50.7
Insurance without drug coverage	36.9
No insurance	12.4

As my research examines the effects of trust and travel costs on behavior, it is important to evaluate how health, health inputs, the use of diagnostic medical care, and demographics vary descriptively between those with and without trust, and those with more as opposed to less travel costs. Tables 4.10 – 4.11 indicate that the use of diagnostic medical is more common among those who report their physicians as better listeners or as providers who take the time to explain options. These individuals also report a higher percentage of good health. The same trend is visible among those who are comfortable with speaking English.

The means from Tables 4.12 – 14.13 appear surprising at first, as those individuals with more travel costs report obtaining more diagnostic medical care. However, these individuals also report poorer health conditions (i.e., higher percentages of retinopathy and renalopathy, with fewer individuals reporting "good" health). This may be explained by the fact that sicker individuals may have to travel greater distances to find doctors who may perhaps provide better care. These individuals report lower income and education levels as well.

Table 4.10 Means of Key Variables by Physician Listening

	Physician Listens to Patient (N = 2,029)	Physician Does Not Listen to Patient (N = 508)
Socio-Demographic Variables		
Age	51.0	51.0
Family Size	2.85	2.73
Income ($)	24,436	24,280
Female	57.2	59.5
White	70.1	69.7
Married	60.1	55.1
Degree		
No Degree	31.1	30.6
High School or GED	49.1	51.0
Bachelor's Degree	15.2	15.5
Master's or Doctorate Degree	4.05	2.98
Diagnostic Behavior		
Visits	82.3	80.6
A1C Tests	79.5	77.6
Foot Checks	54.5	49.0
Blood Pressure Check	97.1	96.4
Cholesterol Check	89.0	86.1
Eye Exam	85.0	83.1
Input Behavior		
Diet	81.9	80.1
Exercise	40.2	38.8
Oral Medication	74.5	76.1
Insulin Injection	29.3	24.4
Health		
Retinopathy	26.9	25.3
Renalopathy	12.9	10.3
Good Health	19.3	17.7
Fair Health	63.3	68.3
Poor Health	17.4	14.0

Table 4.11 Means of Key Variables by Physician Explaining

	Physician Explains Options to Patient (N = 2,389)	Physician Does Not Explain Options to Patient (N = 157)
Socio-Demographic Variables		
Age	51.0	51.4
Family Size	2.83	2.80
Income ($)	24,598	20,520
Female	57.2	59.9
White	70.0	71.3
Married	59.2	59.9
Degree		
No Degree	30.8	31.9
High School or GED	49.6	48.4
Bachelor's Degree	15.6	19.8
Master's or Doctorate Degree	4.03	0.00
Diagnostic Behavior		
Visits	82.2	78.2
A1C Tests	79.3	79.6
Foot Checks	53.9	47.0
Blood Pressure Check	97.1	95.5
Cholesterol Check	88.6	84.6
Eye Exam	84.8	84.7
Input Behavior		
Diet	81.5	82.1
Exercise	41.1	27.6
Oral Medication	74.7	71.8
Insulin Injection	28.5	26.1
Health		
Retinopathy	26.5	28.8
Renalopathy	12.4	12.3
Good Health	19.8	11.5
Fair Health	64.0	66.9
Poor Health	16.2	21.7

Table 4.12 Means of Key Variables by Language

	Patient Comfortable with English (N = 2,155)	Patient Comfortable w/ Language Other than English (N = 423)
Socio-Demographic Variables		
Age	51.1	50.6
Family Size	2.66	3.68
Income ($)	25,285	19,611
Female	56.6	61.7
White	67.2	84.4
Married	57.4	68.8
Degree		
No Degree	24.0	65.6
High School or GED	54.9	23.0
Bachelor's Degree	16.8	10.0
Master's or Doctorate Degree	4.33	1.43
Diagnostic Behavior		
Visits	82.6	78.6
A1C Tests	79.2	79.7
Foot Checks	54.0	50.4
Blood Pressure Check	97.3	95.5
Cholesterol Check	89.0	86.0
Eye Exam	87.2	71.4
Input Behavior		
Diet	81.6	81.0
Exercise	40.6	38.6
Oral Medication	72.4	85.7
Insulin Injection	29.6	21.1
Health		
Retinopathy	25.6	30.5
Renalopathy	12.5	11.6
Good Health	20.0	16.1
Fair Health	63.3	68.1
Poor Health	16.7	15.9

Table 4.13 Means of Key Variables by Travel Time to Physician's Office

	Takes Patient Less Than 15min to Reach Physician (N = 1,165)	Takes Patient More than 30min to Reach Physician (N =392)
Socio-Demographic Variables		
Age	50.5	51.5
Family Size	2.86	2.64
Income ($)	26,047	19,788
Female	57.3	56.1
White	75.3	63.8
Married	59.0	57.1
Degree		
No Degree	30.3	32.0
High School or GED	50.5	47.8
Bachelor's Degree	15.3	17.7
Master's or Doctorate Degree	3.88	2.56
Diagnostic Behavior		
Visits	81.3	83.5
A1C Tests	78.2	82.2
Foot Checks	54.9	55.6
Blood Pressure Check	96.3	98.2
Cholesterol Check	88.2	88.6
Eye Exam	85.8	82.1
Input Behavior		
Diet	81.3	82.5
Exercise	40.9	41.3
Oral Medication	73.5	74.8
Insulin Injection	26.5	31.0
Health		
Retinopathy	25.7	31.8
Renalopathy	12.5	17.5
Good Health	21.2	14.0
Fair Health	63.7	65.6
Poor Health	15.1	20.41

Table 4.14 Means of Key Variables by Difficulty of Reaching Physician's Office

	Not Difficult for Patient to Reach Physician Office (N = 2,289)	Difficult for Patient to Reach Physician (N = 64)
Socio-Demographic Variables		
Age	50.1	53.5
Family Size	2.87	2.4
Income ($)	25,687	11,537
Female	56.3	73.4
White	70.9	65.6
Married	61.5	35.9
Degree		
No Degree	29.2	53.1
High School or GED	50.8	35.9
Bachelor's Degree	15.9	9.38
Master's or Doctorate Degree	4.12	1.56
Diagnostic Behavior		
Visits	81.5	90.3
A1C Tests	79.1	84.3
Foot Checks	53.0	55.9
Blood Pressure Check	96.8	98.4
Cholesterol Check	88.7	82.5
Eye Exam	84.9	80.3
Input Behavior		
Diet	81.3	81.3
Exercise	41.9	39.1
Oral Medication	74.2	75.4
Insulin Injection	27.7	39.1
Health		
Retinopathy	24.6	60.7
Renalopathy	11.4	27.0
Good Health	20.7	6.25
Fair Health	65.3	46.9
Poor Health	14.1	46.9

Chapter 5

EMPIRICAL FRAMEWORK

Obtaining demand functions for insurance, medical care, and health-producing activities requires that I impose functional forms for the utility and health production functions. A Taylor series expansion of the maximum lifetime value function, $V_t^d(H_t, R_t, P_t, Q_t \mid I_t^j)$, suggests the following equations for the input demands.

5.1 Equation Specification

Referring to Figure 3.1 – Timing of Decisions and Health Outcomes – entering each period, the individual first makes a decision about health insurance coverage I_t. The health insurance decision is modeled as a multinomial logit probability of choosing each health insurance alternative[4]. The health insurance decision is specified as:

$$\ln\left[\frac{P(I_t^j = 1)}{P(I_t^0 = 0)}\right] = \alpha_0^j + \alpha_1^j H_t + \alpha_2^j R_t + \alpha_3^j TV_t + \alpha_4^j Q_t + \alpha_5^j X_t^I + a_1^j + u_{1t},\ j = 0,\ 1. \tag{5.1}$$

The dependent variable is the log odds that the individual chooses insurance alternative $I_t^2 = 1$ (insured with drug coverage) or $I_t^1 = 1$ (insured without drug

[4] Consider: Utility (if insurance choice is 0) = $V_t^{j-0}(Z_t) = Z\beta_0^* + \varepsilon_0^*$ and Utility (if insurance choice is 1) = $V_t^{j-1}(Z_t) = Z\beta_1^* + \varepsilon_1^*$, where Z is a vector of state variables and * represents values at the maximum expected lifetime utility level. We can now say that P (insurance choice is 1) $= P(Z\beta_1^* + \varepsilon_1^* > Z\beta_0^* + \varepsilon_0^*)$. If $\beta^* = \beta_1^* - \beta_0^*$ and $\varepsilon^* = \varepsilon_0^* - \varepsilon_1^*$, then P(insurance choice is 1) $= P(Z\beta^* > \varepsilon^*) = \text{logit}(Z\beta^*)$.

coverage) relative to insurance alternative $I_t^0 = 0$ (uninsured). The independent variables include the individual's health entering the period H_t, a vector of trust variables R_t, a vector of travel variables TV_t, a vector of exogenous individual characteristics Q_t, and a vector of exclusion restrictions, X_t, incorporated in equation 5.1 (market level insurance: 18.6% uninsured, 30.8% insured without drug coverage, 50.7% insured with drug coverage), that influence the individual's decision to purchase health insurance (Tao 2007).

The two-part error term in this equation is due to the structure of the dataset. The panels used in this research follow cross sections of individuals over a two-year period. The unobserved factors that affect the independent variable can be divided into two groups: 1) factors that are time-invariant (unobserved effects, unobserved heterogeneity or individual heterogeneity) and 2) factors that are time-variant (idiosyncratic errors). Thus, the error term is written $v_{it} = a_i + u_{it}$, where a_i is the unobserved error and u_{it} is the idiosyncratic error or mean zero random error, distributed logistically (Wooldridge 2003).

The following specification models the health-producing activities and behaviors of the individual. These activities include diet, exercise, taking oral medications and insulin injections.

$$\ln\left[\frac{P(A_t = 1)}{P(A_t = 0)}\right] = \beta_0 + \beta_1 H_t + \beta_2 R_t + \beta_3 TV_t + \beta_4 I_t + \beta_5 Q_t + a_2 + u_{2t}$$

(5.2)

The dependent variable is the log odds that the individual chooses to engage in one of these activities relative to not engaging the activity. The independent variables include the individual's health entering the period H_t, a vector of trust variables R_t, a vector of travel variables TV_t, a vector of exogenous individual characteristics Q_t, and insurance choice I_t.

The demand for each type of diagnostic medical care is modeled as a binary logit:

$$\ln\left[\frac{P(D_t = 1)}{P(D_t = 0)}\right] = \gamma_0 + \gamma_1 H_t + \gamma_2 R_t + \gamma_3 TV_t + \gamma_4 I_t + \gamma_5 Q_t + a_3 + u_{3t},$$

(5.3)

The dependent variable is the log odds that the individual chooses to obtain the diagnostic medical care relative to not receiving the diagnostic medical care (Table 4.6 lists the different types of diagnostic medical care). The independent variables include the individual's health entering the period H_t, a vector of trust variables R_t, a vector of travel variables TV_t, a vector of exogenous individual characteristics Q_t, and insurance choice I_t.

To estimate the health production function, I use a multinomial logit specified as follows:

$$\ln\left[\frac{P(H_{t+1}=h)}{P(H_{t+1}=2)}\right] = \delta_0^h H_t + \delta_1^h D_t + \delta_2^h M_t + \delta_3^h TH_t + \delta_4^h H_t \times D_t + \delta_5^h H_t \times M_t + \delta_6^h H_t \times TH_t + \delta_7^h Q_t + a_4 + u_{4t}. \tag{5.4}$$

The dependent variable is the log odds that the individual is in each of the following health states at time *t+1*:

$$h = \begin{cases} 0 \text{ if in poor health} \\ 1 \text{ if in mediocre health} \\ 2 \text{ if in good health.} \end{cases}$$

The independent variables include the individual's health entering the period H_t, diagnostic medical care D_t, medications M_t, health-producing activities TH_t, and interactions between these variables and the current health state. Including interactions in the model allows for more flexibility in the relationship between health status and the various medical behaviors in the model. Interaction terms allow for inferences about how the effect of one independent variable on the dependent variable depends on the magnitude of another independent variable (Ai and Norton 2003).

In estimating the diabetes-specific health outcomes – eye disease and kidney disease – I use binary logit specifications in the following forms, respectively:

$$\ln\left[\frac{P(O_{t+1}=1)}{P(O_{t+1}=0)}\right] = \theta_0 H_t + \theta_1 D_t + \theta_2 M_t + \theta_3 TH_t + \theta_4 H_t \times D_t + \theta_5 H_t \times M_t + \theta_6 H_t \times TH_t + \beta_7 Q_t + a_5 + u_{5t}. \tag{5.5}$$

$$\ln\left[\frac{P(K_{t+1}=1)}{P(K_{t+1}=0)}\right] = \psi_0 H_t + \psi_1 D_t + \psi_2 M_t + \psi_3 TH_t + \psi_4 H_t \times D_t + \psi_5 H_t \times M_t + \psi_6 H_t \times TH_t + \psi_7 Q_t + a_6 + u_{6t} \tag{5.6}$$

The dependent variable is the log odds that the individual has eye disease or kidney disease relative to not having each of these conditions. The independent variables once again include the individual's health entering the period H_t, diagnostic medical care D_t, medications M_t, health-producing activities TH_t, and interactions between these variables and the current health state.

5.2 Estimation Strategy

5.2.1 Panel Data Error Terms

The panel used in this research follows a cross section of individuals over a two-year period. The unobserved factors that affect the independent variable can be divided into two groups: 1) factors that are time-invariant and 2) factors that are time-variant. Thus, the error term is written $v_{it} = a_i + u_{it}$. There are two options when approaching a_i: the first is to treat it as a constant (fixed effects estimation) and the second, to treat it as a random variable (random effects estimation). Fixed effects estimation tends to be problematic with short panels, thus I use random effects estimation (Wooldridge 2003).

5.2.2 Identification

Health insurance plays an important part in the patient's decision-making process, and the effects of health insurance are identified theoretically by insurance premiums (i.e., the price of insurance). While the MEPS Insurance Component collects detailed information on the types of private insurance plans offered, premiums, and the benefits associated with these plans, the amount of publicly available information from this component is limited.

Thus, I make use of the aggregate insurance characteristics of individuals in the surrounding areas to serve as variables that influence insurance purchase, but not the demand for care; these characteristics include whether the individual is uninsured, insured without drug coverage or insured with drug coverage (Tao 2007).

Insurance characteristics are aggregated at the primary sampling unit (PSU) level. PSUs are determined in the first stage of the NHIS sample selection. PSUs are area samples that consist of one or more counties from which individuals were randomly selected for participation in the survey. MEPS draws survey participants from over 200 PSUs. Each PSU varies widely in the number of households it contains. As the MEPS dataset does not provide state or zip code identifiers, PSUs are the only way to evaluate the sample geographically. A regression of individual insurance on market level insurance and other exogenous variables indicates that individual insurance and market insurance are highly correlated, which allows me to employ market level insurance as an instrument for this study.

Chapter 6

RESULTS

The equations specified in Chapter 5 – Empirical Framework were estimated using STATA software. This chapter presents these results.

Table 6.1 shows the marginal effects of trust and travel variables in the health-producing activities and medications equations (i.e., estimation results for Exercise, Diet, Oral Medication, and Insulin equations).

This table presents the marginal effects of certain trust and travel variables on the patient's decision to exercise, make diet changes, use oral medications, and use insulin. The independent variables are written across the top of the table and the dependent variables are written on the left-hand-side of the table. Trust is measured through the area of communication. In particular, the three variables of Physician Listens, Physician Explains, and Language are used. 'Physician Listens' indicates whether the patient feels the physician listens to him; 'Physician Explains' indicates whether the patient feels the physician explains various treatment options to him, and 'Language' measures whether the patient is comfortable with speaking English. The travel variables are 'Ease of Travel,' which indicates how easy it is for the patient to reach the USC provider's office and 'Less Travel,' which indicates that little time (less than 15 minutes) is spent on traveling to the physician's office.

Table 6.1 summarizes the key results of tables 6.4 – 6.7 for easier evaluation and understanding of the results. Each of the four equations – Exercise, Diet, Oral Medications, Insulin – was estimated and standard errors bootstrapped with 100 replications, followed by a calculation of marginal effects. Each number presented in the table may be multiplied by 100 in order to determine the percent effect of each independent variable on the dependent variable. For instance, if the physician explains the different options available to the patient, the likelihood of that the patient will exercise increases by approximately 12%.

The results indicate that physician explaining plays an important part in determining whether the patient engages in diet and exercise regiments and uses oral medications. In other words, when individuals report that physicians explain available options to the patient, the more likely it is for them to engage in health-producing activities. Furthermore, the individual's comfort with English is important in obtaining oral medication and insulin.

Table 6.1 Summary of Key Results of Health-Producing Activities & Medication Equations

	Physician Listens	Physician Explains	Language	Ease of Travel	Less Travel Time
Exercise	-.0139 (.0529)	.1236** (.0553)	.0251 (.0381)	.0974*** (.0143)	.0027 (.0212)
Diet	.0223 (.0268)	.0193** (.0023)	.0014 (.0143)	-.0154 (.0171)	.0044 (.0141)
Oral Medication	.0206* (.0123)	.0556*** (.0086)	.1486*** (.0083)	-.0665*** (.0203)	-.0191 (.0151)
Insulin Injections	.0334 (.0273)	.0287 (.0659)	.0659* (.0378)	.0379*** (.0027)	-.0103 (.0468)

***Indicates significance at the 1% level. **Indicates significance at the 5% level. *Indicates significance at the 10% level.

Table 6.2 shows the marginal effects of trust and travel variables in the diagnostic medical care equations (i.e., estimation results for Visits, A1C, Foot Checks, Blood Pressure Checks, Cholesterol Checks and Dilated Eye Exam equations).

This table presents the marginal effects of certain trust and travel variables on the patient's decision to obtain diagnostic medical care. The independent variables are written across the top of the table and the dependent variables are written on the left-hand-side of the table. Table 6.2 summarizes the key results of the estimations presented in tables 6.8 – 6.13. Each equation was estimated and standard errors bootstrapped with 100 replications, followed by a calculation of marginal effects. Each number presented in the table may be multiplied by 100 in order to determine the percent effect of each independent variable on the dependent variable.

As Table 6.2 shows, that the three variables of trust have positive and significant effects on whether the patient obtains diagnostic medical care. For example, comfort with English may lead to a 7% increase in the likelihood of obtaining a dilated eye exam. Physician explaining has the most positive and significant outcomes. This may be due to the fact that as patients become more aware of their options and possible outcomes of their condition, they may be more willing and likely to comply with guidelines.

This table shows that as travel costs (as defined by the two travel variables) decrease, the likelihood of obtaining diagnostic medical care increases. The three significant values in the table are all positive. For example, those individuals who report “very easy” travel to the physician’s office are 2% more likely to obtain an A1C test, a important test in determining how well the patient is managing diabetes. and less travel time may lead to more A1C tests and foot checks.

Table 6.2 Summary of Key Results of Diagnostic Medical Care Equations

	Physician Listens	**Physician Explains**	**Language**	**Ease of Travel**	**Less Travel Time**
Physician Visits	.0313 (.0387)	.0233** (.0117)	.0088 (.0112)	-.0105 (.0191)	-.0003 (.0265)
A1C Test	.0310* (.0170)	.0133* (.0026)	.0031 (.0356)	.0190* (.0101)	-.0055 (.0237)
Foot Check	.0446* (.0263)	.0793*** (.0154)	. 0184*** (.0048)	-.0242 (.0284)	.0521*** (.0164)
Cholesterol Check	.0193 (.0163)	.0374* (.0209)	.0133** (.0057)	.0195*** (.0055)	.0076 (.0066)
Blood Pressure Check	.0034 (.0078)	.0230* (.0033)	.0022 (.0033)	-.0215 (.0440)	-.0041 (.0048)
Dilated Eye Exam	.0155* (.0104)	.0111 (.0150)	.0714** (.0308)	-.0029 (.0296)	.0063 (.0178)

***Indicates significance at the 1% level. **Indicates significance at the 5% level. *Indicates significance at the 10% level.

Table 6.3 Estimation Results for Insurance

	Insured w/o Drug Coverage vs. Uninsured		Insured w/ Drug Coverage vs. Uninsured	
	Coefficient	S.E.	Coefficient	S.E.
Age	-.1290***	.0501	-.1777**	.0858
Family Size	-.7378***	.2173	-.7711*	.4423
Income	.9195*	.5018	.8450	.1106
Male	-.2332***	.5791	-.1701	.1208
White	.1647***	.5641	.2135*	.1119
Married	.2674***	.4808	.1357	.1095
Degree	1.249***	.4119	1.269**	.6054
Good Health	-.4357	.6592	-.3953	.1157
Poor Health	-.1861***	.6939	-.1711*	.9865
Less Than 15 Minutes	-.4323	.5086	-.2674	.7601
More Than 30 Minutes	-.1985	.6859	-.1334	.1129
Very Difficult	-.1689	.1281	-.1650	.1908
Not Difficult	-.1681	.7103	-.2587	.1178
Physician Listens	.9002	.6022	-.1080	.9730
Physician Explains	-.1402	.7824	-.3277	.1491
Comfort with English	-.2980*	.4707	-.1080*	.9730
% Insurance in PSU	6.759***	.1733	11.28***	.3042

***Indicates significance at the 1% level. **Indicates significance at the 5% level. *Indicates significance at the 10% level..

Table 6.4 Estimation Results for Health-Producing Activity: Exercise

	Coefficient	S.E.
Age	-.0032***	.0006
Family Size	-.0060	.0068
Income	.0232**	.0117
Male	.0305	.0228
White	.0083	.0068
Married	.0488**	.0221
Degree	-.0038	.0063
Good Health	.0604***	.0070
Poor Health	-.1959***	.0186
Less Than 15 Minutes	.0027	.0212
More Than 30 Minutes	.0532***	.0191
Very Difficult	.0472	.1112
Not Difficult	.0974***	.0143
Physician Listens	-.0139	.0529
Physician Explains	.1236**	.0553
Comfort with English	.0251	.0381
Insurance	.0002	.0011

***Indicates significance at the 1% level. **Indicates significance at the 5% level. *Indicates significance at the 10% level.

Table 6.5 Estimation Results for Health-Producing Activity: Diet

	Coefficient	S.E.
Age	.0015	.0009
Family Size	-.0037***	.0010
Income	.0033	.0023
Male	-.0433***	.0157
White	.0008	.0123
Married	.0725***	.0083
Degree	.0070	.0054
Good Health	.0516***	.0155
Poor Health	.0151*	.0081
Less Than 15 Minutes	.0044	.0141
More Than 30 Minutes	.0191	.0283
Very Difficult	-.0201***	.0055
Not Difficult	-.0154	.0171
Physician Listens	.0223	.0268
Physician Explains	.0193**	.0023
Comfort with English	.0014	.0143
Insurance	-.0005	.0007

***Indicates significance at the 1% level. **Indicates significance at the 5% level. *Indicates significance at the 10% level.

Table 6.6 Estimation Results for Medication: Oral Medication

	Coefficient	S.E.
Age	.0066***	.0003
Family Size	.0063**	.0026
Income	.0270***	.0088
Male	-.0221	.0175
White	-.0054	.0176
Married	.0014	.0130
Degree	-.0095*	.0052
Good Health	-.0120	.0282
Poor Health	-.0078	.0103
Less Than 15 Minutes	-.0191	.0151
More Than 30 Minutes	-.0120	.0138
Very Difficult	-.0462	.0487
Not Difficult	-.0665***	.0203
Physician Listens	.0206*	.0123
Physician Explains	.0556***	.0086
Comfort with English	.1486***	.0083
Insurance	.0021***	.0005

***Indicates significance at the 1% level. **Indicates significance at the 5% level. *Indicates significance at the 10% level.

Table 6.7 Estimation Results for Medication: Insulin

	Coefficient	S.E.
Age	-.0017	.0024
Family Size	-.0044	.0100
Income	-.0267***	.0050
Male	.0488**	.0239
White	-.0781***	.0239
Married	-.0664*	.0342
Degree	.0044	.0102
Good Health	-.0894**	.0376
Poor Health	.1108	.0680
Less Than 15 Minutes	-.0103	.0468
More Than 30 Minutes	.0001	.0362
Very Difficult	.0609	.0818
Not Difficult	.0379***	.0027
Physician Listens	.0334	.0273
Physician Explains	.0287	.0659
Comfort with English	.0659*	.0378
Insurance	-.0003	.0014

***Indicates significance at the 1% level. **Indicates significance at the 5% level. *Indicates significance at the 10% level.

Table 6.8 Estimation Results for Physician Visits

	Coefficient	S.E.
Age	.0030***	.0006
Family Size	-.0113***	.0017
Income	-.0040	.0078
Male	-.0347***	.0054
White	.0323***	.0126
Married	-.0126	.0273
Degree	.0086	.0064
Good Health	-.0522*	.0268
Poor Health	.0937***	.0138
Less Than 15 Minutes	-.0003	.0265
More Than 30 Minutes	.0104	.0194
Very Difficult	.0556	.0490
Not Difficult	-.0105	.0191
Physician Listens	.0313	.0387
Physician Explains	.0233**	.0117
Comfort with English	.0088	.0112
Insurance	.0023***	.0004

***Indicates significance at the 1% level. **Indicates significance at the 5% level. *Indicates significance at the 10% level.

Table 6.9 Estimation Results for A1C Tests

	Coefficient	S.E.
Age	.0042*	.0020
Family Size	.0001	.0077
Income	-.0011	.0076
Male	-.0188***	.0052
White	.0094	.0166
Married	-.01552	.0276
Degree	-.0093**	.0042
Good Health	-.0140	.0110
Poor Health	.0727***	.0272
Less Than 15 Minutes	-.0055	.0237
More Than 30 Minutes	.0455***	.0145
Very Difficult	.0149	.0824
Not Difficult	.0190*	.0101
Physician Listens	.0310*	.0170
Physician Explains	.0133*	.0026
Comfort with English	.0031	.0356
Insurance	.0018***	.0002

***Indicates significance at the 1% level. **Indicates significance at the 5% level. *Indicates significance at the 10% level.

Table 6.10 Estimation Results for Foot Checks

	Coefficient	S.E.
Age	.0038***	.0014
Family Size	-.0156**	.0067
Income	.0054	.0091
Male	.0076	.0078
White	-.0334***	.0121
Married	-.0174	.0330
Degree	-.0042	.0100
Good Health	-.0350***	.0130
Poor Health	.0908***	.0040
Less Than 15 Minutes	.0521***	.0164
More Than 30 Minutes	.0388	.0394
Very Difficult	-.0193	.0515
Not Difficult	-.0242	.0284
Physician Listens	.0446*	.0263
Physician Explains	.0793***	.0154
Comfort with English	.0184***	.0048
Insurance	.0006**	.0003

***Indicates significance at the 1% level. **Indicates significance at the 5% level. *Indicates significance at the 10% level.

Table 6.11 Estimation Results for Blood Pressure

	Coefficient	S.E.
Age	.0004	.0003
Family Size	-.0017	.0021
Income	.0030	.0030
Male	-.0125	.0086
White	.0069	.0075
Married	-.0006	.0076
Degree	.0012	.0011
Good Health	-.0083	.0090
Poor Health	.0112*	.0095
Less Than 15 Minutes	-.0041	.0048
More Than 30 Minutes	.0099	.0537
Very Difficult	-.0502	.8305
Not Difficult	-.0215	.0440
Physician Listens	.0034	.0078
Physician Explains	.0230*	.0033
Comfort with English	.0022	.0033
Insurance	.0007	.0006

***Indicates significance at the 1% level. **Indicates significance at the 5% level. *Indicates significance at the 10% level.

Table 6.12 Estimation Results for Cholesterol Checks

	Coefficient	S.E.
Age	.0049***	.0006
Family Size	-.0072***	.0027
Income	.0112***	.0033
Male	.0054	.0146
White	-.0095	.0077
Married	.0005	.0100
Degree	.0024	.0025
Good Health	.0056	.0051
Poor Health	.0391***	.0082
Less Than 15 Minutes	.0076	.0066
More Than 30 Minutes	-.0025	.0102
Very Difficult	-.0180	.0516
Not Difficult	.0195***	.0055
Physician Listens	.0193	.0163
Physician Explains	.0374*	.0209
Comfort with English	.0133**	.0057
Insurance	.0022***	.0004

***Indicates significance at the 1% level. **Indicates significance at the 5% level. *Indicates significance at the 10% level.

Table 6.13 Estimation Results for Dilated Eye Exams

	Coefficient	S.E.
Age	.0046***	.0007
Family Size	-.0067***	.0018
Income	-.0031	.0060
Male	-.0283***	.0107
White	.0114	.0191
Married	-.0008	.0038
Degree	.0174***	.0038
Good Health	.0191	.0239
Poor Health	.0063	.0168
Less Than 15 Minutes	.0063	.0178
More Than 30 Minutes	-.0315*	.0183
Very Difficult	-.0071	.6025
Not Difficult	-.0029	.0296
Physician Listens	.0155*	.0104
Physician Explains	.0111	.0150
Comfort with English	.0714**	.0308
Insurance	.0028**	.0013

***Indicates significance at the 1% level. **Indicates significance at the 5% level. *Indicates significance at the 10% level.

Tables 6.14, 6.15 and 6.16 present the results for the health outcomes estimations. Health outcomes are measured in three ways: Health Status, Kidney Disease, and Eye Disease. The purpose of these tables is to understand the impact of the use of diagnostic medical care, health producing activities, and medications on different health outcome measures.

Table 6.14 presents the results for the first health outcome measure, 'Health Status.' 'Health Status' observes the probability of an individual being in a "good" versus "poor" health state, and "fair" health state versus "poor" health state. In this table, we are looking at the impact of diagnostic medical care, health-producing activities, and oral medications on self-reported health states.

The table displays results for a set of interaction terms, specified in the model. Interaction terms allow for inferences about how the effect of one independent variable on the dependent variable depends on the magnitude of another independent variable.

When determining the impact of a particular diagnostic medical service, health-producing activity, or medication on health outcomes, we must consider the interaction effect. For instance, in the first column of results, by simply interpreting the coefficient on Cholesterol Checks, one may reach the conclusion that more cholesterol checks lead to poorer health. However, once the interaction effect is considered, it is realized that the impact is actually positive. Another example would be to compare the results of the use of oral medication when comparing ‘fair’ versus ‘poor’ health states and ‘good’ versus ‘poor’ health states. At first glance, it appears that oral medications and negative health outcomes go hand-in-hand; but upon considering the interaction effects, the result is actually positive. Furthermore, oral medications appear to be more effective in obtaining better health outcomes when the individual is going from a ‘poor’ to ‘fair’ health state (.0118) versus going from a ‘poor’ to ‘good’ health state (.0057).

Finally, the second and third measures of health are ‘Kidney Disease’ and ‘Eye Disease.’ The results of these estimations are presented in tables 6.15 and 6.16. Once again, in order to allow for inferences about how the effect of one independent variable on the dependent variable depends on the magnitude of another independent variable, interaction terms are used. These tables include the marginal effects of the interaction variables.

Estimation results presented in these three tables suggest that obtaining diagnostic medical care, engaging in health-producing activities and making use of medications may lead to better health outcomes. For instance, receiving two or more A1C tests within a given year may decrease the likelihood of eye disease by approximately 2%.

Table 6.14 Estimation Results for Health

	Fair Vs. Poor		Good Vs. Poor	
	Coefficient	S.E.	Coefficient	S.E.
Age	.0044	.0600	-.0220	.0797
Family Size	-.1123	.6848	-.0281	.8338
Income	.5238	.5299	.7875	.5405
Male	-.1976	.2152	-.2581	.1819
White	-.1203	.1760	-.1424	.1476
Married	.1097	.1804	.2454	.1852
Degree	-.3267	.1266	.1727	.1392
Good Health	-.1255	.1991	-.4746	.2204
Poor Health	-.2247	.2188	-.1029	.2598
Visits	.2712	.2169	.1391	.2982
A1C Test	.2185*	.1157	.2171	.1471
Foot Check	.2423	.6828	.2540	.1615
Blood Pressure Check	.4138***	.1447	.8086***	.1596
Cholesterol Check	-.2361*	.1361	-.2564	.1752
Eye Exam	.2259**	.0909	.5650***	.1107
Exercise	.3632	.1057	.3025**	.1221
Diet	-.2389**	.0835	-.5985***	.1206
Oral Medication	-.2125***	.0762	-.2056**	.1148
Insulin	-.4451**	.2077	-.4745**	.2294
Good Health x Visits	.1029	.1972	-.3571	.2326
Good Health x A1C	-.2044*	.1140	-.2032	.1446
Good Health x Foot Checks	-.3051	.7184	-.2473	.1619
Good Health x BP Ck	-.4475***	.1405	-.8140***	.1529
Good Health x Chol Ck	.2399*	.1394	.2529	.1775
Good Health x Eye Exam	-.2310**	.9261	-.5631***	.1156
Good Health x Exercise	-.2707	.1088	-.3040**	.1232
Good Health x Diet	.2470***	.8369	.5961***	.1236
Good Health x Meds	.2243***	.7978	.2113*	.1178
Good Health x Insulin	.4545**	.2093	.4774**	.2303

***Indicates significance at the 1% level. **Indicates significance at the 5% level. *Indicates significance at the 10% level.

Table 6.15 Estimation Results for Eye Disease

	Coefficient	S.E.
Age	.0040***	.0007
Family Size	.0028	.0061
Income	-.0236***	.0036
Male	.0023	.0043
White	-.0355***	.0092
Married	-.0304**	.0144
Degree	-.0218***	.0042
Good Health	-.0380	.1561
Poor Health	-.0165	.1405
Visits (2+)	.0677	.0435
A1c (2+)	-.0686***	.0175
Feet (2+)	-.0175	.0471
Blood Pressure Check	.1010	.0740
Cholesterol Check	-.0596*	.0317
Eye Exam	.0207	.0670
Exercise	.0372	.0239
Diet	.1495***	.0183
Oral Medication	.0332	.0322
Insulin	.1966***	.0233
Good Health x Visits	-.0510	.0387
Good Health x A1C	.0506**	.0235
Good Health x Foot Checks	.0726***	.0269
Good Health x BP Ck	-.0729	.0883
Good Health x Chol Ck	.0079	.0374
Good Health x Eye Exam	.0255	.0358
Good Health x Exercise	-.0520***	.0149
Good Health x Diet	-.1061***	.0379
Good Health x Meds	.0194	.0195
Good Health x Insulin	.0442***	.0098

***Indicates significance at the 1% level. **Indicates significance at the 5% level. *Indicates significance at the 10% level.

Table 6.16 Estimation Results for Kidney Disease

	Coefficient	S.E.
Age	.0005	.0004
Family Size	-.0050***	.0019
Income	-.0058	.0061
Male	-.0255*	.0146
White	.0269***	.0034
Married	.0002	.0076
Degree	-.0028	.0030
Good Health	.0713	.1366
Poor Health	-.0459	.0388
Visits	.0278***	.0100
A1C Test	-.0218	.0530
Foot Check	.0437***	.0164
Blood Pressure Check	.0647***	.0220
Cholesterol Check	.0410*	.0230
Eye Exam	-.0324	.0311
Exercise	-.0165	.0293
Diet	.0110	.0344
Oral Medication	.0047	.0149
Insulin	.0632***	.0240
Good Health x Visits	-.0522***	.0147
Good Health x A1C	.0116	.0383
Good Health x Foot Checks	-.0044	.0206
Good Health x BP Ck	-.0807*	.0459
Good Health x Chol Ck	-.0369	.0364
Good Health x Eye Exam	.0062	.0076
Good Health x Exercise	.0072	.0248
Good Health x Diet	-.0174	.0410
Good Health x Meds	.0176	.0327
Good Health x Insulin	.0378**	.0193

***Indicates significance at the 1% level. **Indicates significance at the 5% level. *Indicates significance at the 10% level.

Chapter 7

CONCLUSION & FUTURE RESEARCH

The goal of this research was to provide a picture of the various factors that impact a diabetes patient's use of medical care which can aid us in gaining a detailed understanding of why patients with comparable health conditions vary in the use of medical care and health-producing activities. This research, hopefully, helps us look beyond financial issues to non-financial issues that prevent diabetes patients from seeking treatment and care. This picture, however, is not yet complete; there are numerous other factors that play a part in any patient's decision-making process. Future research could contribute to completing this picture.

Factors to consider may include provider characteristics that perhaps make it difficult for the patient to get in contact with his physician. The following three variables from the MEPS data set assess such aspects of the provider:

OFFHOU – Does the provider have office hours at night or on the weekend?

PHNREG – How difficult is it to access the USC provider by phone?

AFTHOU – How difficult is it to access the USC provider after hours?

Another issue to consider is appointment delays. Lourenço and Ferreira (2005) have found that the elasticity of utilization relative to appointment delay is negative and large. The AC supplemental survey in the MEPS data set gathers information on individuals' abilities to receive treatment and receive it without delay. The respondent is first asked whether he was unable to receive medical treatment (MDUNAB) and whether he was unable to receive prescription medicine treatment (PMUNAB), followed by questions about delays in receiving care. For example, whether he was delayed in receiving medical treatment (DDLAY) or whether he was delayed in receiving prescription medicine treatment (PMDLAY).

Responding "Yes" to these two sets of variables indicates that the person needed treatment but was unable to receive it or was delayed in receiving it. Responding "No" to these two sets of variables indicates that either the person did not need treatment or the person needed treatment and was able to receive it without delay. If the respondent was unable to receive treatment or treatment was delayed, he was asked the following set of questions about the associated reasons:

MDUNRS – Why was he unable to receive medical treatment?

PMUNRS – Why was he unable to receive prescription medicine treatment?

MDDLRS – Why medical treatment was delayed?

PMDLRS – Why prescription medicine treatment was delayed?

Possible responses to these questions include: could not afford care, insurance company would not approve, cover or pay for treatment, doctor refused family insurance plan, problems getting to doctor's office, different language, could not get time off work, didn't know where to go to get care, was refused services, could not get child care, did not have time or took too long, other. As individuals have, to a certain extent, the freedom to choose their usual source of care provider, one may model the question, “Do you have a usual source of care provider?” as a function of various provider characteristics. Careful analysis of these variables may help explain why patients with comparable health conditions vary in the use of medical care.

Further, with an increase in group practices, it would be interesting to evaluate how the effectiveness of these programs is influenced by better patient-provider relationships. For instance, would patients delay receiving treatment until their “usual” physician is available?

Econometrically, it would be interesting to consider correlated error terms among the specified equations (5.1 – 5.6). In this case, the error terms would take the following form: $\eta_j \mu + \varepsilon_{jt}$ where $j = 1,...,6$, consists of time-invariant and time variant components. μ is the unobserved individual heterogeneity factor, η measures the effects of μ in each equation, and ε is the mean zero error, distributed logistically. This creates correlated error terms and calls for joint estimation. In dealing with unobserved heterogeneity, μ is treated as a random effect and integrated out of the model using discrete factor approach described by Mroz (1999) and Tao (2007).

The conditional joint probability of observing data for each individual for all time periods is then:

$$L_i(\Theta \mid \mu) = \prod_{h=0}^{2} P(H_1 = h \mid \mu)^{H_{i1}^h} \times \prod_{t=1}^{T} [\prod_{k=0}^{2} P(I_t = k \mid \mu)^{I_{it}^k} \times \prod_{h=0}^{2} P(H_{t+1} = h \mid \mu)^{H_{it+1}^h}$$
$$\times P(D_t = 1 \mid \mu)^{D_{it}} \times [1 - P(D_t = 1 \mid \mu)]^{(1-D_{it})} \times P(A_t = 1 \mid \mu)^{A_{it}} [1 - P(A_t = 1 \mid \mu)]^{(1-A_{it})}$$
$$\times P(K_t = 1 \mid \mu)^{K_{it+1}} \times [1 - P(K_t = 1 \mid \mu)]^{(1-K_{it+1})} \times P(O_t = 1 \mid \mu)^{O_{it+1}} \times [1 - P(O_t = 1 \mid \mu)]^{(1-O_{it+1})}]$$

where Θ represents the parameters of the model and $P(.)$ represents the logit or multinomial logit probabilities associated with the log odds equations. The unconditional joint probability is obtained by summing over the number of time invariant mass points, and is written as:

$$L_i(\Theta, \theta) = \sum_{m=1}^{M} \theta_m L_i(\Theta \mid \mu_m)$$

where $m = 1,..., M$ is the number of mass points and θ_m are the estimated weights associated with each mass point.

In order to ensure that the weights are between 0 and 1, the discrete factor model searches over a series of parameters, γ_m, that satisfy:

$$\theta_m = \frac{\exp(\gamma_m)}{1 + \sum_{j=1}^{M} \exp(\gamma_m)}$$

where $m = 1,..., M-1$ mass points. The last weight is calculated by subtracting the estimated weights from 1. Mroz (1999) provides methods for choosing the optimal number of mass points.

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APPENDIX

APPENDIX A – Dynamic Programming

Dynamic programming, attributed to Richard Bellman, proves particularly useful when dealing with time and uncertainty together. This method of optimization involves the sequential optimization of static programming problems over time.

The following equation represents a typical Bellman equation without uncertainty:

$$V(y_t, t) = \max_{z_t}\{F(y_t, z_t, t) + V(y_{t+1}, t+1)\}.$$

At any time t, any choice of the control variable z_t will lead to next period's state variable y_{t+1} as defined by $y_{t+1} - y_t = Q(y_t, z_t, t)$, where Q is considered to be a production function. The problem is then solved starting at $t+1$ in order to obtain the maximum value $V(y_{t+1}, t+1)$. Thereby, the first term on the right hand side, $F(y_t, z_t, t)$, indicates the value obtained at once and the second term, $V(y_{t+1}, t+1)$, the value obtained in the future. The individual should choose z_t such that the sum of the two terms on the right hand side is maximized.

The following represents a Bellman equation with the inclusion of both time and uncertainty:

$$V(y_t, t) = \max_{z_t}\{F(y_t, z_t, t) + E[V(y_{t+1}, t+1)]\}.$$

Solving the Bellman equation in both cases begins at the end (time T) and continues recursively backward until time 0. Analytical solutions for this method can only be implemented for simple functions and numerical solutions can be computed when harder functions are involved; however, even obtaining numerical solutions can prove difficult when state variables have more than two dimensions (Dixit 1990).