

A Dynamic Structural Analysis of Health Care Service Market with Information Asymmetry

by

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Abstract

My dissertation provides a dynamic structural analysis of demand and supply in a service market with information asymmetry. Specifically, I examine the health care market, which accounts for 17% of U.S. GDP and arguably is the most personal and important service consumers buy. This industry is particularly interesting for several reasons. First, health care service is very expensive and surpassed \$2.6 trillion in 2008. The increase of health care costs is particularly relevant in the context of chronic diseases, which account for 75% of total health care expenditure. In such a context, consumers have two types of health-care consumption choices: preventive care and curative care. Although the vast majority of cases in chronic diseases could be managed by preventive care according to experts, more than 96% of the health care expenditure goes to more expensive curative care. Second, health care market often suffers from adverse selection and moral hazard problems. Firms' profits depend on both the actions and the identity of consumers.

Despite the importance of health care service markets, there is relatively little empirical work on demand and firm behavior in such markets. This dissertation focuses on two aspects of health care service markets that have received little attention in the literature: the demand of preventive care and curative care, particularly in the chronic disease context, and the impact of consumers' health status information on insurer pricing behavior. To conduct the empirical analysis, I constructed a comprehensive data set including purchases of insurance plans, health care consumption histories,

insurance premium and plan characteristics, and individual demographic information from January 2005 to December 2007. I use this proprietary data to construct econometric models of consumer choices and insurer behavior.

First, I attempt to understand why many consumers opt for more expensive curative care which leads to a significant increase in the health care costs, but only a marginal increase in their welfare. To do so, I build a dynamic structural model of how consumers choose between different insurance plans, and conditional on the insurance plans, how they make the health care consumption decisions. I use the model to investigate the observed health care consumption pattern. The results reveal the following insights: (i) while preventive care mainly provides information about the health status (informative effect), curative care mainly improves the current health status (investment effect). (ii) Decreasing deductible or copayment increases frequency of preventive care more as compared to curative care, and decreasing coinsurance rate does the opposite. (iii) The inefficiencies mainly arise from health care decisions of a sizable segment of risk-averse consumers who are not very sick but are uncertain about their health status. These consumers opt for more comprehensive insurance plans; once in that plan, they prefer to more expensive curative care even when the illness could be managed through preventive care. Using counterfactual simulations, I examine how these inefficiencies can be reduced. I find that while subsidizing curative care increases consumer welfare at the expense of increasing the overall costs, subsidizing preventive care not only increases consumer welfare but also decreases overall health care costs. Moreover, consistent with recent trend of personalized medicine, providing more accurate information about health status through health care increases consumer welfare and decreases overall costs.

I then analyze asymmetric information and moral hazard in the health insurance market based on a dynamic theory of an insuree's dynamic risk through asymmetric learning (adverse selection/advantageous selection) and consumption choices (ex ante and ex post moral hazard). I use the theory to characterize the heterogeneous dynamic change in insurance choices to avoid out-of-pocket expenditure that are generated by the asymmetric learning and their effects on consumption choices between preventive and curative care. I explore these structural implications of adverse/advantageous selection and moral hazard. Unlike much of earlier literature, I find evidence of adverse/advantageous selection and moral hazard.

I also examine the insurance contract design (pricing menu) using this same data set. I combine the demand structure from the previous case with supply-side contract design under adverse selection and moral hazard. To accommodate these, I allow for random sequence of participation. In turn, I explore the implications of asymmetric learning on insurance choices. One particular challenge for this investigation is separating adverse selection from ex ante/ex post moral hazard. Therefore, I employ rich, transaction-level data and the restrictions from optimal contracting behavior to differentiate the effects of hidden information from the effects of pure moral hazard. Combining these data with observed pricing decisions, I can estimate the firm's indirect cost and assess the profitability of alternative pricing policies. This model may be relevant for any service market in which hidden information and hidden actions exist at the same time.

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Chapter 1

Introduction

Health care service is one of the most personal and important service that consumers buy and has a pervasive impact on the quality of daily life and the economy. In the U.S., the insurance companies are the major health insurance providers, covering 58.5% of the total population through employer-sponsored health insurance in 2008 with another 29.0% covered by Medicare and Medicaid (Economic Policy Institute, 2009) (Figure 1.1). In the past decade, the total health care service costs incurred by these providers have increased by more than twice with the price tag of 2.6 trillion in 2008 that constitutes 17% U.S. GDP. Such an increase has resulted in insurance companies to pass on their costs to consumers, which has caused 119% increase in premiums over the past 10 years (NY Times, 2009). Studies disaggregate these cost increases into general inflation, price increases in excess of the Consumer Price Index (CPI), and increase in utilization. The increase in utilization accounted for 25% of the increase (PriceWaterHouseCoopers, 2008) (Figure 1.2).

The rising prices of health care services have been one of the major concerns for consumers, employers, insurers and policy makers. It also contributed to the fact that over 46 million of Americans are uninsured which led to the push for national health insurance reform (Kaiser Family

Foundation, 2009). The increase in health care costs is particularly relevant in the context of chronic diseases, which inflict more than 133 million people, and account for 75% of the overall health care costs (Centers for Disease Control and Prevention Report, 2009). See Table 1.1 for some typical examples of chronic diseases. Unfortunately, a significant share of the spending does not add value or improve health, or what is frequently called, “waste” (The Institute of Medicine, 2009). The PwC Health Research Institute estimated waste at 34-50% of the total 2.6 trillion spending. They define “wasteful spending” as costs that could have been avoided without negative impact on quality.

A number of potential impediments stand in the way of efficiency in the health care service market. The most noted of these are ex ante moral hazard, ex post moral hazard and adverse selection. Moral hazard arises because consumer status may not be contractible and consequently service contracts are not complete. Consumers change their behavior in favor of more risky actions once they have a service contract (insurance). By ex ante moral hazard, it refers to the possibility that a service contract (health insurance) for curative care reduces incentives for prevention. It concerns the effect of insurance on the actions that an individual takes before her health status is known, such as drinking too much after she signs the health insurance contract. By ex post moral hazard, it refers to the possibility that the service contract (health insurance) increases incentives for medical care consumption because health insurance reduces the net price of medical care. Adverse selection is present if consumers have private or unobservable information about their status (Zweifel & Manning, 2001; Chiappori, 2001). These factors cause that even competitive markets may fail to provide an efficient level of insurance and have substantially different implications for optimal service contract (insurance design). On top of these, in the health care service market, consumers face dynamic trade-offs: first, consumers' service contract (insurance plan) decisions depend on their expected

future service utilization that they would incur from consuming the health care services during the contract period; secondly, consumers choose certain types of health care service, such as diagnostic tests, which only provide consumers with information on their health status and do not change the current utility of the consumer, but instead, provide them an option value that would enable them to make more judicious decisions on their health consumption and insurance choices in the future. Insurance providers face a similar dynamic trade-off: longer and more service relationship such as preventive or curative care could help them better know consumers' true health status which comes at the expense of lower premium/copay they could charge today.

These issues lay at the heart of service markets, especially health care service market. Yet, while there is a well-developed literature on the microeconomic theory of insurance market, relatively little work has empirically analyzed these markets from a structural perspective. This imbalance is not due to a lack of intrinsic empirical interest; numerous questions exist that are specific to such markets concerning the inter-related roles of informational asymmetry, service-purchase/consumption separation, consumer learning, dynamic pricing strategies and insurance service contract design. Instead, the lack of empirical analysis is primarily due to the difficulty of getting suitably rich data sets and overcoming modeling and computational obstacles.

This dissertation seeks to address these issues by providing a dynamic structural analysis of consumer demand and firm behavior in the service market. I develop techniques for dealing with the data and modeling problems, and investigate the substantive issues within the context of the health care service market. This industry is particularly interesting because it features the separation of

purchase and consumption of service¹ and potentially suffers from adverse selection/moral hazard problems, and both consumers and insurers learn about consumers' types of health status gradually. While I focus on the health care service industry, the analysis should be relevant for any service industry where purchase and consumption are separate, consumer learning is important and the market might suffer from information asymmetric problems. To conduct the empirical analysis, I have constructed a unique and comprehensive data set including insurance purchases, health care consumption, insurance premiums, and health plan characteristics in an employer-sponsored health insurance setting from January 2005 to December 2007.

The rest of the thesis is organized as follows. Chapter 2 provides some background on the U.S. health care service industry and discusses the related literature. Chapter 3 describes the data set and presents some empirical observation from the data. In Chapter 4, I present a dynamic structural model of how consumers choose between different insurance plans (which vary in terms of the coverage), and conditional on the insurance plans, how they make the health care consumption decisions (i.e., preventive vs. curative care). In Chapter 5, I describe the test for the presence of asymmetric information and empirically analyze moral hazard in the health insurance context. Chapter 6 presents a structural model of insurance pricing menu and concluded.

¹ Majority of consumers purchase health insurance first, then within the insurance contract period, they go for consumption accordingly.

Chapter 2

Background and Some Literature

2.1 (Employer-sponsored) Health Care Service

Over 160 million non-elderly American obtain their health care service through the private health insurance companies. 87 percent of the enrollees are covered through employer-sponsored health insurance plans. In the majority of metropolitan statistical areas, a single health insurer dominates the market. The average single and family premiums for employer-sponsored health insurance plans in 2008 (\$4704 and \$12680) are about 5% higher than the average single and family premiums reported in 2007 (\$4479 and \$12106). The \$12680 average annual family premium in 2008 is 27% higher than the average family premium in 2004 and 119% higher than the average family premium in 1999 (The Kaiser Family Foundation and Health Research & Educational Trust Annual Survey, 2008).

Most covered workers are in a plan that partially or totally limits the cost sharing that a plan enrollee must pay in a year. These limits are generally referred to as out-of-pocket maximum amounts. 80% of workers enrolled in single coverage and 79% of workers enrolled in family

coverage are in a plan that limits the cost sharing amount enrollees have to pay. The plan types, ordered from most to least restrictive in terms of provider choice, are Health Maintenance Organization (HMO), Point of Service (POS), Preferred Provider Organization (PPO), and the Indemnity. HMO and POS plans control utilization of care through primary-care physicians. Only in-network providers are covered by HMOs, while POS plans provide some coverage for out-of-network providers. PPOs engage in less utilization management, and like POS plans, typically cover out-of-network care at a reduced rate. Finally indemnity plans are traditional fee-for-service arrangements in which benefits do not depend on network status of the provider. Over the past decades, there has been a movement towards plans with broader provider networks, such networks tend to reduce the amount of competition in the system.

These plans also use different cost sharing mechanism for medical services. In addition to any required premium contributions, covered workers may be responsible for a general annual deductible before some or all services are covered, and may have to pay copayments (fixed dollar amounts), and/or coinsurance (a percentage of the charge for services) when they receive services. The type and level of cost sharing often varies by the type of plan in which the worker is enrolled. Cost sharing may also vary by the type of service received such as office visits, hospitalizations, or prescription drugs.

Deductibles vary significantly by plan type. 68% of workers in PPOs with single coverage have a general annual deductible. Those workers with no general annual plan deductible often have another form of cost sharing. For workers without a general annual deductible for single coverage, 71% of workers in PPOs are in plans that require cost sharing for hospital admissions. The percentages are similar for family coverage. For workers in PPOs with a general annual deductible for single

coverage, the average annual deductible increased from \$461 in 2007 to \$560 in 2008. The average amounts for workers with an aggregate deductible for family coverage are \$1,053 for HMOs, \$1,344 for PPOs, and \$1,860 for POS plans.

The escalating healthcare costs and the recognition of high cost due to chronic disease forced many employers to shift more cost to their employees and opt for more disease-management programs. 79% of covered workers have a copayment for a physician office visit and 11% have coinsurance. Among covered workers with a copayment for in-network physician office visits, the average copayment is \$19 for primary care and \$26 for specialty physicians. 55% of covered workers have a copayment of \$15 or \$20 for a primary care office visit. For specialty care office visits, 36% of covered workers have copayments of \$20 or \$25. Among the 11% of covered workers with coinsurance only for a physician office visit, the average coinsurance rate for a visit with a primary care physician is 17%.

The increase in health care costs is particularly relevant in the context of chronic diseases, which inflict more than 133 million people, and account for 75% of the overall health care costs in the U.S. Chronic diseases differ from acute diseases (A disease or disorder that lasts a short time, comes on rapidly, and is accompanied by distinct symptoms) and other ailments in two respects: first, unlike other diseases, individuals suffering from chronic diseases require health care over a long horizon because chronic diseases are persistent and lasting; second, different from other ailments, individuals who have chronic diseases can take two types of health care services to manage or treat their illness: preventive care and curative care.

The increased utilization of services is driven by new treatments, aging, lifestyle changes, more intensive procedures/tests, and defensive medicine. However, studies show that a high proportion

of health care spending is considered as waste which is categorized into three main categories – operational, clinical and behavioral (PricewaterhouseCoopers, 2008). See Figure 2.1 for an illustration of the three categories.

- Operational: underuse of information technology and lack of process coordination across the health system stakeholders.
- Clinical: overuse, misuse and under-use of medical care procedures, missed opportunities for earlier medical interventions and overt errors leading to cost, rework and quality issues for the patient.
- Behavioral: individual preventable risk factors such as poor adherence to prescription drug regimens, obesity, smoking and alcohol abuse.

Some firms started to give their employees the option of completing a health risk assessment to help employees identify potential health risks. Health risk assessments generally include questions on medical history, health status, and lifestyle. 38% of firms that offer health risk assessments use them as a method to identify individuals and encourage their participation in wellness programs. Disease management programs try to improve the health of and reduce the costs associated with people with chronic illnesses by teaching patients about their disease, suggesting treatment options, and assessing the treatment process and outcomes.

2.2 Literature Review

Ever since Akerlof (1970), Rothschild & Stiglitz (1976), asymmetric information (i.e., consumers know more about their health state than do insurers) among economic agents which distort the

incentives and leads to adverse selection (i.e., more comprehensive insurance plans tend to attract unhealthy, high cost consumers) has been extensively studied from the theoretical perspective. Rothschild and Stiglitz (1976), Wilson (1977) and Spence (1978) studied the nature of competitive equilibrium in markets with adverse selection. They show that one tends to get segregation of consumers: the unhealthy, who have greater willingness to pay for coverage, buy comprehensive insurance at high premiums, while the healthy, who have lower willingness to pay, buy limited insurance at low premiums. But, as Wilson (1977) and Spence (1978) pointed out, if the plans that appeal to the healthy cross-subsidize the plans that appeal to the unhealthy, it becomes possible for the healthy to get more comprehensive insurance. Since the subsidy lowers the premium in the comprehensive plan, the unhealthy are better off. Furthermore, the limited plan aimed at the healthy can expand its coverage without attracting the unhealthy. As long as the subsidy that the healthy must pay to the unhealthy is less than their willingness to pay for this expanded coverage, they are made better off too. Their idea is that for a single insurer, to implement a cross-subsidy is to offer the insurance options: a comprehensive policy aimed at the unhealthy, and a more limited policy with a lower premium aimed at the healthy.

As Spence (1978) noted, actual design of a menu of insurance options to increase equity and efficiency requires knowing a great deal about consumer taste heterogeneity. To estimate the distribution of consumer taste heterogeneity or willingness to pay for these attributes, one needs data where a range of insurance plans, with a range of different attributes available to consumers. Most existing empirical research tests for the existence and estimates the magnitude of asymmetric information effects, such as Chiappori & Salanie (2003) and Cardon & Hendel (2000). A popular strategy for studying asymmetric information is to test, conditional on observables, for a correlation

between the choice of a contract and the occurrence/severity of an accident. Under adverse selection on risk, high-risk agents are, everything else equal, both more likely to choose a contract with more complete coverage and more likely to have an accident. The basic moral hazard story is very close to the adverse selection one, except for an inverted causality. In a moral hazard context, agents first choose different contracts. Then, an agent facing better coverage and, therefore, weaker incentives will be less cautious and have more accidents. In both cases, the same pattern emerges: controlling for observables, more comprehensive coverage should be associated with higher realized risk - a property that can be tested using appropriate parametric or non-parametric techniques.

The conditional correlation approach has several advantages. It is simple and very robust, as argued by Chiappori et al. (2002). Furthermore, it can be used on static, cross-sectional data that are relatively easy to obtain. However, these qualities come at a cost. The past history of the relationship influences both the current contract (through risk index) and the agent's behavior, and this effect is hard to take into account with cross-sectional data. More importantly, the correlation is not informative on the direction of the causality, which makes the two stories (moral hazard and adverse selection) very hard to distinguish. Still, such a distinction is crucial, if only because the optimal form of regulation of insurance markets varies considerably with the context. To distinguish between adverse selection and moral hazard, we need to rely on the dynamic aspects of the relationship we discuss in the previous paragraph.

Although health economists have a long history working on health insurance market, all the literature try to identify the information asymmetry without being able to identify adverse selection from moral hazard. Moreover economists focus on social welfare perspective of health insurance. However the more fundamental thing of health insurance market is how researchers can identify

moral hazard from adverse selection and based on this to help insurance companies to design optimal plans/benefits even under current government regulation to reduce the skyrocketing health care cost. Consumers with less coverage often overpay, and on the other hand, people with enhanced plans often over-consume medical service which does not necessarily lead to better health . On the supply side, insurance companies spend tons of money on marketing their plans and disease management programs without understanding the associated cost-benefit analysis.

Several authors, notably Cawley and Philipson (1999) and Chiappori and Salanie (2000), have observed that many models of equilibrium with either adverse selection or moral hazard predict that those with more insurance should be more likely to experience the insured risk. With moral hazard, insurance coverage lowers the cost of the insured outcome and thus increases the expected loss. With adverse selection, the insured knows more about risk type ex-ante than the insurance company does. Since the marginal utility of insurance at a given price is increasing in the risk of the insured event, those who know that they are high risk will select contracts with more insurance than those who know that they are low risk. The positive correlation test estimates the correlation between the amount of insurance an individual buys and his ex-post risk experience, conditional on the observable characteristics that are used in pricing insurance policies. It is essential to condition on all the information that is used to set insurance prices. Finding, for example, that smokers demand more life insurance than non-smokers, and that they also have higher mortality risk, is uninformative, since the price of insurance for smokers is adjusted to reflect this differential. Results from the positive correlation test or from the unused observables test are always conditional on the risk classification that the insurance company assigns to the individual (Cutler and Zeckhause, 2000)

However several work such as Cardon and Hendel (2001) and Fang, Keane, and Silverman (2006) did not find this positive correlation. Traditional “Moral Hazard” story in static models of insurance suggests that insurance induces people to engage more risky behaviors. However Khwaja (2001) concludes that provision of subsidized (or even free) health insurance would not cause people to engage more in unhealthy or risky behaviors like drinking and smoking, or less in health behavior like exercise. The key point according to his model is that in a dynamic model, more generous insurance can increase life expectancy, as a better insured person can afford more preventive care and better treatment should she become sick. Increased life expectancy, in turn, enhances one’s incentive to invest in health. Technically, the reason is that in any dynamic model, a longer planning horizon increases returns to investment. More intuitively, if one expects to live longer, it creates an incentive to invest in health to enhance quality of life in old age. This dynamic effect counteracts the moral hazard effect of insurance on investment in health (Fang, Keane, Khwaja, Salm & Silverman, 2006).

With reduced form work, researchers cannot say much about the policy change simulation, and static framework could not capture the inherent dynamics of health insurance market. First, the qualitative characteristics of optimal contracts differ considerably in the two cases. For instance, even though optimal contracts usually exhibit history dependence in both cases, adverse selection typically requires contracts with “flat” memory, in the sense that past performances should be given an equal weight. Although the case of moral hazard is more complex, memory is likely to be “shorter” and more concentrated on recent events. This suggests that a careful empirical investigation of the qualitative properties of the contracts at stake may provide useful insights on the type of problem they are designed to address. Secondly, most real insurance contracts exhibit some

form of experience rating such as risk index score compiled by health insurance companies (although not necessarily the form predicted by theory). Under moral hazard, experience rating has a very interesting property. Any medical claim has an impact upon the next premium, and, if memory is long, on the whole schedule of future premium. This changes not only the expected wealth of the agent and the expected average cost of insurance, but, more importantly, also the discounted marginal cost of a (future) claim. The cost of the next claim (in terms, say, of expected future premium, or of the corresponding certainty equivalent) indeed depends on the current premium, hence on past history. It follows that the occurrence of a claim changes the incentives faced by a driver— hence, under moral hazard, the future claim probability. In other words, under moral hazard, any (possibly suboptimal) pricing schedule where current premium is related to past behavior will de facto introduce a complex autocorrelation in the claim process. Analyzing the corresponding dynamics can then allow to identify the moral hazard component (if any).

Chapter 3

Data Description

The proprietary data underpinning our analysis is provided by an anonymous insurance company. We assemble the comprehensive data set featuring insurance purchases, health care consumption, insurance premiums, and health plan characteristics (i.e., copay and coinsurance rate) in an employer-sponsored insurance setting for the period January 2005-December 2007. The data set includes detailed health care consumption history data and information about the policies offered by a single insurer to each employee working for different employers. These data reflect the key ingredients in this dynamic service contractual relationship: insurance policies offered, health plans chosen, and health care consumption history. According to Centers for Disease Control and Prevention (CDC), health care consumption could be divided into two types: preventive care which constitutes measures such as diagnostic tests and certain drugs that help manage or prevent the illnesses, and curative care which refers to treatments such as surgeries and certain drugs that help improve symptoms or cure medical problems. We map all the diagnostic, procedure and therapeutic codes (ICD-9CM and CPT) and potential combinations of codes to represent preventive and curative care of several clinical conditions, including breast cancer, diabetes, and cardiac arterial disease based on NSQA HETA specifications and US Preventative Services Task Force.

- **Sample Selection:** In our data, all the employers provide health insurance to their employees through the single insurer. We focus on contract holders who are continuously enrolled for the entire period and exclude the individuals who are non-contract holders (family beneficiaries) such as spouse/partner and children, as we do not have the information about the health plan choices of spouses/partners. We also eliminate individuals less than 18 years old from the analysis sample. Since our data include employees from several employers, selection into an employer should not be a cause for concern here. This leaves me 2833 contract holders for estimation.
- **Health Plan Choice and Characteristics:** In general the insurer offered a total of three plans in 2005 through 2007. However the insurer did offer customizations for different employers, and the individuals in our data set face different premiums and may have different plan characteristics defined by copay, coinsurance rate, deductible and out-of-pocket maximum.
- **Claim History:** We have the complete and detailed claim history of all individuals insured by the featured insurer from 2005 to 2007. A claim contains all information needed to process an insurance payment, primary and secondary diagnosis codes, procedure codes and identification of provider. The claim also contains information on the amount paid by the individual and the insurer. For each enrollee we aggregate all their health care claims of each week, each month and each year to formulate the measure of both the total claims paid by the insurer and the total out-of-pocket expenditures incurred by the enrollee. We classify the health care consumption into two types: preventive care such as mammogram and Prostate-Specific Antigen (PSA) Test and curative care such as coronary angioplasty and coronary stent placement. See Table 3.1 for some examples of preventive and curative care.

- **Data Overview:** Table 3.2 provides summary statistics of the health insurance and claim information across three different types of plans customized by the insurer to the employers in our estimation sample. The premium consumers pay for the comprehensive plan is about three times the amount they pay for the basic plan. On the contrary, the coinsurance rate, the deductible and the out-of-pocket maximum decrease as the generosity of the plans increase. For the basic plan on average the coinsurance rate is about 27% coinsurance amount, the deductible is 1008.8 dollars, and the out-of-pocket maximum is \$3107.6, which is about 12 times of comprehensive plans. People enrolled in the basic plan are younger than other plans. With the increasing of the generosity of the plans, consumers seek health care more frequently and pay lower price. On average, people within comprehensive plan seek 22 times health care, which is much higher than people enrolled in basic plan.

Chapter 4

A Dynamic Model of Health Care

Consumption and Health Insurance

Purchase

4.1 Introduction

In the health care context, consumers manage their long-term well-being through preventive care and curative care. These two types of care differ in terms of the mechanisms through which they provide utility to consumers. Previous literature has suggested two different mechanisms: first, preventive or curative care could provide a boost to consumers' current health status, which we refer to as the investment effect (Grossman, 1972); second, they could provide information to consumers about their present health status which would help them judiciously decide the future course of treatment, which we refer to as the informative effect (Arrow, 1963). Although it is an empirical question, we would expect the informative effect to be higher for preventive care since it

includes diagnostic tests which primarily provide information, and investment effect to be higher for curative care since it includes surgeries and drugs to restore health.

The distinction between preventive care and curative care is especially important in the context of chronic diseases, since according to many authorities and experts a vast majority of cases of chronic diseases can be managed by preventive care (Grossman & Rand, 1974; Thorpe, 2008; Partnership to Fight Chronic Disease, 2009). However, the reality is that more than 96% of the health care expenditure for chronic diseases goes to curative care. This suggests that there could be inefficiencies in the current system in managing chronic diseases, i.e., instead of actively seeking (less expensive) preventive care, consumers opt for (more expensive) curative care at later stage that leads to disproportionately higher health care costs.

This preamble directly leads us to the focus of this paper, which is to examine the following issues: (i) whether or not there are inefficiencies in managing chronic diseases, and if so, (ii) the underlying reasons behind these inefficiencies, (iii) the magnitude of these inefficiencies, and (iv) what policies/marketing mixes can be employed to reduce the inefficiencies. Given these issues that we plan to investigate, we next provide a conceptual framework of the modeling effort that is required to address them.

First and foremost, we need to understand how consumers make their health care consumption decisions - i.e., whether or not to consume a health care service, and if so, which type of health care service should they consumer: preventive care or curative care. Further, since most people obtain health care service through their health insurance plans, we also need to understand how consumers make their insurance plan decisions - i.e., whether they should opt for more basic plans (which have low premiums, but only cover a small part of the health care costs incurred by the consumer) or they

should opt for more comprehensive plans (which have high premiums, but share a large part of the health care costs incurred by the consumer). Doing so is important since the health care consumption decisions are inextricably tied to insurance plan decisions because of two reasons. First, consumers' health care consumption decisions are affected by the cost sharing characteristics of their health insurance plans. For instance, the greater the health care expense covered by the insurance plan, the greater will be the likelihood that the consumer would choose to consume health care services as opposed to not choosing at all. This implies that while modeling the consumer's health care consumption decisions, it is important to know the insurance plan used by each consumer. Second, both the health care consumption and insurance plan decisions depend on a common set of unobserved covariates, such as the consumer's health status. For example, consumers who are very sick would tend to purchase comprehensive health plans, and would also consume more health care services – as a result, the consumer's health status, which is an unobserved covariate in the consumer's health care consumption decision, will vary across different plans. This implies that in order to model the consumer's health care consumption decisions, in addition to knowing which insurance plan each consumer falls under (as pointed out in the first reason), it is important to model the consumer's insurance plan decisions; and if we do not do so, our model will suffer from a selection bias.

The above discussion leads to the first objective, which is to model how consumers choose between different health insurance plans, and conditional on the insurance plans, how consumers make their health care consumption decisions. In this regard, we develop a theory-based model, in which health care consumption decision is nested within insurance plan decision. A key feature here is that the two nested decisions are modeled in a dynamic forward looking framework. The forward

looking aspect is crucial in this context for two reasons. First, the consumer's insurance plan decision (which consumers make on an annual basis) depends on her expected future health care costs that she would incur from consuming the health care services during the policy year. Second, modeling the forward looking component is important to rationalize why consumers would choose to consume preventive care options such as diagnostic tests. This is because diagnostic tests only provide consumers with information on their health status, which does not change the current utility of the consumer, but instead, provides her an option value that would enable her to make more judicious decisions on her health consumption and insurance choices in the future.

We model the two nested decisions as follows. With regard to the health care consumption decision, we allow for it to depend on (i) consumer's current health status, the rationale being that if consumer's health is poor, then preventive care may not help her much, and consequently she would be more likely to choose curative care; (ii) consumer's risk aversion resulting from uncertainty associated with her health status, the rationale being that if the consumer is uncertain about her health status, she would go for preventive care such as diagnostic tests rather than curative care; and (iii) consumer's current insurance plan – the rationale being that with more comprehensive plans, consumers would opt for more health care services.. With regard to annual insurance plan choice is concerned, we model it as a tradeoff between the premiums charged in the insurance plan and consumer's expected future health care consumption – where the sensitivity to the premiums depends on the consumer's annual income, and the health care consumption, as discussed before, depends on the consumer's health status, its associated uncertainty and the cost sharing characteristics of the insurance plan.

The second objective is to estimate our proposed model using a novel data set provided by a large insurance company, which includes insurance pricing schemes, consumers' insurance plan choices and health care consumption decisions over time. Our key empirical results are as follows. *First*, curative and preventive cares differ in the mechanism through which they provide utility to the consumer: while the investment effect is much higher for curative care as compared to preventive care, the informative effect is much higher for preventive care as compared to curative care. *Second*, the underlying reason for inefficiencies is that there exists a sizable segment of risk-averse consumers who have a moderate health status, are uncertain about their health, and have higher incomes.. As a result of high uncertainty and high incomes, these consumers choose more comprehensive plans than they need; once in the plan, they prefer to more expensive curative care even when their illness could be managed through preventive care since the overall price of curative care is lower for them (because in the comprehensive plans, there is little difference in their out of pocket expenses when they choose curative care or preventive care). *Third*, decreasing copay or deductible increases the frequency of preventive care more, which leads to higher consumer welfare and lower health care costs. In contrast, decreasing coinsurance rate increases the frequency of curative care more, which results in higher health care costs and lower consumer welfare.

The third objective is to conduct policy simulations to see how the inefficiencies could be mitigated. In the first policy simulation, we assess the impact of subsidizing preventive care on the overall health care costs.^{2 3} On one hand, if policy maker or health insurance provider subsidizes or

² This is consistent with what many health service providers and policy makers advocate recently. See Organization for America, <http://www.barackobama.com/issues/healthcare>

³ For example, Managed Health Services, a subsidiary of St. Louis-based health insurer Centene Corp, one of the companies that administer Medicaid coverage in Indiana, used a new debit card program that rewards people for making regular trips to the doctor, taking checkups and getting screened for some conditions. See "Debit Cards Reward Medicaid Patients for Care", <http://www.nytimes.com/aponline/2009/08/31/business/AP-Health-Debit-Cards.html>.

promotes preventive care, it will encourage consumers to consume more preventive care, which would result in an increase in the health care costs; On the other hand, subsidizing preventive care would decrease the inefficiencies since it would encourage the consumers in the more comprehensive plans with moderate health status and high uncertainty to consume preventive care instead of curative care. These two countervailing forces lead to the question of how promoting preventive care impacts consumer health care consumption behavior and their subsequent costs. Our analysis indicates that subsidizing preventive effects indeed leads to a decrease in the overall health care costs. We also compare this result to the case when we subsidize the curative care option. We find that subsidizing curative care increases the overall costs since it encourages the consumers in the more comprehensive plans with moderate health status and high uncertainty to consume curative care instead of preventive care.

The second policy simulation evaluates the impact of more precise preventive care on consumers' welfare and the overall health care costs. This is in the spirit of personalized medicine in which health care service providers use precise molecular profiling technologies to each individual consumer in order to provide more precise information about her health status and individualized care.⁴ Although these diagnostic tests and individualized care would be more expensive (which lead to high insurance cost for insurance providers), however, if they are more precise, then consumers would be inclined to go for these tests instead of going for more costly treatments after the onset of a disease. We are able to assess, for a given increase in accuracy of the preventive care, the costs saved through the reduction in inefficiencies, which in turn helps us to quantify how much health service providers are willing to invest in personalized medicine.

⁴ See "Submitting to the Science of Prevention", Wall Street Journal, Nov. 26, 2008 for an example of individualized health care plan. <http://online.wsj.com/article/SB122765661371658079.html>

The rest of this paper is structured as follows: We begin with an overview of the relevant literature to differentiate our work from previous research. Given the relatively novel research context to marketing audience, we then describe the industry, our data, and some stylized features to help make the problem more concrete. We then introduce our model followed by the estimation methodology. Subsequently, we discuss the identification of our model parameters. We then discuss the estimation results and present the counterfactual simulations. Finally, we conclude with a discussion of the results and the implications of the study.

4.2 Literature, Institutional Setting and Data Set

Extant literature examines demand for health care as a derived demand from the demand for health itself following Grossman (1972) framework in which past investment (i.e., health care consumption) affect current health, partially offsetting the depreciation of the health stock over time. Yet as Arrow (1963) argue that consumers are not well informed about their health status even if they might know the consequences of their actions (Sloan 2001; MaFadden 2009). Hsieh & Lin (1997) investigate how health information affects the demand for health care. They find that increased health information is positively related to the demand for preventive care. Grossman and Rand (1974) note that preventive care and curative care are essentially substitutes from consumers' perspective. Since Grossman (1972) did not explicitly consider the uncertainty surrounding an individual's health, there was no distinction between preventive and curative care under his framework. However preventive versus curative care decisions are particularly relevant in the context of chronic disease.

Moreover, most of the empirical analyses of demand for health care are based on Grossman's health investment model and treat health insurance exogenous. They consider the presence of health

insurance or characteristics of health insurance plans such as various cost-sharing components as an independent variable of a reduced form regression explaining health care use. Tang (2008) points out that health insurance may reduce preventive care because the insurer will pay for part of the treatment in case of disease. On the other hand, if health insurance covers preventive care as well, the reduced cost of preventive care will encourage the insured to consume more preventive care. Cameron, et al.(1988) propose a two period model where insurance is chosen in the first period and health care is chosen in the second period which accounts for the endogenous effects of each decision on the other. However, the empirical analysis does not jointly estimate health care demand with the insurance demand and reduces to an instrumental variable approach to explain observed insurance status and subsequent health care use. Cardon and Hendel (2001) study health care expenditures and health insurance choices with NMES data in a static framework to detect information asymmetry. Khwaja (2001) construct a dynamic life-cycle model to study consumers' insurance and consumption decisions in Grossman framework without health status information uncertainty. Carlin & Town (2008) estimate a demand model of insurance and health care consumption expenditure to quantify the welfare loss of private information.

A major finding of RAND HIE is that price affects the number of episodes chosen by participants and has much smaller effects on the cost of each episode. Therefore, choosing what type of health care makes more sense for consumers comparing to how much spend. RAND analysis claimed that preventive care and better management of chronic disease could result in 20 million fewer inpatient days and 9 million fewer office visits based only on four chronic diseases. In the terminology of public health, there are two types of preventive services: primary prevention and secondary prevention (Russel, 1986). Primary prevention refers to services that could reduce the

probability of illness, such as vaccinations and some drugs. Secondary prevention refers to services for the early detection of illness such as screening and routine physical exams (Kenkel, 1994).⁵

Consumers often lack the incentives to manage preventive and chronic care to minimize lifetime private and social health care cost once they have health insurance. As health care costs keep climbing, insurers increasingly rely on preventive care coverage, informational mechanisms and cost-sharing schemes to encourage consumers to manage their long-term well-being and save insurance cost. The recent discussion of cost control initiatives such as Consumer Directed Health Care (CDHC) plans ignites great interests among policy makers, insurance companies and consumers. The unique service contractual structure of health insurance balances risk-sharing against the need for efficient utilization incentives. This balance explains why health insurance contracts do not entitle policy holders to unlimited utilization. Instead the insurers charge an ex post co-pay or coinsurance with constraints of deductibles or out-of-pocket maximum besides the premium paid upfront. These ex post payments reduce insurance, but intend to produce less distortion in the health care utilization market, because the consumer faces an individual price that partially reflects the cost.

The pricing structure includes copay, deductible, coinsurance rate and out-of-pocket-maximum. Copay is the specified dollar amount that a consumer must pay out of her own pocket for a specified service at the time the service is rendered. Deductible is the flat amount an individual must pay before the insurer will make any benefit payments. Coinsurance rate is the percentage of all remaining eligible health care expenses after the deductible amount has been paid which is a method

⁵ Someone could argue that preventive care also includes private heal lifestyle decisions such as regular exercises and non-smoking. However from a medical perspective and for the purpose of this study, we focus on the preventive care defined in the medical literature.

of cost-sharing in the health insurance setting. Out-of-pocket-maximum is the dollar amount set by the insurer that limits the amount an individual has to pay out of his/her own pocket for particular healthcare services during a particular time period. See Figure 4.1 for an illustration of pricing structure and the empirical cost sharing from our data.

Table 4.1 and 4.2 present consumers' insurance plan choices and switching behavior across three years. Two observations are immediate. First, a substantial proportion of the sample chose different types of plans regardless of basic or comprehensive. Here we emphasize that the insurance characteristics such as premium, copay, coinsurance rate, and deductible could vary even within the same type of plan if the individuals are from different employers. Second, people did switch plans across years.⁶ The two observations further highlight the importance of the insurance choices and the need to understand the health care consumption behavior across different types of plans. Table 4.3 presents the switch between preventive care and curative care across individuals and time. As shown in the table, consumers are less likely to switch from curative care to preventive care.

4.3 The Model

This section develops a model where individuals preserve noise information about their health status and engage in health investment and information gathering about their health status through health care consumption. We adopt a framework based on Bayesian learning and incorporate both investment and the informative roles of preventive and curative care consumption in a nested framework which allows us to study consumers' consumption decisions with endogenous health insurance choices and identify the inefficiency in the market. The model is cast in a dynamic setting

⁶ Some people might argue the percentage of switch is small. However comparing to other important personal decision such as house, education and marriage, the level of the health insurance plan switches is not small.

where individuals make tradeoffs between preventive and curative care during the health care consumption stage, and between monetary value and health care demand uncertainty during the insurance choice stage, given their forecast of their future states of being. Our model links the health investment consumers make early in their life to their later health outcomes. As early health investment reduces later health expenditure, this simple mechanism could potentially have a big welfare effect.

The dynamic model captures individuals' sequential decision-making processes by modeling insurance choice each year and weekly health care consumption decisions throughout the insurance year. These health care decisions depend on their health status and expected health care utilization in the future. Individuals' health care decisions also depend on the prices of a particular type of care. Each type of care (curative and preventive) requires payment depending on characteristics of the individual's insurance plan, which is chosen annually.

4.3.1 Health Insurance and Health Care Consumption Decisions

We assume there are $i = 1, \dots, I$ consumers who make periodic (i.e. yearly) insurance choices from a set of $j = 1, \dots, J$ health insurance plans (e.g. standard, medium and comprehensive plans)⁷ at time periods $a = 1, \dots, A$, then within each insurance policy period $t = 1, \dots, T$ they make a sub-periodic (i.e. weekly) health care consumption choice decision among preventive care, curative care and no doctor visit.⁸ See Figure 2 for an illustration of the time line of decisions. We use the dummy

⁷ There are three types of health insurance plans customized to different employers by the single insurer in our data set. Individuals from different employers might have different premium, copay or coinsurance rate even they are categorized into the same plan. Since all the individuals in our data set are enrolled into one plan, so we do not include no purchase option ($j = 0$) which represents un-insured.

⁸ The structure of this dynamic programming is like a hierarchical decision process.

variable $d_{ija} = 1$ to denote consumer i 's choice of insurance plan j at time a .

$$(4.1) \quad d_{ija} = \begin{cases} 1, & \text{if consumer } i \text{ chooses plan } j \text{ at year } a \\ 0, & \text{otherwise} \end{cases}$$

We let another dummy variable c_{ikt} to represent the health care consumption decision, where $k \in \{p, c, 0\}$, in which p represents preventive care, c represents curative care, and 0 represents not-seeking doctor visit.

$$(4.2) \quad c_{ikt} = \begin{cases} 1, & \text{if consumer } i \text{ chooses health care service } k \text{ at week } t \\ 0, & \end{cases}$$

The three alternatives are mutually exclusive such that $\sum_{k=1}^K c_{ikt} = 1$.⁹

4.3.2 Perceived Health Status

Health status is the essence of the problem in the context of health care and health insurance because consumers' decision of which type of plan to buy and what type of health care service to seek depends on the individual's assessment of her health status.¹⁰ Following Grossman's framework, health is viewed as a capital stock which degrades over time in the absence of "investments" in health. Health care is both a consumption good that yields direct satisfaction and utility, and an investment good, which yields satisfaction to consumers indirectly through increased productivity, fewer sick days, and higher wages. Investment in health is costly as consumers must trade off time

⁹ People might argue individuals could choose both preventive and curative care at the same time. However in the context of chronic disease, consumers do face such tradeoffs in the small time-unit level (AMA, 2008; WSJ, 2008). We classify preventive and curative care in our data following the American Medical Association criteria provided by the insurance company. A close look at our data set further alleviated this concern. More than 95% of individuals only have one type of service in a given week. If we focus on the chronic diseases, we found this number is close to 100%. Making it in a weekly level makes this even more reasonable. Therefore, we would argue this assumption here is reasonable.

¹⁰ Our notion of health status is in the spirit of individual specific quality (Erdem et al., 2005).

and resources devoted to health. These factors are used to determine the optimal level of health that an individual will demand.

Studies in the literature (Arrow, 1963) show consumers may not be well informed about their true health status Ths_{it} , so the insurance and health care consumption decisions are based on their perceived health status hs_{it} .¹¹ Study in the literature shows that consumers have uncertainty about their health status and uncertainty surrounding the effectiveness of the health care (Hsieh & Lin, 1997; Crawford & Shum, 2005). Consumer i has the perception of her health status at time t , given by

$$(4.3) \quad hs_{it} \sim N(\overline{hs_{it}}, \sigma_{it}^2).$$

Note that the mean $\overline{hs_{it}}$ need not coincide with her true health status, viz., Ths_{it} (although over the time, $\overline{hs_{it}}$ will converge to Ths_{it}). This captures the fact consumers are uncertain about their health status and only hold beliefs about their health status.¹²

On one hand, health care consumption could improve consumers' health status and compensate the depreciation of their health stock (investment effect). On the other hand, Consumers learn about their health status through consumption (informative effect). This also introduces a perspective of asymmetric learning (Abbring, et al. 2003), because consumers could gain health status information through health care consumption signal which may not be equally observed by the insurer. Therefore asymmetric information could emerge gradually as a consequence of different learning

¹¹ Chan and Hamilton (2006) use a similar formulation in the HIV treatment setting.

¹² Different from the quality learning literature in marketing in which product true quality is time-invariant, consumers' true health status is evolving with depreciation and investment effect.

processes even though it may not exist at the beginning of the insurance purchase (i.e., the relative health status of a young person is unknown to her and her insurer).¹³ The insurance plan changes that take place during the insurance contractual relationship then may be informative about the consumer's risk level, even if the initial choice of plan is uncorrelated with residual risk. This again highlights the importance of modeling endogenous health insurance choices.

4.3.3 Investment Effect

In the absence of information uncertainty (complete information), consumers make their health care consumption decisions and insurance choices based on their true health status. Following Grossman's framework, health is viewed as a capital stock and health care service is viewed as an investment into the household production of health, thus consumer i 's true health status Ths_{it} evolves as:

$$(4.4) \quad Ths_{it+1} = \delta_0 Ths_{it} + \sum_k \delta_k c_{ikt}.^{14}$$

Here $(1 - \delta_0) \in [0, 1]$ denotes the rate of depreciation and c_{ikt} represents consumer i 's consumption of preventive or curative care at time t as defined before. The impact of health care consumption (preventive/curative) on health status is choice specific: health status could be strengthened in the different degree of two types of health care service. A significant and positive

¹³ In spite of being the textbook example of a market with adverse selection, evidence on the importance of asymmetric information in health insurance is inconclusive. Chiappori (2000) concludes in his review that the importance of adverse selection is limited. Cardon and Hendel (2001) do not find evidence of adverse selection in the US employer-provided health insurance in a static setting. On the other hand, Finkelstein (2004) find evidence of adverse selection in the Medigap market in the US and Gardiol et al. (2005) provide evidence of adverse selection in a strongly regulated private insurance market in Switzerland.

¹⁴The coefficients cannot be identified at the same time, thus we normalize δ_0 to some fixed value (0.99999). This formulation could be extended to allow the impact of health care consumption on health status to vary by time and individual characteristics, but these should be second-order effects and we leave it for future research.

estimate of δ_k demonstrates the strong investment effect of health care which is differentiated across preventive care and curative care.

4.3.4 Informative Effect

Consumers could update their beliefs of their true health status, Ths_{it} , through the doctor visits (consumption of preventive and curative care). However these doctor visits only provide noisy signals of their true health status. This implies that consumers' true health status may not get revealed completely. Let λ_{ikt} denote the health status signal associated with preventive/curative care (doctor visit) in time t by consumer i specified as follows:

$$(4.5) \quad \lambda_{ikt} = Ths_{it} + \eta_{ikt}.$$

Here $\eta_{ikt} \sim N(0, \sigma_k^2)$ denotes the noise associated with the health care consumption signal, λ_{ikt} . Therefore, by preventive care or curative care visits, consumers get to know more about their true health status. However, because the consumption signal is noisy, their expectation about their true health status, $\overline{hs_{it}}$, may not get updated to Ths_{it} . σ_k^2 is a measure of the informational accuracy of preventive/curative care: $\sigma_k^2 = 0$ corresponds to super precise medical test so that the consumer gets to know her true health status after one doctor visit. Notice, while the consumer observes the realization of $\hat{\lambda}_{ikt}$, the econometrician does not. However the econometrician has the same information set as the consumer. Therefore, conditional on the value of the mean health status at time t , viz., $\overline{hs_{it}}$, the econometrician assume the distribution as $\lambda_{ikt} \sim N(hs_{it}, \sigma_k^2)$ where hs_{it} is the most recent belief of the consumer's health status. Since hs_{it} itself is normally distributed with

$hs_{it} \sim N(\overline{hs_{it}}, \sigma_{it}^2)$, the signal λ_{ikt} will be distributed as $\lambda_{ikt} \sim N(\overline{hs_{it}}, \sigma_{it}^2 + \sigma_k^2)$ (Miller, 1984; Mehta, Rajev & Srinivasan, 2003).

Once the consumer i choose either preventive or curative care, $c_{ikt} = 1$, she receives the realization of consumption signal $\hat{\lambda}_{ikt}$. With the signal, the consumer updates her beliefs about her health status in a Bayesian fashion, given by the following mean and variance (DeGroot, 1970):

$$(4.6) \quad \overline{hs_{it+1}} = \frac{\sigma_k^2 \overline{hs_{it}} + c_{ikt} \sigma_{it}^2 \hat{\lambda}_{ikt}}{\sigma_k^2 + c_{ikt} \sigma_{it}^2}, \text{ and, } \frac{1}{\sigma_{it+1}^2} = \frac{1}{\sigma_{it}^2} + c_{ikt} \frac{1}{\sigma_k^2}.$$

Therefore, the posterior mean $\overline{hs_{t+1}}$ and posterior variance σ_{it}^2 capture consumer i 's perceived health status with which they make their health insurance and health care consumption choices.

However consumer's health status also could depreciate or improve with consumption, therefore consumers' updated mean health status after preventive or curative care consumption becomes

$$(4.7) \quad \overline{hs_{it+1}} = \delta_0 \overline{hs_{it}} + \sum_k (\delta_k + \frac{\eta_{ikt}}{c_{ikt} + \sigma_k^2 / \sigma_{it}^2}) c_{ikt}.$$

This captures the investment effect and the depreciation, in the spirit of locally Bayesian updating (Kruschke, 2006). Note that the posterior variance will not be affected by health investment, and will shrink regardless of the signal's realized value.¹⁵

4.3.5 Effective Payment

¹⁵ The shrinkage implies consumers get more precise information about their health status which is not unreasonable as it looks, especially in the situation of chronic disease where consumers learn about the severity of the disease gradually. We could relax this assumption in future investigation in order to study acute disease.

Insurance characteristics such as deductible and out-of-pocket-maximum change the effective prices of health care over time. We define the dollar amount remaining in one's deductible in period t until the deductible is met, viz., r_{it} as follows

$$(4.8) \quad r_{it} = \begin{cases} ded_{ija} & t = 1 \\ \max \{0, r_{it} - p_{it-1}c_{ikt-1}\} & t = 2, \dots, T_a \end{cases},$$

where p_{it-1} denotes the consumer's effective price (out-of-pocket expenditure minus copay) in period $t-1$ if she consumes health care. Therefore, the effective price p_{ikt} is given by

$$(4.9) \quad p_{ikt} = \begin{cases} p_{ikt}^o & p_{ikt} \leq r_{it} \\ r_{it} + (p_{ikt}^o - r_{it})ci_{ikt} & 0 \leq r_{it} < p_{ikt} \end{cases},$$

where p_{ikt}^o is the total original charge for health care service k during period t . Here the charges at each sub-period influence out-of-pocket costs which in turn influence the dollars remaining in the deductible. In order to avoid discontinuity, we express price (or total costs) in dollar unit and assume a discrete distribution of charges (p_{ikt}). The specification of this charge distribution captures the dynamics resulting from deductibles and out-of-pocket maximum. However, once the deductible is met and health care service prices are scaled by coinsurance rate. Note that coinsurance rate is same across policy year, thus different health care service price will only affect individual's current period utility.¹⁶

¹⁶ For the purpose of the tractability of our empirical implementation, we assume consumer know the total charge before hand for simplification purpose. This may be a strong assumption that does not capture the price-induced dynamics. However for our main purpose here to study the health status induced dynamics and contractual relationship, this is a secondary effect. Moreover, in the case of chronic disease cost information is widely available; therefore this may not be a strong assumption.

4.3.6 Per-subperiod (Weekly) Consumption Utility

Based on Keeler & Rolph (1988), Newhouse et al. (1993) and Vera-Hernandez (2003)'s finding that insurance contracts mainly influence the decision whether or not to seek treatment against an illness episode, rather than the treatment costs, we assume that during the consumption stage, conditional on perceived health status hs_{it} , and insurance characteristics such as $copay_{ikt}$ and effective price P_{ikt} ,

Crawford & Shum (2005) and Gilleskie and Mroz (2004) have applied CARA (Constant Absolute Risk Aversion) exponential specification when studying health insurance and unemployment insurance in labor economics, and demonstrated xxx. We assume a quasilinear utility that is concave in the health status and linear in copay and price.¹⁷ This is also similar to Erdem etc. (2005) [why do you need this?]

$$(4.10) \quad u(hs_{it}, p_{ikt}, \varepsilon_{ikt}) = -\exp(-r \cdot hs_{it}) - \alpha_{li}(\text{copay}_{ikt} + p_{ikt}) + \varepsilon_{ikt},$$

where r measures the degree of risk aversion. [discuss where does the risk refer to?] α_{li} measures consumer price sensitivity, and ε_{ikt} is an additive idiosyncratic error that measures unobservable factors that affect consumer i 's choice of health care k at period t .

4.3.7 Dynamic Consumption Problem

¹⁷ Even with some level of informational asymmetry between doctor and patient, it is still reasonable to assume doctors act as the relatively perfect agent of consumers by taking into account patients' out-of-pocket payment. This corresponds to the situation where the medical guideline that the doctor follows gives the most cost-effective treatment. Consequently, we shall assume that treatment costs come from a given technological relation. We emphasize one important hypothesis in our model: The individual is rational and compares benefits and costs when she decides whether or not to seek treatment. This might be a strong assumption when one is dealing with severe illnesses for which the individual lacks experience and can hardly value the benefits and costs. However given that we focus on chronic disease, this allows individuals to make the trade-off. See Vera-Hernandez (2003) for a similar assumption.

We now describe consumers' decisions in a nested framework, starting with their health care consumption decisions given their insurance plan coverage and perceived health status. We then describe optimal insurance choice conditional on the insurance premium and assume optimal consumption behavior in the health care stage. Each insurance policy is associated with its main characteristics, which includes premium $prem_{ija}$, copay $copay_{ikt}$, deductible ded_{ija} , coinsurance ci_{ikt} and out-of-pocket-maximum opm_{ijt} . Insurance choice sets are exogenous¹⁸ and could be different for individuals from different employers because the insurer customized the contract menus based on the three insurance plans.

Health Status plays the important role because it inter-temporally relates all the insurance purchase and health care consumption occasions (Cardon & Hendel, 2001) and thus introduces dynamics to the consumer problem. It interacts with consumption through the effect of current health care consumption on the next period level of health status and hence all future health care consumptions.

4.3.8 Main-period (Annual) Insurance Purchase Utility and Dynamic Decisions

The objective of a consumer is to choose health care k so as to maximize her discounted lifetime expected utility at period t . Specifically, the value function at period $t < T$ conditional on insurance plan j , is

¹⁸ Given the insurance company who provide health insurance plans to the employers is a local monopoly and charges the insurance premium based on the group average, not particular consumer, the assumption of exogenous insurance choice set is reasonable. In Ni & Gayle (2009), we estimate a equilibrium model and take the contract design endogenously.

$$(4.11) \quad V(S_t^a) = \max_k E[u(hs_{it}, p_{ikt}, \varepsilon_{ikt}) + \beta[V(S_{t+1}^a) | S_t^a]],$$

where S_t^a denotes the values of the state variables in subperiod (week) t of period (year) a . In the last time period $t=T$ of insurance year, when an insurance decision will be made in the following time period, the value function is

$$(4.12) \quad V(S_T^a) = \max_k E[u(hs_{iT}, p_{iKT}, \varepsilon_{iKT}) + \beta W(S_1^{a+1}) | S_T^a],$$

where $W(S_1^{a+1})$ represents the value of future utility at the beginning of the next year when the consumer makes another insurance decision. The value is defined below. $\beta \in [0,1]$ is a weekly discount factor.

At the beginning of each year, a consumer chooses one of the $J=3$ insurance plans in her choice set based on premium ($prem_{ija}$) and her expected utilization¹⁹ of health care for the coming year. So the value of utility of a particular insurance plan j in $t=1$ of period a , is denoted as

$$(4.13) \quad VI(S_1^a) = -\alpha_{li} prem_{ija} + V(S_1^a) + \varphi_{ija},^{20}$$

¹⁹ Ho (2008) models insurance demand in similar spirit by incorporating expected utility of hospital into her health plan demand utility function.

²⁰ We model risk preference in consumption stage because consumers have uncertainty about their health status, but we did not incorporate preference for risk in the insurance plan stage because of the following reasons: first, Cardon & Hendel (2001) noted the CARA risk coefficient, r , is insignificant in the plan choice stage and preference toward risk are determined by both r and concavity of consumption stage utility which we model here; Secondly, given the nature of employer-sponsored health insurance we studied here, individuals have more uncertainty about their health status, not their plans; Thirdly, Vera-Hernandez (2003) pointed out that risk preference is more about health care consumption.

where α_{ij} measures how much consumer values premium, and φ_{ija} is an additive idiosyncratic error that measures idiosyncratic tastes for insurance plans. And the expected lifetime utility at the beginning of period a is $W(S_1^a) = E_{T_{a-1}+1}[\max_j VI(S_1^a)]$.

In our dynamic model with both investment and informative effects, the state variables, S_t^a , include consumer's posterior mean health status \overline{hs}_{it} , number of preventive/curative care visits, and the idiosyncratic errors. The transition rules for all the state variables can be written in Markovian form.

4.4 Heterogeneity, Identification and Estimation

In this Section, we address issues that arise when estimating our model. First, we show how we fit the nested choices framework into the dynamic setting. We then discuss identification of the model's parameters. We conclude the section by discussing heterogeneity and the use of simulated maximum likelihood.

4.4.1. Consumer Health Status Types

When the consumers choose her health insurance plan offered the insurance provider, she assesses her health status and matches with the insurance plan. If she consider her health status excellent, she is more likely to choose comprehensive plan; and if bad, she is more likely to choose basic plan. Because the consumer's belief of health status is not known to the econometrician, this becomes a source of unobserved heterogeneity. Failing to taking into account consumer beliefs at the time of

the initial insurance plan choice and consumption decision could bias the estimates of the degree and consequence of consumer uncertainty in their consumption and insurance choices.

To address this problem, we allow consumer health status is classified into several types such as “excellent”, “good” and “bad”, viz., θ_s (Khwaja, 2001). Consumers with different health status types are likely to react differently to preventive care and curative care, so we allow their prior beliefs regarding the consumption match values to differ across types, which is summarized by $\overline{hs_{i0}} \sim N(\overline{hs_{s0}}, \sigma_s^2)$.

Here $\overline{hs_{s0}}$ and σ_s^2 denote the prior mean and the variance of consumer health status belonging to “excellent”, “good” or “bad” health segment, and the s subscript denotes the health status type.

4.4.2 Nested Choices and Likelihood

For each week t , consumers choose the health care type and at the first week of each year, they also choose the insurance plan. For each consumer i , our data yield observation on the sequence of health care services chosen, $c_{ikt_a} = \{c_{ipt_a}, c_{ict_a}, c_{i0t_a}\}$, as well as the corresponding insurance plan choice $d_{ijt_a} = \{d_{i1t_a}, d_{i2t_a}, d_{i3t_a}\}$. The subscript t_a refers to week t of year a . Here the plan choice (d_{ijt_a}) will only be made at $t = 1$ of each year, therefore in our proposed dynamic model, we impose the following constraints:

$$(4.14) \quad d_{ij(t+1)_a} = d_{ijt_a} \text{ if } 1 < t < T \text{ and } d_{ij(T+1)_a} = d_{ij1_{a+1}} \text{ if } t = T.$$

We assume the distribution of the unobserved components ε_{ikt} and φ_{ija} are independent and identically-distributed extreme value errors, respectively. Their conditional independence and additive inclusion decrease the computational burden associated with solution of the optimization problem (Rust, 1987).

Solution of the optimization problem yields probabilities that define the likelihood of observing the behavior detailed in the data. The relevant probabilities are the probability of choosing a particular insurance plan and the probability of seeking health care consumption during the policy year, respectively. Conditional on the insurance plan chosen by an individual and the state variables, the probability of choosing preventive or curative care is given by

$$(4.15) \quad \Pr(c_{ikt_a} = 1 | d_{ijt_a}, S_t^a) = \frac{\exp(V_k(S_t^a | d_{ijt_a}))}{\sum_{k'=\{p,c,0\}} \exp(V_{k'}(S_t^a | d_{ijt_a}))},$$

Where $V_k(S_t^a)$ denotes the choice-specific value function for preventive care, curative care or no doctor visit, which comes from

$$(4.16) \quad \begin{aligned} V(S_t^a) &= \max_k E[u(hs_{it}, p_{ikt}, \varepsilon_{ikt}) + \beta[V(S_{t+1}^a) | S_t^a]] \\ &= \max_k \{-\exp(-r \cdot \overline{hs}_{it} + \frac{1}{2} r^2 (\sigma_k^2 + \sigma_{it}^2)) - \alpha_{1i} (\text{copay}_{ikt} + p_{ikt}) + \varepsilon_{ikt} + \beta[V(S_{t+1}^a) | S_t^a]\} \\ &= \max_k V_k(S_t^a) \end{aligned}$$

The term $\frac{1}{2} r^2 (\sigma_k^2 + \sigma_{it}^2)$ represents the risk premium, the disutility incurred by consumer i due to uncertainty she faces regarding her health status and the effectiveness of health care. This risk aversion could generate persistence in health care choices via risk premium which could explain why

we see someone rarely pursue preventive care once they seek curative care or do not see doctor in the previous period. To compute the value function, we employ a variant of Keane and Wolpin (1994) approximation method.

The choice probabilities of alternative insurance plans are given as

$$(4.17) \quad \Pr(d_{ijt_a} = 1 | S_t^a) = \frac{\exp(W_j(S_1^a))}{\sum_{j=1}^J \exp(W_j(S_1^a))}.$$

Let Θ denote the vector of parameters to be estimated. The likelihood for consumer i , is

$$(4.18) \quad L_i(\Theta) = \int \dots \int \prod_a \prod_{j=1}^J \Pr(d_{ijt_a} = 1)^{d_{ijt_a}} \left(\prod_t \prod_k \Pr(c_{ikt_a} = 1 | d_{ijt_a})^{c_{ikt_a}} \Phi(dhs_{ik}; \Theta) \right) G(d\omega_i)$$

Integrating over the joint distribution $G(\cdot)$ and $\Phi(\cdot)$ is difficult because its dimension is large. Furthermore, the probabilities that constitute the likelihood function do not have a closed form solution. We therefore simulate these probabilities following literature (Crawford & Shum, 2005).

Similar to Erdem et al. (2005), our notion of (perceived) health status is person-specific. As discussed before, we allow for discrete different types of consumers in terms of perceived health status. This is also consistent with Crawford & Shum (2005), Gilleskie (1998) and Khwaja (2001) where they model individuals' health types in a discrete setting. This categorization is also consistent with the fact that consumers usually categorize their health status into classes such as “excellent”, “good” and “bad”. Other parameters such as price coefficient α , risk parameter r , and health-investment parameter δ are common across all consumers.

4.4.3 Identification and Asymmetric Information

In this section, we provide brief discussion how the model parameters are identified. The variation in health care choices across individuals and time is important for identifying the parameters related to perceived health status (experience signal) distribution. The mean of health status (match-value) distribution \overline{hs}_0 can be identified by variation (market share) of consumers' initial health care consumption because consumers make their health care decisions on their prior beliefs at the beginning. The variance of health status (match-value) distribution σ_0^2 is identified by consumers' health care consumption rate at the end of history – after experience signals have eliminated much of the uncertainty.

The degree of risk aversion parameter r is identified by the degree of persistence in consumers' health care consumption choices, because risk-averse consumers are reluctant to switch between preventive care and curative care even if the health care they choose may not have higher value for them or be cost-efficient.²¹ On the other hand, the number of time periods that consumers take to switch to different type of health care, n_{ikt} identifies the variance of uncertainty due to health care, σ_k^2 .

Price is identified because there are both time variation and cross-sectional variation in insurance policy. Moreover, variation in health care consumption across consumers on different insurance plans also helps the identification.²²

²¹ With a similar rational expectation argument to Crawford & Shum (2005), we rule out the serial correlation argument in the identification of risk aversion parameter.

²² See Cardon & Hendel (2001) for a formal argument about nonparametric identification of price (moral hazard) effect.

Now we provide some brief discussion of identification of the key model parameters in detail. First, prior mean health status could be separately identified from prior variance, since both enter the utility in an additive fashion. Note that consumers with different means and variances would self select themselves into different plans. This would explain how we can identify certain groups of people with different combinations of means and variances. However, the difficulty comes between identifying consumers within the same plan, who have different means and variances. To explain the identification here, it would suffice to explain it for an example case of consumers with different means and variances who opt for the comprehensive plan – that is, how to separately identify consumers with moderate mean and high variance from consumers with moderate variance and low mean, since both types would choose the comprehensive plan. The identification comes from the fact that the utility is concave in the mean and the variance. This implies that it is easier for a consumer with moderate mean and high variance to increase her utility by choosing a health care option that decreases her variance than by choosing an option that increases her mean; and similarly, it will be easier for the consumer for low mean and moderate variance to increase her utility by choosing an option that increases her mean than choosing an option that decreases her variance. Now since preventive care provides more accurate information (decreases the variance in the health status beliefs) more than curative care and the curative care provides higher investment (increases mean), it will imply that consumers with moderate mean and high variance would opt more for preventive care and consumers with low mean and moderate variance would opt for more curative care.

The next identification concern is how to separately identify the investment effect from the informative effect for a given consumption option. It would suffice to show how to separately

identify two cases: first in which the consumption option had high informative but low investment effects, and second in which the consumption option had high investment but low informative effects. Here informative effects can yield a positive or a negative draw of the health status with equal probability. However, investment effects only increase the health status. Next note that consumers with greater health status would opt for more basic plans as compared to consumers with lower health status. These two observations jointly imply that if consumers, after choosing a certain consumption option only move down to more basic plans, then that consumption option has to be high in investment effects (since investment effect increase the health status). If consuming a certain option, consumers are either moving to more comprehensive plans or are moving to more basic plans, then the consumption option has to be informative because informative effects can increase or decrease the health status.

Finally we discuss how to separately identify the investment effect from prior mean health status. Essentially, this is to identify consumers with high mean health status and a high investment effect and low mean health status and low investment effect – note that in both cases, the propensity to go for the option with investment will be small (since the utility is concave). However, the identification comes from the fact that high mean and high investment will choose more basic plan and low mean and low investment will choose comprehensive plan. Although the change in utility after each investment effect will be the same for both, the low mean low investment will choose the comprehensive plan and go for more repeated consumption (since it is cheap in the comprehensive plan) to increase their overall utility. However, the high mean and high investment consumer will choose the basic plan and will not go for repeated care since it is more expensive.

4.5 Empirical Results

4.5.1 Model Fit and Comparison

To evaluate the model, we estimate several different specifications as reported in Table 4.4 including (1) a semi-myopic model in which consumers only forward until the end of current insurance plan period, (2) a dynamic health investment model without health information learning, (3) a dynamic model without separating preventive care and curative care, and (4) the proposed model.

The semi-myopic model (Model 1) performs the worst. The poor performance is due to the fact that fundamentally, a myopic model has difficulty explaining data generated by an inherently dynamic process generates. In particular, the semi-myopic model fails to capture the health informational/investing tradeoff between preventive care and curative care. The dynamic health investment model without health information updating (Model 2) does not take into account the informational benefit of preventive and curative care. A model with health information updating can account for the fact that consumers could time their health care based on information of their health status. A health-investment-only model would lead to larger price coefficients and a smaller relative variance of the idiosyncratic error term. The overestimated price coefficients would lead to the wrong conclusion that consumers place a higher value on health care than what they actual, because it assigns too little importance to the non-seeking-health-care option. Without informative effect, consumers lack the incentive to obtain the option value which violates the intuition. By not separating preventive care from curative care, we lose the information that preventive care might have different degree of investment and informative effects from curative care which has important implication for chronic disease management.

The comparison of the Log-likelihood shows our proposed model performs the best. This illustrates the importance of incorporating informative effect and the distinction of preventive care and curative care when modeling consumer decisions.

4.5.2 Parameter Estimates

Investment Effect: Table 4.5 reports the estimates for the parameters of our dynamic health investment/informative model. The decay parameter δ_0 captures the depreciation of health status and was normalized to 0.99999 for identification. We start by discussing the investment effect. While the estimate of curative-enhancement effect, δ_c (0.089), is significantly larger, the preventive-enhancement parameter is δ_k (0.003) is much smaller, not significantly different from 0. This suggests that curative care mainly acts as health investment. On the other hand, preventive care rarely improves consumers' health directly. This is consistent with the medical literature.

Informational Effect: The estimates of the standard deviation of the health care consumption signals, σ_k , indicate that preventive care σ_p (7.154) yields much less noisy signals than curative care σ_c (15.032), which is consistent with the fact that preventive care such as screening tests and routine checkup provides more precise information about consumers' health status. While curative care could convey some information about individuals' health status, it does so with much less accuracy.

Consumer Types and Insurance Choices

As aforementioned, we allow for a discrete distribution of individual types as Heckman and Singer (1984). In doing so, we first allowed for two unobserved types and then increased the number until there were negligible changes in both model fit and the qualitative conclusions from the model. This yielded an estimated four type parameters.

Each consumer type starts health care consumption with a different initial health status and updates her health status information from different distributions. Hence, for each of the four consumer types, we estimate different initial health status, namely \overline{hs}_1 , \overline{hs}_2 , \overline{hs}_3 and \overline{hs}_4 . The parameter estimates for the distribution of consumer types provide strong support for the notion of health status heterogeneity among people. Table 4.5 shows that type 1 consumers account for 23.7%, type 2 accounts for 30.1%, type 3 accounts for 14.6%, and the rest 31.6% people belong to type 4.

The point estimates for the parameters of the mean health status indicate that for type 1 consumers, their health status $\overline{hs}_1(2.649)$ is highest, followed by type 2 ($\overline{hs}_2, 1.811$), type 3 ($\overline{hs}_3, 1.794$) and type 4 ($\overline{hs}_4, 0.936$). Interestingly, for type 2 consumers, their initial prior mean health status is close to type 3 consumers. Therefore we name type 1 consumers as healthiest segment, type 2 consumers as moderate-1 segment, type 3 consumers as moderate-2 segment, and type 4 consumers as weakest segment. Consumers are offered with three insurance plans here. If without health status information uncertainty, consumer could make their insurance plan choices based on their true health status. Therefore, healthiest consumers will choose basic plan, moderate health consumers will choose medium plan, and weakest consumers will choose the comprehensive plan. However there are 22.2%, 33.9% and 43.9% of consumers, respectively, choose basic, medium

and comprehensive plans. When we compare consumers' segment percentage with their initial health insurance plan choices, we can see the mismatch: Only 31.6% consumers are in the weakest segment, but 43.9% consumers choose comprehensive plan. On the other hand, in total 44.7% consumers have moderate health, but only 33.9% consumers choose medium plan. This implies consumers make their health insurance choices based on both mean health status and associated uncertainty.

The estimated prior standard deviation of health status, σ_s is larger as compared to the magnitudes of the across-health-care-type difference in the mean health status. This finding further highlights the health status uncertainty and the importance of health status information learning in this market. Moreover, the estimated prior standard deviation of health status are quite close for healthiest ($\sigma_1, 2.812$), moderate-1 ($\sigma_2, 2.913$) and weakest ($\sigma_4, 3.025$) segment consumers, however for moderate-2 consumers, the variance ($\sigma_3, 5.417$) is much larger comparing to the other three types of consumers. This indicates consumers in this segment (14.6%) have high information uncertainty comparing to others. Therefore these consumers are more likely to choose more comprehensive plans instead of medium plan which matches their moderate health status best.

Although preventive care serves as better informational sources of health status than curative care, the estimate also implies that the updating (learning) process in general occurs quite slowly. For example, based on our estimation a consumer will need 20 preventive care visits to reduce her health status uncertainty at the initial value of $\sigma_1 = 2.812$ to half of that value. This slow learning speed suggests the switching cost between preventive care and curative care is very small if any. One possible explanation why we observe consumers' slow learning about their health status through

health care consumption is due to defensive medicine. Consumers are often suggested by doctors to take additional, unnecessary services in order to help doctors safeguard against possible malpractice liability, not to ensure the health of the patients.

4.5.3 Price Elasticities

As expected, the coefficients of the copay, effective price (function of deductible, coinsurance, and out-of-pocket maximum) and premium are statistically significant and positive, implying that indirect utility is decreasing in price.

Health insurance and health care demand elasticities are reported in Table 4.6. The elasticity measure is based on the percentage change of average probabilities for each choice following a percentage of price change. The estimated premium elasticity on plan purchase is -0.083 which is smaller as compared to the finding of RAND health insurance experiment, which ranges from -0.1 to -0.2. However the elasticities of other pricing components are bigger. This difference elaborates the different roles of pricing components on changing consumers' health care consumption and health insurance purchase behavior which is not explored in the RAND HIE setting.

We find copay and deductible affect consumers' preventive care more comparing to curative care, and coinsurance does the opposite. We compare the premium elasticity in our model to the sole insurance model, and find that the sole insurance model overestimates price elasticity by approximately 40%. The low premium elasticity in our model suggests that market-based health plan competition will not result in premium near marginal cost.

4.5.4 Policy Experiments and Managerial Implications

The structural parameters of an individual's optimization problem regarding insurance plan choice and health care consumption decisions enable us to simulate alternative policies, and to predict the behaviors of individuals under these new scenarios. We describe three sets of policy simulations: (1) the effect of subsidization and promotion of preventive care; (2) providing more accurate health status information through preventive or curative care; and (3) pricing components manipulation.

Subsidization of Preventive Care

Given that consumers learn about their health status relatively faster from preventive care, there is room to improve the cost inefficiency, especially for consumers who do not have to get costly curative care. In the first counterfactual, we examine how the subsidization of preventive care by the policy maker could change consumers' choice behavior and the corresponding consumer welfare and insurance costs by comparing to the cost incurred in our data.

Table 4.7 presents consumers' insurance plan choice behavior, welfare change and insurance cost change under the scenario that the policy maker subsidizes preventive care by 20%. On one hand, if policy maker or health insurance provider subsidize or promote preventive care, it will encourage consumers to consume more preventive care and increase insurance cost; On the other hand, preventive care such as early diagnosis and treatment can help consumer avoid more costly problems that may develop or be worsened by lack of basic preventive care. These two countervailing effects, namely ex ante and ex post moral hazards (Zweifel & Manning, 2001)²³ lead to the question of how promoting preventive care impacts consumer health care consumption

²³ Ex ante moral hazard entails that individuals respond to changes in incentives by changing the risk of disease. Ex post moral hazard concerns the effects of incentives on getting curative care. Failure to distinguish the two may lead to a conclusion of non-existence of moral hazard because the two moral hazard effects could cancel out each other (Tang, 2008).

behavior and insurance costs. Our analysis indicates that positive preventive effects outweigh the negative moral hazard effect on insurance costs and overall insurance costs. We also compare it to the case when we subsidize the curative care option. We find that while subsidizing curative care increases consumer welfare at the expense of increasing the overall costs, subsidizing preventive care not only increases consumer welfare but also decreases overall health care costs. Overall, we could see across all segments consumer better self-select their insurance plan, welfare increases and cost decreases. The overall social welfare also increases.

Improving Health Status Learning (Personalized Medicine)

Health care service providers use precise molecular profiling technologies to each individual consumer in order to provide more precise information about her health status and individualized care. It is hoped that the much more precise health status information provided by these personalized medicine could avert more costly treatments required after the onset of a disease. Yet these more precise diagnostic tests and individualized care tend to be more expensive, which lead to high insurance cost for insurance providers. On the other hand, consumers' slow learning about their health status could be explained by the practice of defensive medicine where consumers are often suggested to take additional, unnecessary services in order to safeguard against possible malpractice liability, not to ensure the health of the patients. We find if the health care providers could provide much more precise information about consumers' health status, insurance costs for all the segments decrease and consumer welfare also increase. Hence, this trend of personalized medicine could lead to considerable welfare gains across insurance providers and consumers, and reduce the occurrence of defensive medicine (Table 4.8). Moreover, we could quantify how much health service providers are willing to invest in personalized medicine.

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Most insurance providers use sophisticated health insurance plan pricing scheme in order to screen consumers and mitigate the over-usage such as seeking care more frequently, consuming more care per visit, or consuming higher priced care (moral hazard). These pricing components such as annual deductibles and out-of-pocket maximum change the marginal prices of health care over time. This raises the question of whether and how information asymmetries between consumers and insurance provider could be moderated under the complex pricing structure and how insurance provider could utilize the pricing components to alter consumer behavior and reduce the overall insurance cost while still maintaining consumer welfare. We find decreasing copay or deductible could increase frequency of preventive care more, which leads to higher consumer welfare and lower insurance cost although the improvement is relatively small. In contrast, decreasing insurance rate will increase the frequency of curative care more, therefore results in high insurance cost and worse consumer welfare.

4.6 Conclusion, Limitation and Future Research

In this paper, we construct a dynamic model that nests health care consumption into health insurance demand, building upon Grossman's (1972) health investment model and Arrow's (1963) health information gathering hypotheses. We extend existing literature of dynamic demand in two ways. First, we allow health care consumption to have both investment and informative roles. Second, we build individuals' consumption decisions within the service contract (insurance plan) choice.

Our results offer rich implication for the health care service market. We find preventive care mainly provide consumer with health status information, while curative care build up health capital. Consumers have large uncertainty about their health status which causes potential inefficiency in the market. We also find that consumers are risk-averse, implying that they are less likely to switch to different type of care. Interestingly, although we find evidence of learning, the slow learning speed implies the current health care practice may not help consumers to resolve their uncertainty of health status in a reasonable speed. This could be due to the potential effect of defensive medicine. Consumers get health care, especially diagnostic tests which do not give more information about their health status. Alternatively it could be due to the impreciseness of current preventive care tests. Nevertheless, the slow learning speed suggests that significant economic value can be achieved if insurers or policy makers offer more precise preventive care.

As attention on personalized medicine increases, providing more precise health status information through preventive care must be accelerated. Consumers manage their long-term well-being through the tradeoff between preventive care and curative care. Our results also provide insurer and policy makers an important way to better manage chronic disease and reduce health care cost by inducing more preventive care and timing curative care.

Though we cast our model in the context of health care service, we note that the problem, and hence the conceptualization, is even more general. Most service, in which consumers need to purchase the service contract first, and then pace their consumption path within the service contract period, (e.g., entertainment service, auto insurance service and telecommunication service) can be applied with our model. In these contexts, both consumers and service providers are often not sure about consumers' true type in the sense how much they are going to consume the service.

Consumers learn about their true type through their consumption experience and their status might evolve with more consumption. In such a notion, our model serves as a basis for exploring these service contexts.

Although the results are quite encouraging, the analysis relies on several simplifications. Addressing some of the simplifications offers several promising future research avenues. First, our model does not allow the variance of health status to increase with health care consumption. In our health status information updating, consumers always get more precise information about their health status. This could be violated in certain situations. A model that allows both more precise and vaguer health information might shed light on situations when health care consumption may provide even vaguer information about the health status. Second, the health investment effect of both types of care is not time specific in our model. Incorporating time-specific health investment effect could reveal additional insights for both consumers and the insurer in terms of when the health investment effect will be stronger along the health status distribution. Last, the insurance plan in our model is exogenous. If the adverse selection emerges gradually as a consequence of asymmetric learning, then the contractual changes (insurance plans switching) that take place during the relationship may be informative about the agent's risk type, even if the initial choice of a contract is uncorrelated with residual risk. If the insurers realize this as well, they could take this into account when designing the contract. A dynamic equilibrium model of contract design will provide rich understanding.

Chapter 5

Adverse Selection, Advantageous Selection and Moral Hazard in the Health Insurance Context

5.1 Introduction

Economists have been concerned about the potential market failures arising from asymmetric information in private insurance markets since the seminal work of Arrow (1963), Akerlof (1970), and Rothschild & Stiglitz (1976). Asymmetric information may lead to two problems in providing such insurance: moral hazard and adverse selection. The possibility that even competitive market may not result in efficiency creates important yet difficult economic and policy issues. Furthermore, moral hazard and adverse selection have substantially different implications for optimal contract design. Therefore, the empirical analysis to identify and quantify the effects of asymmetric information and trace out its implications for welfare, competition, and policy is of major interest.

One approach to testing for the presence of asymmetric information is based on the theoretical conclusion that, under asymmetric information, contracts with more comprehensive coverage are chosen by agents with higher expected consumption. This conclusion holds under both adverse selection and moral hazard. Under adverse selection, high-risk agents, who expect to incur more consumption, choose to buy more coverage (Rothschild and Stiglitz, 1976). Under (ex post) moral hazard, agents who buy more insurance, become more costly because the extensive coverage reduces incentives for preventive behavior (Holmström, 1979).

Based on this, Chiappori and Salanié (2000) proposed that a positive correlation between coverage and frequency of consumption under asymmetric information should be observed on observationally identical agents. They argue that this prediction is robust to a variety of generalizations. However they do not find evidence of asymmetric information in French car insurance market among young drivers which led them to suspect that such information asymmetry may arise in the course of time due to asymmetric learning about risk. Cardon & Hendel (2001) estimated a structural model using data from National Medical Expenditure Survey. They find that estimated price and income elasticities, as well as demographic difference, can explain the expenditure gap between the insured and the uninsured. Thus they judge the roles of adverse selection to be economically insignificant. Finding like these have also fostered another stream of literature on the possibility that multidimensional private information may lead to what has been called “advantageous selection”. De Meza and Webb (2001) argue that this prediction might not hold in the presence of both selection on risk preferences and moral hazard (Zweifel and Manning, 2000). They argue that selection based on risk aversion is advantageous if those who are more risk averse both buy more insurance coverage and have low risks.

Additionally, in the health insurance context, moral hazard may be solved by the fact that health insurance covers the financial but not the health loss of a serious illness (Kenkel, 2000). However, both arguments fail to explain why we observe little moral hazard in health insurance but a significant amount in auto insurance contexts. Lack of prevention, such as an underuse of cancer screening exams (health insurance) and aggressive driving (automobile insurance), can result in severe health events in both insurance contexts, but none of them cover the health loss. This puzzle could be explained by investigating two types of moral hazard in health insurance (Tang, 2009). On the one hand, health insurance may reduce preventive care because the insurer will pay for part of the treatment in case of disease. This is the classic moral hazard. On the other hand, if health insurance covers preventive care as well, the preventive coverage will encourage the insured to consume more preventive care. These two countervailing effects are referred to as *ex ante* and *ex post* moral hazards¹ (Zweifel and Manning, 2000). Under *ex ante* moral hazard, if the market price of health insurance is actuarially fair and reflects preventive activities, the insured has the correct incentives to spend on prevention because it lowers the price of insurance. But if the insurer cannot observe some of the actions of the insured and therefore the price of insurance does not reflect individuals' cost of prevention, the purchase of market insurance decreases the demand for prevention and creates *ex ante* moral hazard. It stems from an informational asymmetry. On the other hand, *ex post* moral hazard is not caused by asymmetric information and has nothing to do with morality. It is essentially a price effect. The problem of *ex post* moral hazard has received a great deal of attention in health economics, but few works have been done to analyze the *ex post* moral hazard problem in preventive care as it is often thought as an insignificant problem (Cutler & Zeckhauser 2000).

Our paper examines the adverse/advantageous selection and ex ante/ex post moral hazard effects in the health insurance market. In doing so, our paper makes several new contributions to the literature. First, our method of inference for the presence of private information differs from previous study such as Finkelstein & McGarry (2004) and Fang, Keane & Silverman (2008). We find for some consumers there is a statistical significant and quantitatively large negative correlation between ex post medical expenditure and insurance coverage, but for others the relationship reverse. These correlations are inconsistent with no asymmetric information, thus lead us to an interpretation of the results as evidence of both adverse selection and advantageous selection in the health insurance market. Second, our paper is, to our knowledge, the first to examine directly coexistence of adverse selection and advantageous selection. Specifically, we utilized the dynamic demand system estimated from the previous chapter which considers consumers' health risk, risk aversion and the preventive/curative care tradeoff. Third, the empirical evidence in our paper suggests that for the employer-sponsored health insurance market, (ex post) moral hazard, which was much discussed in the previous literature, do not appear to be the only source of inefficiency; instead, our results suggest that selection effects play prominent roles in this market. We also explore the implications of these on insurance pricing.

5.2 The Empirical Test

The elasticity measures based on demand estimation in chapter 4 show that preventive care visits are more sensitive to copay and deductible, while curative care visits respond to coinsurance rate and premium more. Controlling everything else equal, more curative care implies larger ex post moral hazard, and less preventive care implies bigger ex ante moral hazard. On one hand, health insurance

may reduce preventive care because the insurer will pay for part of the treatment in case of disease. This is the classic (ex post) moral hazard. On the other hand, if health insurance covers preventive care as well, the preventive coverage will encourage the insured to consume more preventive care.

The results from the dynamic demand model in chapter 4 also find consumers learn their health status through both preventive care and curative even though the learning speed is pretty slow. This dynamic analysis is informative on the importance of adverse selection (Abbring, Chiappori, Heckman & Pinquet, 2003). In static setting, individuals may not assess their health status any better than insurers. This seems to suggest why in Cardon & Hendel (2001), among others, adverse selection is not found. If individuals and insurers are symmetrically informed initially, asymmetric information on health risk may arise in the course of an insurance relationship due to asymmetric learning (Chiappori & Salanie, 2008). This entails that individuals learn faster about their health state than insurers, for example because they accumulate information on diagnostic tests that they do not seek any treatment. In turn, asymmetric learning may affect dynamic insurance contract selection. Thus, a dynamic form of adverse selection arises. The joint analysis of medical consumption and insurance contract selection processes as in chapter 4 can shed a light on these dynamic selection effects. As discussed earlier and in previous literature, the correlation between ex post medical utilization and insurance coverage may be negative, zero, or positive (Jullien, Salanie, and Salanie, 2007). Figure 5.1 and 5.2 show welfare cost of adverse selection and advantageous selection (Eirav & Finkelstein, 2010).

5.3 Conclusion

Using the estimated parameters from the dynamic demand system in Chapter 4, we test the existence of adverse selection and advantageous selection and find both in the health insurance market. For consumers in the high health status segment, they have lower probability of choosing better insurance; however for low health status segment, consumers have higher probability of choosing better insurance. Interestingly, the middle segment which has moderate health status prefers better insurance coverage which may not be necessary for them. From insurers' perspective, we find they charge low premium for larger employer with more men and young people who have relatively low average age-gender risk index but higher average comprehensive risk index. On the other hand, copay set by the insurer is lower for smaller employer with more women and older people; and coinsurance rate is exactly opposite. Insurers also set low deductible for large employer with more women and older people who have low average comprehensive risk index. These findings suggest different policy implications and invite more future research on this important topic.

Chapter 6

A Structural Model of Insurance

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6.1 Introduction

In many insurance settings such as auto insurance, consumer heterogeneity is not directly observable but can be indirectly elicited by offering menus of insurance contracts and allowing consumers to self-select. However, for health insurance, insurers often could not price directly on consumers' observed characteristics even if they might observe some of them. Moreover, in the U.S., consumer prices of health insurance are typically not adjusted for individual risk, especially in the employer-sponsored health insurance market. Insurers typically contract with employers to create a menu of plans from which employees select coverage. Consumers, therefore, typically face prices that do not vary by individual risk. The U.S. law prohibits employers from charging employees different amounts based on health-related factors (GAO 2003). These suggest that insurance prices may not be optimal in terms of maximizing welfare given the complexities of self-selection in insurance markets.

In this paper, we analyze the effect of insurance pricing on consumer welfare and insurer profit of the employer-sponsored health insurance market, particular in the PPO plan context. Existing work suggests two approaches. First, the form of optimal contracts differs considerably between adverse selection and moral hazard, the two main sources of inefficiency discussed in previous chapters. Thus, the qualitative properties of observed contracts may provide useful insights into the type of problems they are designed to address. On the other hand, instead of solving for the optimal contract, researchers could take the insurance plans as given and concentrate on their implications for observed behavior. Similar to Bundorf, Levin & Mahoney (2010), we adopt the latter approach, estimate a model of monopoly insurer pricing and conduct several counterfactual simulations to analyze the effects on firm profit and welfare from insurance price menu.

Different from most recent papers (Carlin & town, 2007; Einav, Finkelstein & Cullen, 2008) which define efficiency to be best allocation that can be observed with uniform pricing, by recognizing uniform pricing may preclude a large fraction of the welfare gains that could in principle be achieved with available information, and also ignores the welfare loss that is inevitably created by private information about health status, we follow the price discrimination literature (Wilson, 1993; Leslie, 2006; Stole, 2007) to incorporate both second-degree and third-degree price discrimination. We build a utility-based model of consumer behavior that incorporates characteristics suggested by the data and institutional details of the employer-sponsored health insurance. The demand model is designed to be consistent with the observed behavior of the insurer. Setting a set of nonlinear insurance pricing schemes is an example of second-degree price discrimination. Charging different premiums for different employers is the reflection of third-degree price discrimination since the

difference mainly stems from the different average risk indexes across employers which are correlated with consumers' previous claim behavior and demographics such as age and gender.

We specify a random-utility discrete-choice model with endogenously random participation. The structural econometric framework allows us to conduct policy experiments using the estimated demand system. An empirical investigation of the insurer profit and consumer welfare implication of insurer pricing behavior must rely on an ability to analyze behavior with different degree of price discrimination.

Our analysis reveals that the observed nonlinear price increases the insurer's profit by a considerable amount, relatively to a policy of optimal uniform pricing based on average risk index. The gain significantly depends on the degree of the relation between average risk indexes of a particular employer and the premium. In particular, if the average risk index could explain 20% more of the premium for one employer charged by the insurer, firm profit would increase by 11%. From the point of view of employees, the change in aggregate consumer surplus under pricing discrimination relative to uniform price is also significant even after counting the redistribution of surplus among consumers. We also find the increase in profit from reoptimizing prices in the face of changing demand is less when a menu of several price alternatives is used than a single risk-index based price. This explains why the price of health care service is very flexible to some extent.

The remainder of the chapter is as follows. In Section 6.2 the model is presented and the additional data which is not mentioned in previous chapter is summarized. Section 6.3 contains the results of the estimation, including the implied demand elasticities. Based on the estimated demand model a set of policy experiments are explained and the results presented in Section 6.4. The chapter concludes in Section 6.5.

6.2 Structural Econometric Model

Employees face a set of insurance contracts. These are different PPO plans for specific plan qualities, say different preventive or curative coverage. Consumers from different employers might have different premium even they choose the same type of plans because of different average risk indexes across employers. Following the insurance literature (de Meza & Webb, 2001) Consumers are differentiated along two dimensions: degree of risk version captured by income level and their risk level. Let $y_i \geq 0$ denote the income of consumer i , and let $\zeta_i \geq 0$ denote consumer i 's risk level. Both y_i and ζ_i are known to the consumer but unobservable to the insurer. Income is distributed according to the cumulative distribution function $F(y)$ and risk is distributed according to the cumulative distribution function $G(\zeta)$. Both distributions are known to the insurer. For simplicity, we assume F and G are independent.

In our data there are three type of insurance plans offered by the single insurer. They differ in terms of coverage. All consumers prefer more comprehensive plans, but differ in their willingness to pay. As discussed in Chapter 4, there is some coverage variation for plans fallen into the same type if they are offered to different employers. Under assumption of random participation (Rochet & Stole, 2002), consumer choose different type of insurance plans. Let q_{ij} denote the quality of different type of insurance plan j , which we assume as the function of coinsurance as discussed later.²⁴

Each type of plan could be characterized by the duo: coinsurance $Coins_{ij}$ and premium $Prem_{ij}$ discussed in Chapter 4. Here premium stands for the price paid the consumers and coinsurance

²⁴ This assumption is not that restrict as it seems because the coinsurance rate set by the insurer considered the previous consumer evaluation of different PPO plans from the discussion with the insurer.

captures the quality of the PPO plans which have same hospital network in our data. Consumers' quality evaluation of different health insurance plans is linked with the coinsurance they have to pay. Consumer trade between quality (coinsurance), the price (premium) they need to pay and their risk level. We assume the utility of individual i choosing one particular health plan j in a Cobb-Douglas fashion as follows.²⁵

$$(6.1) \quad U_{ij} = q_{ij} [E(y_i) - \text{Pr em}_{ij} - \tau(y_i)]^{\eta_1} \zeta_i^{\eta_2}$$

in which $E(y_i)$ is consumer i 's health care expenditure, and η_1 and η_2 are the parameters which reflects the substitute effect between quality (coinsurance), premium and risk level. They also capture the substitution between premium paid when purchasing insurance plan and future consumption as discussed in Chapter 4. With this specification, the insurer optimally chooses to offer many different PPO plans which vary in terms of quality (coinsurance level). Moreover, consumers' marginal utility from different plans depends on their level of income, leading to a self-selection process in which high income consumers choose high quality (low coinsurance) plans and low income individuals choose low quality low coinsurance) plans. The Function E contains parameters that allow us to estimate the appropriate proportion of income that is relevant for individuals' health care expenditure. We use a specification that allows for wealthier people to spend a greater absolute amount of income on health care, but a lower proportion of their total income, than less wealthy individuals.

We specify E as $E(y_i) = \lambda_1 y_i^{\lambda_2}$, where $\lambda_1 > 0$ and $\lambda_2 \in (0,1]$ are parameters. Consumers first decide how much money to allocate to health care and then subsequently decide how to allocate

²⁵ Alternatively we could use a more general Constant Elasticity of Substitution (CES) utility function. However without adding more insights, it only brings more computational complexity.

between insurance plan premium and medical care consumption (coinsurance). We assume there is no unobserved heterogeneity in budgeting conditional on income since income is already a form of unobserved heterogeneity in the model, so λ parameters are the same for all individuals. Here $\tau(y_i)$ represents the time cost of indeed going for medical care once having insurance. We assume it is a linear function of income as $\tau(y_i) = \tau_1 y_i + \tau_2$, where $\tau_1 \geq 0$ and τ_2 are parameters to be estimated. Since all consumers in our data purchase health insurance, we do not have the outside option here.²⁶

Therefore, the expected demand for particular insurance plan j is equal to

$$(6.2) \quad S_j(\bullet) = M \int_{(y, \zeta) \in A_j} dF(y) dG(\zeta)$$

where $A_j = \{(y_i, \zeta_i) : U_{ij} \geq U_{ik}, \forall k \in J \equiv (B, M, C)\} \subset \mathfrak{R}_+^2$ is the set of consumer types who most prefer plan j and as noted above, we assume F and G are independent.

The distribution of potential consumers' income is imputed from accounting profile and census data. Table 6.1 shows the summary statistics. We fit a log-normal distribution using a minimum distance estimator. The distribution of consumers' health risk may change from year to year. We assume an exponential distribution, $\zeta_i \sim \exp(X_i \beta)$, in which the vector $X_i = \{\text{constant, age, gender, risk index}\}$, and β is the parameter vector.

²⁶ People might argue some employees may not purchase insurance from their employers because they simply do not purchase. Although this could be a valid concern, in our data, we do not observe consumers who do not purchase insurance. Also overall in the U.S., most active workers obtain insurance through their employers. So our assumption may not be restrictive as it seems.

In order to incorporate some employee might get insurance from other sources, say their spouses' employers,²⁷ we assume with probability $\psi(i | \delta) = 1 - \frac{\exp(\alpha y_i + Z_i \delta)}{1 + \exp(\alpha y_i + Z_i \delta)}$ consumer i faces better outside option, where $Z_i = \{\text{constant, spouse, HHSIZE}\}$. With individual income increasing, she is more like to get insurance from her own employer. The vector δ represents the effect of family size or spouse. As mentioned earlier, we also assume a linear relationship between plan quality and the coinsurance consumers need to pay, $q_{ij} = q_j^o \text{Coins}_{ij}$.

In summary, the parameters to be estimated is $\Theta = \{q_j^o, \lambda_1, \lambda_2, \tau_1, \tau_2, \eta_1, \eta_2, \alpha, \beta, \delta\}$. So the predicted market share of plan $j \in J$, in period $t \in \{1, \dots, T\}$, conditional on all parameters, is computed by

$$(6.3) \quad S_{jt}(p_t, X_t, Z_t, \Theta) = \int_{(y, \zeta) \in A_{jt}} dF(y) dG(\zeta | X_t, \beta)$$

The market size, M , is the total number of employees in the data. The log-likelihood function can be stated as

$$(6.4) \quad \ell(\bullet, \Theta) = \sum_{t=1}^T \sum_{j \in J} N_{jt} \log s_{jt}(\bullet, \Theta).$$

Different kinds of price variation contained in the data set could help us to identify the model without relying on function-form assumptions. Consider the most comprehensive plans: the premium and (X_t, Z_t) vary across different plan period. The effects of each of these three time-

²⁷ In the data we observe some individuals purchase insurance in non-consecutive years. In that case, we assume they get insurance from outside during that missing period. This is reasonable from the info obtained from the insurance industry.

varying components are separately identified because each enters non-linearly in different parts of the model. First, the Cobb-Douglas utility specification has been motivated by a behavioral tradeoff. In particular, the separate non-linear components are motivated by distinguishing the utility function from roles played by the distributions of individual risk heterogeneity. Second, there still remains some variation in the data that provides identification without relying on functional form.

In the model the only sources of uncertainty are from the individuals' unobserved heterogeneity. There is no additional logit, probit or other such error term. All of the stochastic elements in the econometric model have specific interpretation within the behavioral framework. This limits the model's ability to explain discrepancies between predicted behavior and actual behavior. To estimate the parameters we use a non-derivative simplex search algorithm.

6.3 Empirical Results

We make several normalizations in order to estimate the model. The quality level of the most comprehensive plan is set to one q_C^o . We also set the value of α to .15 since we do not have data on spouses' health insurance plans.²⁸

The estimated parameters are shown in Table 6.2. The quality parameters imply that the basic plan is 0.402 times worse than the most comprehensive plan, while the medium plan is 0.589 times worse. With the premium of \$2798 paid for the most comprehensive plan and \$873 for basic plan, basic plan buyers pay 0.312 times less for plan what is 0.293 times lower overall quality (taking into account coinsurance).

²⁸ .15 is chosen to be similar to the 17% of U.S. GDP is on health care. Robustness check confirms it is reasonable.

The estimated parameters for the distribution of individuals' risk level are given in Table 6.2 under the heading of β parameters. The δ coefficients explain effects of alternative sources of insurance. Own-price, cross-price and income elasticities are also calculated. These are obtained by computing predicted market shares under the empirical prices and comparing them to predicted market shares following a one percent increase of the premium. Surprisingly, as a monopolist insurer, the own-premium elasticities are less than one.

6.4 Counterfactual Experiments and Welfare Implication

We then perform several counterfactual experiments based on the estimated demand. The experiments involves reoptimizing premiums under different scenarios, such as uniform pricing and linear pricing with risk index, and examine the effect on consumer welfare. Here we assume the insurer choose a set of prices to maximize expected revenue.

By not allowing the insurer to choose the quality levels, the supply-side of the model differs from models of second-degree price discrimination in which the firm chooses both qualities and prices. The restriction is motivated by the institutional setting that the quality of the health care plans mainly depend on the health providers such as hospitals and physicians. As with other multi-product monopoly problems in which the demand for each product is inter-dependent, it is impossible to solve for an analytic solution to the firm's optimization problem, except in unrealistically simple cases such as discrete consumer types or a uniform density of consumer types. The problem is further complicated by the stochastic value of the outside alternative. However it is possible to solve for optimal prices using numerical methods.

In addition to having a well-specified model of demand, it is important that the firm-side of the model is also well-specified. The following counterfactuals concern alternative assumptions as to how much flexibility the insurer has in determining the contract menu. In calculating the welfare effects for consumers we take into account the utility obtained by those consumers who choose the outside alternative.

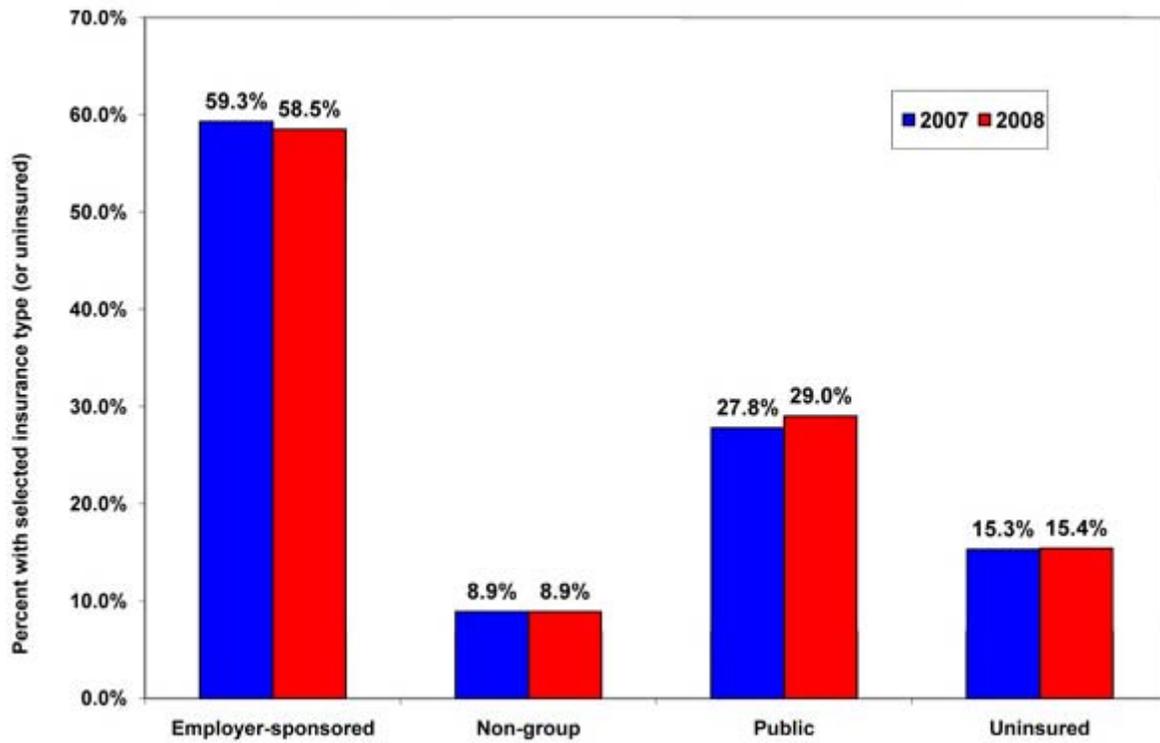
From these simulations, it appears there is less to be gained by the insurer from setting a fixed price menu, than there is from re-optimizing prices over time. The improvement from changing pricing may be huge because the price menu is elastic to health care demand fluctuations. In other words, as demand fluctuates, consumers not only substitute around the plan, but also might drop from the market. For example, when less health care is needed, consumers switch down from more comprehensive plans to basic plan. Therefore re-optimization of prices in the face of fluctuating demand should always benefit the insurer and the benefit could be bigger for an insurer that offers a menu of plans than for an insurer with a single price.

6.5 Conclusion

Researchers have long understood competition in health insurance markets is no guarantee of efficiency. We contribute to the literature that attempts to quantify consumer welfare loss and insurer profit gain in employer-sponsored setting. We find that the observed nonlinear pricing strategy increases the insurer's profit by a considerable amount, relatively to uniform pricing. The gain significantly depends on the degree of the relation between average risk indexes of a particular employer and the premium. In particular, if the average risk index could explain more of the premium for one employer charged by the insurer, firm profit would increase significantly. From the

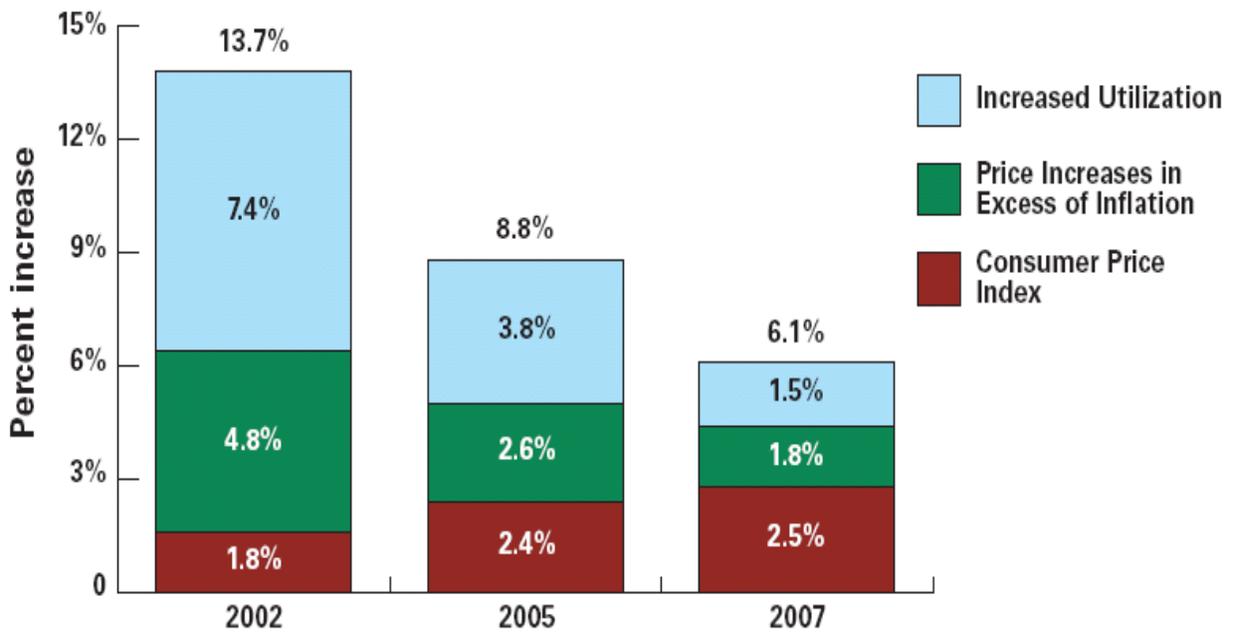
point of view of employees, the change in aggregate consumer surplus under pricing discrimination relative to uniform price is also significant even after counting the redistribution of surplus among consumers. We also find the increase in profit from reoptimizing prices in the face of changing demand is less when a menu of several price alternatives is used than a single risk-index based price. This explains why the price of health care service is very flexible to some extent.

Figure 1.1: Health Insurance by Types of Coverage, 2007-2008



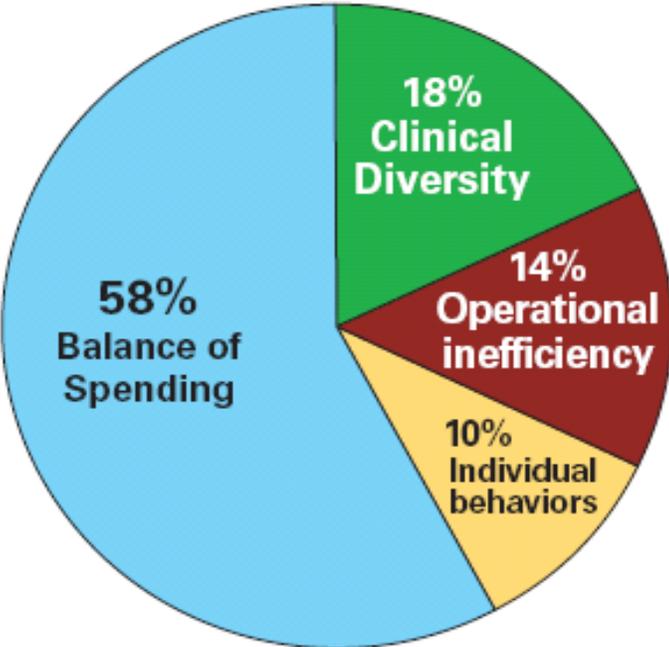
Source: Economic Policy Institute Population Survey Analysis.

Figure 1.2: Factors Driving Increases in Health Insurance Costs



Source: PricewaterhouseCoopers Calculations (2008).

Figure 2.1: Total Health Care Expenditures and Wasteful Spending



Source: “The Price of Excess: Identifying Waste in Health Care Spending”, PricewaterhouseCoopers Health Research Institute, 2008.

Figure 4.1: Cost Sharing for Consumers in Consumption Stage

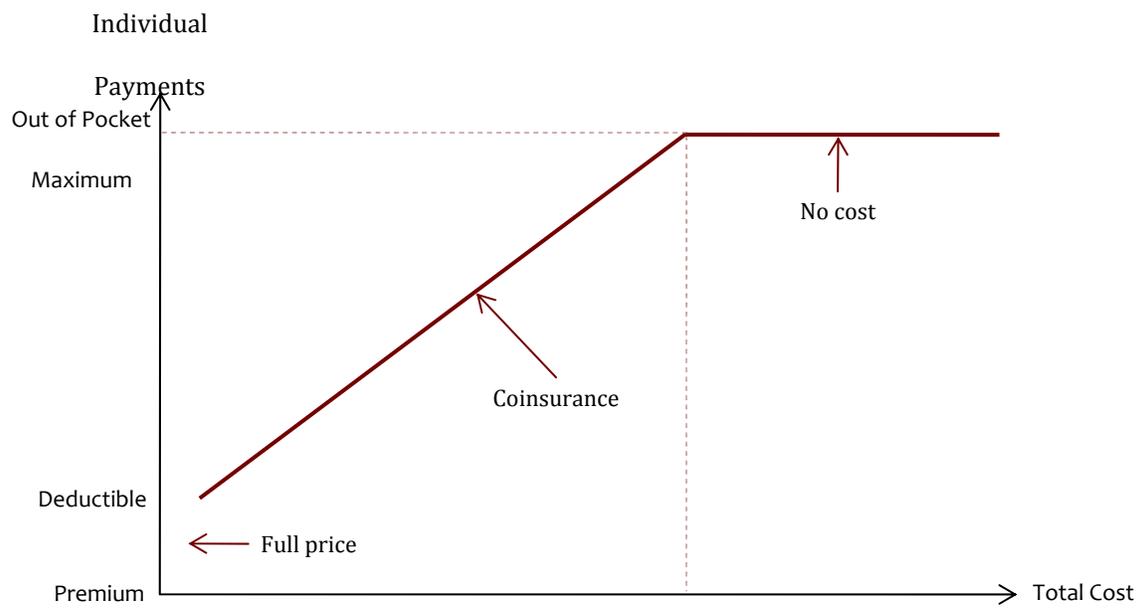


Figure 5.1 Welfare Cost of Adverse Selection

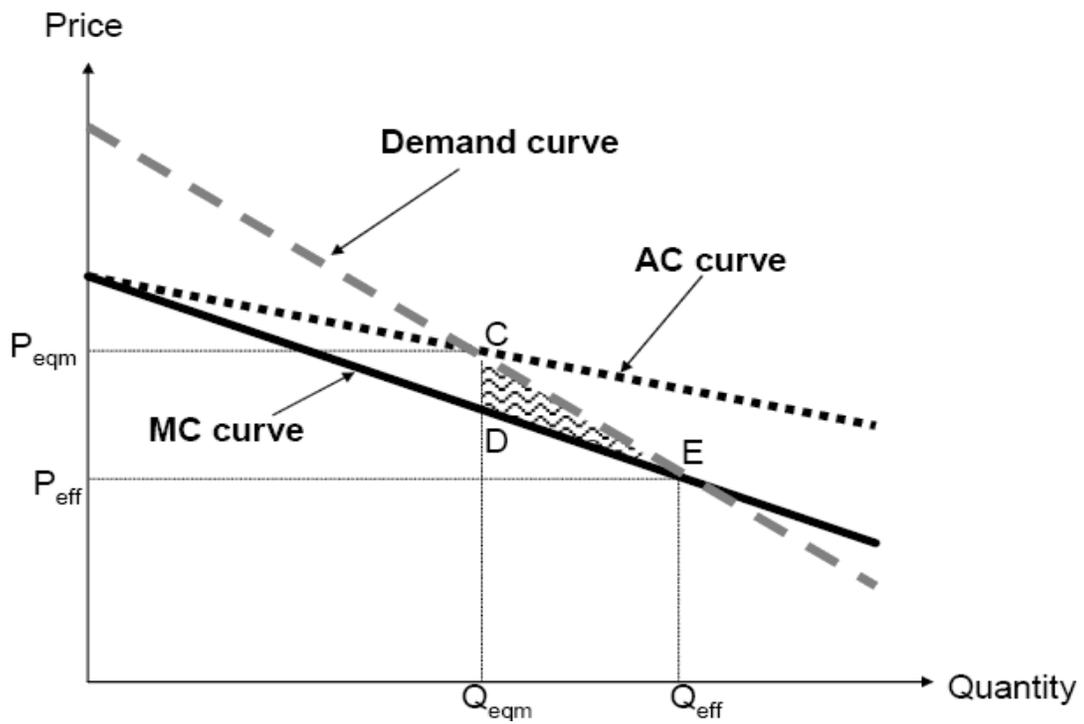


Figure 5.2 Welfare Cost of Advantageous Selection

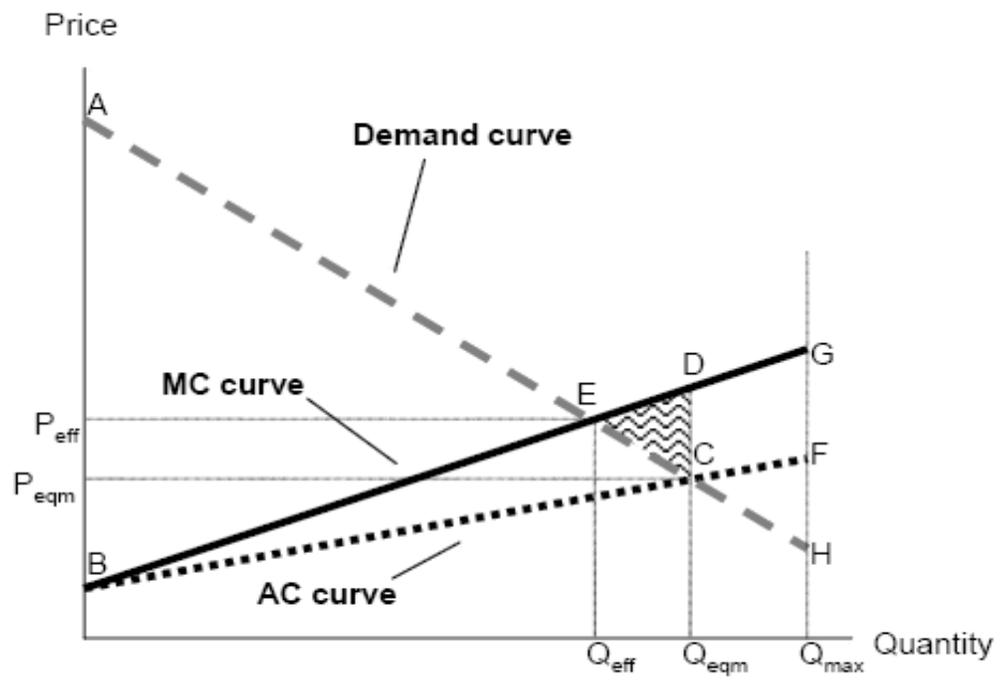


Table 1.1: Examples of Chronic Diseases

Chronic Disease	Morbidity
Prostate Cancer	200,000/per year
Heart Disease and Stroke	80 million
Breast Cancer	1 in 8 women
Diabetes	23.6 million
high blood pressure	1 in 3

Table 3.1: Examples of Preventive/Curative

Chronic Disease	Preventive Care	Curative Care
Prostate Cancer	PSA Goserelin, Leuprolide	Prostatectomy, Brachytherapy Orchiectomy, Cryoablation
Coronary Artery Disease / Arteriosclerotic Heart Disease	Cardiovascular Stress Test, Electrocardiographic Monitoring, Echocardiography, Coronary Angiography, Thallium Stress Test, Aspirin	Coronary Angioplasty Coronary Stent Placement Coronary Artery Bypass

Table 3.2: Summary Statistics across Plans

	Basic	Medium	Comprehensive
Premium (\$)	873.2	1683.8	2797.5
Copay (\$)	19.2	29.8	15.8
Coinsurance rate (%)	27	14	2
Deductible (\$)	1008.8	356.8	112.6
Out-of-pocket Max (\$)	3107.6	1020.5	275.3
No. of visit/year	11.0	15.5	22.0
Total Cost of Preventive/year (\$)	178.3	368.2	1738.6
Total Cost of Curative/year (\$)	1427.5	3928.5	40327.6

Table 4.1: Percentage of Plan Choices

	Basic	Medium	Comprehensive
2005	22.15%	33.92%	43.92%
2006	22.58%	34.06%	43.35%
2007	21.66%	35.72%	42.62%

Table 4.2: Switching Pattern of Insurance Purchase

2005	2006	Basic	Medium	Comprehensive
Basic		91.49%	3.21%	5.30%
Medium		2.89%	94.31%	2.80%
Comprehensive		3.03%	3.08%	93.89%

2006	2007	Basic	Medium	Comprehensive
Basic		91.09%	3.34%	5.57%
Medium		1.88%	93.26%	4.86%
Comprehensive		1.05%	7.39%	91.56%

Table 4.3: Switching Pattern of Health Care Consumption

	Preventive	Curative
Preventive	46.77%	53.23%
Curative	22.19%	77.81%

Table 4.4: Model Comparison (N=147512)

	Benchmark 1 Semi-Myopic	Benchmark 2 Investment only (no learning)	Benchmark 3 Group Preventive /Curative	Proposed model
-LL	27595.4	26823.7	27322.1	24721.6
AIC	55226.8	53,701.4	54,680.2	49,479.2
BIC	55283.8	53,758.4	54,737.2	49,536.2

Table 4.5: Parameter Estimates

Parameter	Est. (Std. Err.)	
Type Probability		
Type 1	0.237 (0.008)	
Type 2	0.301 (0.009)	
Type 3	0.146 (0.006)	
Type 4	0.316 (0.006)	
Informative Effect		
Initial Health Status	Mean	Std. Dev.
Type 1	2.649 (0.317)	2.812 (0.427)
Type 2	1.811 (0.219)	2.913 (0.402)
Type 3	1.794 (0.221)	5.417 (0.895)
Type 4	0.936 (0.102)	3.025 (0.394)
Std. Dev., Signal	Preventive Care	Curative Care
	7.154 (1.305)	15.032 (1.924)
Health Investment		
Decay	0.99999 (-)	
Enhancement	0.003 (0.002)	0.089 (0.021)
Price Coefficient	0.176 (0.062)	
Risk-aversion	0.991 (0.211)	
Discount Factor	0.999 (-)	

Table 4.6: Price Elasticities

	Health Care Consumption		Insurance Purchase
	Preventive	Curative	
Copay	0.524	0.375	0.121
Deductible	0.477	0.314	0.146
Coinsurance	0.398	0.401	0.185
Premium	0.011	0.016	0.083

Table 4.7: Subsidizing Preventive Care (20%)

Health Type		Plan Choice	2005	2006 (Data)	2006 (Simulated)	Welfare	Cost
Healthiest	23.7%	Basic	22.2%	22.6%	23.2%	0.8%	+1.9%
Moderate-1	30.1%	Medium	33.9%	34.1%	36.9%	3.1%	-8.1%
Moderate-2	14.6%						
Weakest	31.6%	Comprehensive	43.9%	43.3%	39.9%	1.4%	-0.3%

Table 4.8: Personalized Medicine: Information Value (1/2 Std.)

Health Type		Plan Choice	2005	2006 (Data)	2006 (Simulated)	Welfare	Cost
Healthiest	23.7%	Basic	22.2%	22.6%	23.6%	1.4%	-0.9%
Moderate-1	30.1%	Medium	33.9%	34.1%	38.4%	5.3%	-9.8%
Moderate-2	14.6%						
Weakest	31.6%	Comprehensive	43.9%	43.3%	38.0%	2.7%	-4.3%

Table 6.1: Demographics and Health Risk Index

2005	Mean (Std.)
Age	46.08 (12.80)
Gender	0.49 (0.50)
Income (\$1,000)	48.47 (6.59)
Agese _x _rrs	1.31 (0.62)
Concurrent_rrs	1.84 (3.63)
Predictive_rrs	1.71 (2.42)
EmployerSize	0.0946

Table 6.2: Estimated Parameters

	Mean (Std.)	β	Mean (Std.)
q_B^o	0.402 (0.015)	Constant	0.256 (0.021)
q_M^o	0.589 (0.054)	Age	0.011 (0.002)
η_1	1.062 (0.004)	Gender	0.007 (0.001)
η_2	0.459 (0.032)	Risk index	0.089 (0.003)
λ_1	5.102 (0.272)	δ	Mean (Std.)
λ_2	0.645 (0.027)	Constant	7.812 (0.205)
τ_1	0.0184 (0.007)	Spouse	0.025 (0.023)
τ_2	6.405 (0.046)	HHS _{ize}	0.003 (0.002)

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