EMPIRICAL AND EXPERIMENTAL APPROACHES TO NONOPTIMAL ALLOCATIONS OF GOODS AND SERVICES

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ABSTRACT OF THE DISSERTATION

Empirical and Experimental Approaches to Nonoptimal Allocations of Goods and Services

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This dissertation studies the nonoptimal outcomes of human behavior related to health care. Health is a major component of human capital, which imposes a significant impact on individuals and the society. This dissertation aims to apply modern economic theories and models to reveal causes of nonoptimal outcomes in health care using various empirical and experimental methods.

The first chapter studies why smokers tend to keep smoking even though they face a serious deterioration in health. This study employs an extension of the dynamic structural model of rational addiction. However, parametric restrictions on the Markov transition process of smoking capital are removed. This new model finds that smokers' disutility from cessation continues to increase for three to four years, thereby making quitting costly. It further proves that the dilemma between the immediate disutility from quitting and the future disutility from deterioration of health clearly exists and influences smokers' decisions.

The second chapter studies the mechanisms behind disparities in the quality of medical care by racial groups and types of insurance. An endogeneity exists between the outcomes and demographic characteristics of patients in any given hospital. This issue is addressed using an instrumental variable that is constructed by simulating a patient's hospital choice.

Our results prove that minority patients are systematically sorted into low quality institutions while Medicaid and charity care patients my contribute to poor outcomes. These findings suggest that hospitals serving a large number of minority patients should be given incentives to improve their quality. On the other hand, hospitals with a large number of Medicaid and charity care patients should be provided with extra funding.

The third chapter studies dynamic voluntary contribution games. Due to free-rider problems, it is difficult for agents to fund public projects. Theoretical models suggest that completion bonuses and gradual contributions are effective mechanisms in preventing subjects from pursuing a non-contributing equilibrium. This chapter uses an experimental approach to investigate what facilitates the completion of public projects. It is found that subjects are able to overcome the free-rider problem when communication is allowed.

(338 words)

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Chapter 1

Introduction

This dissertation is composed of three essays, which shed light on the mechanisms behind important social issues related to health care. We often fail to achieve an optimal allocation of resources even though we know that it is possible to provide the greater good to society and individuals. Smokers are aware that their behavior eventually leads to serious health deterioration. Yet, many of them are unable to quit smoking due to immediate withdrawal symptoms. We are aware that minority and poor patients receive low quality medical care. Yet, our society still fails to improve the quality of medical care for such patients. We are aware that it is good to collaborate to achieve efficient outcomes. Especially in medical care, collaborations among providers are becoming ever more important. Yet, due to the incentive to free-ride, we fail to maximize potential social gains.

The Center for Medicare and Medicaid Services (2012) estimates that we spent 2.8 trillion dollars on health care in the United States in 2012. This translates to $8,915 per person. The true cost of health problems exceeds this amount due to the additional costs of lost wages and services. Among all disciplines that study health care delivery issues, economics is a particularly important discipline due to its comprehensive investigations on market systems and human behavior. The essays in this dissertation apply such empirical and experimental methods developed in economics to health care issues.

The first essay investigates smoking behavior. Using data from the British Household Panel Survey, we develop a fully dynamic structural model of smoking in which smokers are subject to immediate disutilities due to withdrawal symptoms and future deterioration of health. We observe that parametric restrictions that previous studies imposed on stochastic processes of smoking capital development do not reflect reality. As the tenure of smoking

increases, the utility of smoking decreases in relation to other factors such as health status. We further observe that the disutility from quitting smoking increases within the first four years. This indicates that smokers face a significant disutility from withdrawal symptoms for a prolonged period of time. This makes quitting very costly. These new findings are possible only after removing parametric restrictions on the stochastic processes of smoking capital development. Although these findings indicate that further research is required to reveal a better picture of addiction problems, our findings still support the fundamentals of the theory of rational addiction since the results clearly show that health deterioration and smoking history are both important factors for smokers' behavior.

The second essay investigates the mechanisms behind the disparities in the quality of medical care by race and types of insurance. We estimate a model of discrete choice problems taking incidence of adverse outcomes as the dependent variable and the demographic composition of patients at the hospital-level as an independent variable. However, this independent variable could be endogenous to the outcomes. We develop a hospital choice model that simulates patients' choice of hospitals and estimates the expected demographic composition of patients to serve as an instrumental variable. It is found that minority patients are more likely to be treated at low quality institutions whereas patients who are covered by Medicaid and charity care are more likely to cause a degradation in hospital performance possibly due to the low compensation that hospitals receive from social welfare patients.

The third essay investigates a dynamic public investment game. It is important to retain cooperation among agents in order to produce favorable outcomes in many instances. In the health care industry, many providers form teams to treat patients. However, if there is a free-rider problem, it is hard to achieve optimal outcomes. In this essay, we conduct experimental studies to investigate what factors are important for producing better outcomes in a team of non-cooperative subjects. We find that completion bonuses and coordination devices such as cheap talk are important factors for completing a public investment game. It is also found that cheap talk overcomes potential free-rider problems. Our findings generally agree with the theoretical predictions in previous studies. Although some previous studies reported that theory has a very limited ability to explain subjects' behavior, our experiment imposed more realistic conditions for subjects and confirmed that theory explains subjects'

behavior in general although some systematic deviations are evident. This study affirms the importance of theoretical and experimental investigations in developing a more cooperative environment to achieve optimal outcomes in teams.

Each essay is meant to be a building block for greater discussion on the social issues that we face. As it is shown in each of the essays, there are reasons and mechanisms behind choices and actions. However, by providing the right instruments, we are able to avoid undesirable outcomes. The first essay clearly demonstrates that smokers have a better chance of quitting smoking if support is provided for an extended period of time after the cessation of smoking. My investigation suggests such support needs to be extended for a minimum of four years. The second essay recommends a public policy that provides incentives for low quality institutions serving a disproportionately high share of minority patients to improve the quality of medical care that minority patients receive. The third essay demonstrates that subjects react well to incentives in collaborative games. We further find that communication improves the efficiency of cooperation even beyond what the theory predicts. In order to achieve better outcomes in collaborative projects that are widely observed in medical care (for example, Accountable Care Organizations), we should develop a facility for communication and incentives for better practice.

Health services research is a very important field today. The health care industry suffers from ever growing costs and disparities in the quality of medical care. However, it is challenging to reduce costs while simultaneously improving quality. Careful investigation and planning is necessary, and we need to understand what causes the problems that we face in health care today. In other words, we need to understand the mechanisms that play a role behind nonoptimal outcomes in health care. It requires systematic analysis in order to reveal such mechanisms, and quantitative methods and models developed in econometrics, labor economics, industrial organization, and other subfields in economics provide powerful tools for health services researchers. This dissertation demonstrates multiple ways of analyzing healthcare issues using economic models and theories, especially focusing on economic analyses of smokers' behavior, disparities in the quality of medical care, and factors necessary for effective collaborations.

Chapter 2

First Essay: Dynamic Discrete Choice of Smoking and Rational Addiction

Abstract

A dynamic discrete choice algorithm was used to analyze decision making of smokers regarding their smoking habits using data from the British Household Panel Survey. The primary purpose of the study are firstly, to identify if the rational addiction model by Becker and Murphy (1988) still holds when parametric assumptions are removed, and, secondly, to understand what influences a smoker's decision to smoke using a fully dynamic discrete choice model. Multiple issues found in previous studies are resolved using a fully dynamic discrete choice model and the theory of rational addiction is found to reflect the consumers' behavior although our results do not support the original parametric formulation. According to our econometric analysis, we found that smokers suffer from withdrawal symptoms most in their third and fourth years of cessation whereas the standard formulation of rational addiction assumes that the largest disutility is experienced in the first year. We also found that the utility of smoking becomes smaller in relation to other factors such as health. This means that smokers with a long tenure of smoking are more likely to quit smoking when negative consequences from smoking are foreseen.

2.1 Introduction

Dynamic discrete choice problems have been given considerable attention by microeconomists in a variety of fields (Aguirregabiria and Mira, 2010). Dynamic discrete choice problems estimate the expected payoff from a particular activity. The expected payoff is the sum of current and discounted future utilities and depends on the expected stream of future independent variables, which in turn depend on choices that the agent makes today and in the future. The areas of economics that initially deployed dynamic discrete choice problems were labor economics and industrial organization. In these studies, firms and individuals take the expected future conditions of the market into account when they make choices. We now see applications in other fields such as health economics, development economics, political economy, demography and marketing (Keane and Wolpin, 2009). Dynamic discrete choice problems are very unique and very different from conventional statistical methods. These studies examine how today's choices influence future utility and future behavior.

The very first papers in dynamic discrete choice problems were presented independently by many researchers in the mid 1980s (Keane and Wolpin, 2009). However, a contribution by Rust (1987) founded a standard method for numerical solutions to dynamic discrete choice problems.

Around the same time, there was also a break-through in the study on the consumption of addictive goods. Becker and Murphy (1988) conducted a theoretical study of consumers' behavior towards addictive goods. They used a dynamic transition rule, called stock of consumption capital, S_t to model smokers' decisions. The stock of consumption capital is generally expressed as follows:

$$S_{t+1} = (1 - d)(S_t + c_t) \tag{2.1}$$

where c_t is a level of consumption.

By further assuming that smokers realize disutility from smoking (for example, deterioration of health), the chance of smoking equals the chance of the expected discounted sum of utility from smoking exceeding the expected discounted sum of the cost of smoking.

Some attempts have been made in order to empirically analyze and validate the model by

Becker and Murphy (1988). For example, we have seen studies by Becker *et al.* (1994) and Chaloupka (1991). These studies, however, do not attempt to take consumers' expectations into account. Chaloupka (1991) reformulated the structural model of rational addiction into a reduced model in order to see how the stock of consumption capital affects smokers' decisions. The model generally is:

$$c_t = \theta_l c_{t-1} + \theta_f c_{t+1} + X\theta + \epsilon \tag{2.2}$$

where c is the amount of consumption of addictive goods and the matrix X represents bound vectors of other control variables. This formulation has multiple problems. They use the coefficient θ_l as evidence of rational addiction but it is an unconvincing formulation. Indeed, a study by Auld and Grootendorst (2004) found that milk is more addictive then tobacco. They also found that estimates are biased toward finding rational addiction through Monte Carlo studies.

Departing from such models derived from the rational addiction by Becker and Murphy (1988), there are multiple studies that used reduced models in economics and other disciplines. The model of Jones (1994), for example, tries to study if health is a significant factor in consumers' decision making on smoking using the British Household Panel Data. The model is not dynamic but rather a static model that does not take future utilities and disutilities into account. The study finds that people with worse health are less likely to have attempted to quit smoking. It, however, does not explain why these individuals did not quit prior to becoming unhealthy.

Given these previous studies, we now see some studies that opt to use fully dynamic discrete choice models that compute the forward-looking discounted sum of future utilities and disutilities. For example, Darden (2009) examines various factors for smoking decisions using a fully dynamic discrete choice model. The model fully incorporates the dynamic discrete choice model developed by Rust (1987). A generalized version of his function is:

$$U_{it}(A_{it}, d_{it}, R_{it}, X_{it}) = \alpha_0 + (\alpha_1 + \alpha_2 A_{it} + \alpha_3 R_{it} + \alpha_4 X_{it}) I(d_{it} = 1) + \alpha_5 I(d_{it} = 0) + \alpha_6 A_{it} + \epsilon \tag{2.3}$$

In the equation above, we assume that subjects choose one from a set of two choices $d_{it=\{0,1\}}$. The subscript t stands for time , and the subscript i stands for individuals. The value of $I(\cdot)$ is either 0 or 1 depending on the subject's choice. For example, if subject i's choice is $d_{it} = 1$, then $I(d_{it} = 1) = 1$ and $I(d_{it} = 0) = 0$.

Explanatory variables used here are the stock of addiction capital, A, index for health status, R, and a vector of independent demographic variables that serve as control variables, X. Darden (2009), however, assumed that the development of the smoking capital follows the specification of Becker and Murphy (1988) by parametrically restricting the transitional rule being consistent with the specification give by Becker and Murphy (1988).

Our study contributes to the study of smoking decisions using a dynamic discrete choice algorithm. However, our study differs from Darden (2009) and previous studies in multiple ways. First of all, the structural model of Darden (2009) and many others assume the dynamics of smoking capital accumulation proposed by Becker and Murphy (1988) as given (See equation (2.1)). In our study, however, we aim to study if the parametric construction of Becker and Murphy (1988) is plausible by not placing any parametric assumptions on the law of addiction capital accumulation. Furthermore, in order to focus of the validation of the theory of rational addiction, we also develop a more parsimonious model.

In this study, we use the algorithm developed by Hotz and Miller (1993) for computation. As Aguirregabiria and Mira (2002) discussed, the algorithm yields consistent general linear estimates just like the traditional algorithm developed by Rust (1987) but the algorithm significantly reduces the computational burden.

In sum, this analysis makes a contribution to the existing studies of the smoking behavior of smokers by analyzing their behavior using a fully structural dynamic discrete choice model. This study does not impose any parametric assumptions on the structure of addiction capital accumulation. To the best knowledge of the author, no previous studies have used a fully dynamic discrete model to examine the validity of parametric restrictions imposed by Becker and Murphy (1988).

This paper proceeds with a detailed examination of our econometric model. Then, we describe the data that we use for our empirical analysis. The following two sections explain our estimation strategies. The last three sections discuss the results of estimation and

provide concluding remarks.

2.2 Econometric Model

The dynamic discrete choice problems were first studied by many researchers somewhat independently, but the fundamentals of today's solution methods were pioneered by Rust (1987). The estimation method used in his paper is called the nested fixed point algorithm. This method is computationally costly since every time structural parameters are adjusted in an attempt to maximize likelihood, the algorithm needs to solve for a fixed point of the value function again. His model has only one independent variable that changes over time. However, it is clear that as the number of variables increases, the difficulty of solving the structural model increases exponentially.

Hotz and Miller (1993) found that it is possible to avoid such computation. Their method uses conditional choice probabilities to estimate expected changes in independent variables in the future.

Aguirregabiria and Mira (2002) further developed this algorithm. Their approach estimates a function Ψ, which is called a policy iteration operator. Given the expected probability of agents choosing an action P, we have $P = \Psi_A(P)$ where A is a set of discrete actions available to agents (Aguirregabiria, 2001; Aguirregabiria and Mira, 2002). This method does not require unbiased conditional choice probabilities because the operator Ψ finds such probabilities, which are consistent, provided value functions are fully identified at the fixed point of the function Ψ.

In our analysis, since it is possible to obtain the probability of smoking from a large set of data, we opt to use the algorithm by Hotz and Miller (1993) in order to identify the value functions.

First, we assume that there exists a set of observable discrete states $\chi_t \equiv \{1, ..., X\}$ with a finite support. The state at the time t is expressed as $x_t \in \chi_t$. Assuming there are T periods, we let $t \in \mathcal{T} \equiv \{1, ..., T\}$. We further assume $\chi \equiv \chi_t$ for all $t \in \mathcal{T} \setminus T$. The set of actions that consumers can take is discrete, $a_t \in A \equiv \{0, 1, 2, ..., J\}$, and its support is finite. In the case of smoking, $A \equiv \{0, 1\}$ since the choice is either to smoke or not to

smoke.

Secondly, in order to simplify the problem, we assume that the utility function is additively separable in observed vectors and unobserved vectors, which are essentially error terms. The error terms $\{\epsilon_{tj} : j \in A\}$ are independent of x_t, but these error terms depend on choices $j \in A$. These error terms are also independent over time as we assume that our system is time-homogeneous. This assumption is important in order to obtain an explicit form of the "value function" for actions $j \in A$ utilizing a conditional logit framework by McFadden (1977) and a mapping between conditional choice probabilities and value functions (Hotz and Miller, 1993).

Finally, we note that the transition function can be separated into two different functions:

$$\bar{F}(x_{t+1}, \epsilon_{t+1}|x_t, \epsilon_t, a_t) = G(\epsilon_{t+1}|x_{t+1})F(x_{t+1}|x_t, a_t). \tag{2.4}$$

where G has a finite first moment and is twice differentiable.[1] The transition function F needs to be estimated. Parametric assumptions can be placed but, for our analysis, we obtain this function nonparametrically.

Following the notations used in Hotz and Miller (1993), we assume that there are two actions to choose from in every period, namely $d_{tj} \in \{0, 1\}$ for all $(t, j) \in \mathcal{T} \times A$.

Given these variables and functions, we define an optional decision, k:

$$k = \arg\max_{j \in A}[u_t(j, x_t) + \epsilon_{tj} + v_t(j, x_t)] \tag{2.5}$$

[1] Nonparametric and semiparametric extensions have been studied by Fang and Wang (2010), Norets and Tang (2010), and others. Although it is generally good to have less assumptions on structural models, there might be a large cost attached to it. For example, if we employ the nonparametric algorithm by Fang and Wang (2010) , the relationship between covariates and the dependent variable becomes less clear in many cases. This was also the case for the analysis we conducted in the following section. Fang and Wang (2010) estimates both discount factor and value functions using their nonparametric algorithm. In our case, the power of the algorithm is very low even when the discount factor is explicitly provided, and estimation of the discount factor is not possible as likelihood is flat over between 0 and 1. Issues around identification of parameters and power are discussed by Magnac and Thesmar (2002). We opted to impose parametric restrictions on our model due to this reason.

where

$$v_t(j, x_t) = E(\sum_{s=t+1}^{T} \sum_{j \in A} d_{sj}^{\text{optimal}} \beta^s [u_s(j, x_s) + \epsilon_{sj} | x_t, d_{tj} = j]) \tag{2.6}$$

We also assume that utility functions are homogeneous. There is a function u such that $u = u_s$ for all $s \in T$. The term β is widely called a discount factor and its support is restricted to $\beta \in (0, 1)$. Equation 2.5 then implies that the conditional probability of choosing k is (suppressing t in ϵ):

$$p_k(d_{tk}^{\text{optimal}} = k | x_t) = \int_{\epsilon_1=-\infty}^{\epsilon_1=\epsilon_k+u_t(k)+v_t(k)-u_t(1)-v_t(1)} \cdots$$
$$\int_{\epsilon_k=-\infty}^{\epsilon_k=\infty} \cdots \int_{\epsilon_J=-\infty}^{\epsilon_J=\epsilon_k+u_t(k)+v_t(k)-u_t(J)-v_t(J)} dG(\epsilon_1, ..., \epsilon_k, ..., \epsilon_J | x_t) \tag{2.7}$$

Letting g_j be the marginal density function for j of G Hotz and Miller (1993) claim that there is a mapping $Q(v_1, ..., v_J, x_t, j)$, which is invertible in $\{v_1, ..., v_J\}$ for each x_t. Furthermore, the mapping $Q(\cdot)$ is defined as follows:

$$Q(v_t(1), ..., v_t(J), x_t, j) = \int g_j(\epsilon_j + u_t(j) - u_t(1)$$
$$+(v_t(j) - v_t(J)) - (v_t(1) - v_t(J)), ..., \epsilon_j + u_t(j) - u_t(J)$$
$$+(v_t(j) - v_t(J)) - (v_t(J) - v_t(J))|x_t) d\epsilon_j \tag{2.8}$$

where,

$$p_{tk}(d_{tk}^{\text{optimal}} = k | x_t) = Q([v_t(1), ..., v_t(J) | x_t], x_t, k) \tag{2.9}$$

Like McFadden (1977) and Hotz and Miller (1993), we assume that ϵ follows the type-I (Gumbel type) extreme distribution with its mode being zero, and therefore the unconditional mean is $E(\epsilon) = \gamma$ where γ is the Euler-Mascheroni constant.[2]

Because we assume ϵ to follow the type-I extreme distribution, we may represent the

[2] $\gamma = \int_1^\infty \left(\frac{1}{\lfloor x \rfloor} - \frac{1}{x} \right) dx$

conditional choice probability as:

$$p_{tk}(d_{tk} = 1|x_t) = \left(\sum_{j \in A} \exp(v_t(j|x_t) - v_t(k|x_t)) \right)^{-1} \tag{2.10}$$

Then, following Arcidiacono and Ellickson (2011), we utilize McFadden's corollary for Theorem 1 (McFadden, 1977) to define the function V:

$$V(x_t) = \ln \left(\sum_{k \in A} \exp(v_t(k|x_t)) \right) + \gamma \tag{2.11}$$

$$= \ln \left(\frac{\sum_{k \in A} \exp(v_t(k|x_t))}{\exp(v_t(j|x_t))} \exp(v_t(j|x_t)) \right) + \gamma \tag{2.12}$$

$$= \ln \left(\sum_{k \in A} \exp(v_t(k|x_t) - v_t(j|x_t)) \right) + v_t(j|x_t) + \gamma \tag{2.13}$$

$$= -\ln(p_{tj}(d_{tj} = 1|x_t)) + v_t(j|x_t) + \gamma \tag{2.14}$$

where $j \in A$. Furthermore, the function V is bijective in x_t (see Equation 2.9), and we have an alternative representation of the value function V (following McFadden (1977)):

$$V(x_t) = E\{\max_{k \in A}(v(k|x_t) + \epsilon_k)\} \tag{2.15}$$

Therefore, the unobservable coefficient ϵ_k has a closed representation:

$$E(\epsilon_k) = -\ln(p_k(d_k = 1|x)) + \gamma \tag{2.16}$$

Furthermore, we note that the value function $V(x_t)$ can also be represented as a recursive ex-ante value function as follows:

$$V(x_t) = E\{\max_{k}(v(k|x_t) + \epsilon_k)\} \tag{2.17}$$

$$= \sum_k p(k|x_t)(v(k|x_t) + \epsilon_k) \tag{2.18}$$

$$= \sum_k p(k|x_t)(u_t(k, x_t) + \beta \sum_{x_{t+1} \in \chi_{t+1}} V(x_{t+1}) F(x_{t+1}|x_t, k) + \epsilon_k) \tag{2.19}$$

Then, following Aguirregabiria and Mira (2002), the function V for each $x_t \in \chi_t$ can be represented as a matrix $V_t \equiv [V(x_t = 1), ..., V(x_t = X)]'$ to obtain an alternative representation of Equation 2.19. Suppressing time t of V_t because our system is homogeneous in time, we have:

$$V = \sum_{k \in A} P(k) \circ (U(k) + \epsilon_k + \beta F(k) V) \tag{2.20}$$

$$= \left(I - \beta \sum_{k \in A} (P(k) \circ F(k)) \right)^{-1} \left(\sum_{k \in A} P(k) \circ [U(k) + \epsilon_k] \right) \tag{2.21}$$

where $\circ$ is the Hadamard product. The function $U(k)$, where $k \in A$, is a vector of utility values. More specifically, $U(k) = [u(k, x = 1), ..., u(k, x = X)]'$. Furthermore, the function, $P(k) = [p(k|x = 1), ..., p(k|x = X)]'$, is a vector of choice probabilities.

We further we assume that we can decompose the utility function into $U(k) = U(k, \theta) = Z(k)\theta$ where $Z(k)$ is a vertical stack of functions $z(k, x)$ where $z(k, x)$ is a bijective mapping $z : \chi \overset{k}{\mapsto} \mathbb{R}^N$ and θ is a vector of $N \times 1$.

Once we impose such parametric restrictions on the utility function, then, following Aguirregabiria (2001), we may express choice probabilities as a system of equations assuming that the error terms independently and identically follow the type-I extreme distribution:

$$p(j|x_t, \theta) = \frac{\exp(\tilde{z}_j(x_t, P)\theta + \tilde{\epsilon}_j(x_t, P))}{\sum_{k \in A} \exp(\tilde{z}_j(x_t, P)\theta + \tilde{\epsilon}_j(x_t, P))} \tag{2.22}$$

$$\tilde{z}_j(x_t, P) = z(j, x_t) + \beta \sum_{x_{t+1} \in \chi} f(x_{t+1}|x_t, j)\, W_z(P(j)) \tag{2.23}$$

$$\tilde{\epsilon}_j(x_t, P) = \beta \sum_{x_{t+1} \in \chi} f(x_{t+1}|x_t, j)\, W_\epsilon(P(j)) \tag{2.24}$$

$$W_z(P(k)) = \left(I - \beta \sum_{k \in A} P(k) \circ F(k) \right)^{-1} \left(\sum_{k \in A} P(k) \circ Z(k) \right) \tag{2.25}$$

$$W_\epsilon(P(k)) = \left(I - \beta \sum_{k \in A} P(k) \circ F(k) \right)^{-1} \left(\sum_{k \in A} P(k) \circ (\gamma - \ln(P(k))) \right) \tag{2.26}$$

In our analysis, we assume that smokers choose either to smoke or not to smoke. A smoker

smokes if

$$\tilde{z}_1(x_t, P)\theta + \tilde{\epsilon}_1(x_t, P) > \tilde{z}_0(x_t, P)\theta + \tilde{\epsilon}_0(x_t, P) \tag{2.27}$$

where the left hand side of the equation above represents the utility that a smoker draws from smoking, and the right hand side of the equation represents the utility that a smoker draws from not smoking. When the inequality above is violated, one decides not to smoke.

We also note that $u_t(j, x_t) + v_t(j, x_t) = \tilde{z}_j(x_t, P)\theta + \tilde{\epsilon}_j(x_t, P)$ and the detailed forms of the matrices above are as follows:

$$P(j) = [p(j|x = 1), ..., p(j|x = X)]' \tag{2.28}$$

$$F(j) = \begin{bmatrix} f(x' = 1|x = 1, j) & \cdots & f(x' = 1|x = X, j) \\ \vdots & \ddots & \vdots \\ f(x' = X|x = 1, j) & \cdots & f(x' = X|x = X, j) \end{bmatrix} \tag{2.29}$$

$$f(x' = p|x = q, j) = \text{Prob}(x' = p|x = q, j) \text{ where } \{p, q\} \in \chi \times \chi \tag{2.30}$$

$$Z(j) = [z(j, x = 1), ..., z(j, x = X)]'$$

$$\text{Note } z(j, x) \text{ is a } 1 \times N \text{ vector.} \tag{2.31}$$

$$\theta = [\theta_1, ..., \theta_N]' \tag{2.32}$$

where $x' \equiv x_{t+1}$ and $x \equiv x_t$ for any $t \in \mathcal{T} \setminus T$.

Since we know every components of the system of equations above except θ, the logit framework can be applied to estimate θ in this parametrically specified case. Therefore, we construct a conditional likelihood function to be maximized, assuming that the set of individuals is $\mathcal{I} \equiv \{1, ..., N\}$:

$$\ln L(\theta, \beta, F) = \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{I}} \sum_{j \in A} d_{itj} \ln(p(a_{it} = j|x, \theta, \beta, F(j))) \tag{2.33}$$

Provided the likelihood function, the maximum likelihood estimator of θ is $\hat{\theta}$, and this estimator is defined as:

$$\hat{\theta}(\beta, F) = \underset{\theta}{\text{argmax}} \ln L(\theta, \beta, F) \tag{2.34}$$

In sum, by constructing the discounted sum of observable and unobservable covariates, $\tilde{z}_j$ and $\tilde{\epsilon}_j$, for all $j \in A$ utilizing the invertible function Q discussed by Hotz and Miller (1993), we estimate the set of coefficients θ by maximizing the likelihood function 2.33. Because of the bijective mapping of Q, our knowledge of p identifies the value function the same way as a static logit problem does. Compared to the original nested fixed point algorithm by Rust (1987), our method based on Hotz and Miller (1993) is much faster to solve.

2.3 Data and Construction of Decision Model

Our data are drawn from the British Household Panel Survey using a data management software package called PanelWhiz.[3] This is a panel survey of individuals and households in the U.K. The survey started in 1991 and the project is still active. The data represent the general population of the U.K. including both smokers and nonsmokers. For our analysis, we use data that come from smokers who smoked anytime between 1991 and 2008.[4]

< Table 2.1 >

Tables are attached at the end of this chapter.

The variables used are summarized in Table 2.1. It shows that there is a wide range in years smoked. In our model, it is desirable to keep track completely of "stock of smoking." However, since an addition of a single year doubles the number of states, we keep track of years that smokers smoked for up to five years and make any year beyond the fifth as an absorbing state. The number of years that a smoker has smoked at the time of observation increases by one each year of smoking, and once he or she stops smoking, it stops increasing, and he or she starts accumulating "detachment from smoking." This is a negative utility due to withdrawal symptoms. These disutilities vary depending on "years since cessation." These two variables are used as proxies for "stock of consumption capital," defined in equation 2.1. This is a variant of what was used in the study by Becker

[3]The author would like to thank the author of PanelWhiz, Professor Haisken-DeNew, for providing the data management software package.

[4]Newer data are available in raw format but these are not yet incorporated to PanelWhiz, and we opt not to use these new data as we have no practical way to access the data in such a format suitable for analysis.

and Murphy (1988). In our model, the stock of consumption capital does not depreciate. We assume that smokers enjoy smoking by satisfying their urge to smoke. However, once a smoker detaches himself from smoking, depending on the number of years since his last use of tobacco, the smoker experiences a disutility called "detachment from smoking." This formulation allows us to study whether the accumulation shown in equation 2.1 because one of the purposes of our study is to see if the accumulation of smoking capital follows the theory of Becker and Murphy (1988) in the absence of parametric restrictions.

The utilities and disutilities resulting from smoking are relative to other factors that patients experience. It is, most notably, health status. In our study, we use a subjective understanding of health status. There are many variables indicating health status in the British Household Panel Survey, and it is possible to make use of objective variables. The reason that we do not use these variables is that we are not aware of how one could foresee the likelihood of getting a particular disease. For the health indicator that we use, participants are asked to report how they evaluate their health status at the time of survey on an ordinal scale between 1 and 5, where "1" is the most healthy, and "5" indicates the least healthy.

Given the above independent variables, we construct the following conditional utility functions for smokers' decisions:

$$\begin{aligned}&\text{Conditional utility function: smoking at period } t\\ &u_{it} = c + \text{factor variables for years smoked}_{it} * \theta_1 +\\ &\text{factor variables for health}_{it} * \theta_3 + \epsilon \qquad (2.35)\\ &\text{Conditional utility function: not smoking at period } t\\ &u_{it} = \text{factor variables for years smoked}_{it} * \theta_1 +\\ &\text{factor variables for years in cessation}_{it} * \theta_2 + \text{factor variables for health} * \theta_3 + \epsilon \qquad (2.36)\end{aligned}$$

In the above equation, θ_x has a different value for each factor. For example, the value of θ_1 for those who have only smoked for one year is different from the value of θ_1 for those who have already smoked for two years.

The standard theory assumes that addiction capitals become more and more important as a smoker increases his tenure of smoking. This is also true compared to his health. Therefore, θ_1 must be positive and increase as each year of smoking accumulates. On the other hand, θ_3 must have the smallest number for those with poor health. Furthermore, θ_3 must be monotonically larger for better health statuses because we assume smokers strictly prefer to have better health. Once a smoker decides to stop smoking, he experiences a large disutility. Therefore, θ_2 is negative and smallest in the initial year of cessation and this value becomes larger as a person continues to stay away from smoking. However, this value does not become positive as both ex-smokers and current smokers strictly prefer to smoke according to the theory of rational addiction. We further believe that the coefficient c must be negative because this term represents the global cost of smoking. We assume that smokers smoke in order to satisfy their addiction capital but if a person does not have such capital, we assume that he or she does not want to smoke. One reason for this might be the cost of tobacco products. In sum, our estimates will show if the standard theory of rational addiction reflects reality.

< Table 2.2 >

Tables are attached at the end of this chapter.

In many studies, if two agents are in the same state, we regard them as trying to solve the exact same utility maximization problem. This is, however, not realistic because there are factors that influence the future utility but are not direct components of the utility function. In order to incorporate such variables, we include a few variables that are excluded in the utility function (which we call exclusion variables) to compute transition matrices. For example, we assume that income affects the health condition of individuals since income indicates how much money can be spent on healthcare. Table 2.2 indicates that the transition of health is quite different depending on whether income is above or below the median. In general, we observe that those with a higher income stay healthier at a higher chance than those with a lower income. This is very important because it generates heterogeneity among agents in our otherwise homogeneous model. It is also important as it creates a higher degree of freedom that is necessary in order to identify additional parameters such

as discount factors (Fang and Wang, 2010; Magnac and Thesmar, 2002). Although discount factors are theoretically identified with exclusion restrictions and parametric restrictions, it is usually hard to identify them in empirical analyses. This will be discussed further in subsequent sections.

Transitional probabilities of states, which we discussed in detail are non-parametrically identified (including one shown in Table 2.2). Since our data are longitudinal, we see that some individuals did not participate every year. As we require two consecutive periods in order to compute transitional probabilities, those individuals with no consecutive observations for two or more years are dropped when transition matrices are computed.

Each entry in the transition matrices is obtained using the following equation assuming there are T periods in the observation:

$$f(x_{i,t+1} = s | x_{i,t} = s, a_{i,t} = j) = \frac{\sum_{t=1}^{T-1} \sum_{i=1}^{I} I(x_{i,t+1} = s) I(x_{i,t} = s) I(a_{i,t} = j)}{\sum_{t=1}^{T-1} \sum_{i=1}^{I} I(x_{i,t} = s) I(a_{i,t} = j)} \quad (2.37)$$

where $I = 1$ if the condition indicated in the function is met, and $I = 0$ in all other instances. In preparation of data, all continuous variables are discretized.

Exclusion variables for transition matrices are income, marriage status and education. These variables are important indicators for the likelihood of smoking.[5] However, these variables enter into the equation as exclusion variables since it is unknown if there are direct effects on the choice to smoke. For example, Waldron and Lye (1989) identify those people who have never married as having a lower chance of smoking compared to those who are married. However, it is unconvincing that the fact that someone is married itself world affect the utility of smoking. Therefore, in our study, we use these variables known to affect the chance of smoking as exclusion variables in order to introduce heterogeneity in the model.

2.4 Estimation of Coefficients

Given the econometric model discussed so far, we develop an estimation algorithm to find a maximum likelihood estimator, θ that appears in equation 2.22 given a calibrated discount

[5]For some examples of studies, see Sander (1995) and Waldron and Lye (1989).

factor β. Our estimation follows the steps shown below:

Step 1: Discretize data if continuous, label each state, and construct a transition matrix according to the procedure shown in equation 2.37. Also obtain the probability of smoking and not smoking for each state using the function shown below:

$$p(a_{it} = j | x_{it} = k) = \frac{\sum_{i=1}^{I} \sum_{t=1}^{T} I(a_{it} = j) I(x_{it} = k)}{\sum_{i=1}^{I} \sum_{t=1}^{T} I(x_{it} = k)} \tag{2.38}$$

Step 2: Using equations 2.23 and 2.24, construct $\tilde{z}_j(x_t, P)$ and $\epsilon_j(x_t, P)$ for each $x_t \in \chi_t$.

Step 3: Obtain natural log of the conditional likelihood using the equations 2.22 and 2.33 with an arbitrarily assigned θ_0. Using any algorithm to maximize the likelihood to obtain $\hat{\theta}$, which is a consistent estimate of θ.

We are restricting covariates to a relatively limited set of indicators. It is, first of all, due to the curse of dimensionality. As has been discussed, the size of transition matrices in equation 2.29 become exponentially larger as more covariates are added. It also bears a large computational cost in comuting transitional matrices (equation 2.37), and inversion of the matrices which appears in equations 2.25 and 2.26. We also note that the existence of exclusion variables in these transition matrices also add more dimensions to them.

2.5 Estimation of Discount Factor

Following Fang and Wang (2010), the discount factor β can be estimated by maximizing the likelihood obtained using equation 2.34. Assuming that there is a true discount factor $\beta \in (0, 1)$, we have an estimator, $\hat{\beta}$ for β :

$$\hat{\beta} = \underset{\beta}{\operatorname{argmax}} \ln L(\hat{\theta}(\beta, F)) \tag{2.39}$$

It generally means that we estimate $\hat{\theta}$ for an initial value of β, β_0, and using the maximum likelihood algorithm, we obtain $\hat{\beta}$, which yields the maximum likelihood value. This causes the estimation to have two loops; one "external loop" searches for β and one "inner loop" searches for θ. The external loop significantly increases the computational burden.

2.6 Discussion on Estimation of Discount Factors

We first discuss the estimation result for the discount factor β. Since the discount factor must satisfy $\beta \in (0, 1)$, we conducted a constrained maximization of the discount factor, which searches for the smallest absolute value of log-likelihood. This resulted in a corner solution indicating $\beta = 1 - \delta$ where δ is a very small number. Log-likelihood for different β values is shown in Table 2.3 and their corresponding estimates are shown in Table 2.4.

< Tables 2.3 and 2.4 >

Tables are attached at the end of this chapter.

Magnac and Thesmar (2002) indicate that discount factors are identified if parametric restrictions are imposed on the "utility" function in their theoretical examination, and exclusion variables in transition matrices must strengthen the power of estimation. It is, however, also known that it is still very hard to identify discount factors in practice (Dube *et al.*, 2011). The reason why the discount factor approaches 1 in our estimation is unclear, although it is widely observed that theoretically identifiable variables turn out to be unidentifiable in estimation (Dube *et al.*, 2011). For example, Arcidiacono *et al.* (2007) tried to estimate the discount factor for consumption of addictive goods including smoking. Their point estimate reached $\beta = 0.91$. However, their likelihood surface over $\beta \in (0, 1)$ was almost completely flat,[6] making the confidence interval of the discount factor practically $(0, 1)$. Darden (2009) did not estimate the discount factor. However, it was set to 0.95. To the best knowledge of the author, many researchers opted to use a discount factor that "makes the most sense." This lack of knowledge regarding discount factors is a drawback in dynamic discrete programming.

In macroeconomics, it is widely believed that the interest rate, r, can be used to identify the discount factor, which is given by $\beta = (1 + r)^{-1}$. However, this is not appropriate for many studies in dynamic models. There have not been many studies that have investigated the identification issues regarding discount factors.

[6] In their study, log-likelihood for $\beta = 0$ is –17,199, and $\beta = 0.91$ is –17,194. They used the logit form, and therefore, the likelihood function was defined in a similar manner to our study.

2.7 Discussion on Estimation of Coefficients

Among all the different estimates given to different discount factors, we further study one with $\beta = 0.90$. The full estimation results are provided in Table 2.5.

< Table 2.5 >

Tables are attached at the end of this chapter.

First of all, rational addiction is clearly evident to the extent that consumers gain utility from smoking given the lack of smoking capital. However, the direct utility of smoking decreases as one accumulates more years of smoking capital beyond the first two years of smoking. This means that smokers enjoy smoking the most in the earlier tenure of smoking.

This finding carries an important meaning. In comparison to short-term smokers, long-term smokers do not gain much utility from smoking and if a smoker expects future health problems due to smoking (or an improvement in health after a cessation), they are more likely to quit smoking. It also means that the intercept term, which captures the global cost of smoking, is more important for long-term smokers. These observations, in sum, mean that long-term smokers are more likely to quit smoking.

Secondary, our analysis indicates that ex-smokers are the most vulnerable to starting to smoke again after 3 and 4 years of cessation compared to individuals who have only stopped for 1 and 2 years. However, the disutility returns to almost the same level as the first and second year of cessation after 5 years. This is not consistent with the theory of Becker and Murphy (1988). According to the model of rational addiction, smokers must experience the largest disutility in the first year of cessation. Our analysis indicates that smokers continue to experience large and even increasing disutility for a prolonged period (i.e. four years) from cessation. This makes it even more difficult for smokers to quit than what the model of Becker and Murphy (1988) initially indicated.

We now turn our attention to health status. Our analysis indicates that poor health imposes a significant cost to consumers especially when one's health status is fair or worse. Our analysis further indicates that consumers gain a much higher utility when they enjoy good health compared to worse conditions. This observation is consistent with findings in previous studies such as a study by Jones (1994). We also note that smokers who have

been smoking for a long period of time value their health more, compared to smokers with a short tenure of smoking.

Finally, we find that the intercept is negative, and this negative intercept captures the universal cost of smoking. This coefficient is small in absolute value compared to other coefficients. However, it is important because this coefficient causes smokers to experience disutility as long as they are smoking.

In sum, our model indicates that smokers gain both utility and disutility from smoking, and smokers conduct dynamic evaluations on the utility of smoking or not smoking. Our finding generally supports the model of Becker and Murphy (1988) to the extent that smokers prefer to smoke due to the smoking capital and they experience significant disutility when they quit smoking. However, after removing parametric restrictions from the dynamic structure that Becker and Murphy (1988) used, we found that smokers experience prolonged withdrawal symptoms after cessation and long-term smokers do not enjoy smoking as much as short-term smokers. These are new findings in the study of smoking decisions in economics and there is a need for further studies to understand what revisions the original model of rational addiction by Becker and Murphy (1988) need in order to reflect smokers' decisions more accurately.

2.8 Concluding Remarks

This paper studied factors that affect smokers' decisions on whether to continue smoking or quit using a dynamic discrete choice model. Our results demonstrated that smokers make a decision based on utility and disutility of smoking today and in the future. By removing parametric restrictions on the formation process of addiction capital from Becker's original model (Becker and Murphy, 1988), we found that smokers draw less utility from smoking as their tenure of smoking increases. We also found that smokers suffer from withdrawal symptoms for a prolonged period of time. Becker and Murphy (1988) assumed that smokers experience the largest disutility in the first year of cessation and the disutility decreases as time passes. Our results, being contrary to the original assumption, indicate that the disutility even increases during the first four years of cessation before the level of disutility

decreases in the fifth year.

The structural analysis conducted in this research paper confirms the advantages of dynamic structural analyses. Many variables, such as health status, are inherently endogeneous to choices that smokers make and cross-sectional analyses would not be able to take such endogeneity issues and consumers' expectations on outcomes into account.

Our findings indicate that the model of rational addiction Becker and Murphy (1988) needs to be reevaluated. Our analysis removed some parametric restrictions from their model and transition probabilities between states were nonparametrically identified. Hence, it was not practical to include a large number of control variables. The combination of a less restrictive model and a more efficient numerical algorithm will allow future studies to include more control variables. To further examine if any other revisions are required for the existing models of rational addiction.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	
Years smoked (1)	1.00	10.00	22.00	23.76	35.00	85.00	
	This observation exists only for these who is smoking and has smoked.						
Years since quitting (1)	1.00	1.00	3.00	4.34	6.00	17.00	
	This observation exists only for these who quitted.						
Education (2)	1.00	1.00	3.00	3.33	5.00	7.00	
	Please refer to the code book below.						
Marriage (2)	1.00	1.00	2.00	1.69	2.00	2.00	
	Single 1 and Married 2						
Log Income (2)	0.05	8.67	9.29	9.15	9.83	14.02	
	In GBP, inflation adjusted.						
Health (1)	1.00	2.00	2.00	2.22	3.00	5.00	
	Health (Ordered): 5 Indicates worst, and 1 indicates best.						
Variables followed by 1 are in decision function. Variables followed by 1 and 2 are in transition of states.							
Year of Birth	1901	1939	1954	1952	1966	1983	
	Never used in estimation.						
Proportion of Categorical Data							
Health	Better		< – >		Worse		
	5	4	3	2	1		
	0.022	0.078	0.219	0.459	0.222		
Education	Lower			< – >			Higher
	1	2	3	4	5	6	7
	0.262	0.021	0.295	0.108	0.194	0.097	0.023
Code for Education							
1	Primary						
2	Low Secondary						
3	Low Secondary or Vocational						
4	High Secondary or Mid-Vocational						
5	High Vocational						
6	First Degree						
7	Higher Degree						
Number of Observations: 152,057							

Table 2.1: Descriptive Statistics of Data

	Low Income (Less than median)					High Income (Higher than median)					
	Most Healthy			$\longleftrightarrow$ **Least Healthy**		**Most Healthy**			$\longleftrightarrow$ **Least Healthy**		
	1	2	3	4	5	1	2	3	4	5	Pr $(>\|\chi^2\|)$
1	0.5103	0.4027	0.0664	0.0183	0.0023	0.5870	0.3496	0.0585	0.0049	0.0000	
	(0.0239)	(0.0235)	(0.0119)	(0.0064)	(0.0023)	(0.0199)	(0.0192)	(0.0095)	(0.0028)	(0.0000)	6.5e-04
2	0.1464	0.6185	0.1982	0.0309	0.0060	0.1643	0.6613	0.1396	0.0306	0.0043	
	(0.0112)	(0.0153)	(0.0126)	(0.0055)	(0.0024)	(0.0108)	(0.0138)	(0.0101)	(0.0050)	(0.0019)	2.0e-05
3	0.0388	0.3623	0.4362	0.1349	0.0277	0.0748	0.4266	0.3850	0.1025	0.0111	
	(0.0083)	(0.0207)	(0.0213)	(0.0147)	(0.0071)	(0.0138)	(0.0260)	(0.0256)	(0.0160)	(0.0055)	5.7e-05
4	0.0161	0.1667	0.3710	0.3441	0.1022	0.0273	0.2000	0.3545	0.3364	0.0818	
	(0.0092)	(0.0273)	(0.0354)	(0.0348)	(0.0222)	(0.0155)	(0.0381)	(0.0456)	(0.0450)	(0.0261)	7.1e-01
5	0.0213	0.1277	0.2340	0.3617	0.2553	0.0556	0.2222	0.2222	0.3333	0.1667	
	(0.0210)	(0.0487)	(0.0618)	(0.0701)	(0.0636)	(0.0540)	(0.0980)	(0.0980)	(0.1111)	(0.0878)	5.8e-01

Direction of transition is row to column.
Variances are in (parentheses).
Probability in the last column indicates the statistical probability of two vectors being not different from each other.

Table 2.2: Transitional Matrix for Health conditioned on Income

β	0.30	0.50	0.70	0.90	0.99
$\ln L(\theta, \beta, F)$	-65532.79	-67306.75	-70996.32	-72733.45	-73576.31

Table 2.3: Log-likelihood for different discount factors

	Estimates	Std. Dev	Estimates	Std. Dev	Estimates	Std. Dev	Estimates	Std. Dev	Estimates	Std. Dev
Discount Factor	0.990		0.900		0.700		0.500		0.300	
(Intercept)	-0.086	0.015	-0.359	0.013	-0.732	0.012	-0.885	0.011	-0.948	0.010
Years of smoking (1 year)	3.488	0.078	4.777	0.085	5.908	0.109	6.623	0.153	8.498	0.257
Years of smoking (2 years)	5.607	0.158	6.890	0.172	7.388	0.206	7.739	0.275	9.623	0.450
Years of smoking (3 years)	2.253	0.073	3.567	0.084	4.938	0.118	5.782	0.176	7.542	0.309
Years of smoking (4 years)	3.504	0.125	4.250	0.135	5.158	0.173	6.056	0.246	8.103	0.419
Years of smoking (5 years)	1.732	0.086	2.093	0.093	1.887	0.122	0.777	0.179	-2.071	0.316
Years of smoking (6 years +)	1.530	0.052	2.387	0.062	2.264	0.094	0.397	0.146	-3.344	0.263
Cessation (1 - 2 years)	-2.928	0.045	-3.316	0.051	-4.348	0.069	-6.065	0.102	-10.206	0.181
Cessation (3 - 4 years)	-4.836	0.060	-6.096	0.070	-8.104	0.100	-10.467	0.152	-16.001	0.271
Cessation (5 years +)	-2.804	0.072	-3.527	0.082	-4.858	0.113	-5.914	0.169	-8.151	0.297
Health 2 - Good	2.945	0.066	4.039	0.074	7.512	0.103	13.560	0.160	27.196	0.291
Health 3 - Fair	-1.133	0.087	-1.348	0.097	-1.471	0.141	-1.464	0.217	-1.040	0.379
Health 4 - Poor	-1.725	0.082	-2.297	0.097	-3.958	0.149	-5.016	0.239	-5.717	0.431
Health 5 - Very Poor	0.512	0.068	-0.486	0.091	0.343	0.139	2.684	0.214	7.545	0.381

Health is ordinal. 1 indicates most healthy, and 5 indicates least healthy. 1 is suppressed.
Values for coefficients in *italic* are not significant at 5 per cent level.
Others are all significant at the level.

Table 2.4: Estimated coefficient for different discount factors

Coefficients	Estimate θ	$\exp(\theta)$	Std. Error	z value	Pr $(>\|z\|)$	
$\beta = 0.9$						
(Intercept)	-0.359	0.699	0.013	-26.942	$<$ 2e-16	***
Years of smoking (1 year)	4.777	118.699	0.085	56.172	$<$ 2e-16	***
Years of smoking (2 years)	6.890	982.775	0.172	40.043	$<$ 2e-16	***
Years of smoking (3 years)	3.567	35.399	0.084	42.344	$<$ 2e-16	***
Years of smoking (4 years)	4.250	70.107	0.135	31.468	$<$ 2e-16	***
Years of smoking (5 years)	2.093	8.111	0.093	22.402	$<$ 2e-16	***
Years of smoking (6 years +)	2.387	10.882	0.062	38.659	$<$ 2e-16	***
Cessation (1 - 2 years)	-3.316	0.036	0.051	-64.417	$<$ 2e-16	***
Cessation (3 - 4 years)	-6.096	0.002	0.070	-87.016	$<$ 2e-16	***
Cessation (5 years +)	-3.527	0.029	0.082	-43.122	$<$ 2e-16	***
Health (2) - Good	4.039	56.780	0.074	54.537	$<$ 2e-16	***
Health (3) - Fair	-1.348	0.260	0.097	-13.894	$<$ 2e-16	***
Health (4) - Poor	-2.297	0.101	0.097	-23.800	$<$ 2e-16	***
Health (5) - Very Poor	-0.486	0.615	0.091	-5.327	9.96E-08	***

$R^2 = 0.2423$
Significance of P-value, $\Pr(>|z|)$; $0 <$ *** < 0.001 ** < 0.01 * < 0.05
Health is ordinal. 1 indicates most healthy, and 5 indicates least healthy. 1 is suppressed.
Note that $\exp(\theta)$ is the odd ratio in unit increase in covariate.

Table 2.5: Parameter Estimates for the Logit Estimate of Dynamic Smoking Decisions

Chapter 3

Second Essay: Why Do Poor and Minority Patients Receive Lower Quality Care? The Role of Unobservable Patient Selection.

Abstract

This paper analyzes the mechanisms behind disparities in the quality of medical care among certain demographic groups of patients based on race and insurance type. Patients in a certain demographic group may be a burden to hospitals for a variety of reasons such as a lower rate of reimbursement. On the other hand, some patients may be systematically assigned to low quality institutions when high quality institutions are able to use market power to avoid certain groups of patients. This study attempts to analyze the endogeneity issue between the quality of care and the demographic compositions of patients in hospitals in order to understand why some patients receive lower quality care. Our unique data set comes from administrative billing data (Uniform Billing), charity care data, and death certificate data between 2008 and 2010 in the State of New Jersey for colon, breast, and prostate cancer patients. Using this data set, we study the disparities between non-white and white patients as well as patients under different insurance types. We use death and readmission as dependent variables and formulate a binary choice model at the patient-level. Our naïve probit model, which does not control for endogeneity, finds that a higher share of non-white patients or patients under Medicaid and charity care (henceforth "social welfare") has a strong correlation with low quality medical care. However, after controlling for endogeneity, it is found that non-white patients are assigned to low quality institutions and patients under social welfare might be a burden for hospitals in some instances. These findings indicate that it is important to control for endogeneity and demonstrate the need

for further studies to develop better public funding programs.

3.1 Introduction

This paper investigates why patients in certain demographic groups are provided with lower quality medical care. Disparities in medical care have been given considerable attention and a number of studies have been performed in order to understand which groups of patients receive low quality medical care. For example, Dimick *et al.* (2013) and Jha *et al.* (2011) found that non-white patients are more likely to receive treatment at low quality hospitals compared to white patients, and these patients exhibit worse outcomes after treatment. Jha *et al.* (2011) also found that the cost of treatment for non-white patients tends to be more expensive even though they receive low quality care.

Many of these hospitals that Jha *et al.* (2011) studied are also identified as safety-net hospitals. These hospitals treat a disproportionate share of patients who tend to have limited financial resources and may impose an extra burden on hospitals. For example, Ross *et al.* (2007) found that safety-net hospitals, which serve a disproportionate share of Medicaid patients, tend to provide low quality medical care and exhibit a higher likelihood of adverse outcomes for AMI (acute myocardial infarction) patients. In order to alleviate potential disparities in the quality of medical care, state and federal programs heavily subsidize safety-net hospitals. For example, both Medicare and Medicaid provide Disproportionate Share Hospital Payments to qualifying institutions (Ross *et al.*, 2007). For such payments, the share of patients who are reimbursed by Medicare or Medicaid is used to determine eligibility.

Not many studies, however, have attempted to understand the mechanisms behind the disparities in the quality of medical care. Although it has been consistently found that patients in certain demographic groups (such as non-white patients and patients who are covered by social welfare) exhibit poor outcomes and tend to cluster in particular hospitals, we do not know if they are systematically assigned to low quality institutions or if they impose a burden on such hospitals. This suggest that we need to examine if the demographic composition of patients in a hospital is endogenous to the health outcomes. This present

paper develops an instrumental variable to control for endogeneity to distinguish between the two effects.

It is important to know which effect is present because there are currently two very different types of public policies that may compromise the cost-effectiveness of such policies if they are incorrectly implemented. First, disproportionate share hospital payments are based on the idea that patients who are in certain demographic groups, such as those covered by Medicaid, are a burden to hospitals and, therefore, hospitals must be compensated for this burden to prevent them from providing low quality care. This type of funding does not provide incentives for hospitals to improve the quality of medical care and only improves the quality of medical care in hospitals that suffer from resource-intensive patients.

On the other hand, performance-based compensation systems were established under the assumption that hospitals must be provided with financial incentives to improve their quality of medical care and they must be penalized for not making improvements. Performance-based compensation systems ignore reasons as to why some providers perform poorly, and instead push hospitals to improve their quality. This type of policy adversely affects the quality care if hospitals provide low quality of medical care due to a disproportionate share of patients who are a burden on them. In such cases, disproportionate share hospital payments must be made in order to improve quality.

In the simplest terms, this study tries to understand the relationship between the quality of medical care and the demographic composition of patients in hospitals. If a disproportionate share of patients who fall in a particular group causes the quality of medical care to degrade, the direction of effect is from hospital characteristics (the share of patients who belong to a particular demographic group) to outcomes. On the other hand, if a disproportionate share of patients is assigned to low quality hospitals, the direction of effect is from outcomes to hospital characteristics. This means that there is an endogeneity problem behind our question. However, to the best knowledge of the author, no previous studies have taken the endogeneity issue into account when studying the relationship between the demographic composition of patients and the quality of hospitals.

In the study of the industrial organization of the health care market, however, endogeneity issues between the quality of medical care and hospital characteristics other than

demographic composition have been studied extensively. For example, Kessler and McClellan (2000), Kessler and Geppert (2005), and Town and Vistnes (2001) discussed the importance of controlling for the endogeneity issue between market competition and the outcomes of medical care. Market competition is a hospital-level characteristic and the outcome of medical care is individual-level. They also assume that high quality hospitals (which yield better outcomes) attract patients from wider areas and that the quality of a hospital also affects the size of its market. They assume that competition improves the quality of a hospital and yields better outcomes, and these better hospitals make their surrounding market more competitive by attracting patients from wider areas. Therefore, there is a loop of causality between the outcomes of medical care and the competition indices of the market. The studies by Kessler and McClellan (2000), Kessler and Geppert (2005), and Town and Vistnes (2001) controlled for endogeneity issues by constructing indices for market competition using exogenous variables such as the distance between hospitals and patients' home locations. These studies generally found that competition increases the quality of medical care after controlling for endogeneity.

In this paper, we adopt a variation of the models adopted in the study of market competition and the quality of medical care such as models used by Kessler and McClellan (2000), Kessler and Geppert (2005), and Town and Vistnes (2001) in order to control for endogeneity between disproportionate patient share and the outcomes of medical care.

Medical care costs have been increasing in the United States, and subsidies to hospitals have been a burden to state and federal governments. Levit *et al.* (1994) already warned that medical care costs had been increasing rapidly since the 1960s and public funding programs would become less sustainable due to a foreseeable increase in medical costs. There is a limit on public funding; for example, hospitals are only partially reimbursed for charity care in New Jersey (DeLia, 2007). In this paper, we study the mechanisms behind the disparities in order to aid implementations of public policies and funding programs so that policies and programs can effectively reduce disparities in the quality of medical care without wasting hospital resources.

3.2 Review of Studies in Quality of Medical Care and Their Research Designs

In health economics, many efforts have been made to reveal the relationship between market competition and the quality of medical care. As noted by Gaynor and Town (2012), there have been two types of studies on competition in the health care market. One type of study analyzes competition in the market and hospital prices. The other type of study analyzes market competition and the quality of medical care. Both types of studies tend to use indices for market competitiveness such as Herfindahl Hirschman Index (henceforth HHI), and some studies investigate both hospital prices and quality because the same competition indices can be used for both studies. For example, Kessler and McClellan (2000) found that competition improved the well-being of patients in the 1990s and this may be explained by the penetration of HMOs (Health Management Organizations) in the market. Kessler and Geppert (2005) extended the work of Kessler and McClellan (2000) and examined the differences in the quality of medical care that high-risk and low-risk patients received and the associated medical costs. The findings by Kessler and McClellan (2000) generally carry over to Kessler and Geppert (2005) but it was found that high-risk patients in competitive markets receive low quality medical care, indicating that hospitals allocate resources to low-risk patients in order to achieve good net-outcomes while simultaneously keeping medical costs low.

Other studies found that competition improves social welfare as well. Town and Vistnes (2001) found that competition in a market with a high penetration of HMOs decreases hospital prices because HMOs can seek alternative hospitals to provide medical care to their members. Shen (2003) found that financial pressures from HMOs and the Medicare Prospective Payment System (henceforth, PPS) adversely affect outcomes in the short run. She, however, did not find adverse effects in the long run, indicating that HMOs and PPS reduce medical care costs while maintaining the quality of medical care in the long run.

In general, these studies share a number of common features. The most important feature is instruments for endogenous variables. As it was discussed in the previous section, there is an endogeneity problem between the competitiveness of the market and the quality of medical care. Kessler and McClellan (2000) developed instrumental variables for HHI

from the estimated market share for each hospital using a model of patients' choice of hospitals. This approach first estimated a model of hospital choice using exogenous variables only, and computed the expected market share for each hospital. We adopt a modified version of the instrument developed by Kessler and McClellan (2000) in our econometric model.

Another shared feature among these previous studies is the use of death and readmission as proxies for the quality of medical care. These measures are readily available in administrative data sets and are used as indicators of the quality of medical care for Medicare quality reporting (Dharmarajan *et al.*, 2013). Therefore, a majority of studies on the quality of medical care used these measures (see Gaynor and Town (2012) for a meta-analysis). We also use these indicators in our analysis.

We also observe that these studies discussed above examined acute illness such as acute myocardial infarction and pneumonia. These diseases are known to reflect the quality of medical care well, and are used for Medicare quality reporting (Dharmarajan *et al.*, 2013). However, these are acute conditions and patients are often admitted to hospitals through emergency rooms, leaving little room for them to choose which hospital to go to.

On the other hand, a non-acute but potentially fatal disease such as any type of cancer allows patients enough time to decide which hospital to receive treatment at. Therefore, any concentration of patients under a certain insurance plan or in a particular racial group may be attributed to consumer choice.

In our analysis, we study colon, breast and prostate cancer. These types of cancer have not been studied in health economics frequently but have been widely used in health care outcomes research. For example, Breslin *et al.* (2009) studied racial disparities in breast and colon cancer care, and found that black patients are more likely to suffer from adverse outcomes. They found that hospital fixed effects explain a significant portion of adverse outcomes, and concluded that it is important to improve the medical care quality at low quality institutions in order to reduce disparities in the outcome of cancer care.

A study by Lubeck *et al.* (2001) showed disparities in the outcomes of treatment for prostate cancer between white and black patients. The study followed approximately one

thousand patients and found that black patients showed slower rates of improvement compared to white patients.

The previous studies clearly show the disparities in the quality of medical care between cancer patients. However, none of the previous studies investigated the bidirectional effects between the quality of medical care and the demographic composition of patients at a hospital. We used a modified version of the methods that Kessler and McClellan (2000), Kessler and Geppert (2005), and Town and Vistnes (2001) adopted in their studies in order to control for endogeneity in studying the effect of the demographic composition of patients on the quality of medical care at a particular hospital.

3.3 Multi-Stage Model of Disparities in Health Care

An outcome of medical care is an inherently individual-level observation whereas the composition of patients in a hospital is a hospital-level observation. In other words, our study investigates how hospital-level and individual-level characteristics affect the outcome on an individual level.

In this chapter, we first introduce our parametric model for the quality of medical care. We use patient-level data and formulate it as a binary outcome model with the outcomes being either adverse or favorable. We identify the endogeneity problem and develop instruments for the demographic composition of patients in a hospital. Following Kessler and McClellan (2000), Kessler and Geppert (2005), and Town and Vistnes (2001), we formulate a model of hospital choice for patients using exogenous variables. Then, we compute the expected demographic composition of patients for each hospital. The expected demographic composition does not cause problems in the estimation of our econometric model because it is not endogenous to the quality of medical care in contrast to the observed demographic composition, which is endogenous to the quality of medical care. Therefore, given patient-level data on the choice of hospitals by patients, we formulate a hospital choice problem and compute the expected demographic composition for each hospital.

Since we use patient-level data in order to study the risks of adverse outcomes such as death and readmission, and these outcomes are binary, individual probabilities of death

and readmission may be estimated using a class of limited dependent variable models. We denote D as the revealed outcomes of medical care and we assign patients to either $D = 1$ or $D = 0$ according to the following decision mechanism:

$$D_i = 1 \text{ if and only if } y^*_{ih} > 0 \text{ where } y^*_{ih}(h, x_i, x_h, \alpha, \beta, \gamma) = \alpha + x_i\beta + x_h\gamma + e_{ih},$$
$$D_i = 0 \text{ otherwise.} \tag{3.1}$$

In the equation above, adverse outcomes are expressed by $D = 1$. An absence of an adverse outcome is indicated by $D = 0$. In the set of equations above, we denote different hospitals by h and patients by i. The variables in the $1 \times k_h$ vector x_h are hospital characteristics and the variables in the $1 \times k_i$ vector x_i are patient characteristics. The value y^*_{ih} is a continuous variable and when it exceeds 0, patients exhibit adverse outcomes. The vectors of size 1×1, α, $k_i \times 1$, β, and $k_h \times 1$, γ are unknown coefficients for the independent variables. Lastly, the error term e_{ih} is distributed according to the normal distribution.

A variable $x_{eh} \in x_h$ is the share of patients with particular demographic characteristics at hospital h. This is an endogenous variable as already discussed. We assume other variables $x_{hi} \equiv \{x_i, x_h\} \setminus x_{eh}$ to be exogenous variables.

Since x_{eh} is an endogenous variable, it is necessary to find an instrument to prevent biased estimates of coefficients α, β, and γ. Let us assume the share of patients whose expenses are paid by social welfare for x_{eh}. If the quality of medical care affects the share of patients under social welfare, the error term e_{ih} is not independently and identically distributed if x_{eh} is used in the estimation because of the bidirectional effects between x_{eh} and y^*_{ih}. Therefore, we are in need of finding an instrumental variable for x_{eh}.

Let us further assume that there are two hospitals that share the same over-lapping market and are geographically proximal to each other. If there is no difference in the quality of medical care between them, for any patient, the likelihood of going to one hospital over another should be half. However, if one hospital is high in quality and is able to exercise market power to attract patients with particular demographic characteristics (such as white patients and patients with private insurance) in order to enjoy, for example, potentially higher revenues due to their financial status, another hospital would be forced to treat a

disproportionately higher share of under-served patients (such as non-white patients and social welfare patients). The expected share of patients in each demographic category, however, is still the same for the two hospitals as they share the same market.

This means that a high quality hospital, in which patients face a lower likelihood of experiencing adverse outcomes, will have a lower share of patients who reimburse the hospital less than others (for example, patients under social welfare). Since high quality hospitals are reimbursed better, they will further improve their quality of medical care. This loop of causality results in the observed share of patients being correlated with the error term e_{ih}. In order to control for endogeneity and estimate our model without bias, we need to use the expected share of patients as an instrumental variable.

In order to compute the expected share of patients, it is essential to know the potential market for each hospital and the composition of patients in these markets. As it was assumed in many previous studies (see Kessler and McClellan (2000), Kessler and Geppert (2005), Town and Vistnes (2001), Gowrisankaran and Town (1999) and Geweke *et al.* (2003) among others), we assume that the distance between home and any given hospital would be an important factor for patients' decisions on hospital choice.

In the analysis of market competition and penetration of HMOs, Kessler and McClellan (2000) opted to use the estimated market concentration as an indicator for market competition. A classic index of market concentration, the Herfindahl Hirschman Index, requires exogenously defined regions for potential markets. However, Kessler and McClellan (2000) claim that it causes a bias in estimation because the size of the market is not fixed for all hospitals. Some hospitals are larger than others and have a more extensive network of doctors whom patients are referred from, whereas other hospitals are smaller. In our analysis, we adopt their idea of computing the expected share of patients under different demographic categories. To do so, we first construct a hospital choice model for patients. We assume that hospitals reach potential patients in their neighborhood but their reach diminishes as distance between the hospital and patients increases. Then, our hospital choice function is characterized as follows.

$$u_{ih}^{ICD} = \xi_h I_h + \phi d_{ih} + v_{ih} \tag{3.2}$$

In the function above, d_{ih} indicates the distance between hospital h and the patient i's home. The dummy variable I_h and its coefficient ξ_h indicates the hospital specific intercept, which is an adjustment for hospital-specific market sizes. The error term v_{ih} is distributed according to the Extreme-I distribution. Given the equation above, the patient i chooses to go to hospital $h \in H$, which is the set of hospitals, if and only if

$$u_{ih}^{ICD} > u_{ij}^{ICD} \text{ for all } j \in H \setminus h \tag{3.3}$$

where *ICD* indicates clinical classifications developed by the health care Cost and Utilization Project. This means that Equation 3.2 is independent across different clinical classifications. Since the choice of hospital is provided in the data for each patient, we estimate ϕ and ξ_h using the variation among patients as it was first proposed by McFadden (1974).

Given estimated coefficients, we recover the chance of going to each hospital in the data set for each patient. Since we assumed that the error terms, v_{ih}, are distributed according to the Extreme-I distribution, dropping the subscript i and the superscript *ICD*, we have:

$$\hat{Prob}(u_h > u_j) = \frac{exp(\hat{V}_h)}{\sum_{j \in H \setminus h} exp(\hat{V}_j)} \text{ for any } h \text{ and } j \in H \tag{3.4}$$

$$\text{where } \hat{V}_k = \hat{\xi}_k + \hat{\phi} d_k \text{ for any } k \in H \tag{3.5}$$

Using this expected likelihood of going to a particular hospital for each patient, we obtain the demographic composition of patients under different categories in the market that hospitals locate.

First, we estimate the share of patients who are non-white for the market for hospital h, $z_{ha}^{ICD} \equiv E[y_{2ha}^{**ICD} | \{ V_{ih}^{ICD} | i \in I, h \in H \}]$, as follows (omitting superscripts *ICD*):

$$z_{ha} \equiv E(y_{2ha}^{**}) \equiv \frac{E(y_{2ha})}{E(y_{2ha}) + E(y_{2hb})} \tag{3.6}$$

$$\text{where } E(y_{2ha}) = \sum_{i \in I} I_i(a) \hat{Prob}(u_{ih} > u_{ij}) \forall j \in H \setminus h \tag{3.7}$$

$$\text{and } E(y_{2hb}) = \sum_{i \in I} I_i(b) \hat{Prob}(u_{ih} > u_{ij}) \forall j \in H \setminus h \tag{3.8}$$

where we have $I_i(a) = 1$ and $I_i(b) = 0$ and $I_i(a) = 0$ and $I_i(b) = 1$ for white patients. This estimated share of patients is the share of non-white patients residing around the hospital h weighted for distance from the hospital. This indicates the demographic composition in the market for hospital h. The expected share of non-white patients is computed for each hospital $h \in H$, and is used as an instrumental variable for x_e, which is the observed share of patients.

This measure can be computed for different insurance statuses as well. In our data set, there are multiple categories. These are private insurance, HMO, Medicare, and social welfare, which includes Medicaid and charity care, and other types of payments (including self-pay). In this case,

$$z_{hr} \equiv E(y^{**}_{2hr}) \equiv \frac{E(y_{2hr})}{\sum_{s \in S} E(y_{2hs})} \tag{3.9}$$

where r is a type of insurance and S is the set of insurance types.

Given the instrumental variables, we propose two designs to estimate the marginal effect of the share of patients under a certain demographic group.

Our first model uses a control function approach. Under this approach, we reformulate our model in equation 3.1 as follows:

$$\begin{aligned} &D_i = 1 \text{ if and only if } y^*_{ih} > 0 \\ &\quad \text{where } y^*_{ih}(h, x_i, x_h, \alpha, \beta, \gamma, \gamma_e) = \alpha + x_i\beta + x_h\gamma + \gamma_e(x_{eh} - z_h) + r_{ih}, \\ &D_i = 0 \text{ otherwise.} \end{aligned} \tag{3.10}$$

In the equation above the term $x_{eh} - z_h$ is the difference between the observed and expected share of patients. As we discussed, we assume that the independent variables $\{x_h, x_i\} \setminus x_{eh}$ are exogenous variables and x_{eh} is an endogenous variable. Given an expected share of patients who fall under a particular demographic group, z_h, we assume any deviation from the expectation is a result of the selective assignment of patients stemming from the quality of the hospital. For example, assuming lower quality hospitals are receiving more

social welfare patients exceeding their expected share, the difference positively correlates to the error term e_{ih}. If the naïve probit model is used without controlling for endogeneity, we would have biased estimates of α, β, and γ. In short, the relationship above can be summarized as follows:

$$e_{ih} = \gamma_e(x_{eh} - z_h) + r_{ih} \tag{3.11}$$

where r_{ih} is distributed identically and independently for all patients according to normal distribution.

The other model uses the general method of moments, assuming the orthogonal condition between the expected demographic composition of patients and the error term in equation 3.1. Given this assumption, we have the following condition for the probit model shown in equation 3.2:

$$E(z^*_{ih}\epsilon_{ih}) = E(z^*_{ih}(D_{ih} - \Phi(y^*_{ih}(h, x_i, x_h, \alpha, \beta, \gamma)))) = 0 \tag{3.12}$$

where $z^*_{ih} \equiv \{x_h, x_i, z_h\} \setminus x_{eh}$, and the function Φ is the cumulative distribution function for the normal distribution. We further assume that there is a unique set of $\theta_0 \sim \theta \equiv \{\alpha, \beta, \gamma\}$ such that $E(z^*_{ih}\epsilon_{ih}) = 0$. Furthermore, assuming $g(\theta) \equiv z^*_{ih}(D_{ih} - \Phi(y^*_{ih}(\cdot)))$, we have an objective function:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}}(g(\theta)' W^{-1} g(\theta)) \tag{3.13}$$

In our estimation, the choice of the matrix W is trivial since the system is just identified.

We also estimate the naïve probit model (which does not control for endogeneity) using the GMM estimator explained above. In order to do so, we let $z^*_{ih} \equiv \{x_h, x_i\}$. We note that the estimators for probit are not equivalent between GMM shown above and maximum likelihood method Method although their solutions must be very similar to each other (see the appendix for a discussion).

It is also important to note that the standard errors computed using the delta method in equations 3.1 and 3.10 are problematic because our model is two-stage. Therefore, we estimate standard errors using an empirical Bootstrap method. We sample estimates 50

times for each model to obtain standard errors.

We estimate coefficients and standard errors for the probit model without controlling for endogeneity using both likelihood and GMM methods and we also estimate the two models (Control function approach and GMM) controlling for endogeneity. We use the a naïve probit model as a bench mark. In the following section, we will discuss the data that we analyze using the estimation strategies discussed above.

3.4 Data

The data that we analyze in this present research comes from the Uniform Billing records, charity care records, and death certificate records collected by the State of New Jersey in the calendar years 2008, 2009, and 2010. Hospitals in New Jersey are compensated for medical care in several ways. Most reimbursement comes from private insurance and Medicare. In addition to these traditional insurance plans, HMOs are active in medical care as well. The remaining patients do not carry insurance policies or participate in HMOs. If they are eligible, their expenses may be reimbursed through social welfare systems such as Medicaid and charity care. In New Jersey, charity care systems are maintained by the State. Since its annual budget is fixed, hospitals are not fully reimbursed for the treatments that they provided (DeLia, 2007). It is important, therefore, to capture which records were paid by charity care or other forms of social welfare.

It is also important to note that the Uniform Billing records do not usually capture any incidence after a discharge. Therefore it is insufficient to regard the discharge status as an indicator of the quality of health care. Shen (2003) collected data from patients after their discharge for 2 years and computed statistical results using different lengths of time spanning from seven days to 2 years. These results were generally consistent to each other. Although we do not have an established consensus on the length of time that discharged patients should be followed up, we use 30-day all cause mortality and 30-day all cause readmission rates as dependent variables. We are, therefore, required to look into additional records such as death certificates. We are also required to identify individual patients in the database. The Uniform Billing records are compiled for administrative purposes and are not designed

to keep track of patients over time. Therefore, in order to know if any patient is readmitted within a certain amount of time, we are required to look for additional records associated with that particular patient in the database.

The identification of unique patients requires a series of complex and systematic comparisons of entries in data sets. Demographic information in medical records is not complete in general as has been discussed, and the number of entries can be extremely large. In the Uniform Billing data set on which we conduct our analyses, there are 13,626,431 (approximately 13.6 million) records excluding records for new-born babies and same-day surgeries. Unlike acute conditions, it is problematic to use each episode as a separate incident for non-acute conditions. Patients with non-acute and potentially fatal conditions must be followed over their courses of treatment. Through the identification process, we find that 13,626,431 records correspond to 4,866,264 unique patients. If there is more than one data entry from the same patient in the data set for econometric analysis, it is faulty to assume that error terms are identically and independently distributed. It means that any econometric and statistical model, which assumes that error terms are identically and independently distributed, will not yield unbiased results.

The data linkage process that we adopt stems from the outcome of a project funded by the Substance Abuse and Mental Health Services Administration (Whalen and Busch, 2001). We use an implementation of the algorithm, The Link King software[1] to conduct data linkage. The linkage process consists of two parts. The first part is called deterministic linkage and the second part is called probabilistic linkage. Deterministic linkage establishes Cartesian products of data entries and computes a linear combination of predetermined scores for agreement and disagreement between entries. For example, if a pair has the same first name, the pair is given a predetermined agreement score (Whalen and Busch, 2001). If a pair has different first names, the pair is given a predetermined disagreement score (Whalen and Busch, 2001). This scoring is done for for determinants called linkage variable. In our case, linkage variables are first name, last name, birthdate, race, age, and social security number. Once all pairs are scored for all linkage variables, we use a predetermined threshold

[1]We greatly appreciate the author of The Link King, Dr. Kevin Campbell for providing the software and valuable consultations throughout the process of data linkage. The software is provided at http://the-link-king.com/.

to decide which pairs are linked in the deterministic linkage process.

Once deterministic linkages are established, we use the information to conduct probabilistic linkages. This stage iteratively updates scoring weights for each linkage variable. The weights are used to compute a weighted linear combination of agreement and disagreement scores for a pair, and weights are updated using the formula below (Whalen and Busch, 2001).

$$w = \log_2(p_k(match)/p_k(unmatch)) \tag{3.14}$$

For example, for any pair with the last name Smith, we compute how many pairs are matched and unmatched in a previous iteration (or in the deterministic linkage if it is the first iteration). Given this information, the weight for Smith is captured using equation 3.14. This process will be used for all pairs, including pairs with partial agreement (such as McIntosh and Macintosh), and a phonetic equivalence (such as Raleigh and Raliegh) under the algorithm developed by the New York State Immunization Information System. Once a new linkage is established for all records, another round of linkage is conducted until asymptotic stability of weighted scores is achieved.

The Uniform Billing entries are linked to the other two databases, the death records and the charity care claims database, to obtain complete information about patients. The data-linkage process across the three data sets yields an individual-level inpatient data set for the State of New Jersey between 2008 and 2010. At this point, we identify patients who were treated for colon, prostate, and breast cancer for further analysis.

In order to identify patients with colon, prostate, or breast cancer, we use the last admission episode for each patient. Last admission episodes are records with the latest admission dates among all records corresponding to particular patients. Given the last inpatient records for all patients in my data sets, we extract patients who list colon, prostate or breast cancer within the first four diagnosis codes. The extraction is done independently for the three types of cancer, so we obtain three analytical data sets.

After obtaining analytical data sets, we extract records for analysis for each of the dependent variables that we use. For death, we use the last admission episodes for each

patient. For readmission, there may be unobserved but significant differences in the likelihood of readmission between first inpatient episodes and subsequent inpatient episodes. We therefore use the initial inpatient episodes for patients who do not have any inpatient care in the preceding one year. For our research, we identified patients who did not have any inpatient admissions in 2008 and extracted the first admission episodes for these patients.

We, therefore, use only the first inpatient episodes for analysis. We define first inpatient episodes as such inpatient admissions for patients who did not receive inpatient care for one year prior to admission.

Although the linkage process will provide a single observation for each patient, and error terms in equation 3.1 are now distributed independently after controlling for endogeneity, we are still required to control for patient conditions, which are important determinants of outcomes In general, patients with comorbid conditions tend to have higher risks. In order to take comorbidities into account in clinical research, many clinical indicators have been developed (Hall, 2006). Among these indicators, we use the Charlson index because this index is based on an empirical study of actual clinical data. Comorbidity indices are not severity measures, so we set out to obtain such measures, which indicate the severity of illness for patients. Data resulting from clinically-oriented epidemiological surveillance usually contain severity of illness but administrative data, including Uniform Billing data, lack such information. Milcent (2005) found that the number of secondary diagnoses is a good proxy for severity of illness. Therefore, in our study, we group patients with the same type of cancer into three groups; the first group consists of patients with number of diagnoses below the 33rd percentile among whom have the same type of cancer, the second group consists of patients who fall between the 33rd and 66th percentiles, and similarly the third group consists of patients who are above the 66th percentile.

These two measures, along with the patient's age, control for individual risks for negative outcomes.

Our study also requires us to obtain hospital-level information about patient demography. The Uniform Billing data from the state of New Jersey are unique because racial information is mostly available and reliable due to the state's effort to collect such information. The information on insurance types are deemed reliable because the data set is

originally intended for billing purposes. Using the information available in the Uniform Billing data, we define the following categories.

- Patients who are minorities (non-white)
- Private insurance holders (excluding HMOs)
- Patients in HMOs
- Patients whose bills are paid for by social welfare (Medicaid and Charity Care)
- Patients covered by Medicare (including Medicare HMOs)
- Patients whose bills are paid for by other means

In our analysis, we estimate marginal mortality risks for each of the demographic categories listed above using a separate regression. For each regression analysis, we include dummy variables for patient-level demographic characteristics. For analysis on minority patients, we include a dummy variable for white patients, and for analysis on insurance types, we include a dummy variables for each insurance type. Tables 3.1 and 3.2 show the statistics for white and non-white patients who were treated for the three types of cancer. It shows that the mortality rates are sometimes even higher for white patients than non-white patients. It is, however, consistently true that non-white patients are much younger than white patients. Age is one of the important factors for negative outcomes for many health conditions. Therefore, it is important to control for individual factors such as age in order to accurately evaluate any difference between groups.

< Tables 3.1 and 3.2 >

Tables are attached at the end of this chapter.

When the outcomes are tabulated depending on insurance types (see Table 3.3), we observe that it is generally true that Medicare patients and social welfare patients face a higher chance of an adverse outcome. For Medicare patients this is partially, if not mostly, because Medicare covers older patients. However, Medicaid and charity care do not restrict eligibility to those who are retired. Therefore, the patients' age alone does not explain the higher likelihood of adverse outcomes.

< Tables 3.3 and 3.4 >

Tables are attached at the end of this chapter.

As we have discussed, we assume that the risk of having adverse outcomes also depends on the Charlson index and the number of secondary diagnosis codes. Table 3.4 summarizes the for the three types of cancer. We observe that patients who had negative outcomes had a higher number of secondary diagnosis codes on average and a slightly higher Charlson index in general. The Charlson index is the weighted sum of comorbid diagnoses which are known to impose a higher risk of negative outcomes to patients and is a natural number. We use raw numbers for the Charlson index.

These patient-level data are, then, matched with hospital-based data taken from the American Hospital Association Annual Survey Database so we have both hospital-level and patient-level measures that potentially affect prognosis of patients. This survey includes the location of each hospital in New Jersey and their geographical coordinates as well. These coordinates are used to compute the distance between patients and hospitals for equation 3.2, using centroids of each zip code area for patients' location as patients' locations are identified to the zip-code level only.

We now estimate the expected shares of patients for the categories explained above. For the estimation of the model, we limit our observations to patients who were treated in hospitals that treated at least a certain number of patients between 2008 and 2010 for the disease in question. For mortality, the minimum patient load is 100, and for readmission, the minimum is 50. The list of hospitals used in the analyses is shown in Table 3.5.

< Table 3.5 >

Tables are attached at the end of this chapter.

We also use some hospital characteristics as covariates for regression analysis presented in equations 3.1 3.10, and 3.12 Many studies have found that non-profit status and teaching affiliation are important. In New Jersey, most hospitals are non-profit and we use teaching affiliation as defined in the American Hospital Association Annual Survey Database as an additional hospital-level characteristic.

3.5 Results

Before discussing the results of our analyses on the outcomes of medical care, we briefly discuss the result of the conditional logit analysis on patients' choice of hospitals and the expected demographic composition of patients for each hospital (see equation 3.2). For the estimated weight for distance, we find that the estimates are negative similar to those found in many other studies (see Table 3.6).

< Table 3.6 >

Tables are attached at the end of this chapter.

Hospital specific coefficients ξ vary among different hospitals. We used Hackensack University Medical Center as a reference hospital for our estimation. This hospital is one of the largest hospitals in New Jersey and has an extensive reach to patients through its network of physicians and affiliation with New Jersey Medical School. Therefore, as expected, the estimated coefficients for other hospitals are mostly negative as shown in Table 3.6. In sum, we found that the distance between a patient's home and a hospital is negatively correlated with the probability of the patient choosing that hospital, and this finding is consistent with other studies, including Kessler and Geppert (2005).

Now, we first discuss the effects of the non-white patients' share in the quality of medical care. Table 3.7 has three panels for each cancer type that we analyze, and Table 3.9 summarizes estimated coefficients between the composition of patients and the outcomes. In Table 3.9, we only show if estimates are positive or negative in order to show the direction of effects. In general, using the naïve models, we find that it is indeed the case that the non-white patients' shares have a positive correlation with negative outcomes. This finding aligns with many other studies in health care outcomes research.

< Tables 3.7, 3.8, and 3.9 >

Tables are attached at the end of this chapter.

For example, Breslin *et al.* (2009) found that black patients had lower 5-year survival rates after surgical operations for both breast and colon cancers. Their analyses on the

hazard of 5-year mortality found that excess mortality rates due to hospital fixed effects are 26.19 percent and 42.86 percent for breast and colon cancer respectively whereas patient factors, such as age, sex, comorbidities and cancer stages, are 40.48 percent and 7.14 percent for breast and colon cancer respectively. Therefore, Breslin *et al.* (2009) claims that it is important to improve the quality of care at minority-serving institutions. In an analysis of prostate cancer, Barocas *et al.* (2012) found that white patients are more likely to be treated by high-volume surgeons in high-volume hospitals, and they claim that this is one of the major contributing factors in racial disparities.

Given the results in Table 3.7, we observe that the naïve probit models indicate that the share of non-white patients in hospitals considerably increases the mortality of patients except in the case of prostate cancer. The excess mortality rates due to an increase by 10-percent points in the non-white patient share are estimated at 0.14 percent points and 0.97 percent points for breast and colon cancers respectively using the likelihood method; the GMM yields almost the same results. These positive coefficients become, however, insignificant for colon cancer and even negative for breast cancer when the endogenous selection effects are taken into account. Both the control function and the GMM with instrumental variable (GMM-IV) approach confirm this result. In addition to these two cancer types, after controlling for endogeneity, we observe that the non-white share is statistically significant for prostate cancer patients' mortality and the estimated coefficient is a negative value. This clearly indicates that the naïve probit model produced biased estimates.

For the effects of endogeneity, we consistently find that endogeneity is a source of bias for all three diagnoses. In other words, we find that poor outcome is associated with excess in the non-white patients' share in a hospital. The control function approach indicates that a 10-percent-point increase in excess non-white share increases mortality rates by 1.08 percent points, 1.84 percent points and 0.887 percent points for breast, colon and prostate cancer respectively. The excess share of minority patients is, as discussed, a hospital-level characteristic; these results indicate that hospital where minorities are selectively treated at a higher rate have a lower quality of medical care . This in turn means that minority patients are selectively treated at lower quality institutions.

Our results for readmission also indicate that an excess in the non-white patient share is associated with a higher likelihood of being readmitted. The likelihood-based naïve probit model estimates that the excess readmission rates due to a 10-percent-increase in the non-white patients' share are 0.498 percent points and 1.07 percent points respectively for breast and colon cancers and the estimate for prostate cancer is statistically insignificant. The GMM estimation also finds very similar results when endogeneity is not controlled for. However, when endogeneity is controlled for, the control function approach and GMM-IV approach show that these estimates are statistically insignificant for colon and breast cancer, and even possibly negative for prostate cancer according to the control function approach. It is shown that the excess share of non-white patients is responsible for the excess probability of readmission; these estimates indicate that the marginal effects are 1.60 percent points, 1.88 percent points and 2.48 percent points respectively for breast, colon and prostate cancer for a 10 percent-point increase in the excess non-white patient share.

These results align with findings in previous research articles. Foe example, Gaskin *et al.* (2008) state that black patients are more likely to seek care at lower quality hospitals. Yet, after controlling for patient-level and hospital-level characteristics, we find that white patients are still likely to face a lower chance of being exposed to negative outcomes. One possible explanation is a biological factor. Elledge *et al.* (1994), for example, state that breast cancer advances faster among black women compared with their white counterparts. Another explanation might be that white patients are more likely to receive higher quality care than non-white patients even in the same hospital. This finding calls for a detailed analysis of the reasons behind the disparities in access to high quality medical care between non-white and white patients.

Other patient-level covariates also align with conventional wisdom. Age is an important factor for negative outcomes across all the three types of cancer except for readmission of colon cancer patients. The Charlson index, which indicates any comorbidity of illness, significantly increases the chance of a negative outcome across all the three types of cancer for both mortality and readmission.

The estimated coefficients for the number of secondary diagnoses also indicate that patients with more complications exhibit worse outcomes. Given the estimates, it is clear

that the hazard for the 66th percentile and below is lower than the 66th percentile and above. However, we found that, contrary to expectation, patients in the lowest 33rd percentile exhibit a higher incidence of negative outcomes compared to the patients between the 33rd and 66th percentile in most cases. This finding calls for more detailed studies preferably using data from disease surveillance that include clinical indicators of complications such as cancer stages.

These consistent results that we obtained across all three cancer types support our hypothesis that the disparities in the quality medical care between white and non-white patients are real, and hospitals in which non-white patients are treated at a higher probability of are relatively low-quality. At the same time, our analyses find that increasing the share of non-white patients would not contribute to a lower quality of medical care for any of the three cancer types for either quality indicator (i.e. death or readmission rates). This is an important finding because this calls for a compensation system similar to the performance-based compensation system in order to provide incentives to improve the quality of medical care: simple subsidies for such hospitals would not improve quality if no incentives for quality improvement are furnished.

Secondly, we pay close attention to the share of patients under social welfare because they are financially disadvantaged and their share is deemed relevant to health care quality in hospitals.

The naïve probit models indicate that the share of social welfare patients is positively correlated with worse outcomes across all the three cancer types for both mortality and readmission rates (See Tables 3.8 and 3.9). When endogeneity is controlled for using the control function approach, there is no evidence for correlation between the quality of care and the excess share of patients under social welfare. The naïve probit model estimates that mortality rates increase by 4.2 percent points and readmission rates increase by 3.7 percent points for a 10 percent-point increase in the share of social welfare patients. The GMM method also yields similar results without controlling for endogeneity. After controlling for endogeneity, the GMM-IV approach yields almost the same results; 4.3 and 3.7 percent points respectively. The control function approach does not yield statistically significant results but the marginal effects are almost the same as the effects estimated by the GMM-IV

approach. This implies that an increase in the share of patients under social welfare systems decreases the quality of medical care significantly. It is also found that the excess in social welfare patients is estimated to have statistically insignificant effects on either outcome measure. These findings indicate that there is no evidence that selective assignment of social welfare patients occurs in the lower quality institutions.

Similarly, it is also found that in the higher the share of breast cancer patients under social welfare, the lower the quality of medical care they receive when readmission is used as an indicator for qualitys. The likelihood-based naïve probit model estimates that readmission rates increase by 1.35 percent points for a 10 percent-point increase in the share of social welfare patients. This result stays significant even after endogeneity is controlled for. The GMM-IV regression approach estimates that readmission rates increase by 1.80 percent points for every 10-percent point of social welfare patients. The control function approach does not produce any significant result once endogeneity is controlled for, although the coefficient for social welfare stays positive and the estimate is close to the GMM-IV result. The excess share of social welfare patients exhibits no statistically significant effects on the quality of medical care.

On the other hand, it is found that hospitals which are more likely to treat social welfare patients in excess of the market demographic composition, are low quality hospitals when mortality is used for analysis for breast cancer patients. According to the likelihood-based naïve probit model, a 10 percent-point increase in the share of social welfare patients increases mortality rates by 1.15 percent points. The GMM based estimation yields almost the same results. However, once endogeneity is controlled for, the GMM-IV regression and the control function approach yield an insignificant effect. Furthermore, using the control function approach, it is found a 10 percent-point increase in the excess social welfare patients' share increases mortality rates by 2.45 percent points.

For prostate cancer, our results indicate that the share of social welfare patients is insignificant for both death and readmission when endogeneity is controlled for, although the estimated coefficients are both positive, possibly indicating that the two effects are present and the statistical power was not strong enough to show the effects.

The results shown above indicate that the reasons behind disparities in the quality of medical care among social welfare patients are complicated. They are different from disparities among non-white patients for whom we have clear evidence that selective assignment of non-white patients to low quality institutions occurs.

The inconsistent results for breast cancer can partially be attributed to the nature of readmission and mortality as quality indicators. Some studies such as Krumholz *et al.* (2013) indicate that there is a limited correlation between mortality and readmission.

However, it is important to note that our findings for non-white and social welfare patients show that it is important to control for endogeneity. Although we must note that the findings are not necessarily robust across all types of cancer and different proxies for quality, we conclude that for non-white patients, it is unambiguous that hospitals, which are admitting non-white patients at a disproportionately higher share than each market's demographic share, are low quality hospitals. Our results also indicate that social welfare patients might pose a burden to hospitals.

For the share of patients under HMOs, the naïve probit model finds that increasing the share of such patients is associated in general with higher quality medical care when either readmission or mortality are used as a dependent variable. However, according to our analyses, estimated coefficients are not statistically significant for colon cancer patients.

When readmission rates are considered for both breast and prostate cancer, we find that increasing the share of patients under HMO significantly decreases mortality after controlling for endogeneity. This results is similar to what naïve probit models find. On the other hand, when mortality is considered for prostate cancer, we find that patients in hospitals with a higher excess share of HMO patients have a lower likelihood of death; indicating that HMO patients are treated at higher quality hospitals. However, our model is inconclusive in identifying the direction of causality when mortality is used for breast cancer patients.

It has generally been shown that increasing the HMO share has an association with better outcomes although our results indicate that the direction of effects is not identified in many cases. Even in the cases where the direction of effects is identified, the results are not robust across the different measures of quality and cancer types. However, we must note

that the positive effects of HMO penetration have been well documented in economics and health outcomes research. Mukamel *et al.* (2001) found that HMOs have spill-over effects to patients under other payment types. Our results align with this finding. The effect of endogeneity was not as clear as what we obtained for the non-white patients' share and further investigations are needed as to how the mechanism behind HMOs contributes to the hospital choice of members.

Other insurance types also provide insights on the direction of causality. The share of patients under private insurance has a correlation with better outcomes in general. Patients with prostate cancer under private insurance are found to be assigned to a better hospital but the share of patients does not affect the outcomes. This is true for breast cancer patients when readmission rates are used as proxies for quality. The share of patients under Medicare and other types of insurance also have an effect on outcome in limited circumstances. Our results are not always statistically significant, however, we observe indications of endogeneity and the results show that it is important to consider this endogeneity when analyzing the quality of medical care at hospitals.

The study found statistically consistent indications that non-white patients are selectively assigned to low quality hospitals across all three cancer types. On the other hand, we found indications that a higher share of social welfare patients pose a burden to hospitals. This burden was represented by moretality rates for colon cancer and readmission rates for breast and colon cancer. However, the result was not as robust as the finding of selective assignments among non-white patients. We have found that breast cancer patients are assigned to low quality hospitals when mortality is used as a proxy for quality. The compositions of patients under other insurance types also show the importance of controlling for endogeneity because GMM-IV regression and the control function approach often indicate selective assignments of patients into lower and higher quality hospitals.

3.6 Concluding Remarks

This study aimed to understand the reasons behind the disparities in the quality of medical care among certain demographic groups of patients. It is well-known that non-white patients

and patients with limited financial means receive lower quality care. Previous studies have only provided a limited answer to our question: are such patients possibly lowering the quality of medical care at hospitals due to high resource use and low reimbursement rates, or are such patients selectively assigned to lower quality institutions?

We formulated this issue in terms of endogeneity between negative outcomes and the demographic composition of patients at hospitals, and adopted a composition of patients in each hospital's estimated market as an instrumental variable for regression analyses. This approach eliminated the endogeneity problem, which arises if the observed demographic composition of patients is used. We adopted modeling techniques and ideas from previous studies in an industrial organization to estimate a market for each hospital rather than defining a market using geographical boundaries. It is unnatural for a market to end at a specific geographical boundary, and it is important to know deviations from the potential demographic composition because deviations are assumed to reflect selective assignments.

Our research was also unlike other studies because of the use of probabilistic linkage among three administrative data sets in order to obtain complete information about the medical histories of patients. This step was critical in finding unique patients in the data set and enabled us to use non-acute diseases, such as cancer, in our analysis. Patients are often not given enough time to decide where to receive medical care for acute conditions, but patients have enough time to decide for non-acute conditions. Therefore non-acute conditions reflect patients' decisions much better than acute conditions.

Given the unique data, our analysis found that it is critically important to control for endogeneity. The naïve probit model found that there is often a correlation between the demographic composition of patients and their outcomes. However, controlling for endogeneity, we found that it is often not the case that demographic composition affects outcomes. Rather, we found that patients who belong to a specific demographic group are selectively assigned to hospitals which are lower or higher in quality. In particular, our analyses found consistent indications for selective assignments of non-white patients. Non-white patients with the three types of cancer that we studied are more likely to be treated at hospitals which are lower in quality. Our result calls for further investigations on the detailed mechanism behind these selective assignments and ways to improve medical care

for impacted patients.

This study did not analyze the reactions and strategies of hospitals. Previous studies suggest that hospitals are subject to market competition, and react to market conditions in order to achieve profitability. There have not been many studies on supply-side reactions to patient composition. Our findings call for supply-side analyses to understand market mechanisms behind the disparities in the quality of medical care.

Table 3.1: Share of Non-White and White Patients and Outcomes for Three Cancer Types

		Alive	Dead	Total	No Readmission	Readmission	Total
		Prostate Cancer					
Non-White	Frequency	2978	302	3280	2187	519	2706
	Percent	23.25	2.36	25.61	20.34	4.83	25.16
	Row %	90.79	9.21		80.82	19.18	
White	Frequency	8395	1133	9528	6553	1495	8048
	Percent	65.54	8.85	74.39	60.94	13.90	74.84
	Row %	88.11	11.89		81.42	18.58	
Total	Frequency	11373	1435	12808	8740	2014	10754
	Percent	88.8	11.2	100	81.27	18.73	100
		Colon Cancer					
Non-White	Frequency	1703	522	2225	1184	436	1620
	Percent	17.72	5.43	23.15	16.39	6.03	22.42
	Row %	76.54	23.46		73.09	26.91	
White	Frequency	5540	1847	7387	4232	1374	5606
	Percent	57.64	19.22	76.85	58.57	19.01	77.58
	Row %	75.00	25.00		75.49	24.51	
Total	Frequency	7243	2369	9612	5416	1810	7226
	Percent	75.35	24.65	100	74.95	25.05	100
		Colon Cancer					
Non-White	Frequency	4741	423	5164	2869	608	3477
	Percent	22.84	2.04	24.88	18.87	4.00	22.87
	Row %	91.81	8.19		82.51	17.49	
White	Frequency	14174	1416	15590	9829	1899	11728
	Percent	68.3	6.82	75.12	64.64	12.49	77.13
	Row %	90.92	9.08		83.81	16.19	
Total	Frequency	18915	1839	20754	12698	2507	15205
	Percent	91.14	8.86	100	83.51	16.49	100

Table 3.2: Age of Non-White and White Patients

	# Patients	Mean	Std Dev	10th Pctl	Lower Quartile	Median	Upper Quartile	90th Pctl
Prostate Cancer Patients - Age								
Non-White	3280	67.0	10.8	53	59	67	74	82
White	9528	70.5	11.4	56	62	70	80	86
Colon Cancer Patients - Age								
Non-White	2225	65.8	14.2	47	56	67	76	84
White	7387	72.6	13.8	53	63	75	83	89
Breast Cancer Patients - Age								
Non-White	5164	58.5	13.4	42	49	58	67	77
White	15590	64.2	14.4	46	53	64	76	84

Table 3.3: Insurance Types and Outcomes for Three Types of Cancer

		Outcome			Outcome			Outcome			Outcome		
		Alive	Dead	Total	No-RA	RA	Total	Alive	Dead	Total	No-RA	RA	Total
		Prostate Cancer						**Colon Cancer**					
HMO	**Frequency**	2313	76	2389	1584	274	1858	1154	216	1370	782	249	1031
	Percent	18.06	0.59	18.65	14.73	2.55	17.28	12.01	2.25	14.25	10.82	3.45	14.27
	Row %	96.82	3.18		85.25	14.75		84.23	15.77		75.85	24.15	
Medicare	**Frequency**	5738	1216	6954	4750	1350	6100	4275	1762	6037	3388	1152	4540
	Percent	44.8	9.49	54.29	44.17	12.55	56.72	44.48	18.33	62.81	46.89	15.94	62.83
	Row %	82.51	17.49		77.87	22.13		70.81	29.19		74.63	25.37	
Other	**Frequency**	341	20	361	291	61	352	239	44	283	178	66	244
	Percent	2.66	0.16	2.82	2.71	0.57	3.27	2.49	0.46	2.94	2.46	0.91	3.38
	Row %	94.46	5.54		82.67	17.33		84.45	15.55		72.95	27.05	
Private	**Frequency**	2756	104	2860	1956	270	2226	1304	262	1566	871	240	1111
	Percent	21.52	0.81	22.33	18.19	2.51	20.7	13.57	2.73	16.29	12.05	3.32	15.38
	Row %	96.36	3.64		87.87	12.13		83.27	16.73		78.4	21.6	
Social	**Frequency**	225	19	244	159	59	218	271	85	356	197	103	300
	Percent	1.76	0.15	1.91	1.48	0.55	2.03	2.82	0.88	3.7	2.73	1.43	4.15
	Row %	92.21	7.79		72.94	27.06		76.12	23.88		65.67	34.33	
Total	**Frequency**	11373	1435	12808	8740	2014	10754	7243	2369	9612	5416	1810	7226
	Percent	88.8	11.2	100	81.27	18.73	100	75.35	24.65	100	74.95	25.05	100
		Breast Cancer											
HMO	**Frequency**	4727	191	4918	3009	459	3468						
	Percent	22.78	0.92	23.7	19.79	3.02	22.81						
	Row %	96.12	3.88		86.76	13.24							
Medicare	**Frequency**	7254	1246	8500	5273	1258	6531						
	Percent	34.95	6	40.96	34.68	8.27	42.95						
	Row %	85.34	14.66		80.74	19.26							
Other	**Frequency**	943	40	983	611	108	719						
	Percent	4.54	0.19	4.74	4.02	0.71	4.73						
	Row %	95.93	4.07		84.98	15.02							
Private	**Frequency**	5114	268	5382	3272	533	3805						
	Percent	24.64	1.29	25.93	21.52	3.51	25.02						
	Row %	95.02	4.98		85.99	14.01							
Social	**Frequency**	877	94	971	533	149	682						
	Percent	4.23	0.45	4.68	3.51	0.98	4.49						
	Row %	90.32	9.68		78.15	21.85							
Total	**Frequency**	18915	1839	20754	12698	2507	15205						
	Percent	91.14	8.86	100	83.51	16.49	100						

RA: Readmission

Table 3.4: Severity Measures and Outcomes

		Prostate			Colon			Breast		
Outcome		**# Patients**	**Mean**	**Std Dev**	**# Patients**	**Mean**	**Std Dev**	**# Patients**	**Mean**	**Std Dev**
Alive	charlson index	11373	0.0	0.3	7243	0.0	0.4	18915	0.1	0.5
	secondary diagnosis		3.7	4.0		4.7	4.7		2.7	3.5
Dead	charlson	1435	0.3	1.0	2369	0.4	0.9	1839	1.2	2.3
	secondary diagnosis		9.4	6.1		9.7	5.3		8.5	5.6

		Prostate			Colon			Breast		
Outcome		**# Patients**	**Mean**	**Std Dev**	**# Patients**	**Mean**	**Std Dev**	**# Patients**	**Mean**	**Std Dev**
No-Readmission	charlson index	8740	0.0	0.3	5416	0.1	0.4	12698	0.1	0.7
	secondary diagnosis		3.9	4.3		5.2	5.0		3.0	3.8
Readmission	charlson index	2014	0.1	0.4	1810	0.1	0.4	2507	0.2	1.0
	secondary diagnosis		4.8	5.2		6.0	5.4		3.9	4.8

Table 3.5: List of Hospitals

	Death			Readmissions		
	Prostate	Colon	Breast	Prostate	Colon	Breast
ATLANTICARE REG MC (CITY)			215	72	51	168
ATLANTICARE REG MC (MAINLAND)	198	194	273	136	140	208
BAYONNE MC		122			75	61
BAYSHORE COMMUNITY HOSP		150	161	61	99	129
BURDETTE TOMLIN MEM HOSP	113	150	175	88	106	152
CAPITAL HEALTH SYSTEM AT FULD	132			120	50	59
CAPITAL HEALTH SYSTEM AT MERCER	115		219	88	70	155
CENTRASTATE MC	232	248	458	179	175	319
CHILTON MEM HOSP	270	161	429	225	123	325
CHRIST HOSP		134	125	72	85	99
CLARA MAASS MC	161	172	295	125	135	189
COMMUNITY MC	486	416	819	416	303	577
COOPER UNIV HOSP	101	170	397	67	104	249
EAST ORANGE GENERAL HOSP				52		
ENGLEWOOD HOSP AND MC	337	262	996	255	172	657
HACKENSACK UNIV MC	1361	464	1134	926	308	732
HACKETTSTOWN REG MC			160	52		131
HOLY NAME HOSP	308	260	569	218	171	368
HUNTERDON MC		116	228	88	95	173
JERSEY CITY MC					63	
JERSEY SHORE UNIV MC	294	259	540	228	159	352
JOHN F KENNEDY MC	377	276	633	286	217	446
KENNEDY MEM HOSP UNIV MC STRATFORD				56		
KENNEDY MEM HOSP UNIV MC WASHINGTON	150		154	134	88	139
KIMBALL MC	155	112	227	107	91	147
LOURDES MC OF BURLINGTON COUNTY	166		169	132	71	125
MONMOUTH MC	358	182	571	268	111	431
MOUNTAINSIDE HOSP	202	163	324	156	122	242
NEWARK BETH ISRAEL MC	451	139	243	303	73	123
NEWTON MEM HOSP	145	107	250	118	83	170
OCEAN MCBRICK DIV	287	261	429	234	202	333
OUR LADY OF LOURDES MC	526	120	189	378	97	154
OVERLOOK HOSP	411	351	883	341	272	653
PALISADES MC				50		65
RARITAN BAY MCOLD BRIDGE				60		88
RARITAN BAY MCPERTH AMBOY			124	54		95
RIVERVIEW MC	211	244	485	172	184	323
ROBERT WOOD JOHNSON UNIV HOSP	701	323	680	553	202	432
ROBERT WOOD JOHNSON UNIV HOSP AT HAMILTON	221	240	386	158	152	264
ROBERT WOOD JOHNSON UNIV HOSP AT RAHWAY	173	137	200	135	88	138
SHORE MEM HOSP		113	219	93	75	166
SOMERSET MC	206	248	484	179	192	350
SOUTHERN OCEAN COUNTY HOSP	181	151	253	147	125	184
SOUTH JERSEY HC REG MC	169	169	250	150	111	187
SOUTH JERSEY HOSP ELMER				53		87
ST BARNABAS MC	470	334	1133	350	206	756
ST CLARES HOSP DENVILLE	392	179	383	282	122	289
ST CLARES HOSP DOVER	127		177	108	56	125
ST CLARES HOSP SUSSEX						53
ST FRANCIS MC	113		112	81		63
ST JOSEPHS HOSP AND MC	153	171	290	116	115	189
ST MARYS HOSP PASSAIC		142	138		111	120
ST MARY HOSP HOBOKEN			132	78	52	114

ST MICHAELS MC	170	169	238	130	90	149
ST PETERS UNIV HOSP	144	208	411	119	142	310
TRINITAS HOSP	186	123	270	139	83	202
UNDERWOOD MEM HOSP	128	143	208	110	107	170
UNIV HOSP	200	118	271	148	87	169
UNIV MC AT PRINCETON	290	158	510	222	103	376
VALLEY HOSP	761	617	1087	547	398	752
VIRTUA MEM HOSP OF BURLINGTON COUNTY	251	248	430	206	164	339
VIRTUA WEST JERSEY HOSP SYSTEM MARLTON	225	203	225	148	127	164
VIRTUA WEST JERSEY HOSP SYSTEM VOORHEES		185	393	96	151	287
VIRTUA WEST JERSEY HOSP SYSTEM BERLIN						52
WARREN HOSP				89	72	81
TOTAL	12808	9612	20754	10754	7226	15205

Table 3.6: Estimates of Conditional Logit Analysis of Hospital Choice

Breast Cancer		Colon Cancer		Prostate Cancer	
distance	-0.112	distance	-0.126	distance	-0.0958
	(0.000744)		(0.00124)		(0.000838)

Unit of distance is kilometer. Standard errors are in parentheses.

Hospital Specific Coefficients		Hospital Specific Coefficients		Hospital Specific Coefficients	
maximum	0.174	maximum	0.409	maximum	-0.581
minimum	-5.409	minimum	-4.802	minimum	-7.630
mean	-1.782	mean	-1.365	mean	-2.703
std dev	1.087	std dev	1.046	std dev	1.241

Table 3.7: Probit Outcome Analysis (Non-white and White patients)

Panel 1: Breast Cancer																
	Death								Readmissions							
VARIABLES	Likelihood	mgnl effct	GMM	mgnl effct	ctrl fn	mgnl effct	GMM IV	mgnl effct	Likelihood	mgnl effct	GMM	mgnl effct	ctrl fn	mgnl effct	GMM IV	mgnl effct
excess minority share					1.028***	0.108							0.666***	0.16		
					(0.219)								(0.244)			
age	0.0224***	0.00236	0.0232***	0.00243	0.0223***	0.00234	0.0231***	0.00243	0.00638***	0.00154	0.00647***	0.00156	0.00627***	0.00151	0.00645***	0.00155
# diagnosis lower 33 %il	(0.000926)		(0.00103)		(0.000917)		(0.00102)		(0.000966)		(0.000980)		(0.000964)		(0.000981)	
charlson index	0.291***	0.0307	0.299***	0.0314	0.291***	0.0305	0.299***	0.0314	0.111***	0.0266	0.110***	0.0266	0.111***	0.0267	0.110***	0.0266
	(0.0146)		(0.0119)		(0.0146)		(0.0119)		(0.0166)		(0.0177)		(0.0166)		(0.0177)	
# diagnosis lower 33 %il	-0.769***	-0.0812	-0.762***	-0.08	-0.767***	-0.0806	-0.758***	-0.0797	-0.0909***	-0.0219	-0.0901***	-0.0217	-0.0927***	-0.0223	-0.0897***	-0.0216
(top 33 %il is omitted)	(0.0380)		(0.0387)		(0.0378)		(0.0388)		(0.0280)		(0.0323)		(0.0282)		(0.0323)	
# diagnosis mid 33 %il	-0.862***	-0.091	-0.849***	-0.0891	-0.875***	-0.092	-0.853***	-0.0897	-0.167***	-0.0402	-0.168***	-0.0404	-0.173***	-0.0417	-0.172***	-0.0413
(top 33 %il is omitted)	(0.0410)		(0.0453)		(0.0416)		(0.0450)		(0.0317)		(0.0310)		(0.0315)		(0.0313)	
teaching hospital	0.0250	0.00264	0.0156	0.00164	0.0481	0.00505	0.0348	0.00366	-0.000856	-0.0142	0.000857	-0.0139	0.00884	0.00213	0.0102	-0.0211
	(0.0302)		(0.0358)		(0.0321)		(0.0375)		(0.0290)		(0.0282)		(0.0297)		(0.0284)	
white patients dummy	-0.0771**	-0.00814	-0.0720*	-0.00756	-0.0752**	-0.0079	-0.121***	-0.0127	-0.0591**	-0.000206	-0.0579	0.000206	-0.0589**	-0.0356	-0.0873**	0.00247
	(0.0342)		(0.0398)		(0.0345)		(0.0442)		(0.0298)		(0.0392)		(0.0298)		(0.0432)	
minority patients share	0.127*	0.0135	0.160*	0.0168	-0.415***	-0.0437	-0.123	-0.0129	0.207***	0.0498	0.205**	0.0494	-0.148	-0.0356	0.0333	0.00802
	(0.0734)		(0.0835)		(0.126)		(0.117)		(0.0642)		(0.0919)		(0.143)		(0.117)	
Constant	-2.477***		-2.550***	-0.268	-2.343***		-2.443***	-0.257	-1.331***		-1.338***		-1.243***		-1.275***	
	(0.0775)		(0.0945)		(0.0776)		(0.0903)		(0.0685)		(0.0937)		(0.0721)		(0.101)	
* indicates a naïve model without control for endogeneity																

Panel 2: Colon Cancer																
	Death								Readmissions							
VARIABLES	Likelihood	mgnl effct	GMM	mgnl effct	ctrl fn	mgnl effct	GMM IV	mgnl effct	Likelihood	mgnl effct	GMM	mgnl effct	ctrl fn	mgnl effct	GMM IV	mgnl effct
excess minority share					0.643**	0.184							0.598**	0.188		
					(0.296)								(0.250)			
age	0.0184***	0.00527	0.0190***	0.00543	0.0185***	0.00529	0.0189***	0.00542	0.00117	0.000367	0.00116	0.000365	0.00123	0.000388	0.00113	0.000357
	(0.00143)		(0.00151)		(0.00143)		(0.00151)		(0.00141)		(0.00142)		(0.00141)		(0.00142)	
charlson index	0.411***	0.118	0.448***	0.128	0.411***	0.117	0.448***	0.128	0.0961**	0.0302	0.0952**	0.03	0.0966**	0.0304	0.0945**	0.0297
	(0.0394)		(0.0416)		(0.0393)		(0.0415)		(0.0424)		(0.0427)		(0.0421)		(0.0423)	
# diagnosis lower 33 %il	-1.102***	-0.315	-1.093***	-0.313	-1.103***	-0.315	-1.092***	-0.313	-0.156***	-0.0491	-0.156***	-0.0491	-0.158***	-0.0498	-0.156***	-0.0491
(top 33 %il is omitted)	(0.0376)		(0.0395)		(0.0378)		(0.0397)		(0.0351)		(0.0352)		(0.0352)		(0.0349)	
# diagnosis mid 33 %il	-0.681***	-0.195	-0.670***	-0.192	-0.676***	-0.194	-0.666***	-0.191	-0.327***	-0.103	-0.326***	-0.103	-0.322***	-0.101	-0.322***	-0.101
(top 33 %il is omitted)	(0.0374)		(0.0320)		(0.0378)		(0.0326)		(0.0419)		(0.0418)		(0.0424)		(0.0417)	
teachinng hospital	0.0244	0.00698	0.0128	-0.0229	0.0188	0.00536	0.0333	-0.0313	0.0107	0.00337	0.00991	0.00312	0.00334	0.00105	0.0256	0.00806
	(0.0428)		(0.0457)		(0.0435)		(0.0453)		(0.0417)		(0.0420)		(0.0421)		(0.0417)	
white patients dummy	-0.0755*	-0.0216	-0.0800**	0.00366	-0.0757*	-0.0217	-0.109***	0.00955	-0.0414	-0.013	-0.0398	-0.0125	-0.0419	-0.0132	-0.0700	-0.022
	(0.0394)		(0.0391)		(0.0396)		(0.0385)		(0.0447)		(0.0450)		(0.0447)		(0.0443)	
minority patients share	0.339***	0.097	0.336***	0.0963	0.0217	0.0062	0.154	0.0442	0.339***	0.107	0.338***	0.106	0.0507	0.016	0.173	0.0544
	(0.102)		(0.107)		(0.159)		(0.117)		(0.116)		(0.118)		(0.176)		(0.142)	
Constant	-1.580***		-1.623***		-1.511***		-1.558***		-0.660***		-0.660***		-1.511***		-0.601***	
	(0.120)		(0.136)		(0.120)		(0.136)		(0.123)		(0.124)		(0.120)		(0.126)	
* indicates a naïve model without control for endogeneity																

Standard errors are in parentheses * indicates p-value: * less than 0.1 ** less than 0.05 ** less than 0.01 marginal effects are computed at means of covariates

marginal effects are computed at means of covariates

Panel 3: Prostate Cancer	Death								Readmissions							
VARIABLES	Likelihood	mgnl effct	GMM	mgnl effct	ctrl fn	mgnl effct	GMM IV	mgnl effct	Likelihood	mgnl effct	GMM	mgnl effct	ctrl fn	mgnl effct	GMM IV	mgnl effct
excess minority share					0.806**	0.0887							0.974***	0.248		
					(0.318)								(0.291)			
age	0.0488***	0.00538	0.0490***	0.00544	0.0488***	0.00538	0.0490***	0.00543	0.0169***	0.0043	0.0170***	0.00434	0.0166***	0.00422	0.0170***	0.00433
	(0.00189)		(0.00197)		(0.00191)		(0.00198)		(0.00173)		(0.000972)		(0.00168)		(0.000971)	
charlson	0.315***	0.0346	0.324***	0.0359	0.313***	0.0345	0.325***	0.036	0.0715	0.0182	0.0699	0.0178	0.0707	0.018	0.0683	0.0174
	(0.0500)		(0.0576)		(0.0503)		(0.0579)		(0.0490)		(0.0445)		(0.0491)		(0.0451)	
# diagnosis lower 33 %il*	-0.774***	-0.0852	-0.782***	-0.0867	-0.777***	-0.0856	-0.781***	-0.0865	-0.0671*	-0.0171	-0.0681*	-0.0173	-0.0679**	-0.0173	-0.0660*	-0.0168
	(0.0443)		(0.0424)		(0.0443)		(0.0424)		(0.0348)		(0.0402)		(0.0340)		(0.0392)	
# diagnosis mid 33 %il*	-1.018***	-0.112	-0.996***	-0.11	-1.011***	-0.111	-0.993***	-0.11	-0.218***	-0.0557	-0.219***	-0.0558	-0.224***	-0.0571	-0.223***	-0.0567
	(0.0633)		(0.0593)		(0.0636)		(0.0593)		(0.0838)		(0.0613)		(0.0792)		(0.0592)	
teachinng hospital	-0.103***	-0.0114	-0.103**	-0.00939	-0.0933***	-0.0103	-0.0844*	-0.0135	-0.0103	-0.0171	-0.00703	-0.0164	0.0191	0.00486	0.0105	-0.0282
	(0.0323)		(0.0474)		(0.0313)		(0.0476)		(0.0345)		(0.0356)		(0.0361)		(0.0368)	
dummy_white	-0.0966**	-0.0106	-0.0847**	-0.0114	-0.0955**	-0.0105	-0.122***	-0.00934	-0.0672**	-0.00262	-0.0642**	-0.00179	-0.0670**	-0.0171	-0.111***	0.00268
	(0.0468)		(0.0421)		(0.0471)		(0.0394)		(0.0320)		(0.0301)		(0.0322)		(0.0370)	
minority_share	0.0601	0.00662	0.0538	0.00596	-0.379*	-0.0418	-0.213*	-0.0236	0.115	0.0294	0.115	0.0294	-0.434**	-0.11	-0.152	-0.0388
	(0.0997)		(0.106)		(0.203)		(0.124)		(0.104)		(0.0900)		(0.204)		(0.156)	
Constant	-4.315***		-4.337***		-4.207***		-4.246***		-2.004***		-2.018***		-1.852***		-1.917***	
	(0.161)		(0.160)		(0.174)		(0.163)		(0.135)		(0.0841)		(0.131)		(0.0972)	

Standard errors are in parentheses * indicates p-value: * less than 0.1 ** less than 0.05 ** less than 0.01 marginal effects are computed at means of covariates

marginal effects are computed at means of covariates

Breast Cancer Mortality	Control Function Approach										IV Regression (GMM)									
	social share		private share		hmo share		medicare share		other share		social share		private share		hmo share		medicare share		other share	
	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct
age	0.0216***	0.00224	0.0213***	0.00222	0.0214***	0.00223	0.0213***	0.00222	0.0213***	0.00222	0.0229***	0.00238	0.0228***	0.00237	0.0228***	0.00237	0.0227***	0.00236	0.0228***	0.00237
	(0.00138)		(0.00139)		(0.00138)		(0.00139)		(0.00139)		(0.00121)		(0.00121)		(0.00120)		(0.00121)		(0.00120)	
charlson index	0.289***	0.03	0.288***	0.0301	0.289***	0.03	0.288***	0.0301	0.288***	0.0301	0.297***	0.0308	0.297***	0.0308	0.297***	0.0308	0.297***	0.0308	0.297***	0.0308
	(0.0147)		(0.0145)		(0.0144)		(0.0145)		(0.0145)		(0.0118)		(0.0118)		(0.0118)		(0.0118)		(0.0117)	
# diagnosis lower 33 percentile	-0.760***	-0.0789	-0.764***	-0.0796	-0.772***	-0.0804	-0.765***	-0.0798	-0.768***	-0.0801	-0.760***	-0.0789	-0.761***	-0.0791	-0.763***	-0.0792	-0.761***	-0.079	-0.760***	-0.079
(top 33 percentile is omitted)	(0.0386)		(0.0390)		(0.0393)		(0.0392)		(0.0392)		(0.0386)		(0.0390)		(0.0386)		(0.0389)		(0.0394)	
# diagnosis mid 33 percentile	-0.871***	-0.0904	-0.870***	-0.0907	-0.870***	-0.0906	-0.872***	-0.0909	-0.870***	-0.0907	-0.855***	-0.0888	-0.855***	-0.0889	-0.860***	-0.0893	-0.860***	-0.0893	-0.856***	-0.089
(top 33 percentile is omitted)	(0.0418)		(0.0410)		(0.0418)		(0.0410)		(0.0408)		(0.0449)		(0.0452)		(0.0449)		(0.0438)		(0.0450)	
dummy - social welfare patients	0.323***	0.0335	0.356***	0.0371	0.353***	0.0367	0.359***	0.0374	0.362***	0.0377	0.324***	0.0337	0.341***	0.0354	0.339***	0.0352	0.343***	0.0357	0.341***	0.0355
	(0.116)		(0.115)		(0.116)		(0.115)		(0.116)		(0.115)		(0.118)		(0.117)		(0.118)		(0.119)	
dummy - private insurance	0.0716	0.00743	0.0662	0.0069	0.0494	0.00514	0.0487	0.00508	0.0636	0.00663	0.0418	0.00434	0.0314	0.00326	0.0292	0.00303	0.0280	0.00291	0.0223	0.00231
	(0.0916)		(0.0902)		(0.0911)		(0.0907)		(0.0903)		(0.115)		(0.113)		(0.113)		(0.114)		(0.118)	
dummy - hmo patients	-0.0654	-0.00679	-0.0850	-0.00886	-0.0726	-0.00756	-0.0893	-0.00931	-0.0752	-0.00784	-0.0937	-0.00973	-0.105	-0.0109	-0.0921	-0.00957	-0.105	-0.0109	-0.112	-0.0116
	(0.106)		(0.104)		(0.104)		(0.104)		(0.104)		(0.106)		(0.105)		(0.104)		(0.105)		(0.111)	
dummy - medicare	0.0707	0.00734	0.0586	0.00611	0.0495	0.00515	0.0403	0.0042	0.0623	0.00649	0.0163	0.0017	0.00538	0.000559	0.00453	0.00047	-0.00249	-0.000259	-0.00277	-0.000288
	(0.0916)		(0.0908)		(0.0911)		(0.0917)		(0.0901)		(0.120)		(0.119)		(0.118)		(0.119)		(0.122)	
teaching hospital	0.0176	0.00183	0.0838**	0.00873	0.0312	0.00325	0.0573	0.00598	0.0581*	0.00605	0.0129	0.00134	0.0279	0.0029	0.0228	0.00237	0.0492	0.00511	0.0213	0.00222
	(0.0329)		(0.0420)		(0.0332)		(0.0368)		(0.0335)		(0.0382)		(0.0422)		(0.0350)		(0.0433)		(0.0357)	
social welfare patients share	-0.745	-0.0773									0.533	0.0553								
	(0.986)										(0.447)									
private insurance patiets share			-0.00189	-0.000197									-0.0397	-0.00412						
			(0.320)										(0.302)							
HMO patients share					-0.170	-0.0177									-0.300	-0.0311				
					(0.273)										(0.186)					
Medicare patients share							0.329	0.0343									0.241	0.0251		
							(0.226)										(0.196)			
Other patients share									-1.789	-0.186									-0.360	-0.0374
									(1.698)										(1.093)	
excess social share	2.363*	0.245																		
	(1.206)																			
excess private share			-0.602	-0.0627																
			(0.465)																	
excess hmo share					-0.438	-0.0456														
					(0.363)															
excess medicare share							-0.127	-0.0132												
							(0.307)													
excess other share									2.933	0.306										
									(1.943)											
constant	-2.474***		-2.493***		-2.440***		-2.612***		-2.409***		-2.585***		-2.539***		-2.475***		-2.643***		-2.525***	
	(0.151)		(0.145)		(0.136)		(0.162)		(0.149)		(0.126)		(0.137)		(0.121)		(0.137)		(0.148)	
Number of Observations	20754		20754		20754		20754		20754		20754		20754		20754		20754		20754	

Standard errors are in parentheses * indicates p-value: * less than 0.1 ** less than 0.05 ** less than 0.01 marginal effects are computed at means of covariates

Table 3.8: Probit Outcome Analyses on Insurance Types

Panel 1a	Naïve Probit Model (Likelihood Estimation)										Naïve Probit Model (GMM Estimation)									
Breast Cancer Mortality	social share		private share		hmo share		medicare share		other share		social share		private share		hmo share		medicare share		other share	
	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct
age	0.0216***	0.00224	0.0214***	0.00223	0.0214***	0.00223	0.0213***	0.00222	0.0214***	0.00223	0.0230***	0.00238	0.0227***	0.00236	0.0228***	0.00236	0.0227***	0.00236	0.0228***	0.00237
	(0.00138)		(0.00138)		(0.00139)		(0.00138)		(0.00138)		(0.00121)		(0.00120)		(0.00120)		(0.00120)		(0.00121)	
charlson index	0.289***	0.0301	0.289***	0.0301	0.289***	0.0301	0.288***	0.0301	0.289***	0.0301	0.297***	0.0308	0.297***	0.0308	0.297***	0.0308	0.297***	0.0308	0.297***	0.0308
	(0.0146)		(0.0145)		(0.0144)		(0.0145)		(0.0145)		(0.0117)		(0.0118)		(0.0118)		(0.0117)		(0.0118)	
# diagnosis lower 33 %il	-0.762***	-0.0792	-0.764***	-0.0797	-0.769***	-0.0801	-0.766***	-0.0799	-0.768***	-0.0801	-0.758***	-0.0785	-0.759***	-0.0788	-0.763***	-0.0792	-0.761***	-0.079	-0.763***	-0.0793
(top 33 %il is omitted)	(0.0391)		(0.0390)		(0.0394)		(0.0391)		(0.0391)		(0.0391)		(0.0392)		(0.0390)		(0.0390)		(0.0384)	
# diagnosis mid 33 %il	-0.866***	-0.09	-0.867***	-0.0904	-0.874***	-0.091	-0.871***	-0.0909	-0.866***	-0.0904	-0.855***	-0.0885	-0.855***	-0.0888	-0.862***	-0.0895	-0.859***	-0.0893	-0.855***	-0.0888
(top 33 %il is omitted)	(0.0408)		(0.0408)		(0.0412)		(0.0408)		(0.0406)		(0.0454)		(0.0451)		(0.0449)		(0.0448)		(0.0448)	
dummy - social welfare patients	0.324***	0.0337	0.353***	0.0369	0.354***	0.0369	0.360***	0.0375	0.358***	0.0374	0.306***	0.0316	0.337***	0.035	0.338***	0.0351	0.343***	0.0357	0.341***	0.0355
	(0.116)		(0.116)		(0.116)		(0.116)		(0.115)		(0.115)		(0.118)		(0.117)		(0.118)		(0.118)	
dummy - private insurance	0.0743	0.00773	0.0619	0.00646	0.0491	0.00512	0.0483	0.00504	0.0627	0.00654	0.0572	0.00592	0.0414	0.0043	0.0289	0.003	0.0281	0.00292	0.0446	0.00463
	(0.0913)		(0.0904)		(0.0912)		(0.0908)		(0.0902)		(0.114)		(0.114)		(0.113)		(0.113)		(0.114)	
dummy - hmo patients	-0.0665	-0.00692	-0.0907	-0.00946	-0.0725	-0.00755	-0.0897	-0.00935	-0.0778	-0.00812	-0.0796	-0.00824	-0.106	-0.011	-0.0881	-0.00914	-0.105	-0.0109	-0.0914	-0.00949
	(0.106)		(0.105)		(0.104)		(0.104)		(0.104)		(0.105)		(0.105)		(0.104)		(0.105)		(0.104)	
dummy - medicare	0.0724	0.00752	0.0522	0.00544	0.0484	0.00504	0.0404	0.00421	0.0616	0.00643	0.0311	0.00322	0.00877	0.000911	0.00437	0.000454	-0.00220	-0.000228	0.0196	0.00203
	(0.0915)		(0.0909)		(0.0912)		(0.0917)		(0.0898)		(0.119)		(0.119)		(0.118)		(0.118)		(0.118)	
teaching hospital	0.00899	0.000934	0.0637	0.00664	0.0317	0.0033	0.0608*	0.00634	0.0376	0.00392	-0.000266	-2.75E-05	0.0539	0.0056	0.0226	0.00234	0.0482	0.005	0.0288	0.00299
	(0.0323)		(0.0397)		(0.0326)		(0.0364)		(0.0327)		(0.0361)		(0.0382)		(0.0353)		(0.0391)		(0.0343)	
social welfare patients share	1.110***	0.115									1.143***	0.118								
	(0.302)										(0.254)									
private insurance patiets share			-0.320	-0.0334									-0.311	-0.0323						
			(0.202)										(0.204)							
HMO patients share					-0.406**	-0.0423									-0.396**	-0.0411				
					(0.169)										(0.173)					
Medicare patients share							0.265	0.0276									0.232	0.0241		
							(0.167)										(0.142)			
Other patients share									0.581	0.0606									0.651	0.0677
									(0.482)										(0.465)	
constant	-2.560***		-2.407***		-2.383***		-2.585***		-2.518***		-2.632***		-2.477***		-2.452***		-2.639***		-2.591***	
	(0.131)		(0.137)		(0.137)		(0.140)		(0.128)		(0.124)		(0.118)		(0.123)		(0.132)		(0.126)	
Number of Observations	20754		20754		20754		20754		20754		20754		20754		20754		20754		20754	

Standard errors are in parentheses * indicates p-value: * less than 0.1 ** less than 0.05 ** less than 0.01 marginal effects are computed at means of covariates

Table 3.8: Probit Outcome Analyses on Insurance Types

Panel 1b	Naïve Probit Model (Likelihood)										Naïve Probit Model (GMM)									
Breast Cancer Readmissions	social share		private share		hmo share		medicare share		other share		social share		private share		hmo share		medicare share		other share	
	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct
age	0.00421***	0.00101	0.00406***	0.000975	0.00407***	0.000979	0.00395***	0.000949	0.00411***	0.000987	0.00432***	0.00104	0.00418***	0.00101	0.00421***	0.00101	0.00409***	0.000984	0.00422***	0.00101
	(0.00136)		(0.00134)		(0.00135)		(0.00135)		(0.00135)		(0.00131)		(0.00132)		(0.00131)		(0.00132)		(0.00131)	
charlson index	0.108***	0.0261	0.108***	0.0259	0.108***	0.026	0.107***	0.0258	0.108***	0.026	0.108***	0.026	0.108***	0.0259	0.108***	0.026	0.107***	0.0258	0.108***	0.0259
	(0.0166)		(0.0166)		(0.0166)		(0.0166)		(0.0165)		(0.0175)		(0.0174)		(0.0174)		(0.0174)		(0.0174)	
# diagnosis lower 33 %il	-0.0875***	-0.021	-0.0855***	-0.0206	-0.0948***	-0.0228	-0.0906***	-0.0218	-0.0883***	-0.0212	-0.0877***	-0.0211	-0.0855***	-0.0206	-0.0949***	-0.0228	-0.0906***	-0.0218	-0.0885***	-0.0213
(top 33 %il is omitted)	(0.0278)		(0.0276)		(0.0274)		(0.0277)		(0.0279)		(0.0324)		(0.0328)		(0.0322)		(0.0326)		(0.0326)	
# diagnosis mid 33 %il	-0.168***	-0.0404	-0.171***	-0.0411	-0.176***	-0.0422	-0.177***	-0.0425	-0.170***	-0.0408	-0.169***	-0.0406	-0.171***	-0.0412	-0.175***	-0.0421	-0.177***	-0.0425	-0.170***	-0.0409
(top 33 %il is omitted)	(0.0312)		(0.0317)		(0.0311)		(0.0312)		(0.0313)		(0.0306)		(0.0307)		(0.0306)		(0.0305)		(0.0308)	
dummy - social welfare patients	-0.0362	-0.00872	-0.0330	-0.00793	-0.0494	-0.0119	-0.0480	-0.0116	-0.0120	-0.00288	0.213***	0.0513	0.234***	0.0562	0.227***	0.0545	0.241***	0.0579	0.237***	0.057
	(0.0806)		(0.0827)		(0.0806)		(0.0805)		(0.0802)		(0.0753)		(0.0738)		(0.0742)		(0.0736)		(0.0742)	
dummy - private insurance	-0.0786	-0.0189	-0.0886	-0.0213	-0.0692	-0.0166	-0.0876	-0.0211	-0.0575	-0.0138	-0.0368	-0.00885	-0.0329	-0.00791	-0.0499	-0.012	-0.0478	-0.0115	-0.0122	-0.00294
	(0.0738)		(0.0749)		(0.0734)		(0.0746)		(0.0725)		(0.0533)		(0.0551)		(0.0533)		(0.0536)		(0.0523)	
dummy - hmo patients	0.0472	0.0113	0.0427	0.0103	0.0363	0.00873	0.0280	0.00674	0.0692	0.0166	-0.0780	-0.0188	-0.0877	-0.0211	-0.0689	-0.0166	-0.0865	-0.0208	-0.0565	-0.0136
	(0.0835)		(0.0843)		(0.0838)		(0.0832)		(0.0832)		(0.0551)		(0.0554)		(0.0536)		(0.0553)		(0.0542)	
dummy - medicare	0.00443	0.00107	0.0422	0.0102	0.0135	0.00325	0.0507	0.0122	0.0288	0.00692	0.0459	0.011	0.0415	0.00997	0.0348	0.00837	0.0265	0.00638	0.0683	0.0164
	(0.0297)		(0.0319)		(0.0282)		(0.0322)		(0.0279)		(0.0591)		(0.0593)		(0.0581)		(0.0585)		(0.0587)	
teaching hospital	0.00443	0.00107	0.0422	0.0102	0.0135	0.00325	0.0507	0.0122	0.0288	0.00692	0.00578	0.00139	0.0435	0.0105	0.0151	0.00362	0.0523	0.0126	0.0298	0.00716
	(0.0297)		(0.0319)		(0.0282)		(0.0322)		(0.0279)		(0.0284)		(0.0317)		(0.0280)		(0.0318)		(0.0286)	
social welfare patients share	0.561**	0.135									0.554**	0.133								
	(0.251)										(0.275)									
private insurance patiets share			-0.311*	-0.0747									-0.313**	-0.0754						
			(0.169)										(0.159)							
HMO patients share					-0.476***	-0.114									-0.467***	-0.112				
					(0.139)										(0.143)					
Medicare patients share							0.384***	0.0923									0.389**	0.0935		
							(0.131)										(0.161)			
Other patients share									1.393***	0.335									1.382***	0.332
									(0.507)										(0.420)	
constant	-1.223***		-1.115***		-1.071***		-1.338***		-1.284***		-2.585***		-2.539***		-2.475***		-2.643***		-2.525***	
	(0.101)		(0.102)		(0.108)		(0.119)		(0.106)		(0.126)		(0.137)		(0.121)		(0.137)		(0.148)	
Number of Observations	15205		15205		15205		15205		15205		15205		15205		15205		15205		15205	

Standard errors are in parentheses * indicates p-value: * less than 0.1 ** less than 0.05 ** less than 0.01 marginal effects are computed at means of covariates

Breast Cancer Readmissions	Control Function Approach										IV Regression (GMM)									
	social share		private share		hmo share		medicare share		other share		social share		private share		hmo share		medicare share		other share	
	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct
age	0.00423***	0.00102	0.00399***	0.00096	0.00400***	0.000961	0.00395***	0.000949	0.00410***	0.000986	0.00435***	0.00105	0.00423***	0.00102	0.00418***	0.001	0.00404***	0.00097	0.00422***	0.00101
	(0.00135)		(0.00135)		(0.00136)		(0.00135)		(0.00135)		(0.00130)		(0.00132)		(0.00132)		(0.00133)		(0.00130)	
charlson index	0.108***	0.026	0.107***	0.0258	0.108***	0.0258	0.108***	0.0259	0.108***	0.026	0.108***	0.0261	0.108***	0.0259	0.108***	0.026	0.107***	0.0257	0.108***	0.0259
	(0.0166)		(0.0166)		(0.0167)		(0.0166)		(0.0166)		(0.0175)		(0.0174)		(0.0175)		(0.0174)		(0.0173)	
# diagnosis lower 33 %il	-0.0869***	-0.0209	-0.0844***	-0.0203	-0.0903***	-0.0217	-0.0894***	-0.0215	-0.0884***	-0.0212	-0.0872***	-0.021	-0.0886***	-0.0213	-0.0988***	-0.0237	-0.0911***	-0.0219	-0.0886***	-0.0213
(top 33 %il is omitted)	(0.0278)		(0.0277)		(0.0275)		(0.0278)		(0.0277)		(0.0324)		(0.0332)		(0.0326)		(0.0326)		(0.0329)	
# diagnosis mid 33 %il	-0.166***	-0.04	-0.175***	-0.0421	-0.185***	-0.0445	-0.179***	-0.0429	-0.170***	-0.0408	-0.168***	-0.0404	-0.170***	-0.041	-0.179***	-0.0429	-0.179***	-0.043	-0.170***	-0.0409
(top 33 %il is omitted)	(0.0316)		(0.0321)		(0.0319)		(0.0310)		(0.0309)		(0.0307)		(0.0305)		(0.0313)		(0.0309)		(0.0308)	
dummy - social welfare patients	-0.0354	-0.00851	-0.0281	-0.00676	-0.0496	-0.0119	-0.0465	-0.0112	-0.0121	-0.0029	0.207***	0.0497	0.233***	0.056	0.223***	0.0534	0.244***	0.0586	0.237***	0.0569
	(0.0809)		(0.0832)		(0.0806)		(0.0805)		(0.0803)		(0.0749)		(0.0733)		(0.0748)		(0.0737)		(0.0756)	
dummy - private insurance	-0.0790	-0.019	-0.0829	-0.0199	-0.0688	-0.0165	-0.0867	-0.0209	-0.0574	-0.0138	-0.0324	-0.00778	-0.0456	-0.011	-0.0506	-0.0121	-0.0473	-0.0114	-0.0131	-0.00315
	(0.0736)		(0.0755)		(0.0735)		(0.0746)		(0.0725)		(0.0546)		(0.0566)		(0.0535)		(0.0540)		(0.0606)	
dummy - hmo patients	0.0478	0.0115	0.0486	0.0117	0.0361	0.00868	0.0288	0.00693	0.0692	0.0166	-0.0734	-0.0176	-0.0901	-0.0217	-0.0538	-0.0129	-0.0848	-0.0204	-0.0573	-0.0138
	(0.0836)		(0.0848)		(0.0837)		(0.0833)		(0.0832)		(0.0559)		(0.0556)		(0.0531)		(0.0555)		(0.0634)	
dummy - medicare	0.00228	0.000549	0.0683*	0.0164	0.0126	0.00302	0.0409	0.00983	0.0295	0.00708	0.0499	0.012	0.0363	0.00874	0.0346	0.00831	0.0235	0.00564	0.0675	0.0162
	(0.0302)		(0.0355)		(0.0280)		(0.0333)		(0.0309)		(0.0603)		(0.0595)		(0.0580)		(0.0591)		(0.0662)	
teaching hospital	0.00228	0.000549	0.0683*	0.0164	0.0126	0.00302	0.0409	0.00983	0.0295	0.00708	0.00276	0.000664	0.0200	0.00482	0.0167	0.004	0.0666*	0.016	0.0294	0.00708
	(0.0302)		(0.0355)		(0.0280)		(0.0333)		(0.0309)		(0.0293)		(0.0342)		(0.0281)		(0.0342)		(0.0313)	
social welfare patients share	1.090	0.262									0.749*	0.18								
	(0.842)										(0.395)									
private insurance patiets share			0.0974	0.0234									-0.0628	-0.0151						
			(0.225)										(0.201)							
HMO patients share					-1.115***	-0.268									-0.794***	-0.19				
					(0.308)										(0.192)					
Medicare patients share							0.566***	0.136									0.533***	0.128		
							(0.208)										(0.194)			
Other patients share									1.250	0.3									1.351	0.325
									(2.000)										(0.902)	
excess social share	-0.698	-0.168																		
	(1.162)																			
excess private share			-0.777**	-0.187																
			(0.394)																	
excess hmo share					1.070**	0.257														
					(0.438)															
excess medicare share							-0.349	-0.0839												
							(0.291)													
excess other share									0.174	0.0418										
									(2.404)											
constant	-1.249***		-1.225***		-0.918***		-1.414***		-1.277***		-1.244***		-1.176***		-1.007***		-1.409***		-1.288***	
	(0.108)		(0.116)		(0.129)		(0.132)		(0.136)		(0.101)		(0.0999)		(0.112)		(0.120)		(0.127)	
Number of Observations	15205		15205		15205		15205		15205		15205		15205		15205		15205		15205	

Standard errors are in parentheses * indicates p-value: * less than 0.1 ** less than 0.05 ** less than 0.01 marginal effects are computed at means of covariates

Table 3.8: Probit Outcome Analyses on Insurance Types

Panel 2a	Naïve Probit Model										Naïve Probit Model (GMM)									
Prostate Cancer	social share		private share		hmo share		medicare share		other share		social share		private share		hmo share		medicare share		other share	
Mortality	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct
age	0.0466***	0.00508	0.0460***	0.00497	0.0462***	0.00502	0.0458***	0.00496	0.0466***	0.00507	0.0472***	0.00517	0.0465***	0.00505	0.0468***	0.00512	0.0464***	0.00506	0.0472***	0.00516
	(0.00237)		(0.00241)		(0.00244)		(0.00246)		(0.00239)		(0.00230)		(0.00230)		(0.00234)		(0.00236)		(0.00229)	
charlson index	0.310***	0.0338	0.308***	0.0332	0.310***	0.0337	0.309***	0.0335	0.309***	0.0337	0.319***	0.0349	0.317***	0.0344	0.318***	0.0348	0.318***	0.0347	0.318***	0.0348
	(0.0502)		(0.0500)		(0.0497)		(0.0495)		(0.0503)		(0.0572)		(0.0572)		(0.0568)		(0.0568)		(0.0569)	
# diagnosis lower 33 %il	-0.775***	-0.0844	-0.773***	-0.0835	-0.782***	-0.085	-0.780***	-0.0845	-0.776***	-0.0845	-0.784***	-0.0858	-0.781***	-0.0848	-0.791***	-0.0865	-0.788***	-0.086	-0.785***	-0.0859
(top 33 %il is omitted)	(0.0434)		(0.0425)		(0.0437)		(0.0436)		(0.0431)		(0.0417)		(0.0419)		(0.0424)		(0.0421)		(0.0421)	
# diagnosis mid 33 %il	-1.010***	-0.11	-1.011***	-0.109	-1.009***	-0.11	-1.011***	-0.11	-1.008***	-0.11	-0.991***	-0.109	-0.993***	-0.108	-0.990***	-0.108	-0.992***	-0.108	-0.989***	-0.108
(top 33 %il is omitted)	(0.0633)		(0.0631)		(0.0631)		(0.0629)		(0.0630)		(0.0587)		(0.0576)		(0.0587)		(0.0585)		(0.0583)	
dummy - social welfare patients	0.188	0.0205	0.227	0.0245	0.245	0.0266	0.286	0.0309	0.208	0.0226	0.237	0.0259	0.279	0.0303	0.294	0.0322	0.334	0.0364	0.260	0.0284
	(0.220)		(0.223)		(0.223)		(0.225)		(0.224)		(0.229)		(0.215)		(0.219)		(0.218)		(0.219)	
dummy - private insurance	-0.0259	-0.00283	0.0221	0.00239	-0.0369	-0.00401	-0.0273	-0.00296	-0.00233	-0.000254	0.0348	0.00382	0.0820	0.0089	0.0210	0.0023	0.0314	0.00342	0.0594	0.00649
	(0.143)		(0.143)		(0.142)		(0.142)		(0.142)		(0.129)		(0.128)		(0.131)		(0.131)		(0.125)	
dummy - hmo patients	-0.170	-0.0185	-0.151	-0.0163	-0.157	-0.0171	-0.163	-0.0176	-0.150	-0.0163	-0.124	-0.0136	-0.108	-0.0118	-0.114	-0.0125	-0.119	-0.013	-0.103	-0.0113
	(0.147)		(0.146)		(0.146)		(0.145)		(0.146)		(0.161)		(0.160)		(0.162)		(0.163)		(0.158)	
dummy - medicare	0.0128	0.00139	0.0247	0.00267	-0.00227	-0.000247	-0.0114	-0.00124	0.0296	0.00322	0.0527	0.00577	0.0613	0.00665	0.0336	0.00368	0.0239	0.0026	0.0707	0.00773
	(0.146)		(0.144)		(0.144)		(0.144)		(0.143)		(0.142)		(0.143)		(0.145)		(0.146)		(0.140)	
teaching hospital	-0.0994***	-0.0108	0.0517	0.00559	-0.0733**	-0.00797	0.0107	0.00115	-0.0854***	-0.0093	-0.102**	-0.0112	0.0523	0.00567	-0.0750	-0.0082	0.00655	0.000714	-0.0872*	-0.00954
	(0.0316)		(0.0442)		(0.0344)		(0.0391)		(0.0324)		(0.0455)		(0.0474)		(0.0478)		(0.0438)		(0.0451)	
social welfare patients share	0.893**	0.0974									0.952**	0.104								
	(0.351)										(0.430)									
private insurance patiets share			-1.109***	-0.12									-1.151***	-0.125						
			(0.217)										(0.243)							
HMO patients share					-0.598***	-0.0651									-0.594***	-0.065				
					(0.210)										(0.223)					
Medicare patients share							0.619***	0.067									0.613***	0.0669		
							(0.114)										(0.144)			
Other patients share									1.798***	0.196									1.874***	0.205
									(0.684)										(0.683)	
constant	-4.215***		-3.981***		-4.056***		-4.505***		-4.270***		-4.304***		-4.055***		-4.142***		-4.586***		-4.362***	
	(0.200)		(0.209)		(0.214)		(0.194)		(0.203)		(0.194)		(0.205)		(0.211)		(0.179)		(0.182)	
Number of Observations	12808		12808		12808		12808		12808		12808		12808		12808		12808		12808	

Standard errors are in parentheses * indicates p-value: * less than 0.1 ** less than 0.05 ** less than 0.01 marginal effects are computed at means of covariates

Prostate Cancer Mortality	Control Function Approach										IV Regression (GMM)									
	social share		private share		hmo share		medicare share		other share		social share		private share		hmo share		medicare share		other share	
	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct
age	0.0466***	0.00508	0.0455***	0.0049	0.0461***	0.00499	0.0455***	0.00492	0.0465***	0.00506	0.0472***	0.00518	0.0469***	0.00513	0.0471***	0.00517	0.0468***	0.00513	0.0472***	0.00517
	(0.00239)		(0.00235)		(0.00244)		(0.00242)		(0.00242)		(0.00231)		(0.00239)		(0.00231)		(0.00240)		(0.00233)	
charlson index	0.310***	0.0338	0.306***	0.0329	0.309***	0.0335	0.308***	0.0333	0.309***	0.0336	0.320***	0.0351	0.319***	0.0349	0.320***	0.0351	0.319***	0.035	0.319***	0.035
	(0.0502)		(0.0499)		(0.0499)		(0.0496)		(0.0504)		(0.0575)		(0.0573)		(0.0574)		(0.0571)		(0.0572)	
# diagnosis lower 33 %il	-0.775***	-0.0844	-0.779***	-0.084	-0.784***	-0.0849	-0.783***	-0.0846	-0.778***	-0.0847	-0.783***	-0.0858	-0.781***	-0.0855	-0.783***	-0.0859	-0.785***	-0.086	-0.783***	-0.0859
(top 33 %il is omitted)	(0.0434)		(0.0423)		(0.0439)		(0.0436)		(0.0436)		(0.0418)		(0.0422)		(0.0430)		(0.0426)		(0.0422)	
# diagnosis mid 33 %il	-1.008***	-0.11	-1.015***	-0.109	-1.016***	-0.11	-1.019***	-0.11	-1.007***	-0.11	-0.993***	-0.109	-0.992***	-0.109	-0.993***	-0.109	-0.992***	-0.109	-0.991***	-0.109
(top 33 %il is omitted)	(0.0636)		(0.0629)		(0.0626)		(0.0622)		(0.0635)		(0.0585)		(0.0581)		(0.0587)		(0.0585)		(0.0576)	
dummy - social welfare patients	0.190	0.0207	0.216	0.0233	0.237	0.0257	0.285	0.0308	0.202	0.022	0.291	0.032	0.287	0.0314	0.293	0.0322	0.311	0.0341	0.281	0.0308
	(0.220)		(0.223)		(0.223)		(0.226)		(0.225)		(0.209)		(0.216)		(0.217)		(0.216)		(0.220)	
dummy - private insurance	-0.0268	-0.00292	0.0183	0.00197	-0.0220	-0.00238	-0.0287	-0.0031	-0.00400	-0.000436	0.00967	0.00106	0.0414	0.00454	0.0103	0.00112	0.0188	0.00206	0.0279	0.00306
	(0.143)		(0.143)		(0.142)		(0.142)		(0.142)		(0.140)		(0.131)		(0.129)		(0.128)		(0.146)	
dummy - hmo patients	-0.168	-0.0183	-0.147	-0.0159	-0.146	-0.0159	-0.165	-0.0178	-0.148	-0.0161	-0.150	-0.0164	-0.132	-0.0144	-0.146	-0.0161	-0.136	-0.015	-0.133	-0.0145
	(0.147)		(0.146)		(0.147)		(0.146)		(0.147)		(0.172)		(0.163)		(0.159)		(0.160)		(0.178)	
dummy - medicare	0.0122	0.00133	0.0271	0.00292	0.0117	0.00127	-0.00890	-0.000961	0.0294	0.0032	0.0265	0.0029	0.0412	0.00452	0.0266	0.00291	0.0247	0.00271	0.0426	0.00467
	(0.145)		(0.144)		(0.144)		(0.145)		(0.144)		(0.155)		(0.145)		(0.145)		(0.146)		(0.158)	
teaching hospital	-0.0966***	-0.0105	0.0685	0.00739	-0.0524	-0.00567	0.0278	0.00301	-0.0831**	-0.00905	-0.0931**	-0.0102	-0.0277	-0.00303	-0.0908**	-0.00996	-0.0479	-0.00525	-0.0904**	-0.00991
	(0.0318)		(0.0441)		(0.0371)		(0.0422)		(0.0335)		(0.0466)		(0.0609)		(0.0459)		(0.0529)		(0.0458)	
social welfare patients share	-0.282	-0.0308									0.0321	0.00353								
	(2.128)										(0.831)									
private insurance patiets share			-0.431	-0.0465									-0.512	-0.056						
			(0.386)										(0.387)							
HMO patients share					0.133	0.0145									-0.0661	-0.00725				
					(0.388)										(0.318)					
Medicare patients share							0.208	0.0224									0.276	0.0303		
							(0.280)										(0.264)			
Other patients share									0.269	0.0293									0.737	0.0808
									(2.607)										(1.553)	
excess social share	1.311	0.143																		
	(2.428)																			
excess private share			-1.019**	-0.11																
			(0.436)																	
excess hmo share					-1.136**	-0.123														
					(0.512)															
excess medicare share							0.592*	0.064												
							(0.341)													
excess other share									1.838	0.2										
									(3.091)											
constant	-4.192***		-4.102***		-4.205***		-4.268***		-4.221***		-4.263***		-4.166***		-4.248***		-4.404***		-4.299***	
	(0.206)		(0.230)		(0.224)		(0.225)		(0.221)		(0.204)		(0.225)		(0.222)		(0.174)		(0.201)	
Number of Observations	12808		12808		12808		12808		12808		12808		12808		12808		12808		12808	

Standard errors are in parentheses * indicates p-value: * less than 0.1 ** less than 0.05 ** less than 0.01 marginal effects are computed at means of covariates

Table 3.8: Probit Outcome Analyses on Insurance Types

Panel 2b	Naïve Probit Model										Naïve Probit Model (GMM)									
Prostate Cancer	social share		private share		hmo share		medicare share		other share		social share		private share		hmo share		medicare share		other share	
Readmissions	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct
age	0.0154***	0.00392	0.0151***	0.00384	0.0152***	0.00387	0.0151***	0.00383	0.0154***	0.00391	0.0156***	0.00397	0.0153***	0.00389	0.0154***	0.00393	0.0153***	0.00389	0.0156***	0.00396
	(0.00162)		(0.00160)		(0.00162)		(0.00160)		(0.00163)		(0.00143)		(0.00148)		(0.00145)		(0.00148)		(0.00143)	
charlson index	0.0694	0.0176	0.0672	0.0171	0.0678	0.0172	0.0669	0.017	0.0682	0.0173	0.0679	0.0173	0.0658	0.0167	0.0662	0.0168	0.0654	0.0166	0.0668	0.017
	(0.0483)		(0.0480)		(0.0478)		(0.0480)		(0.0479)		(0.0447)		(0.0450)		(0.0443)		(0.0447)		(0.0446)	
# diagnosis lower 33 %il	-0.0669*	-0.017	-0.0643*	-0.0164	-0.0700**	-0.0178	-0.0677**	-0.0172	-0.0658*	-0.0167	-0.0699*	-0.0178	-0.0671*	-0.017	-0.0734*	-0.0186	-0.0708*	-0.018	-0.0689*	-0.0175
(top 33 %il is omitted)	(0.0348)		(0.0343)		(0.0347)		(0.0343)		(0.0345)		(0.0398)		(0.0397)		(0.0392)		(0.0389)		(0.0392)	
# diagnosis mid 33 %il	-0.215***	-0.0547	-0.215***	-0.0548	-0.219***	-0.0556	-0.219***	-0.0557	-0.217***	-0.0551	-0.217***	-0.0551	-0.217***	-0.0551	-0.221***	-0.0561	-0.221***	-0.0561	-0.219***	-0.0555
(top 33 %il is omitted)	(0.0818)		(0.0809)		(0.0802)		(0.0799)		(0.0817)		(0.0570)		(0.0559)		(0.0560)		(0.0556)		(0.0566)	
dummy - social welfare patients	0.311*	0.0792	0.349**	0.0886	0.344**	0.0876	0.357**	0.0907	0.351**	0.0892	0.318**	0.0807	0.354***	0.09	0.352***	0.0894	0.364***	0.0924	0.357***	0.0909
	(0.164)		(0.166)		(0.166)		(0.165)		(0.166)		(0.127)		(0.123)		(0.123)		(0.123)		(0.124)	
dummy - private insurance	-0.146	-0.0372	-0.144	-0.0367	-0.165	-0.0419	-0.162	-0.0411	-0.160	-0.0407	-0.144*	-0.0366	-0.142*	-0.0361	-0.160**	-0.0407	-0.158*	-0.04	-0.157*	-0.0399
	(0.0978)		(0.0993)		(0.101)		(0.100)		(0.0991)		(0.0820)		(0.0823)		(0.0815)		(0.0817)		(0.0826)	
dummy - hmo patients	-0.0632	-0.0161	-0.0736	-0.0187	-0.0680	-0.0173	-0.0749	-0.019	-0.0772	-0.0196	-0.0595	-0.0151	-0.0689	-0.0175	-0.0626	-0.0159	-0.0693	-0.0176	-0.0727	-0.0185
	(0.107)		(0.108)		(0.107)		(0.108)		(0.107)		(0.0877)		(0.0860)		(0.0883)		(0.0865)		(0.0858)	
dummy - medicare	-0.0386	-0.00982	-0.0479	-0.0122	-0.0578	-0.0147	-0.0620	-0.0158	-0.0509	-0.0129	-0.0372	-0.00944	-0.0458	-0.0116	-0.0541	-0.0137	-0.0583	-0.0148	-0.0484	-0.0123
	(0.0936)		(0.0950)		(0.0953)		(0.0957)		(0.0935)		(0.0716)		(0.0711)		(0.0706)		(0.0696)		(0.0702)	
teaching hospital	0.00250	0.000636	0.0531	0.0135	0.0174	0.00442	0.0454	0.0115	0.00945	0.0024	0.00569	0.00145	0.0536	0.0136	0.0199	0.00506	0.0465	0.0118	0.0119	0.00303
	(0.0328)		(0.0389)		(0.0320)		(0.0384)		(0.0321)		(0.0378)		(0.0393)		(0.0376)		(0.0386)		(0.0381)	
social welfare patients share	0.901**	0.229									0.861*	0.219								
	(0.458)										(0.489)									
private insurance patiets share			-0.400**	-0.102									-0.385**	-0.0979						
			(0.193)										(0.183)							
HMO patients share					-0.310*	-0.0789									-0.305	-0.0775				
					(0.172)										(0.225)					
Medicare patients share							0.257*	0.0652									0.249	0.0634		
							(0.145)										(0.157)			
Other patients share									0.238	0.0605									0.205	0.0522
									(0.718)										(0.692)	
constant	-1.892***		-1.777***		-1.793***		-1.986***		-1.868***		-1.908***		-1.797***		-1.813***		-2.001***		-1.885***	
	(0.131)		(0.129)		(0.136)		(0.158)		(0.134)		(0.137)		(0.149)		(0.149)		(0.162)		(0.142)	
Number of Observations	10754		10754		10754		10754		10754		10754		10754		10754		10754		10754	

Standard errors are in parentheses * indicates p-value: * less than 0.1 ** less than 0.05 ** less than 0.01 marginal effects are computed at means of covariates

Prostate Cancer Readmissions	Control Function Approach										IV Regression									
	social share		private share		hmo share		medicare share		other share		social share		private share		hmo share		medicare share		other share	
	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct
age	0.0154***	0.00391	0.0147***	0.00372	0.0152***	0.00387	0.0151***	0.00383	0.0150***	0.00382	0.0154***	0.00391	0.0156***	0.00397	0.0152***	0.00385	0.0151***	0.00383	0.0152***	0.00388
	(0.00162)		(0.00159)		(0.00162)		(0.00161)		(0.00162)		(0.00163)		(0.00160)		(0.00162)		(0.00159)		(0.00163)	
charlson index	0.0688	0.0175	0.0675	0.0171	0.0677	0.0172	0.0669	0.017	0.0685	0.0174	0.0683	0.0174	0.0696	0.0177	0.0675	0.0172	0.0669	0.017	0.0678	0.0173
	(0.0484)		(0.0482)		(0.0480)		(0.0482)		(0.0480)		(0.0481)		(0.0476)		(0.0479)		(0.0483)		(0.0488)	
# diagnosis lower 33 %il	-0.0664*	-0.0169	-0.0713**	-0.0181	-0.0681**	-0.0173	-0.0677**	-0.0172	-0.0709**	-0.018	-0.0654*	-0.0166	-0.0640*	-0.0163	-0.0726**	-0.0184	-0.0676*	-0.0172	-0.0598*	-0.0152
(top 33 %il is omitted)	(0.0345)		(0.0345)		(0.0346)		(0.0341)		(0.0353)		(0.0346)		(0.0349)		(0.0363)		(0.0355)		(0.0342)	
# diagnosis mid 33 %il	-0.216***	-0.0549	-0.219***	-0.0556	-0.222***	-0.0564	-0.219***	-0.0557	-0.221***	-0.0562	-0.217***	-0.0553	-0.220***	-0.0561	-0.219***	-0.0558	-0.219***	-0.0557	-0.230***	-0.0587
(top 33 %il is omitted)	(0.0812)		(0.0799)		(0.0788)		(0.0798)		(0.0789)		(0.0812)		(0.0822)		(0.0797)		(0.0804)		(0.0798)	
dummy - social welfare patients	0.311*	0.0791	0.343**	0.0871	0.348**	0.0885	0.357**	0.0907	0.339**	0.0862	0.353**	0.0897	0.358**	0.0912	0.340**	0.0865	0.357**	0.0907	0.375**	0.0956
	(0.165)		(0.166)		(0.166)		(0.165)		(0.168)		(0.162)		(0.165)		(0.168)		(0.164)		(0.160)	
dummy - private insurance	-0.147	-0.0374	-0.153	-0.0388	-0.168*	-0.0427	-0.162	-0.0411	-0.165*	-0.042	-0.162	-0.0413	-0.181*	-0.0461	-0.165	-0.0418	-0.162	-0.0411	-0.219**	-0.0558
	(0.0978)		(0.0999)		(0.101)		(0.100)		(0.0992)		(0.105)		(0.100)		(0.101)		(0.100)		(0.107)	
dummy - hmo patients	-0.0626	-0.0159	-0.0759	-0.0193	-0.0702	-0.0178	-0.0749	-0.019	-0.0708	-0.018	-0.0797	-0.0203	-0.0891	-0.0227	-0.0618	-0.0157	-0.0750	-0.0191	-0.131	-0.0334
	(0.107)		(0.109)		(0.107)		(0.108)		(0.107)		(0.113)		(0.107)		(0.107)		(0.107)		(0.112)	
dummy - medicare	-0.0401	-0.0102	-0.0528	-0.0134	-0.0609	-0.0155	-0.0620	-0.0158	-0.0506	-0.0129	-0.0535	-0.0136	-0.0605	-0.0154	-0.0589	-0.015	-0.0620	-0.0157	-0.105	-0.0269
	(0.0937)		(0.0948)		(0.0959)		(0.0958)		(0.0935)		(0.0994)		(0.0942)		(0.0959)		(0.0968)		(0.0973)	
teaching hospital	0.0118	0.00299	0.0698*	0.0177	0.0101	0.00258	0.0455	0.0116	0.0220	0.00559	0.00719	0.00183	-0.0343	-0.00872	0.0215	0.00547	0.0451	0.0115	-0.00185	-0.000473
	(0.0343)		(0.0394)		(0.0340)		(0.0388)		(0.0335)		(0.0328)		(0.0504)		(0.0328)		(0.0496)		(0.0339)	
social welfare patients share	-0.546	-0.139									0.0358	0.0091								
	(1.796)										(1.096)									
private insurance patiets share			0.519	0.132									0.375	0.0954						
			(0.369)										(0.335)							
HMO patients share					-0.548	-0.139									-0.449*	-0.114				
					(0.390)										(0.272)					
Medicare patients share							0.254	0.0645									0.254	0.0646		
							(0.291)										(0.266)			
Other patients share									-4.530***	-1.151									-2.831**	-0.722
									(1.643)										(1.180)	
excess social share	1.630	0.414																		
	(2.058)																			
excess private share			-1.280***	-0.325																
			(0.416)																	
excess hmo share					0.381	0.0968														
					(0.550)															
excess medicare share							0.00374	0.000952												
							(0.338)													
excess other share									6.105***	1.551										
									(1.904)											
constant	-1.863***		-1.936***		-1.746***		-1.984***		-1.691***		-1.859***		-1.930***		-1.764***		-1.985***		-1.696***	
	(0.141)		(0.140)		(0.147)		(0.220)		(0.151)		(0.145)		(0.139)		(0.139)		(0.199)		(0.160)	
Number of Observations	10754		10754		10754		10754		10754		10754		10754		10754		10754		10754	

Standard errors are in parentheses * indicates p-value: * less than 0.1 ** less than 0.05 ** less than 0.01 marginal effects are computed at means of covariates

Table 3.8: Probit Outcome Analyses on Insurance Types

Panel 3a	Naïve Probit Model										Naïve Probit Model (GMM)									
Colon Cancer	social share		private share		hmo share		medicare share		other share		social share		private share		hmo share		medicare share		other share	
Mortality	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct
age	0.0214***	0.00613	0.0212***	0.00608	0.0211***	0.00605	0.0211***	0.00606	0.0212***	0.00607	0.0224***	0.00641	0.0222***	0.00636	0.0221***	0.00633	0.0221***	0.00634	0.0222***	0.00635
	(0.00165)		(0.00164)		(0.00164)		(0.00164)		(0.00165)		(0.00152)		(0.00152)		(0.00152)		(0.00152)		(0.00153)	
charlson index	0.411***	0.118	0.409***	0.117	0.410***	0.117	0.410***	0.117	0.410***	0.117	0.448***	0.128	0.447***	0.128	0.447***	0.128	0.447***	0.128	0.448***	0.128
	(0.0394)		(0.0396)		(0.0394)		(0.0395)		(0.0396)		(0.0420)		(0.0418)		(0.0417)		(0.0418)		(0.0419)	
# diagnosis lower 33 %il	-1.101***	-0.315	-1.099***	-0.315	-1.102***	-0.316	-1.103***	-0.316	-1.101***	-0.315	-1.093***	-0.313	-1.092***	-0.313	-1.095***	-0.314	-1.096***	-0.314	-1.094***	-0.314
(top 33 %il is omitted)	(0.0376)		(0.0378)		(0.0379)		(0.0377)		(0.0378)		(0.0398)		(0.0404)		(0.0404)		(0.0402)		(0.0405)	
# diagnosis mid 33 %il	-0.677***	-0.194	-0.670***	-0.192	-0.676***	-0.193	-0.676***	-0.194	-0.673***	-0.193	-0.667***	-0.191	-0.660***	-0.189	-0.665***	-0.191	-0.665***	-0.191	-0.663***	-0.19
(top 33 %il is omitted)	(0.0371)		(0.0368)		(0.0368)		(0.0371)		(0.0363)		(0.0308)		(0.0316)		(0.0316)		(0.0317)		(0.0309)	
dummy - social welfare patients	0.188	0.0537	0.217	0.0621	0.218	0.0624	0.217	0.0621	0.220	0.063	0.181	0.0518	0.212	0.0606	0.212	0.0607	0.211	0.0605	0.215	0.0615
	(0.135)		(0.135)		(0.134)		(0.135)		(0.135)		(0.147)		(0.148)		(0.147)		(0.147)		(0.148)	
dummy - private insurance	-0.0109	-0.00312	-0.0140	-0.00401	-0.0338	-0.00967	-0.0343	-0.00984	-0.0177	-0.00507	-0.00895	-0.00256	-0.0144	-0.00414	-0.0349	-0.00999	-0.0351	-0.0101	-0.0176	-0.00506
	(0.115)		(0.113)		(0.114)		(0.114)		(0.114)		(0.112)		(0.112)		(0.111)		(0.112)		(0.115)	
dummy - hmo patients	-0.0521	-0.0149	-0.0683	-0.0195	-0.0723	-0.0207	-0.0708	-0.0203	-0.0572	-0.0164	-0.0505	-0.0145	-0.0684	-0.0196	-0.0714	-0.0205	-0.0704	-0.0202	-0.0570	-0.0163
	(0.109)		(0.107)		(0.109)		(0.108)		(0.107)		(0.116)		(0.115)		(0.116)		(0.115)		(0.116)	
dummy - medicare	-0.155	-0.0445	-0.170	-0.0486	-0.173*	-0.0496	-0.172*	-0.0494	-0.159	-0.0454	-0.174*	-0.0498	-0.191*	-0.0548	-0.195*	-0.0558	-0.194*	-0.0556	-0.179*	-0.0513
	(0.105)		(0.103)		(0.103)		(0.104)		(0.104)		(0.105)		(0.106)		(0.105)		(0.106)		(0.108)	
teaching hospital	0.0211	0.00605	0.0962**	0.0275	0.0679*	0.0194	0.0637	0.0182	0.0622	0.0178	0.00748	0.00214	0.0839**	0.024	0.0559	0.016	0.0526	0.0151	0.0497	0.0142
	(0.0434)		(0.0395)		(0.0399)		(0.0440)		(0.0408)		(0.0453)		(0.0406)		(0.0414)		(0.0467)		(0.0422)	
social welfare patients share	1.468***	0.42									1.487***	0.426								
	(0.560)										(0.505)									
private insurance patiets share			-0.553**	-0.158									-0.558**	-0.16						
			(0.251)										(0.247)							
HMO patients share					0.0754	0.0216									0.0430	0.0123				
					(0.295)										(0.305)					
Medicare patients share							-0.0495	-0.0142									-0.0378	-0.0108		
							(0.187)										(0.192)			
Other patients share									1.069	0.306									1.083	0.311
									(0.963)										(0.848)	
constant	-1.728***		-1.580***		-1.658***		-1.616***		-1.698***		-1.793***		-1.641***		-1.714***		-1.684***		-1.760***	
	(0.158)		(0.159)		(0.149)		(0.200)		(0.155)		(0.152)		(0.154)		(0.147)		(0.184)		(0.156)	
Number of Observations	9612		9612		9612		9612		9612		9612		9612		9612		9612		9612	

Standard errors are in parentheses * indicates p-value: * less than 0.1 ** less than 0.05 ** less than 0.01 marginal effects are computed at means of covariates

Colon Cancer Mortality	Control Function Approach										IV Regression									
	social share		private share		hmo share		medicare share		other share		social share		private share		hmo share		medicare share		other share	
	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct
age	0.0214***	0.00613	0.0213***	0.00608	0.0212***	0.00606	0.0211***	0.00605	0.0212***	0.00608	0.0224***	0.00641	0.0222***	0.00635	0.0221***	0.00633	0.0221***	0.00634	0.0221***	0.00634
	(0.00165)		(0.00163)		(0.00165)		(0.00165)		(0.00165)		(0.00154)		(0.00152)		(0.00153)		(0.00152)		(0.00150)	
charlson index	0.411***	0.118	0.408***	0.117	0.410***	0.117	0.410***	0.117	0.411***	0.118	0.448***	0.128	0.447***	0.128	0.448***	0.128	0.447***	0.128	0.447***	0.128
	(0.0394)		(0.0396)		(0.0395)		(0.0394)		(0.0397)		(0.0420)		(0.0417)		(0.0419)		(0.0420)		(0.0419)	
# diagnosis lower 33 %il	-1.101***	-0.315	-1.099***	-0.315	-1.104***	-0.316	-1.103***	-0.316	-1.101***	-0.315	-1.093***	-0.313	-1.093***	-0.313	-1.095***	-0.314	-1.096***	-0.314	-1.095***	-0.314
(top 33 %il is omitted)	(0.0376)		(0.0377)		(0.0377)		(0.0378)		(0.0378)		(0.0400)		(0.0404)		(0.0402)		(0.0403)		(0.0401)	
# diagnosis mid 33 %il	-0.677***	-0.194	-0.670***	-0.192	-0.681***	-0.195	-0.678***	-0.194	-0.673***	-0.193	-0.667***	-0.191	-0.662***	-0.19	-0.666***	-0.191	-0.666***	-0.191	-0.664***	-0.19
(top 33 %il is omitted)	(0.0374)		(0.0368)		(0.0366)		(0.0371)		(0.0360)		(0.0312)		(0.0312)		(0.0317)		(0.0316)		(0.0314)	
dummy - social welfare patients	0.188	0.0537	0.216	0.0619	0.214	0.0614	0.217	0.062	0.219	0.0628	0.181	0.0517	0.212	0.0606	0.213	0.061	0.210	0.0601	0.213	0.061
	(0.136)		(0.135)		(0.135)		(0.135)		(0.135)		(0.150)		(0.148)		(0.147)		(0.147)		(0.148)	
dummy - private insurance	-0.0109	-0.00313	-0.0125	-0.00359	-0.0385	-0.011	-0.0374	-0.0107	-0.0190	-0.00544	-0.00850	-0.00243	-0.0237	-0.00679	-0.0322	-0.00923	-0.0346	-0.00991	-0.0282	-0.00807
	(0.116)		(0.113)		(0.114)		(0.114)		(0.114)		(0.111)		(0.111)		(0.111)		(0.112)		(0.118)	
dummy - hmo patients	-0.0521	-0.0149	-0.0655	-0.0188	-0.0763	-0.0219	-0.0725	-0.0208	-0.0586	-0.0168	-0.0501	-0.0144	-0.0693	-0.0199	-0.0772	-0.0221	-0.0704	-0.0202	-0.0650	-0.0186
	(0.109)		(0.107)		(0.109)		(0.108)		(0.107)		(0.115)		(0.115)		(0.117)		(0.115)		(0.117)	
dummy - medicare	-0.155	-0.0445	-0.168	-0.0482	-0.178*	-0.051	-0.175*	-0.05	-0.160	-0.0457	-0.174*	-0.0497	-0.193*	-0.0553	-0.192*	-0.055	-0.191*	-0.0547	-0.189*	-0.0541
	(0.105)		(0.104)		(0.103)		(0.104)		(0.104)		(0.105)		(0.106)		(0.105)		(0.106)		(0.114)	
teaching hospital	0.0212	0.00605	0.112***	0.032	0.0724*	0.0207	0.0701	0.0201	0.0610	0.0175	0.00667	0.00191	0.0715*	0.0205	0.0543	0.0156	0.0436	0.0125	0.0535	0.0153
	(0.0437)		(0.0421)		(0.0406)		(0.0470)		(0.0400)		(0.0531)		(0.0419)		(0.0418)		(0.0516)		(0.0422)	
social welfare patients share	1.484	0.425									1.511*	0.433								
	(1.091)										(0.801)									
private insurance patiets share			-0.206	-0.0591									-0.309	-0.0887						
			(0.359)										(0.271)							
HMO patients share					0.604	0.173									0.315	0.0902				
					(0.502)										(0.437)					
Medicare patients share							-0.166	-0.0476									-0.134	-0.0384		
							(0.319)										(0.297)			
Other patients share									-0.374	-0.107									0.438	0.126
									(3.413)										(1.790)	
excess social share	-0.0229	-0.00654																		
	(1.404)																			
excess private share			-0.829	-0.237																
			(0.672)																	
excess hmo share					-1.105	-0.316														
					(0.889)															
excess medicare share							0.229	0.0656												
							(0.509)													
excess other share									1.815	0.52										
									(4.094)											
constant	-1.729***		-1.642***		-1.730***		-1.540***		-1.656***		-1.795***		-1.671***		-1.754***		-1.624***		-1.729***	
	(0.162)		(0.162)		(0.162)		(0.263)		(0.172)		(0.155)		(0.154)		(0.154)		(0.236)		(0.161)	
Number of Observations	9612		9612		9612		9612		9612		9612		9612		9612		9612		9612	

Standard errors are in parentheses * indicates p-value: * less than 0.1 ** less than 0.05 ** less than 0.01 marginal effects are computed at means of covariates

Table 3.8: Probit Outcome Analyses on Insurance Types

Panel 3a	Naïve Probit Model										Naïve Probit Model (GMM)									
Colon Cancer	social share		private share		hmo share		medicare share		other share		social share		private share		hmo share		medicare share		other share	
Readmissions	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct
age	0.00175	0.00055	0.00161	0.000508	0.00165	0.000519	0.00159	0.000499	0.00163	0.000512	0.00183	0.000574	0.00161	0.000506	0.00169	0.000532	0.00161	0.000507	0.00165	0.000518
	(0.00168)		(0.00167)		(0.00166)		(0.00167)		(0.00166)		(0.00172)		(0.00169)		(0.00168)		(0.00168)		(0.00169)	
charlson index	0.0994**	0.0312	0.0969**	0.0305	0.0966**	0.0304	0.0976**	0.0307	0.0972**	0.0306	0.0986**	0.031	0.0956**	0.0301	0.0952**	0.03	0.0964**	0.0303	0.0958**	0.0301
	(0.0428)		(0.0423)		(0.0424)		(0.0424)		(0.0422)		(0.0433)		(0.0427)		(0.0428)		(0.0427)		(0.0422)	
# diagnosis lower 33 %il	-0.155***	-0.0487	-0.156***	-0.049	-0.157***	-0.0493	-0.157***	-0.0493	-0.155***	-0.0488	-0.155***	-0.0486	-0.159***	-0.0499	-0.157***	-0.0494	-0.157***	-0.0493	-0.156***	-0.049
(top 33 %il is omitted)	(0.0341)		(0.0340)		(0.0338)		(0.0339)		(0.0336)		(0.0344)		(0.0341)		(0.0337)		(0.0341)		(0.0342)	
# diagnosis mid 33 %il	-0.318***	-0.1	-0.313***	-0.0985	-0.313***	-0.0984	-0.317***	-0.0997	-0.315***	-0.0992	-0.317***	-0.0997	-0.314***	-0.0988	-0.311***	-0.0978	-0.315***	-0.0992	-0.313***	-0.0984
(top 33 %il is omitted)	(0.0405)		(0.0401)		(0.0401)		(0.0405)		(0.0404)		(0.0409)		(0.0395)		(0.0401)		(0.0402)		(0.0404)	
dummy - social welfare patients	0.0111	0.00348	0.0467	0.0147	0.0451	0.0142	0.0292	0.00918	0.0461	0.0145	0.130	0.0409	0.187*	0.059	0.182	0.0573	0.182	0.0573	0.188*	0.0592
	(0.0410)		(0.0415)		(0.0385)		(0.0433)		(0.0391)		(0.115)		(0.112)		(0.112)		(0.112)		(0.110)	
dummy - private insurance	0.143	0.0448	0.190*	0.0598	0.188*	0.0591	0.186*	0.0584	0.197*	0.0619	-0.167*	-0.0524	-0.205**	-0.0644	-0.202**	-0.0635	-0.188*	-0.059	-0.186**	-0.0587
	(0.111)		(0.112)		(0.111)		(0.112)		(0.112)		(0.0976)		(0.0951)		(0.0979)		(0.0984)		(0.0949)	
dummy - hmo patients	-0.172*	-0.054	-0.192**	-0.0605	-0.199**	-0.0626	-0.188*	-0.0591	-0.173*	-0.0545	-0.102	-0.032	-0.120	-0.0378	-0.114	-0.0358	-0.119	-0.0374	-0.115	-0.0363
	(0.0976)		(0.0949)		(0.0978)		(0.0981)		(0.0932)		(0.0855)		(0.0845)		(0.0848)		(0.0842)		(0.0823)	
dummy - medicare	-0.106	-0.0333	-0.121	-0.0381	-0.117	-0.0368	-0.120	-0.0377	-0.106	-0.0334	-0.116	-0.0366	-0.141	-0.0443	-0.147	-0.0464	-0.127	-0.04	-0.132	-0.0415
	(0.0851)		(0.0849)		(0.0849)		(0.0849)		(0.0832)		(0.0948)		(0.0933)		(0.0929)		(0.0945)		(0.0951)	
teaching hospital	-0.119	-0.0376	-0.138	-0.0435	-0.144	-0.0453	-0.126	-0.0398	-0.118	-0.0372	0.00309	0.000971	0.0328	0.0103	0.0457	0.0144	0.0307	0.00967	0.0461	0.0145
	(0.0938)		(0.0925)		(0.0928)		(0.0942)		(0.0924)		(0.0434)		(0.0401)		(0.0378)		(0.0453)		(0.0389)	
social welfare patients share	1.191***	0.374									1.421*	0.447								
	(0.402)										(0.744)									
private insurance patiets share			-0.0371	-0.0117									0.317	0.0999						
			(0.262)										(0.387)							
HMO patients share					-0.203	-0.064									-0.327	-0.103				
					(0.231)										(0.309)					
Medicare patients share							-0.233	-0.0734									-0.220	-0.0691		
							(0.169)										(0.256)			
Other patients share									1.085	0.341									0.385	0.121
									(0.771)										(1.395)	
constant	-0.601***		-0.528***		-0.502***		-0.390**		-0.589***		-0.618***	-0.194	-0.575***	-0.181	-0.485***	-0.153	-0.400**	-0.126	-0.555***	-0.175
	(0.131)		(0.132)		(0.128)		(0.164)		(0.129)		(0.139)		(0.141)		(0.131)		(0.193)		(0.152)	
Number of Observations	7226		7226		7226		7226		7226		7226		7226		7226		7226		7226	

Standard errors are in parentheses * indicates p-value: * less than 0.1 ** less than 0.05 ** less than 0.01 marginal effects are computed at means of covariates

Colon Cancer Readmissions	Control Function Approach										GMM IV Regression									
	social share		private share		hmo share		medicare share		other share		social share		private share		hmo share		medicare share		other share	
	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct	estimates	mgnal effct
age	0.00175	0.000551	0.00161	0.000507	0.00163	0.000514	0.00159	0.000499	0.00163	0.000514	0.00179	0.000564	0.00164	0.000517	0.00167	0.000525	0.00161	0.000507	0.00166	0.000522
	(0.00167)		(0.00167)		(0.00166)		(0.00166)		(0.00167)		(0.00170)		(0.00169)		(0.00168)		(0.00168)		(0.00168)	
charlson index	0.0994**	0.0312	0.0988**	0.0311	0.0969**	0.0305	0.0976**	0.0307	0.0977**	0.0307	0.0980**	0.0308	0.0957**	0.0301	0.0954**	0.03	0.0964**	0.0303	0.0961**	0.0302
	(0.0428)		(0.0420)		(0.0423)		(0.0425)		(0.0422)		(0.0432)		(0.0426)		(0.0427)		(0.0427)		(0.0425)	
# diagnosis lower 33 %il	-0.155***	-0.0487	-0.157***	-0.0493	-0.157***	-0.0492	-0.157***	-0.0493	-0.155***	-0.0487	-0.155***	-0.0487	-0.156***	-0.049	-0.157***	-0.0493	-0.157***	-0.0493	-0.155***	-0.0488
(top 33 %il is omitted)	(0.0343)		(0.0337)		(0.0340)		(0.0342)		(0.0339)		(0.0341)		(0.0340)		(0.0338)		(0.0339)		(0.0336)	
# diagnosis mid 33 %il	-0.320***	-0.1	-0.314***	-0.0989	-0.311***	-0.0979	-0.316***	-0.0996	-0.313***	-0.0986	-0.316***	-0.0994	-0.312***	-0.0981	-0.311***	-0.098	-0.315***	-0.0993	-0.314***	-0.0987
(top 33 %il is omitted)	(0.0412)		(0.0399)		(0.0406)		(0.0404)		(0.0400)		(0.0405)		(0.0401)		(0.0401)		(0.0405)		(0.0404)	
dummy - social welfare patients	0.0105	0.0033	0.0606	0.0191	0.0436	0.0137	0.0285	0.00898	0.0487	0.0153	0.140	0.044	0.186*	0.0584	0.184*	0.0578	0.182	0.0573	0.192*	0.0604
	(0.0416)		(0.0424)		(0.0384)		(0.0434)		(0.0404)		(0.111)		(0.112)		(0.111)		(0.112)		(0.112)	
dummy - private insurance	0.143	0.0449	0.189*	0.0596	0.185*	0.0584	0.185*	0.0582	0.196*	0.0616	-0.172*	-0.054	-0.192**	-0.0605	-0.198**	-0.0624	-0.187*	-0.0589	-0.174*	-0.0546
	(0.111)		(0.113)		(0.112)		(0.112)		(0.112)		(0.0975)		(0.0947)		(0.0976)		(0.0979)		(0.0930)	
dummy - hmo patients	-0.172*	-0.0539	-0.191**	-0.06	-0.200**	-0.0631	-0.188*	-0.059	-0.175*	-0.055	-0.105	-0.0331	-0.120	-0.0379	-0.117	-0.0367	-0.119	-0.0374	-0.106	-0.0334
	(0.0976)		(0.0951)		(0.0982)		(0.0981)		(0.0928)		(0.0848)		(0.0846)		(0.0844)		(0.0845)		(0.0827)	
dummy - medicare	-0.106	-0.0333	-0.121	-0.0381	-0.119	-0.0374	-0.120	-0.0376	-0.104	-0.0329	-0.120	-0.0379	-0.139	-0.0437	-0.144	-0.0453	-0.126	-0.0398	-0.119	-0.0375
	(0.0847)		(0.0850)		(0.0851)		(0.0851)		(0.0838)		(0.0938)		(0.0925)		(0.0927)		(0.0941)		(0.0921)	
teaching hospital	-0.119	-0.0375	-0.136	-0.0429	-0.145	-0.0457	-0.126	-0.0397	-0.119	-0.0373	0.0107	0.00336	0.0477	0.015	0.0458	0.0144	0.0297	0.00936	0.0465	0.0146
	(0.0938)		(0.0920)		(0.0929)		(0.0941)		(0.0922)		(0.0409)		(0.0412)		(0.0382)		(0.0430)		(0.0388)	
social welfare patients share	1.584	0.498									1.172***	0.369								
	(1.028)										(0.402)									
private insurance patiets share			0.673	0.212									-0.0430	-0.0135						
			(0.576)										(0.263)							
HMO patients share					-0.431	-0.136									-0.188	-0.0591				
					(0.400)										(0.229)					
Medicare patients share							-0.205	-0.0646									-0.234	-0.0737		
							(0.329)										(0.169)			
Other patients share									-0.294	-0.0924									1.060	0.334
									(1.958)										(0.772)	
excess social share	-0.549	-0.173																		
	(1.156)																			
excess private share			-1.376	-0.433																
			(0.906)																	
excess hmo share					0.397	0.125														
					(0.560)															
excess medicare share							-0.0492	-0.0155												
							(0.475)													
excess other share									1.731	0.544										
									(2.528)											
Constant	-0.618***		-0.641***		-0.467***		-0.407*		-0.544***		-0.603***	-0.19	-0.529***	-0.166	-0.506***	-0.159	-0.391**	-0.123	-0.590***	-0.186
	(0.139)		(0.162)		(0.137)		(0.231)		(0.140)		(0.131)		(0.132)		(0.128)		(0.164)		(0.129)	
Number of Observations	7226		7226		7226		7226		7226		7226		7226		7226		7226		7226	

Standard errors are in parentheses * indicates p-value: * less than 0.1 ** less than 0.05 ** less than 0.01 marginal effects are computed at means of covariates

Table 3.9: Summary of Effects of Share of Patients

		Breast Death		Breast Readmission		Colon Death		Colon Readmission		Prostate Death		Prostate Readmission	
		Effect	Selection	Effect	Selection	Effect	Selection	Effect	Selection	Effect	Selection	Effect	Selection
minority_share	naïve probit (likelihood)	+		+		+		+					
	naïve probit (GMM)	+		+		+		+					
	control function	−	+		+		+		+	−	+	−	+
	IV (GMM)									−			
social_share	naïve probit (likelihood)	+		+		+		+		+		+	
	naïve probit (GMM)	+		+		+		+		+		+	
	control function		+										
	IV (GMM)			+		+		+					
private_share	naïve probit (likelihood)			−		−				−		−	
	naïve probit (GMM)			−		−				−			
	control function				−						−		−
	IV (GMM)												
hmo_share	naïve probit (likelihood)	−		−						−		−	
	naïve probit (GMM)	−		−						−			
	control function			−	+						−		
	IV (GMM)			−								−	
medicare_share	naïve probit (likelihood)			+						+		+	
	naïve probit (GMM)			+						+			
	control function			+							+		
	IV (GMM)			+									
other_share	naïve probit (likelihood)			+						+			
	naïve probit (GMM)			+						+			
	control function											−	+
	IV (GMM)											−	

+ indicates the estimator being positive and − indicates the estimator being negative at p-value of 0.1 or smaller.
The dependent variable is 1 for negative outcomes (such as death and readmissions)

Chapter 4

Third Essay: Achieving Goals in Collaboration: Effective Coordination Devices for Dynamic Voluntary Contribution Games

Abstract

This experimental study analyzes the conditions in which a group of subjects would voluntarily furnish public goods in a dynamic contribution game. Previous theoretical studies found that contributing equilibria exist in various game structures. In this study, we present experimental studies on one of the most representative and well-studied games. Our setting is more realistic than previous experimental studies, which are too restrictive in the choices that subjects are allowed to make. In realistic conditions, we find that subjects furnish public goods at a much higher rate if there exist contributing equilibria for the games that they play. We also find that subjects generally follow behavioral patterns consistent with theory. Therefore, we conclude that the existing theoretical findings reflect the actual behavior of subjects unlike some previous studies. However, we find that, when non-binding communication is allowed, subjects behave in a very different way. For those games in which contributing equilibria exist, if subjects are allowed to communicate with each other before they play a game, subjects behave cooperatively and overcome the free-rider problem. This indicates that communication is an alternative enforcement mechanism that works even better than conventional "punishment strategies" for subjects to achieve a common goal.

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4.1 Introduction

Many attempts have been made to understand conditions in which public goods are voluntarily provided (see Bergstrom, Blume and Varian, 1986, for discussions of early attempts). It is because the free-rider problem severely inhibits subjects to achieve Pareto optimal outcomes. In these games, players are given opportunities to make nonrefundable contributions to a public fund; in turn, group members receive equal dividends regardless of their private contributions. Therefore, there always is an incentive to free-ride on other group members' contributions. Early theoretical investigations found that there are instances in which a Nash equilibrium allows subjects to furnish a public good, (Bergstrom *et al.*, 1986) but the efforts did not provide much insights as to what factors, as a practical matter, might increase voluntary private provisions of public goods.

The study by Admati and Perry (1991) was among the first comprehensive studies on nonrefundable dynamic contribution games. Their study characterized a subgame perfect equilibrium path for games with alternating investment opportunities in groups of two. They found that as the time between periods shrinks, the outcomes approach Pareto optimal outcomes. In recent years, it has been shown that some designs of dynamic contribution games yield larger voluntary contributions compared to static counterparts (Marx and Matthews, 2000). This is not only a theoretically important finding, but also a practically meaningful one because many actual contribution games have a dynamic structure. For example, a charitable fund drive could run for a few weeks and the total contributions would be updated and released to the public periodically. Upon successful funding of the project, benefits are enjoyed by the donors and potentially other people. Coauthors of an academic research paper might exert efforts individually and their progress might be updated periodically among them. The authors share authorship of the final products. Therefore, unless readers are aware how much efforts individuals exerted, the authors share equally in the academic achievement. Larger cooperative projects are also voluntary contribution games. For example, the Kyoto Protocol requires participating countries to reduce emissions of greenhouse gases. However, the agreement is not strictly binding. The protocol requires multiple years of voluntary contributions, and participating countries may observe

efforts exerted by other countries.

Lately, dynamic voluntary contribution games have become very relevant to health care providers who are part of Accountable Care Organizations (ACOs). Under the ACO scheme, independent health care providers form a team to provide medical care for patients, and there are financial incentives for ACOs that provide medical care at reduced costs (Gold, 2014). These incentives are usually not allocated to ACOs until savings are actually realized. The providers in an ACO are able to observe efforts exerted by coordinating physicians and providers but there are incentives to free-ride on others. Frandsen and Rebitzer (2014) found that free-riding within an ACO is so severe that a standard pay-for-performance (it is essentially pay-for-outcomes) payment scheme within an ACO would not provide enough incentives for providers to improve the quality of their practice. This finding coincides with a report by Gold (2014) that one third of the initial Medicare ACOs dissolved. It is, therefore, essential to structure ACOs to provide right incentives to achieve desired outcomes.

A large body of literature provides insights on the importance of dynamic structure in public investment games. For example, Marx and Matthews (2000) showed that a small completion bonus is a key for a public project to be successfully funded if subjects are given finite opportunities to make contributions. The structure of the game studied by Marx and Matthews (2000) affords members of a group opportunities to make simultaneous contributions to a public good. The public good is considered complete when the total contribution exceeds a predefined threshold. It was found that many dynamic games with a discontinuous increase in utility at the threshold sustain contributing Nash equilibria even when static counterparts do not have any such equilibrium. The benefit jump provides subjects incentives to make the last contributions, and thus any prior contributions are made as long as benefits from the public good exceeds the cost, and deviations are prevented by punishment mechanisms implemented in the game.

Compte and Jehiel (2004) studied a game in which subjects may terminate the game at will. They also found similar features as were found by Marx and Matthews (2000). Compte and Jehiel (2004) found that a benefit jump is needed for subjects to reach certain thresholds and also found that games need to be dynamic in order to provide goods in most cases where subjects are able to use termination as punishment to other members.

Lockwood and Thomas (2002) introduced "level of cooperation" as a mechanism to induce incentives for members to follow their contributing profiles. Their study also found that a dynamic structure is required to increase the level of cooperation little by little.

Differences in designs of games would produce unique features in contributing equilibria. However, most of the literature agrees that if each stage has the prisoner's dilemma structure and if it is irrational for a singleton coalition to complete the game unilaterally, the game needs to be dynamic and subjects need to reach a goal gradually. It is also widely observed that the theory predicts multiple equilibria. There is no way to find which equilibrium would be adopted by subjects, though it is possible to have a unique equilibrium by refining equilibria and placing restrictions on the game structure.

These theoretical findings are built upon specific game structures. A comprehensive generalization was recently provided by Matthews (2013). This study characterized necessary and sufficient conditions for achievable profiles in more general conditions. Notably, Matthews (2013) found that all achievable profiles are in the *undercore*. The concept of the *undercore* is similar to the core in cooperative game theory but profiles might be inefficient in the undercore. Matthews (2013) also characterized achievability of profiles under general conditions and revisited the theoretical analyses by Marx and Matthews (2000).

The paper by Matthews (2013) is complemented with theoretical investigations by Battaglini, Nunnari and Palfrey (2012). Battaglini *et al.* (2012) focus on Markov perfect equilibria. This refinement makes the set of equilibria smaller and it is easier to predict behavior of subjects under this refinement. One of the earliest experimental studies on Markov equilibria was presented by Choi, Gale and Kariv (2008) who found that experimental observations in general yield patterns of behavior that are in accordance with symmetric Markov perfect equilibria. Choi et al. (2008) focused on Markov equilibria because the set of all Nash equilibria is too large to provide any prediction on behavior of subjects. They also found some consistent deviations from what the symmetric Markov perfect equilibria predict, such as larger contributions in early periods. However, these choices can still be explained by subgame perfect equilibria studied by Matthews (2013).[1] The parameterizations and structure of the experiment by Choi et al. (2008) do not necessarily reflect

[1] Further discussions on the nature of Markov perfect equilibria are provided by Battaglini et al. (2013).

realistic investment games since their research focused on having results that clearly reflect features of their theoretical findings. For instance, the choice set is extremely small in many instances; in most cases, subjects choose from two options; invest or not.

Duffy, Ochs and Vesterlund (2007) also conducted experimental investigations on theoretical findings by Marx and Matthews (2000). Contrary to Choi et al. (2008), Duffy et al. (2007) found that the existence of a completion benefit does not increase the total provision of public goods. It was also found that subjects do not condition their contributions on prior contributions by other group members. They claim that dynamic games afford more opportunities for participants to make contributions by mistake. In short, Duffy et al. (2007) found that the theoretical findings by Marx and Matthews (2000) do not reflect the actual behavior of contributors.

It is inherently difficult to conduct experimental studies on the theoretical findings by Marx and Matthews (2000). It is mainly because there are a large number of equilibria for dynamic contribution games, and in order to sustain the contributing strategy profiles characterized by Matthews (2013) and Marx and Matthews (2000), it is essential for subjects to agree with a single strategy profile to play. Therefore, Duffy et al. (2007) decided to limit the number of contributing equilibria. In their experiment, denominations of experimental currency were coarse. Each subject was essentially given two or three choices at each stage of the game; invest 0 or 1 (which might have been considered as a natural focal point), or possibly 2. The construction of the game was meant to reduce coordination problems. However, it also meant that the set of choices that each participant had was small, too.

We suspect that the small number of equilibria make subjects more tempted to revert to a non-contributing strategy profile. The structure of the game discussed by Marx and Matthews (2000) always includes the non-contributing strategy profile as a Nash equilibrium. Therefore, subjects always have the option to revert to contributing nothing to public projects if they feel that the contributing equilibria that they have in their mind are not achievable. Since this outside option always exists, the structure of the game used by Duffy et al. (2007) might increase the chance of subjects choosing the outside option as the strategy profile to play since a small chance of "trembling hands" — other players making mistakes — might be detrimental to any contributing equilibrium. This might be a reason

why Duffy et al. (2007) observed many groups not completing the game even in cases where there were contributing equilibria. In other words, we suspect that the limitation that Duffy et al. (2007) imposed increased the chance of subjects reverting to non-contributing equilibria more so than it reduced the chance of not coordinating on a single strategy profile.

In order to address the issue, we depart from the structure of the game deployed by Duffy et al. (2007) in a few ways. First and foremost, rather than limiting the size of the set of contributing equilibria to mitigate coordination problems, some of our subjects are given opportunities to talk to each other prior to the contribution game. In this way, members in each group may find it easier to arrive at an agreed strategy profile.

Secondly, we also set experimental parameters differently. For instance, as was done by Duffy et al. (2007), our subjects are provided with either a positive bonus or no bonus. However, we introduce much finer denominations than in the experimental game by Duffy et al. (2007). In this way, our game invites a lower chance of making an agreement on one strategy profile, but, it might reduce the chance of subjects reverting to the outside option if they are willing to forgive small mistakes by other subjects (or if their strategy profiles and reaction functions are more immune to "trembling hands").

< Figure 4.1 >

Figures and tables are attached at the end of this chapter.

In addition, we provide a larger endowment to subjects so that risk averse subjects would not be reluctant to make contributions. Let us assume that a subject evaluates the chance of having a contributing equilibrium chosen by other subjects being p, and the chance of having a non-contributing equilibrium chosen by other subjects being $1 - p$. In addition, if we assume that a typical subject has a strictly concave utility function f, then Figure 4.1-a and Figure 4.1-b show that a subject will prefer $x_i = x$ if the function f is flatter and $x_i = 0$ if the function f is steeper. This means that it might be problematic to use a small endowment to analyze behavior because, in reality, allocations of personal resources to public goods consist of a relatively small portion of personal resources in most instances (and thus the utility function should be rather flatter).

In sum, our study will add a more realistic parameterization to the experimental literature on dynamic provision of public goods. Given more realistic parameters and opportunities to mitigate coordination issues, we expect subjects would find it easier to pursue contributing equilibria such as those studied by Marx and Matthews (2000) and Matthews (2013).

In Section 4.2, we revisit theoretical aspects of dynamic contribution games. We then discuss the experimental procedures in Section 4.3. The data that we obtained in our experiment will be thoroughly examined in proceeding sections. Section 4.4 discusses descriptive statistics and Section 4.5 discusses statistical analyses. The last section concludes our study.

4.2 Theoretical Analysis

Our theoretical analysis of a dynamic contribution game that we adopt in our experiments relies on the work of Marx and Matthews (2000), Matthews (2013), Duffy et al. (2007), and Choi et al. (2008). Our model is similar to those investigated by Marx and Matthews (2000) and Duffy et al. (2007). However, we have seen further developments in theoretical investigations since these papers were authored. Using these new findings, in this section, we provide more comprehensive theoretical analyses.

We first let N be the number of subjects and an individual $i \in \{1, ..., N\}$ faces exactly the same parameters and utility functions as other individuals $\{1, ..., N\} \backslash i$. The contribution game lasts T periods. In any period $t \in \{1, ..., T\}$, all subjects are furnished with opportunities to make contributions $g_i(t)$. We further define $G(t) = \sum_{i \in \{1,...,N\}} g_i(t)$. Each subject is provided with an endowment denoted $w \in \mathbb{R}_+$ prior to $t = 1$. At the end of period T, player i's payoff is computed using the following function:

$$u_i = w - \sum_{t=1}^{T} g_i(t) + f(\sum_{t=1}^{T} G(t)) \tag{4.1}$$

where $df(x)/dx \geq 0$ for any $0 \leq x \leq \bar{G}$ and $df(x)/dx = 0$ for any $x > \bar{G}$.

We call the exogenously provided number $\bar{G}$ the threshold. When the sum of contributions reaches this amount, the public project is considered complete and each subject is

provided with a completion bonus $b \in \mathbb{R}_+$. The marginal return of an individual contribution is $0 \leq \lambda < 1$ when $\sum_{t=1}^{T} G(t) \leq \bar{G}$ In sum, our payoff function is:

$$f(\sum_{t=1}^{T} G(t)) = \begin{cases} \lambda \sum_{t=1}^{T} G(t) & \text{if } \sum_{t=1}^{T} G(t) < \bar{G} \\ B = b + \lambda \bar{G} & \text{if } \sum_{t=1}^{T} G(t) \geq \bar{G} \end{cases} \tag{4.2}$$

At the conclusion of period t, player i is informed of $h_i^t = \{g_i(\tau), G(\tau)\}_{\tau=1}^{t}$, and then in the next period, the player decides $g(t+1) \leq w - \sum_{\tau=1}^{t} g_i(\tau)$ according to h_i^t. As has been discussed by Marx and Matthews (2000) and Duffy et al. (2007) among others, the social dilemma of free-riding is an issue only when the bonus is relatively small, so that it is individually irrational to form a singleton coalition to complete the project. Here, we define our version of more general *minmax* individual rationality.

Definition 1. It is individually rational to play y if $u_i(y) \geq u_i^*(0)$ where $u_i^*(x) := u_i^*(x_i, x_{-i}) := \max_{x_i' \geq x_i} u(x_i', x_{-i})$ and $u_i(y) \equiv u_i(y_i, y_{-i})$ where we define the strategy profile x as a set of subjects' contributions up to the period t such that $x = \{\{x_i^t\}_{t=1}^{T}\}_{i=1}^{N}\}$.

In order to prevent any singleton coalition from completing the project, we let $\bar{G} > B$, and we also place the restriction that $\bar{G} < N \cdot B$ in order for it to be individually rational for members of some coalition to complete the project. We note that it is sufficient for a profile to have the following two conditions for the profile to be an equilibrium path and achievable (Lemma 5, Matthews, 2013).

Condition 1. The game meets the prisoner's dilemma condition.

Condition 2. A profile that subjects adopt, x, is sequentially rational ($u_i(x_i^{t-1}, x_{-i}^t) \leq u_i(x)$ for all $t \geq 1$, $i \in N$).

As it shown by Marx and Matthews (2000) and Duffy et al. (2007), there does not exist any contributing profile which completes a project in finite time satisfying the two conditions above if $b = 0$ and $N \cdot B > \bar{G} > B$. Condition 2 states that a profile needs to prescribe an sequentially rational schedule of contribution in any of the subgames. However, if $b = 0$, it always is sequentially irrational to make any contribution in the last period (which forms a subgame), therefore, no contributing profile is achievable. Regardless of b, Condition 1

is satisfied under our payoff structure.[2]

For example, given $b = 20$, $\bar{G} = 210$, $N = 3$, $w = 140$, $T = 7$ and $\lambda = .5$, there are many contributing Nash equilibria and the non-contributing profile is also a Nash equilibrium. For example, $x = \{10, 10, 10\}_{t=1}^{7}$ reaches the threshold in seven periods and this profile satisfies both conditions 1 and 2 if the *grim* strategy[3] is used for any deviation. This strategy profile is meant to be the focal point of the game. There also is a contributing profile, which completes the project at the end of period 4; for example, $x = \{\{20, 20, 20, 10\}, \{20, 20, 20, 10\}, \{20, 20, 20, 10\}\}$ satisfies both conditions 1 and 2, and thus is an achievable equilibrium. We could also have asymmetric equilibria such as $x = \{15, 10, 5\}_{t=1}^{7}$, which is also achievable.

On the other hand, if $b = 0$ while other parameters remain the same, there is no contributing equilibrium because Condition 2 is not met if $b = 0$. Given any strategy profile, which satisfies $\sum_{t=1}^{T} G(t) \geq \bar{G}$, of which $7 \geq T > 1$, Condition 2 is not met because $\lambda < 1$. After period T, there are no further contributions made by other members, and the marginal benefit of individual contributions is less than 1, therefore, the marginal profit of investment is negative and the investment in this period will not affect investments by other members. This means that Condition 2 is violated at $t = T$. This results in only one rational decision, $g(T) = 0$, for all members. Therefore, it is sequentially irrational to make investments in the last period T. However, many profiles indeed provide subjects positive profits and thus these profiles are individually rational. For example, a profile $x = \{10, 10, 10\}_{t=1}^{7}$ provides $u_i(x) = w - \sum_{t=1}^{T} g_i(t) + f(\sum_{t=1}^{T} G(t)) = 140 - 70 + 105 = 175 > u_i^*(0) = 140$. Furthermore, these allocations are not *underblocked* by coalitions smaller than the grand

[2] We first prove that there is only one Nash equilibrium in each stage game and the solution is not Pareto optimal.

First, we assume that there exists a Nash equilibrium such that a subject i contributes $x_i > 0$. Since marginal payoff is negative (because $\lambda < 1$), given any x_{-i}, $u(x_i, x_{-i}) < u(0, x_{-i})$. In other words, the set $r = \underset{x_i \geq 0}{\text{argmax}}\ u(x_i, x_{-i})$ is not empty and includes one element $\{0\} \equiv r$. The subject i at time τ can invest $0 \leq x_i \leq w - \sum_{1 \leq t \leq \tau} g_i(t)$. The set is compact, convex and nonempty (since $x_i = 0$ always exist as an option). The set r is upper hemicontinuous, convex and nonempty. Therefore, according to Kakutani's fixed point theorem, r is a fixed point, and there exists a Nash equilibrium.

On the other hand, this equilibrium is not Pareto optimal. Let us assume $c > 0$, and for any c, we have $u(x_i = c, x_{-i} = c) = (N\lambda - 1)c > u(x_i = 0, x_{-i} = 0) = 0$ provided $N = 3$ and $\lambda = .5$ (or for any combination such that $N\lambda > 1$).

[3] Under a *grim* strategy, subjects follow a prescribed profile unless there is any deviation by any member. Once a deviation occurs, all subjects revert to a prescribed punishing strategy and remain in the alternative strategy for the remainder of the game.

coalition. Following Matthews (2013), we define:

Definition 2. A profile x is underblocked by a coalition S if $z \leq x$ exists such that $z_{-S} = 0$ and $u_S^*(z) \gg u_S(x)$. Note that $x = \{x_i, x_{-i}\}$, $z = \{z_i, z_{-i}\}$, $z_{-S} \equiv \{\forall z_j\}$ such that $j \notin S$ and $z_S \equiv \{\forall z_j\}$ such that $j \in S$.

Corollary 1. Under the maintained assumption, no efficient profile is underblocked by a smaller coalition S if $b = 0$.

Proof. See Appendix.

Additionally, these profiles are *satiation profiles* as defined by Matthews (2013).

Definition 3. A profile x is a *satiation profile* provided $u(x) = u^*(x)$.

Corollary 2. Under the maintained assumption, a profile x is a satiation profile.

Proof. It immediately follows from the construction of the game in which marginal return of investment λ is strictly less than 1. ■

Definition 4. The undercore of a game is the set of satiation profiles which are not underblocked by any smaller coalitions.

Therefore, efficient profiles are in the undercore, even if $b = 0$, and according to Matthews (2013), these profiles satisfy necessary conditions for achievable profiles. However, it is another question if there exists an equilibrium path for a particular game. As has been shown by Marx and Matthews (2000) and Duffy et al. (2007), we unfortunately do not have any equilibrium path in our game due to the construction of the game.

Observation 1. If $b = 0$, $\bar{G} = 210$, $N = 3$, $w = 140$, $T = 7$ and $\lambda = .5$, then there are individually rational satiation profiles by which group members make strictly positive contributions. These profiles are not achievable (see Marx and Matthews, 2000, for discussions). There also is a non-contributing equilibrium and the equilibrium is achievable.

Observation 2. If $b = 20$, $\bar{G} = 210$, $N = 3$, $w = 140$, $T = 7$ and $\lambda = .5$, then there are individually rational satiation profiles by which group members make strictly positive contributions. Some of these profiles satisfy both Conditions 1 and 2, therefore, there are achievable profiles and these achievable profiles always satisfy $\sum_{t=1}^{T} G(t) = \bar{G}$. There also is a non-contributing equilibrium and the equilibrium is achievable.

By the theoretical observations noted so far, we do not expect subjects to make contributions if $b = 0$. However, we have witnessed many situations in which subjects prefer to cooperate. For example, Andreoni and Samuelson (2006) studied two-stage prisoner's dilemma games and they found that subjects in general have preference toward cooperation even if it is theoretically infeasible to make subjects cooperate (such as the last period in games with $b = 0$). Therefore, if subjects prefer to cooperate and they feel that it is feasible to do so, we shall observe some groups completing the project even if no bonus is given, albeit the degree of cooperation might not be strong enough to bring a large proportion of groups to complete the project.

By the theoretical discussions thus far presented, and previous experimental results by Andreoni and Samuelson (2006), Duffy et al. (2007) and Choi et al. (2008), we predict:

Prediction 1. Groups of subjects who are given a bonus and opportunities to communicate with each other have a higher chance of completing the project compared to groups with a bonus only because it is easier for members to coordinate to follow an equilibrium.

Prediction 2. Groups of subjects who are not given a bonus have a significantly lower completion rate.

Prediction 3. Subjects will condition their contributions on previous contributions by other members.

4.3 Design of Experiment

As has been shown by previous studies, there are a large number of contributing equilibria, but there has not been much investigation of how subjects come to agree upon one strategy profile. If subjects are to deploy the strict *grim strategy* as is assumed by Marx and Matthews (2000), a very slight coordination problem among group members would trigger a punishment. Duffy et al. (2007) opted to limit the size of the set of contributing equilibria by providing a small number of denominations in the experimental currency. Namely, for a group of three, the members were given 6 virtual coins per person and the threshold was set to 12. For symmetric profiles, each member needs to contribute 4 coins and since the number of contributing periods was 4, subjects did not have a room to be forgiven for a

"trembling hand," *e.g.* mistakenly contributing 0 or 2 in some period.

As we discussed previously, our experiment provides generous endowments in order to mitigate the risk of reverting to the security payoff $u^*(x)$ when subjects are risk averse and have strictly concave utility functions. The denomination and unit of experimental currency would not change the preference ordering of outcomes. However, if subjects are concerned with "trembling hands" of others, and if the initial endowment is small, there would be an increasing chance of an incomplete project. In our experiment, we attempt to mitigate the danger of subjects falling back to the outside option (the non-contributing equilibrium) by having finer denominations in the experimental currency and providing an endowment that is twice as much as what symmetric contributing equilibria require subjects to contribute.

We also provide more opportunities to make contributions. In our case, there are 7 contributing periods. As Marx and Matthews (2000) discuss, the longer the contributing game, the larger the set of contributing equilibria that we have. This implementation shall also open opportunities for subjects to choose from a wider set of equilibria.

The design requirements discussed above are satisfied by the parameters used in the examples in the previous section. These parameters are $\bar{G} = 210$, $N = 3$, $w = 140$, $T = 7$ and $\lambda = .5$, and we use two different bonus amounts, $b = 20$ and $b = 0$, for the experiment to see if the observed behavior of subjects is consistent with the theoretical prediction. We also allow some subjects to communicate each other among group members prior to each game that they play whereas other subjects are not allowed to do so. More specifically, members in some groups are allowed to speak to each other for 2 minutes before entering into a dynamic investment game. They are not allowed to communicate with each other once the two-minutes is over. This means that there are two treatments for b, and there are two treatments for prior discussions, thus there are four treatments in total.

All sessions of the experiment were conducted on computers in the Wachtler Experimental Economics Laboratory at Rutgers University. Participants were recruited from a pool of undergraduate students at Rutgers University. Each session involved 12, 15, or 18 inexperienced subjects. In a given session, subjects were seated at computers and were given a set of written instructions, a payoff description, and a short quiz. The experimenter read the instructions aloud to all participants then participants were asked to complete a

quiz. The answers were immediately reviewed and subjects were asked to begin the experiment. They played a total of 15 games, each of which were prescribed with the very same treatment condition. Prior to each new game, subjects were randomly and anonymously matched with two other participants. Following completion of the 15th game, subjects were paid their earnings from all games played and also received a 5-dollar show-up payment. We conducted one session of each of four treatments. The experiment typically lasted between 90 and 120 minutes and participants' earnings averaged approximately 25 dollars. The computer program was written in z-Tree (Fischbacher, 2007).

4.4 Descriptive Statistics of Results

In this section, we present some key descriptive statistics and analysis of our results. First, we observe clear differences in completion rates between treatments with a bonus and without a bonus. Table 4.1 shows descriptive statistics for total contributions and ways that games were played (i.e. as if a static game or as if a dynamic game). These statistics are computed separately for the first, second, and the last five games. Our results show that more than 80% of games played reached the threshold when a bonus was provided except for the last five games without communication. On the other hand, our results show that the completion rates were between 40% and 50% when a bonus was not given, but communication was allowed. The completion rates go down to less than 20% when communication was not allowed and a bonus was not given. As Matthews (2013) and Marx and Matthews (2000) clearly indicate, if there is no bonus, there is no contributing equilibrium. Furthermore, the chi-square test for binary outcomes (see Table 4.2) indicates that there is a statistically significant difference in outcomes in games with a bonus and without a bonus. More precisely, there is a statistically significant difference in outcomes depending on the bonus amount and the availability of an opportunity for pre-game communication.

< Tables 4.1, 4.2, Figures 4.2 and 4.3 >

Figures and tables are attached at the end of this chapter.

Figures 4.2 and 4.3 show the distribution of contributions. For groups that have a positive bonus for completion, we see that total group contributions are highly concentrated

around the threshold. On the other hand, groups that are not provided with any bonus had two or more peaks. We typically see one peak below 100 and another between 100 and 200. This indicates that a large number of groups at least raised some funds regardless of availability of a bonus, but a bonus was an important motivator for members to complete the project. We also observe that under the condition without a bonus, subjects are much more likely to complete a public good project if communication is allowed. This indicates that subjects may be able to overcome free-riding issues and complete the project at a higher frequency if communication is allowed. It means that communication is not only a coordination device but also a mechanism that enforces cooperation beyond what the theory predicts.

< Table 4.3 and Figure 4.4 >

Figures and tables are attached at the end of this chapter.

Figure 4.4 provides further insights on the total investment that groups provided. When the bonus is provided, there is a high chance for participants to complete the game and it is consistently seen except in the last five games without communication. When a bonus is not provided, we still see that many groups invested a large sum. As discussed above, the theoretical analysis indicates that there are only non-contributing equilibria and it is not sequentially rational to invest any money in the sense that $u_i(x_i^{t-1}, x_{-i}^t) \leq u_i(x)$ for all $t \geq 1, i \in N$ (see further discussions in Section 4.2). However, some investment profiles are individually rational in the sense that $u_i(x) = u_i^*(x_i, x_{-i}^{t=1})$ where $x > 0$ (see further discussions in Section 4.2). As Figure 4.4 indicates, groups with no bonus achieve lower milestones (105, 150, and 200) at a higher frequency if communication is allowed as opposed to groups without communication. As Table 4.3 indicates, some 80% of outcomes are individually rational regardless of opportunities to communicate. It indicates that higher profits were earned by those who communicatde but their chance of making a loss was not any greater than those who did not communicate.

< Figure 4.5 >

Figures and tables are attached at the end of this chapter.

This binding feature of cheap talk is also clearly seen in Figure 4.5. The first round contributions of subjects with cheap talk tend to cluster around 70 as well. It means that many subjects invested one third of the goal although the game is designed to have each subject invest gradually, for example, 10 per period. There are asymmetric equilibria that prescribe one member to submit 70 in one period. However, there is no equilibrium in which two or more members would contribute 70 in one period.[4]

In fact, it is impossible, as a theoretical matter, to make two or more members invest 70. Let us assume that two members are investing 70 each. The last subject gains $(70 \cdot 2) \cdot \lambda = 70$ given $\lambda = .5$ in that period whereas she gains $-(210 - 70 \cdot 2)\lambda + (70 \cdot 2) \cdot \lambda + b = 55$ given $b = 20$ if she decides to finish the project. Therefore, her rational choice is not to invest any. This means that the analytical framework developed in previous theoretical studies cannot explain the behavior that we observed in which subjects make a large contribution to finish a game in one period.

As Table 4.1 indicates, when subjects are given a bonus and cheap talk opportunities, they played 40%, 73% and 60% of the first, middle and last 5 games, respectively, as if they were static games, where we define a game being played as if it were a static game if everybody contributed at least 40 each in the first period and the sum of contributions exceeds 150. We further observe that almost all of these games reached the threshold. On the other hand, when a bonus is not provided while cheap talk is maintained, a small number of games are played as static games, and the completion rate is much lower than the games with a positive bonus. Over the initial five games, we observed that 4% of games were played as if a static game, but the frequency went down to 0% for the last 10 games. if cheap talk is not provided, it is found that subjects play games as dynamic games at almost all times.

Given these results, it is clear that cheap talk opens non-equilibrium paths to complete a game when contributing equilibria exist. Specially, subjects try to complete the game in one period, as if the game is static, when cheap talk is allowed and a bonus is given. In our games, total contributions after the final period are the only relevant measure of

[4] There are many equilibria that ask one member to invest 70 in the first period while other members are allowed to invest less. For example, the following investment profile, $\{\{70, 15, 15\}, \{0, 25, 30\}, \{0, 25, 30\}\}$, completes the game in 3 periods and one player is required to invest 70 in the first period.

final output. Therefore, there must not be any benefit to completing a project instantly. In reality, it might be costly to make decisions and if subjects are sure that other group members will make significant contributions (or complete the game jointly), it could be efficient to finish the game instantly.

This observed behavior that cannot be explained by theory requires additional investigations. In the following section, we analyze to what extent observed choices could be explained by the theory and we also try to analyze the sources of non-equilibrium choices.

4.5 Statistical and Theoretical Analyses

This section analyzes data in accordance with the theoretical and experimental findings by Marx and Matthews (2000), Duffy et al. (2007), Choi et al. (2008) and Matthews (2013). We investigate whether the theoretical findings and previous experimental results are observed in decisions made in our experiment.

In this section, we first compute *observance rates*. This is the rate at which subjects followed the theoretically supported strategy choice. This criterion is called sequential rationality and is defined as $u_i(x_i^{t-1}, x_{-i}^t) \leq u_i(x)$ for all $t \geq 1, i \in N$ (see further discussions in Section 4.2). We then analyze why some games were played as if static games when cheap talk was allowed. Furthermore, we explore the factors for groups to decide to invest in a one-shot manner.

The analysis of experimental data is difficult because there are many equilibria. Choi et al. (2008) studied whether choices that subjects make would reflect symmetric Markov perfect equilibria instead of subgame perfect Nash equilibria. They observed that contribution behavior reflects the feature of Markov perfect equilibria. Namely, decisions depend only on the outcome-relevant state of the game: the remaining contribution periods and the balance in the public and private accounts. This indicates that subjects are likely to base their decisions on contributions by other members in previous periods. In this section, we investigate whether this type of behavior is observed using panel data estimation methods. We will also investigate whether individual heterogeneity is an important part of contribution behavior. An extreme example of individual heterogeneity leading to the failure of

Nash equilibria to predict decisions by subjects was reported by Duffy et al. (2007).

First, we analyze if subjects have made sequentially rational decisions or not in our experiment. As is shown in Table 4.3, the majority of decisions made in the game were sequentially rational. For games with a strictly positive bonus, there are sequentially rational profiles for a group to complete the public project, and the frequency of subjects making sequentially rational decisions in completed games is between 80% and 90% except the middle and last five games for games with communication. This is because many groups opted to complete the game in the first period, and these groups contributed to the low rates of sequentially rational decisions. On the other hand, the frequency of sequentially rational decisions for games with no bonus is around 50% for completed games. The low rates are expected by the theory because there is no completing strategy profile which allows all decisions to be sequentially rational if there is no bonus.

For incomplete games, we observe a quite different frequency of sequentially rational decisions. First, we observe a much higher frequency for games without any bonus compared to completed games. According to the theory, the unique equilibrium is the non-completion profile if no bonus is provided and the higher frequency of theoretically supported decisions show that theoretically supported decisions should not complete a project. Therefore, it makes sense that we observed a high frequency of sequentially rational decisions in incomplete games without a bonus. On the other hand, subjects in games with a bonus but without communication produced a much lower frequency of sequentially rational decisions in incomplete games. The games with a bonus have a large set of contributing equilibria, but, the non-contributing equilibrium is the only equilibrium, therefore, any profile containing positive contributions contains sequentially irrational choices. As Table 4.1 and Figure 4.4 indicate, a sizable number of games were funded to a large degree albeit the rate of completion was not necessarily high. For example, the share of groups which reached a total contribution of 150 was approximately 64% for groups with communication and 33% for groups without communication. However, these rates went down to approximately 45% and 15% respectively for the threshold, which was set at 210. Among these incomplete games, we observed that the rate of sequentially rational decisions is 10 - 25% higher than the decisions made in completed games. This indicates that many subjects made decisions that

are theoretically supported and groups did not reach the threshold at a high probability, being consistent with theory.

We observe that the frequency of subjects following sequential rationality for groups with a bonus and communication is particularly low for completed projects compared to incomplete games. This also confirms that many groups decided to play dynamic games as if they were static games, and these decisions are not rationalized by sequential rationality.

We also note that the final outcomes yielded mostly individually rational outcomes where individual rationality is defined as a profile y such that $u_i(y) \geq u_i^*(0)$ where $u_i^*(x) = \max_{x_i' \geq x_i} u(x_i', x_{-i}))$. As Table 4.3 shows, 77% or more outcomes are individually rational, meaning that subjects earned positive profits. It confirms that the subjects' decisions are rational in the sense that they seek profits although these profiles might not be sequentially rational.

In general, the differences in frequencies of sequentially rational decisions among different treatment show that subjects indeed follow the behavior predicted by theoretical investigations except for the special cases observed in games with communication. Duffy et al. (2007) found that the contributions made by subjects are largely erroneous. However, our results show that the majority of decisions are not erroneous and observed behavior is consistent with theory. On the other hand, it cannot be ignored that many decisions are not sequentially rational, either. As it is universally seen in experimental studies, deviations from equilibria and sequential rationality are not unusual. In the following analysis, we also show what deviations are seen and where the sources of these deviations are.

< Figure 4.6 >

Figures and tables are attached at the end of this chapter.

We now analyze why some groups ignore the dynamic feature of the game when communication is allowed. We assume that there exist *over-investors* who drive their groups to invest a large amount in the first period as if the game were static. Figure 4.6 shows that groups with particular individuals are more likely to invest 210 in the initial period if a bonus is given and communication is allowed. However, it is not the case when a bonus is not given and communication is not allowed. In order to identify such individuals, we

estimate the following model;

$$Y_c^* = \text{constant}_c + I_c\beta_c + t_c\gamma_c + \epsilon \tag{4.3}$$

where the game is played as if static when $Y_c^* > 0$ and

the game is played as a dynamic game otherwise.

The vector Y_c^* is an unknown vector of $K \times 1$ latent variables where K is the number of games played under the control environment c. It means that the model is estimated for each of four controls. The vector constant_c has the same dimension as well. The matrix I_c is $K \times (N-1)$ and is a collection of vector $1 \times (N-1)$, which consists of dummy variables for each subject. The matrix t_c is $K \times 2$ and consists of dummy variables for the middle and last 5 games played in the particular session.

< Table 4.4 >

Figures and tables are attached at the end of this chapter.

In the equation above, we define that a game is played as if static if three group members invested a minimum of 150 in total, provided each invested at least 40 in the first period. We assume that error terms are identically and independently distributed according to the extreme-I (logit) distribution. This model assumes that there are agents who suggest that the entire group should finish the game in one period when communication is allowed, and actually influence others to do so when they are asked to make individual and anonymous decisions in the first period. Table 4.4 indicates the result of the estimation above for games with a bonus. We observe that there are such individuals who convince their groups to invest a large amount in the first period. We especially observe that there are three such subjects out of 18 when a bonus is given in addition to communication at the 10% confidence level. There also are two individuals who discourage such strategies. These results are robust to other specifications (for example, four out of five statistically significant estimates remain significant when we have an additional restriction that requires all subjects to invest a minimum of 40 each).

< Table 4.5 >

Figures and tables are attached at the end of this chapter.

As Table 4.5 indicates that those individuals who encourage other subjects to invest in a one-shot manner influence other group members to play the game as a one-shot game in most cases, and the frequency of successful completion is large. This indicates that heterogeneity plays a significant role in contribution behavior and makes an out-of-equilibrium strategy profile possible. On the other hand, we observe that those individuals who discourage other subjects to invest in a one-shot manner influence other members to play the game as a dynamic game, and the frequency of successful completion is much smaller.

These results indicate that individual heterogeneity is a major source of differences in decisions that subjects make. Choi et al. (2008) found that subjects follow symmetric equilibria in general. However, our experimental study shows that it is not necessarily the case when the set of choices is much larger. As has been shown by Choi et al. (2008) and Battaglini et al. (2012), symmetry among subjects is a key aspect of identifying Markov perfect equilibria. Moreover, as has been shown by Matthews (2012) and Marx and Matthews (2000), it is not clear if there is any way to predict outcomes when more general subgame perfect equilibria are used for analysis.

Due to the reasons above, it is difficult to construct a structural model that fully reflects the theoretical findings to analyze decision making patters of subjects using the data we obtained. Instead, our analysis focuses on a few features observed and predicted in previous studies. Namely, we analyze whether subjects condition their investment decisions on previous contributions by other members. We also investigate if individual heterogeneity plays a significant role or not. In the following models, a panel consists of a maximum of seven decisions made by a subject in a game. Each subject played 15 games, therefore, there are 15 panels for each subject.

Our estimation models are as follows:

$$\text{Model 1-a} \quad g^c_{i,\zeta}(t) = \text{constant}^c + I^c\beta^c + \bar{g}^c_{-i,\zeta}(t-1)\gamma^c + \nu^c_{i,\zeta} + \epsilon^c_{i,\zeta}(t) \tag{4.4}$$

$$\text{Model 1-b} \quad g^c_{i,\zeta}(t) = \text{constant}^c + I^c\beta^c + g^c_{-i,\zeta}(t-1)\theta^c + \nu^c_{i,\zeta} + \epsilon^c_{i,\zeta}(t) \tag{4.5}$$

$$\text{where } \epsilon^c_{i,\zeta}(t) = \rho_c\epsilon^c_{i,\zeta}(t-1) + \eta^c_{i,\zeta}(t)$$

$$\text{Model 2-a} \quad g^c_{i,\zeta}(t) = \text{constant}^c + I^c\beta^c + \bar{g}^c_{-i,\zeta}(t-1)\gamma_c + t^c_{i,\zeta}\tau^c + \nu^c_{i,\zeta} + e^c_{i,\zeta}(t) \tag{4.6}$$

$$\text{Model 2-b} \quad g^c_{i,\zeta}(t) = \text{constant}^c + I^c\beta^c + g^c_{-i,\zeta}(t-1)\theta^c + t^c_{i,\zeta}\tau^c + \nu^c_{i,\zeta} + e^c_{i,\zeta}(t) \tag{4.7}$$

for all i, c, ζ

The dependent variable $g^c_{i,\zeta}(t)$ is the contribution made by the subject i who was in the control c experiment in period t in some game ζ in which the subject participated. It means that there are multiple panels for each individual since each subject participated in multiple games (in our study, the number is 15). The vector I_c is $1 \times (N-1)$ and it is a collection of individual dummy variables while the first subject is omitted. Therefore, β_c is $(N-1) \times 1$ and this is the collection of subject-specific shifts in intercept. The variable $\bar{g}_{-i}(t-1)$ is the average of the contributions per person made by the other two members of the same game in periods $\{1, ..., t-1\}$. The average contributions are further converted into factors of intervals $\{[5, 10), [10, 15), [15, 20), [20, 25), [25, 30), [30, \infty)\}$. Therefore the vector, $\bar{g}_{-i}$, is 1×6 and γ_c is 6×1. Similarly, $g_{-i}(t-1)$ is a 1×6 vector of contributions made by other members in immediately preceding period factored into the same intervals as the average contributions. The vector t is the collection of dummy variables for periods 3 through 7, and the dimension is 1×5.

For the first two models, the variables ν, ϵ, and η are all error terms. The error term ν is specific to each panel and distributed *i.i.d.* The another error term η are distributed *i.i.d.* over the 7 period but ϵ has the autoregressive feature as described in the equation. In the two other models, e is an *i.i.d.* error term that varies across the 7 periods, and ν is specific to each panel and distributed *i.i.d.*

Our first and second models assume that the individual error terms are autoregressive. This means that contributions made in previous periods affect decisions in the current

period. This model is related to the third and fourth models, which do not assume autoregressive error term. We do include dummy variables for each period for these models, however.

< Table 4.6 >

Figures and tables are attached at the end of this chapter.

Tables 4.6-a and 4.6-b show the results of the unbalanced panel analyses on contributions in period 2 and proceeding periods described above. Tables 4.6-a shows the results in abbreviated form, and does not include estimated coefficients for individual dummies, whereas Table 4.6-b includes all estimates.

First of all, across all four different treatments, we see that estimates of coefficients between autoregressive models and period-dummy models agree with each other in general. For different treatments, we observe that games with a bonus but no communication are very different from games in other treatments. Almost all estimates are not statistically significant except for the intercepts for games with a bonus but no communication. This means that decisions that subjects make are either random, predetermined or dependent on other factors that are not included as independent variables. We discussed previously that a large number of games with a bonus and communication were completed in the first period in a one-shot game manner, and it is because the behavior was predetermined in communication. These regression results show that subjects do not change their contributions in response to other members' contributions, supporting the idea that communication is very effective in enforcing the contributing profiles and strategies.

< Table 4.7 >

Figures and tables are attached at the end of this chapter.

On the other hand, when a bonus is given but no communication is allowed, we observe that subjects react to lagged contributions by other members. When other members contribute more, one contributes more too. However, the reaction is not one-to-one. Table 4.7 shows marginal effects of lagged investments by other subjects. A subject increases his or her investment by a small amount between 0.36 and 1.81 with an average of 0.66 as the

other subjects increase their investments by 5, on average. This means that contributions by subjects depend on previous investments by other subjects, but, marginal effects are not one-to-one.

The same pattern exists for games without a bonus. However, the reaction of subjects to lagged investments by other subjects are more significant. The marginal investment of lagged contributions by others generally falls between 0.3 and 7.4 per 5 unit increase in an investment by other subjects with three negative observations, -2.00, -9.66, and -1.34. This is much larger in absolute value than games with a bonus but no communication. This means that subjects react more if no bonus is given. As has been discussed, there are no contributing equilibria for games with no bonus when the grim strategy is used. Therefore, there should not be any investment profile that everyone can agree on prior to the game. The result indicates that subjects relied on tit-for-tat more heavily than in the games with a bonus.

It is important to note that marginal investment is negative between the 25-30 range and 30+ when a bonus is not given. The estimated marginal investments are -9.66 and -1.34 respectively. This indicates that subjects free-ride on other members' investments. Since the marginal return of investment is always negative, it makes sense to free-ride on others when other members are contributing a large amount to the public good.

It is also remarkable that estimated coefficients on average contributions by other members for all previous periods are significant for games without a bonus unlike games with a bonus. This also indicates that subjects are more sensitive to other contributions in previous periods. In general, subjects increase their investment by a small amount, 1.11 and 0.67 for communication and no communication treatments respectively, given a 5-unit increase in average contributions for all previous periods.

We will now turn our attention to effects of contributing periods estimated using Models 2-a and 2-b. Table 4.6-a shows the estimates for dummy variables for each period. Except for the communication and bonus treatment, for which no estimates are statistically significant, we observe that subjects tend to invest less as a game progresses. It was also shown by Choi et al. (2008) that subjects tend to invest more in beginning stages of the game and decrease their investments as a game progresses. Our results are consistent with the finding

by Choi et al. (2008).

Lastly, we discuss heterogeneity among subjects. Table 4.6-b shows estimated shifts for each individual, and Table 4.6-a shows a summary of the estimates. First of all, no individual effects are statistically significant for communication and bonus treatment. On the other hand, other treatments show significant individual heterogeneity. For the model with a bonus but no communication, we observe that 8 out of 11 individual effects are found significant for all four models. For the model with communication but no bonus, we found between 3 and 5 out of 14 individual effects are found significant, depending on the models. For the model without communication nor a bonus, we found that 8 or 9 out of 17 individual effects are found significant depending on the models. Although here are slight variations in the number of statistically significant effects depending on models, the estimated coefficients clearly show that individual heterogeneity is a very important part of investment decision.

In sum, we observe that subjects refer to previous contributions made by other members when they decide on their contributions. We generally observe that members would contribute more when other members contribute more. Indications of free-riding are found for very limited cases where some members contribute a excessively large amount (such as 30 or more). We found that when a bonus is not given, previous group contributions are more influential compared to games with a bonus. When a bonus is not provided, there is no contributing equilibrium, and this means that subjects would not have a contributing profile. Therefore, it is reasonable that subjects rely on other information to make decisions such as previous group contributions.

4.6 Concluding Remarks

Our experimental study revisited the dynamic voluntary contribution game previously studied by Marx and Matthews (2000), Duffy et al. (2007), Choi et al. (2008) and Matthews (2013). These theoretical studies in general do not produce any meaningful insights on how subjects choose one equilibrium over another. An experimental study was conducted by Duffy et al. (2007) and found that subjects largely get confused and do not follow any

equilibrium. On the other hand, another experimental study by Choi et al. (2008) found that the behavior of subjects generally follows theoretical findings.

In our study, we found that the majority of decisions that subjects made by our experiment can be explained by the framework of theoretical investigations by Marx and Matthews (2000) and subsequent literature. Furthermore, the systematic deviations found by Choi et al. (2008) were also observed in our experiment; namely, that in general subjects invested more in initial periods. There has been no theoretically convincing study that explains the reason behind this. We also found evidence that individual heterogeneity plays a significant role as was found by Duffy et al (2007). Although individual heterogeneity plays a significant role, subjects react to different parameter settings. We observed significantly larger contributions when a bonus was provided. However, due to heterogeneity, we did not observe contributions being symmetrical as was assumed in the theoretical investigations by Choi et al. (2008).

Our results are at the middle-ground between the findings of Choi et al. (2008) and Duffy et al. (2007) where Choi et al. (2008) found strong evidence to support their refinements of broader solution concepts provided by Marx and Matthews (2000) whereas Duffy et al. (2007) found that the theoretical findings do not reflect subjects' behavioral patterns.

Our findings further indicate that without communication, subjects tend to behave as non-cooperative agents. However, when subjects were given an opportunity to communicate with each other, we observed that subjects cooperated with each other for the public good. Experimental studies that were conducted previously did not allow subjects to communicate with each other, and these studies found that subjects were reluctant to make contributions. This lack of cooperation, together with the structure of the games that might have made subjects intolerant of trembling hands, resulted in many groups failing to reach the goal.

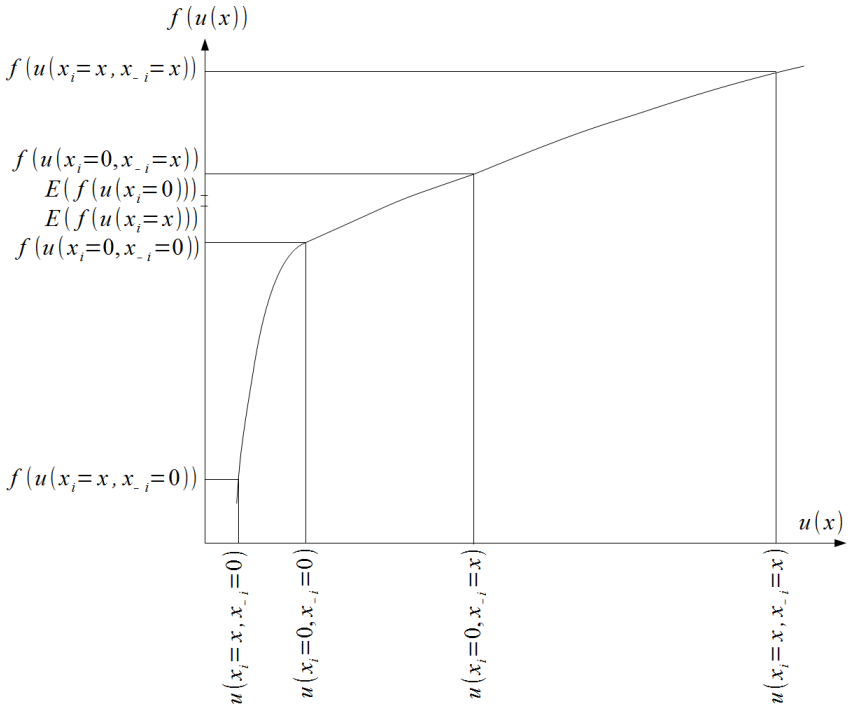
Although it is still too early to conduct a comprehensive evaluation of the performance of Accountable Care Organizations, experts have identified that communication is a key component of a successful ACO. However, partly due to regulations, practitioners rely on conventional modes of communication such as the telephone in order to communicate with each other, and these modes of communication are unnecessarily slowing down doctors' decision making and imposing unnecessary costs to doctors and patients (Kelly, 2013). Our

experiment would seem to imply that this is where payers such as Medicare and ACOs can work together to improve the efficiency of communication so that practitioners can become more cooperative. Most importantly, practitioners in ACOs must be given clear incentives for their collaborative efforts, and these potential incentives must be communicated clearly prior to forming an ACO. Although this experimental study demonstrated that communication helps subjects to behave cooperatively, there must be non-cooperative contributing equilibria for subjects to be cooperative. There have been many criticisms of the current performance measures and ACOs are facing a risk of not receiving incentives even after making efforts to reduce the cost of medical care. Therefore, each ACO contract should be tailored in such a way that the ACO is able to foresee their bonus given the level of effort that they exert. This is because the mappings from actions to payoffs, as in any naturally occurring environment, is not as neat and clear as it is in a experiment.

In sum, this study found that subjects are able to overcome the free-rider problem in many ways. Conventional theoretical studies are capable of finding non-cooperative equilibria that reflect subjects' behavior. These theoretical studies in general rely on punishment strategies such as the *grim* strategy. However, there might be other enforcing mechanisms that are as effective as punishment strategies. Our study found that communication is a powerful tool that allows subjects to overcome the free-rider problem and behave cooperatively. Future studies should investigate if there would be any other enforcing mechanism that overcomes the free-rider problem and encourages subjects to furnish the public good.

Figure 4.1: Concave Transformation of Earnings

(a) Figure 4.1-a: Concave Transformation of Earnings when Endowment is Small



(b) Figure 4.1-b: Concave Transformation of Earnings when Endowment is Large

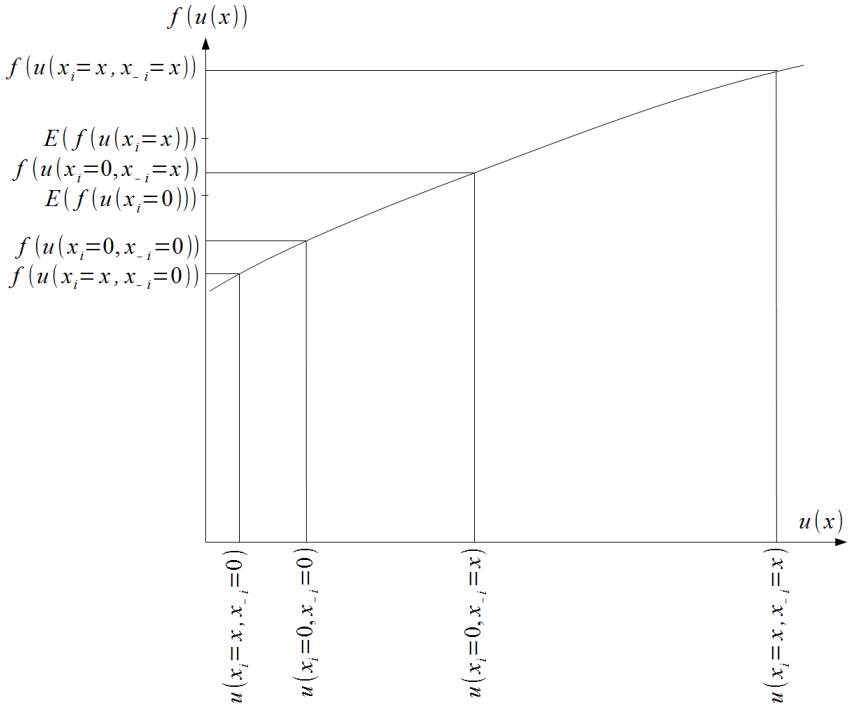


Figure 4.2: Total Group Contributions (No Bonus)

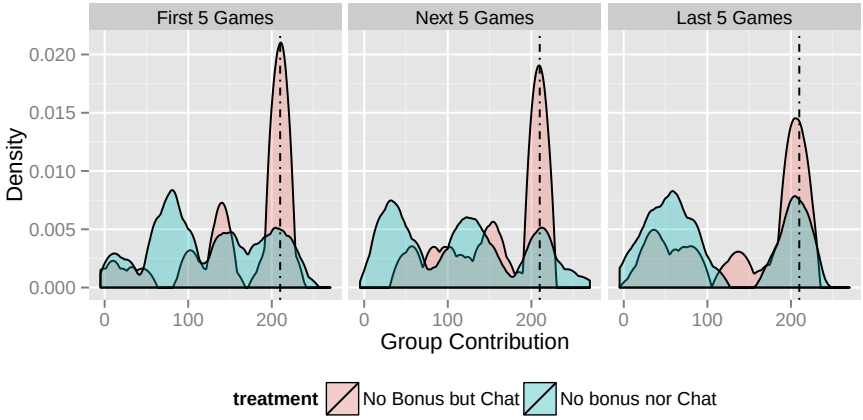


Figure 4.3: Total Group Contributions (With Bonus)

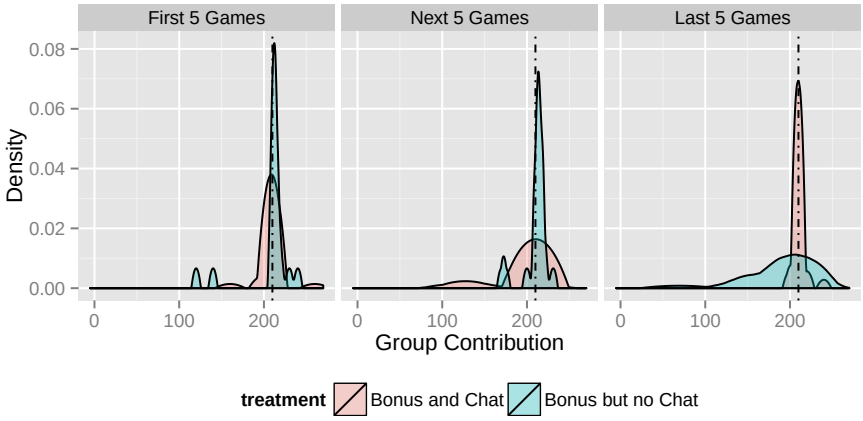


Figure 4.4: Group Investment

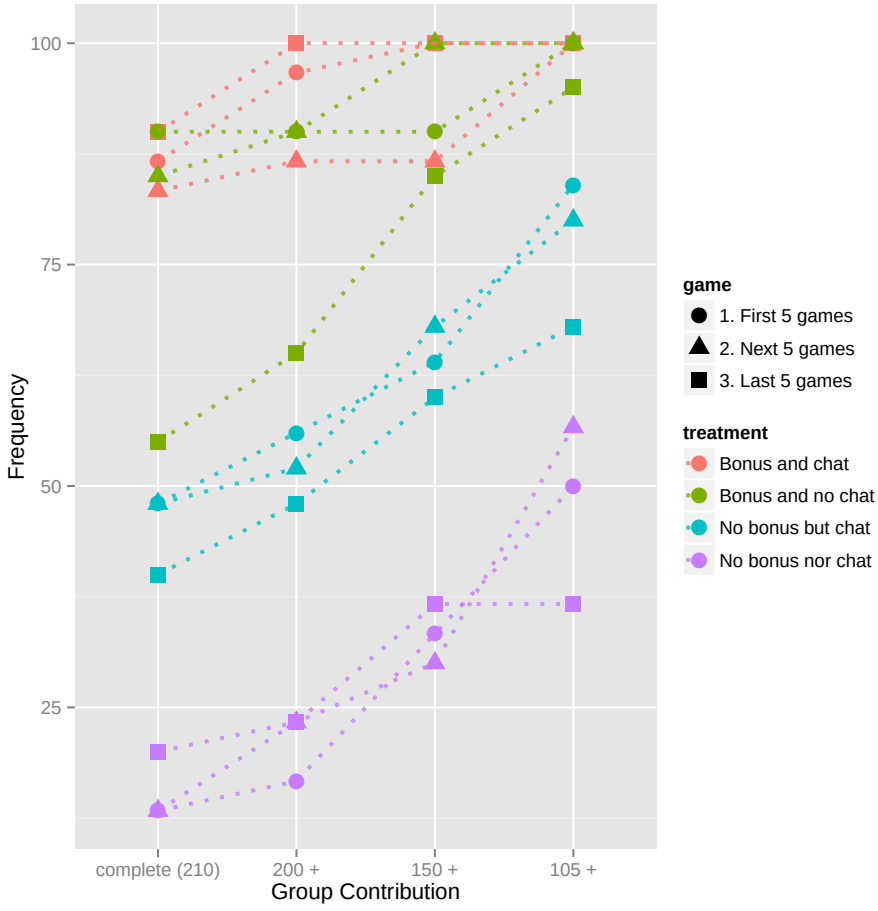
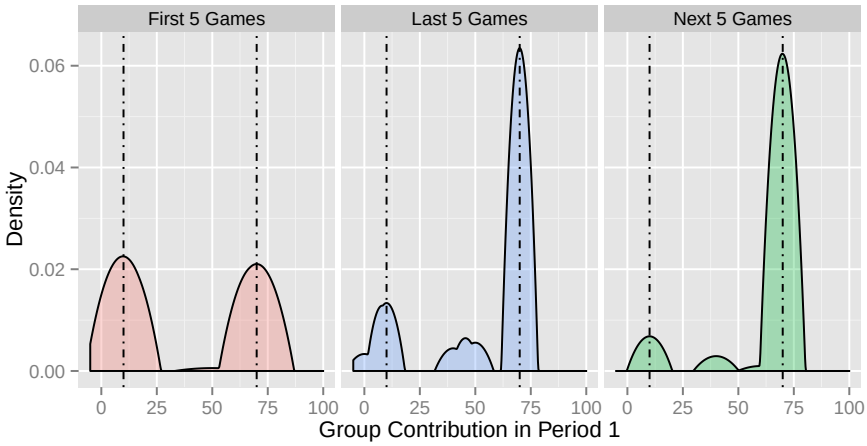


Figure 4.5: First period contributions

Figure 4.5-a
Control: Bonus and chat



Control: Bonus but no chat

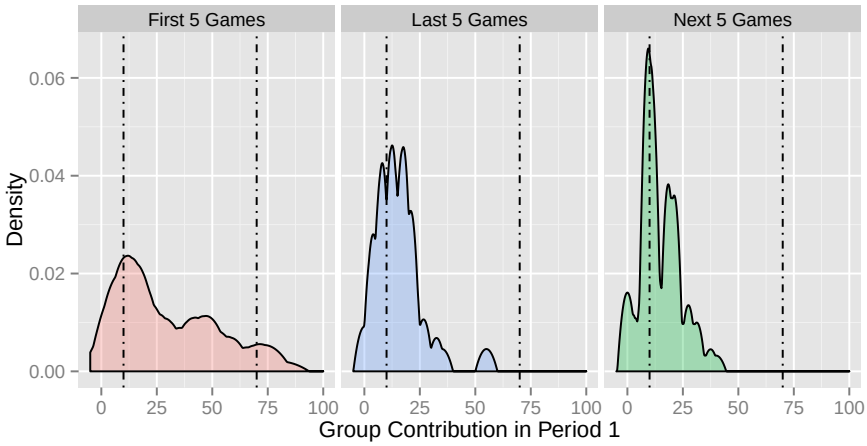
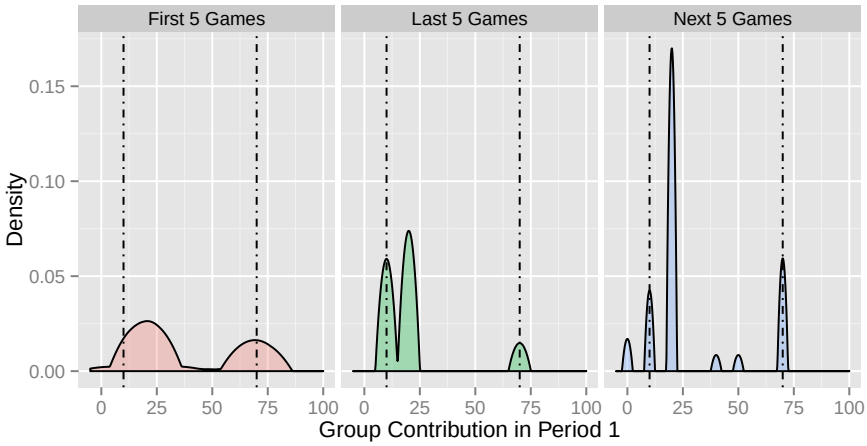


Figure 4.5 (cont): First period contributions

Figure 4.5-b
Control: No bonus but chat



Control: No bonus nor chat

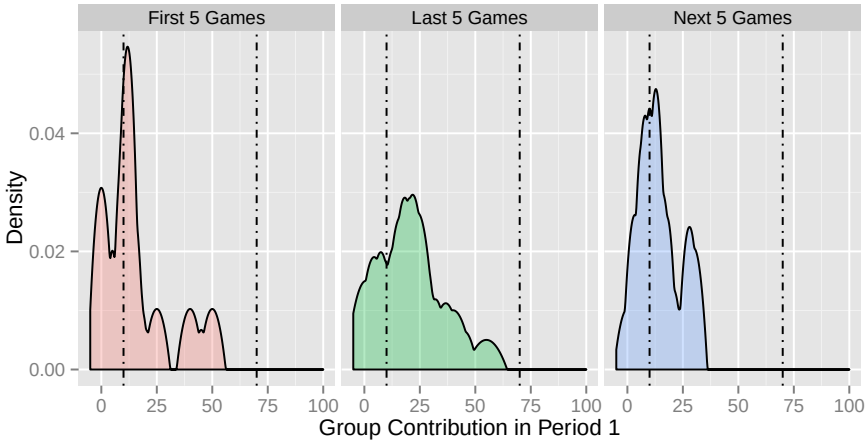
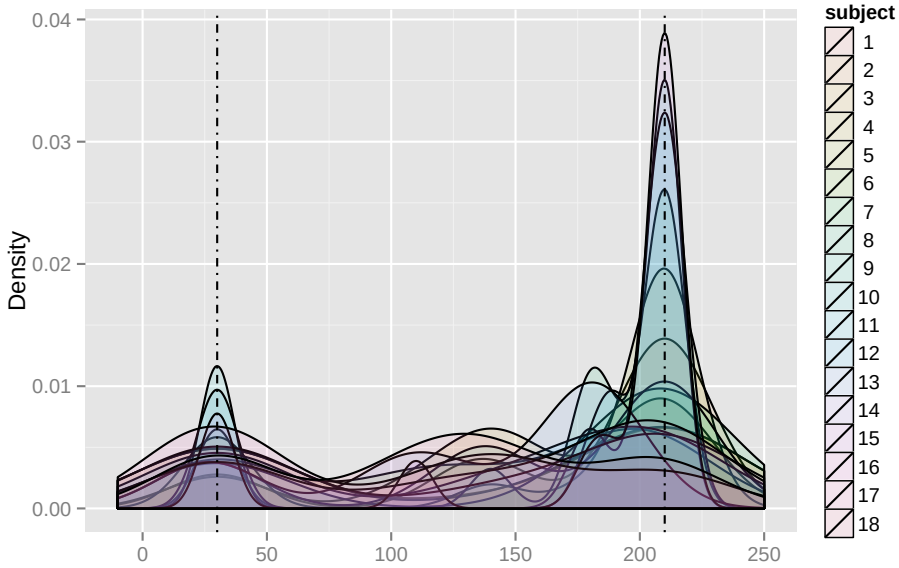


Figure 4.6: First period group investments in groups which each subject participated.

(a) Figure 4.6-a: First period group investments in groups which each subject participated. Chat and bonus treatment.



(b) Figure 4.6-b: First period group investments in groups which each subject participated. Chat and no bonus treatment.

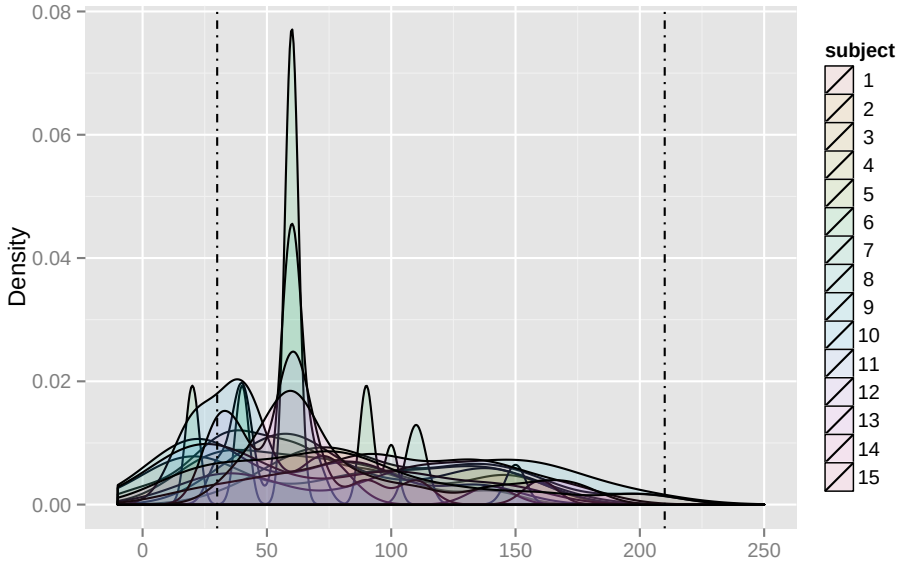


Table 4.1: Descriptive Statistics

bonus	game	chat	# games	Group Investment mean	median	min	max	Frequency of games with total investment exceeding 210 (in %)	200 (in %)	150 (in %)	105 (in %)
20	First 5	yes	30	209.00	210.00	160.00	260.00	86.67	96.67	100.00	100.00
20	Second 5	yes	30	201.63	210.00	110.00	280.00	83.33	86.67	86.67	100.00
20	Last 5	yes	30	210.83	210.00	200.00	240.00	90.00	100.00	100.00	100.00
20	First 5	no	20	206.85	212.50	120.00	240.00	90.00	90.00	90.00	100.00
20	Second 5	no	20	210.30	213.50	170.00	231.00	85.00	90.00	100.00	100.00
20	Last 5	no	20	190.25	210.00	69.00	227.00	55.00	65.00	85.00	95.00
0	First 5	yes	25	164.44	207.00	0.00	223.00	48.00	56.00	64.00	84.00
0	Second 5	yes	25	162.88	200.00	50.00	210.00	48.00	52.00	68.00	80.00
0	Last 5	yes	25	148.08	190.00	20.00	210.00	40.00	48.00	60.00	68.00
0	First 5	no	30	121.97	111.00	1.00	234.00	13.33	16.67	33.33	50.00
0	Second 5	no	30	113.63	114.00	13.00	254.00	13.33	23.33	30.00	56.67
0	Last 5	no	30	109.13	76.50	8.00	222.00	20.00	23.33	36.67	36.67

bonus	game	chat	# games	Frequency of games played as if static (in %)	nonstatic (in %)	Frequency of games played as if dynamic and completed	static and completed	dynamic and not completed	static and not completed	Sum
20.00	First 5	yes	30	40.00	60.00	46.67%	40.00%	13.33%	0.00%	100.00%
20.00	Second 5	yes	30	73.00	27.00	10.00%	73.33%	16.67%	0.00%	100.00%
20.00	Last 5	yes	30	60.00	40.00	30.00%	60.00%	10.00%	0.00%	100.00%
20.00	First 5	no	20	5.00	95.00	85.00%	5.00%	10.00%	0.00%	100.00%
20.00	Second 5	no	20	0.00	100.00	85.00%	0.00%	15.00%	0.00%	100.00%
20.00	Last 5	no	20	0.00	100.00	55.00%	0.00%	45.00%	0.00%	100.00%
0.00	First 5	yes	25	4.00	96.00	44.00%	4.00%	52.00%	0.00%	100.00%
0.00	Second 5	yes	25	0.00	100.00	48.00%	0.00%	52.00%	0.00%	100.00%
0.00	Last 5	yes	25	0.00	100.00	40.00%	0.00%	60.00%	0.00%	100.00%
0.00	First 5	no	30	0.00	100.00	13.33%	0.00%	86.67%	0.00%	100.00%
0.00	Second 5	no	30	0.00	100.00	13.33%	0.00%	86.67%	0.00%	100.00%
0.00	Last 5	no	30	0.00	100.00	20.00%	0.00%	80.00%	0.00%	100.00%

Table 4.2: Chi Square Test

	Bonus & Chat		Bonus but no chat		No bonus but chat	
	χ^2	P-value	χ^2	P-value	χ^2	P-value
Bonus but no chat	1.8630	0.1723	NA	NA	NA	NA
No bonus but chat	30.1872	0.0000	12.2885	0.0005	NA	NA
No bonus nor chat	88.2436	0.0000	53.5012	0.0000	16.1712	0.0001

Table 4.3: Frequencies of Sequentially and Individually Rational Decisions

bonus	game	chat	# of observations	Follow rate for all decisions: Completed Games	Incomplete Games	Total
20	First 5 games	yes	30	88.05%	78.57%	86.07%
20	Second 5 games	yes	30	55.10%	81.90%	66.27%
20	Last 5 games	yes	30	72.15%	69.84%	71.67%
20	First 5 games	no	20	88.33%	59.52%	84.80%
20	Second 5 games	no	20	90.12%	58.73%	85.01%
20	Last 5 games	no	20	89.06%	69.84%	79.53%
0	First 5 games	yes	25	51.06%	74.73%	66.67%
0	Second 5 games	yes	25	53.09%	74.73%	66.67%
0	Last 5 games	yes	25	66.07%	80.32%	75.36%
0	First 5 games	no	30	50.00%	65.93%	64.50%
0	Second 5 games	no	30	50.00%	70.51%	68.30%
0	Last 5 games	no	30	54.02%	72.62%	69.88%

bonus	game	chat	Follow rate for 1st period decisions: Completed Games	Incomplete Games	Total	Frequency of individually rational Outcomes
20	First 5 games	yes	53.85%	91.67%	58.89%	98.89%
20	Second 5 games	yes	17.33%	46.67%	22.22%	92.22%
20	Last 5 games	yes	35.80%	66.67%	38.89%	97.78%
20	First 5 games	no	81.48%	50.00%	78.33%	93.33%
20	Second 5 games	no	94.12%	66.67%	90.00%	93.33%
20	Last 5 games	no	87.88%	81.48%	85.00%	93.33%
0	First 5 games	yes	55.56%	53.85%	54.67%	77.33%
0	Second 5 games	yes	66.67%	53.85%	60.00%	88.00%
0	Last 5 games	yes	80.00%	48.89%	61.33%	80.00%
0	First 5 games	no	66.67%	61.54%	62.22%	80.00%
0	Second 5 games	no	75.00%	65.38%	66.67%	78.89%
0	Last 5 games	no	55.56%	59.72%	58.89%	77.78%

Table 4.4: Individual marginal effect on Game to be played as static game (Bonus and Chat treatment)

	Estimate	Std. Error	z value	Pr($>\|z\|$)	
(Intercept)	-1.36	2.61	-0.52	0.6019	
Player 2	2.07	1.25	1.66	0.0977	E
Player 3	1.54	1.18	1.30	0.1932	
Player 4	-0.34	1.36	-0.25	0.8051	
Player 5	0.50	1.44	0.34	0.7304	
Player 6	-1.31	1.33	-0.99	0.3226	
Player 7	0.37	1.10	0.34	0.7376	
Player 8	2.06	1.21	1.71	0.0872	E
Player 9	-0.51	1.33	-0.38	0.7031	
Player 10	0.79	1.21	0.65	0.5135	
Player 11	2.08	1.60	1.29	0.1957	
Player 12	0.32	1.44	0.22	0.8247	
Player 13	-0.77	1.18	-0.65	0.5151	
Player 14	-0.91	1.16	-0.78	0.4332	
Player 15	3.14	1.61	1.94	0.0518	E
Player 16	-0.02	1.33	-0.01	0.9887	
Player 17	-2.72	1.40	-1.95	0.0515	D
Player 18	-2.10	1.13	-1.85	0.0638	D
Second 5 games	3.14	0.97	3.22	0.0013	
Last 5 games	1.77	0.77	2.32	0.0205	

E: Individuals who encourage games to be played in a one-shot manner.
D: Individuals who discourage games to be played in a one-shot manner.

Table 4.5: Games played by influencial individuals (Chat and Bonus treatment)

		Game Completed	
		No	Yes
One-shot Encouraged			
Game played as ststic	No	1	10
	Yes	0	34
One-shot Discouraged			
Game played as ststic	No	9	13
	Yes	0	8

Table 4.6-a: Unbalanced Panel Model

		Unbalanced Panel Analysis (Bonus but no Chat)								Unbalanced Panel Analysis (Bonus but Chat)							
		Autregressive 1		Autregressive 2		Period Dummy 1		Period Dummy 2		Autregressive 1		Autregressive 2		Period Dummy 1		Period Dummy 2	
		Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
2.Average Other Contributions So Far Between	[5,10)	-0.717	1.38			0.745	1.26			0.271	2.59			-0.211	2.13		
3.Average Other Contributions So Far Between	[10,15)	-0.801	1.38			0.704	1.25			0.93	2.76			0.531	2.31		
4.Average Other Contributions So Far Between	[15,20)	-0.14	1.46			-0.167	1.31			-0.793	2.75			-1.332	2.31		
5.Average Other Contributions So Far Between	[20,25)	-0.135	1.67			-0.952	1.52			2.02	2.99			1.225	2.62		
6.Average Other Contributions So Far Between	[25,30)	2.026	2.32			0.872	2.19			0.067	2.89			-1.252	2.51		
7.Average Other Contributions So Far Between	30+	1.785	1.94			-0.551	1.79			1.108	2.76			-0.973	2.38		
2.Lagged Other Contribution Between	[5,10)			2.291**	0.84			1.738*	0.82			-2.228	1.15			-2.804**	1.07
3.Lagged Other Contribution Between	[10,15)			3.954***	0.85			3.260***	0.83			-1.173	1.28			-1.453	1.34
4.Lagged Other Contribution Between	[15,20)			4.316***	0.98			2.872**	0.98			-1.355	2.89			-0.783	2.7
5.Lagged Other Contribution Between	[20,25)			4.937***	1.22			2.452*	1.24			1.278	3.01			1.354	2.7
6.Lagged Other Contribution Between	[25,30)			6.750***	1.63			4.759**	1.67			-2.486	3.91			-3.377	3.61
7.Lagged Other Contribution Between	30+			7.410***	1.49			4.441**	1.56			0.527	0.94			-0.403	1.03
3.Period						-1.758*	0.87	-1.283	0.86					-0.053	0.64	0.359	0.71
4.Period						-2.841**	0.89	-1.936*	0.89					-0.912	0.69	-0.333	0.72
5.Period						-4.037***	0.91	-2.989***	0.91					-1.154	0.7	-0.7	0.72
6.Period						-6.266***	0.97	-4.732***	0.97					-0.267	0.71	0.321	0.72
7.Period						-6.048***	1.08	-4.009***	1.09					-0.252	0.72	0.262	0.74
Constant		11.901***	1.71	8.263***	1.28	14.296***	1.55	11.524***	1.3	8.524*	4.11	9.892**	3.34	9.395	5.13	10.033*	4.82
Number of Statistically Significant Individual Dummies^{+}		8		8		8		8		0		0		0		0	
Number of Individual Dummies (N-1)		11		11		11		11		17		17		17		17	
Max		7.598		7.904		6.731	1.37	7.337		12.79		12.052		14.466		13.641	
Min		-9.553		-9.65		-9.314	1.28	-9.651		-5.879		-6.284		-5.521		-6.135	
Average		-1.805		-1.7741818		-1.8567273	1.32	-1.9043636		0.4314706		0.1498235		1.0292941		0.6261765	
* p<0.05, ** p<0.01, *** p<0.001, + at 5% level																	
N		927		930		927		930		684		684		684		684	

		Unbalanced Panel Analysis (No Bonus but Chat)								Unbalanced Panel Analysis (No Bonus and No Chat)							
		Autregressive 1		Autregressive 2		Period Dummy 1		Period Dummy 2		Autregressive 1		Autregressive 2		Period Dummy 1		Period Dummy 2	
		Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
2.Average Other Contributions So Far Between	[5,10)	2.316*	0.91			1.817*	0.9			2.657***	0.44			2.275***	0.42		
3.Average Other Contributions So Far Between	[10,15)	2.966**	1.05			2.800**	1.07			3.220***	0.56			2.616***	0.55		
4.Average Other Contributions So Far Between	[15,20)	7.749***	1.01			6.281***	1.16			5.778***	0.83			4.617***	0.82		
5.Average Other Contributions So Far Between	[20,25)	5.520***	1.37			4.061**	1.53			7.606***	1.04			5.937***	1.03		
6.Average Other Contributions So Far Between	[25,30)	7.390***	1.63			3.940*	1.82			5.881***	1.72			3.969*	1.7		
7.Average Other Contributions So Far Between	30+	8.791***	1.17			4.552**	1.43			5.995**	1.89			3.846*	1.84		
2.Lagged Other Contribution Between	[5,10)			1.998**	0.74			0.85	0.77			3.009***	0.41			2.340***	0.43
3.Lagged Other Contribution Between	[10,15)			3.593***	0.7			1.788*	0.78			5.343***	0.51			4.368***	0.54
4.Lagged Other Contribution Between	[15,20)			3.921**	1.28			2.362	1.3			3.343***	0.89			2.368**	0.92
5.Lagged Other Contribution Between	[20,25)			9.471***	0.85			7.163***	1.03			5.427***	1.06			4.324***	1.08
6.Lagged Other Contribution Between	[25,30)			16.874***	2.84			14.286***	2.88			9.182***	1.18			8.090***	1.21
7.Lagged Other Contribution Between	30+			7.210***	0.86			4.278***	1.08			7.838***	1.31			6.515***	1.32
3.Period						-1.979**	0.71	-0.504	0.72					-0.631	0.57	0.186	0.56
4.Period						-4.758***	0.75	-2.963***	0.74					-1.791**	0.58	-0.644	0.57
5.Period						-4.439***	0.83	-2.695**	0.83					-2.524***	0.59	-1.259*	0.59
6.Period						-4.403***	0.88	-3.060***	0.87					-3.662***	0.6	-2.325***	0.61
7.Period						-4.102***	0.88	-2.966***	0.89					-4.098***	0.61	-2.591***	0.63
Constant		2.333	1.54	2.656*	1.22	6.662***	1.94	6.045***	1.71	1.192	0.84	1.238	0.8	3.747***	0.92	2.799**	0.93
Number of Statistically Significant Individual Dummies^{+}		4		6		3		3		9		9		9		8	
Number of Individual Dummies (N-1)		14		14		14		14		17		17		17		17	
Max		6.044		5.198		6.236		5.686		21.842		21.067		21.253		20.806	
Min		-5.596		-4.793		-5.865		-5.224		-3.506		-2.879		-3.477		-2.955	
Average		-0.1746429		0.1467857		-0.2864286		-0.0300714		1.8283529		1.5395882		1.7140588		1.4908235	
* p<0.05, ** p<0.01, *** p<0.001, + at 5% level																	
N		1061		1107		1061		1107		1490		1532		1490		1532	

Table 4.6-b: Unbalanced Panel Model - Detailed

		Unbalanced Panel Analysis (Bonus but no Chat)								Unbalanced Panel Analysis (Bonus but Chat)							
		Autregressive 1		Autregressive 2		Period Dummy 1		Period Dummy 2		Autregressive 1		Autregressive 2		Period Dummy 1		Period Dummy 2	
		Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
2.Average Other Contributions So Far Between	[5,10)	-0.717	1.38			0.745	1.26			0.271	2.59			-0.211	2.13		
3.Average Other Contributions So Far Between	[10,15)	-0.801	1.38			0.704	1.25			0.93	2.76			0.531	2.31		
4.Average Other Contributions So Far Between	[15,20)	-0.14	1.46			-0.167	1.31			-0.793	2.75			-1.332	2.31		
5.Average Other Contributions So Far Between	[20,25)	-0.135	1.67			-0.952	1.52			2.02	2.99			1.225	2.62		
6.Average Other Contributions So Far Between	[25,30)	2.026	2.32			0.872	2.19			0.067	2.89			-1.252	2.51		
7.Average Other Contributions So Far Between	30+	1.785	1.94			-0.551	1.79			1.108	2.76			-0.973	2.38		
2.Lagged Other Contribution Between	[5,10)			2.291**	0.84			1.738*	0.82			-2.228	1.15			-2.804**	1.07
3.Lagged Other Contribution Between	[10,15)			3.954***	0.85			3.260***	0.83			-1.173	1.28			-1.453	1.34
4.Lagged Other Contribution Between	[15,20)			4.316***	0.98			2.872**	0.98			-1.355	2.89			-0.783	2.7
5.Lagged Other Contribution Between	[20,25)			4.937***	1.22			2.452*	1.24			1.278	3.01			1.354	2.7
6.Lagged Other Contribution Between	[25,30)			6.750***	1.63			4.759**	1.67			-2.486	3.91			-3.377	3.61
7.Lagged Other Contribution Between	30+			7.410***	1.49			4.441**	1.56			0.527	0.94			-0.403	1.03
2.individual		-3.965*	1.58	-4.038**	1.54	-3.988**	1.3	-4.061**	1.28	-1.284	5	-1.565	4.89	-1.604	7.23	-1.975	7.22
3.individual		3.359*	1.62	3.432*	1.57	3.204*	1.33	3.275*	1.31	-5.879	4.37	-6.284	4.3	-5.521	6.26	-6.135	6.27
4.individual		-9.553***	1.56	-9.650***	1.52	-9.314***	1.28	-9.651***	1.27	7.782	4.52	7.662	4.41	9.081	6.57	9.078	6.55
5.individual		0.054	1.64	-0.185	1.6	-0.05	1.36	-0.25	1.34	-2.741	4.99	-2.636	4.87	-2.588	7.23	-2.595	7.21
6.individual		-4.855**	1.58	-4.729**	1.54	-4.868***	1.3	-4.937***	1.28	-0.706	4.09	-1.135	4.01	0.014	5.89	-0.549	5.88
7.individual		-3.452*	1.57	-3.132*	1.54	-3.452**	1.29	-3.201*	1.28	1.231	4.92	1.027	4.8	1.424	7.18	1.172	7.16
8.individual		0.207	1.6	0.167	1.56	-0.237	1.32	-0.1	1.3	0.542	4.59	-0.033	4.5	1.103	6.61	0.24	6.61
9.individual		7.598***	1.65	7.904***	1.61	6.731***	1.37	7.337***	1.35	-4.334	4.54	-4.509	4.44	-4.04	6.59	-4.317	6.58
10.individual		-2.339	1.59	-2.508	1.55	-2.242	1.31	-2.474	1.29	-3.601	4.78	-3.931	4.67	-3.421	6.89	-3.951	6.87
11.individual		-3.552*	1.6	-3.309*	1.55	-3.045*	1.32	-3.222*	1.28	-1.664	4.91	-2.025	4.8	-1.625	7.18	-2.098	7.16
12.individual		-3.357*	1.61	-3.468*	1.56	-3.163*	1.34	-3.664**	1.29	-3.839	4.19	-3.867	4.09	-3.583	6.07	-3.751	6.06
13.individual										-5.7	3.92	-5.8	3.86	-5.281	5.66	-5.685	5.67
14.individual										9.836*	4.32	9.621*	4.21	11.407	6.23	11.199	6.21
15.individual										12.790*	5.07	12.052*	4.96	14.466*	7.26	13.641	7.25
16.individual										-2.641	4.31	-2.856	4.21	-2.492	6.22	-2.845	6.22
17.individual										11.316**	4.05	10.962**	3.96	13.355*	5.87	13.063*	5.86
18.individual										-3.773	4.05	-4.136	3.96	-3.197	5.87	-3.847	5.86
3.Period						-1.758*	0.87	-1.283	0.86					-0.053	0.64	0.359	0.71
4.Period						-2.841**	0.89	-1.936*	0.89					-0.912	0.69	-0.333	0.72
5.Period						-4.037***	0.91	-2.989***	0.91					-1.154	0.7	-0.7	0.72
6.Period						-6.266***	0.97	-4.732***	0.97					-0.267	0.71	0.321	0.72
7.Period						-6.048***	1.08	-4.009***	1.09					-0.252	0.72	0.262	0.74
Constant		11.901***	1.71	8.263***	1.28	14.296***	1.55	11.524***	1.3	8.524*	4.11	9.892**	3.34	9.395	5.13	10.033*	4.82
N		927		930		927		930		684		684		684		684	

* p<0.05, ** p<0.01, *** p<0.001

		Unbalanced Panel Analysis (No Bonus but Chat)								Unbalanced Panel Analysis (No Bonus and No Chat)							
		Autregressive 1		Autregressive 2		Period Dummy 1		Period Dummy 2		Autregressive 1		Autregressive 2		Period Dummy 1		Period Dummy 2	
		Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
2.Average Other Contributions So Far Betwe	[5,10)	2.316*	0.91			1.817*	0.9			2.657***	0.44			2.275***	0.42		
3.Average Other Contributions So Far Betwe	[10,15)	2.966**	1.05			2.800**	1.07			3.220***	0.56			2.616***	0.55		
4.Average Other Contributions So Far Betwe	[15,20)	7.749***	1.01			6.281***	1.16			5.778***	0.83			4.617***	0.82		
5.Average Other Contributions So Far Betwe	[20,25)	5.520***	1.37			4.061**	1.53			7.606***	1.04			5.937***	1.03		
6.Average Other Contributions So Far Betwe	[25,30)	7.390***	1.63			3.940*	1.82			5.881***	1.72			3.969*	1.7		
7.Average Other Contributions So Far Betwe	30+	8.791***	1.17			4.552**	1.43			5.995**	1.89			3.846*	1.84		
2.Lagged Other Contribution Between	[5,10)			1.998**	0.74			0.85	0.77			3.009***	0.41			2.340***	0.43
3.Lagged Other Contribution Between	[10,15)			3.593***	0.7			1.788*	0.78			5.343***	0.51			4.368***	0.54
4.Lagged Other Contribution Between	[15,20)			3.921**	1.28			2.362	1.3			3.343***	0.89			2.368**	0.92
5.Lagged Other Contribution Between	[20,25)			9.471***	0.85			7.163***	1.03			5.427***	1.06			4.324***	1.08
6.Lagged Other Contribution Between	[25,30)			16.874***	2.84			14.286***	2.88			9.182***	1.18			8.090***	1.21
7.Lagged Other Contribution Between	30+			7.210***	0.86			4.278***	1.08			7.838***	1.31			6.515***	1.32
2.individual		4.591*	1.92	4.397**	1.69	4.459	2.29	4.600*	2.18	-3.230**	1.15	-2.879**	1.08	-3.188**	1.11	-2.904**	1.08
3.individual		-3.125	1.99	-3.668*	1.72	-3.463	2.35	-4.142	2.2	0.437	1.17	0.119	1.11	0.422	1.13	0.116	1.1
4.individual		-1.889	1.91	-0.878	1.63	-2.002	2.29	-1.338	2.13	2.449*	1.13	2.275*	1.09	2.335*	1.09	2.238*	1.08
5.individual		1.61	1.93	2.406	1.7	2.084	2.28	2.534	2.17	4.338***	1.16	3.896***	1.12	4.332***	1.12	3.963***	1.11
6.individual		2.8	1.97	1.799	1.7	2.548	2.32	1.723	2.18	-0.54	1.13	-0.931	1.08	-0.698	1.1	-1.005	1.07
7.individual		6.044**	1.98	5.198**	1.75	6.236**	2.31	5.686**	2.2	-1.721	1.12	-1.783	1.08	-1.874	1.09	-1.89	1.07
8.individual		-4.718*	1.91	-3.358*	1.62	-4.660*	2.31	-3.722	2.12	3.710**	1.13	2.995**	1.09	3.625***	1.1	3.049**	1.08
9.individual		-3.077	1.96	-2.851	1.72	-3.652	2.32	-3.267	2.21	3.551**	1.14	3.276**	1.1	3.381**	1.1	3.165**	1.09
10.individual		-5.596**	1.85	-4.793**	1.62	-5.865**	2.23	-5.224*	2.12	-0.466	1.12	-0.586	1.09	-0.56	1.09	-0.623	1.08
11.individual		-3.941*	1.9	-2.992	1.64	-4.164	2.29	-3.532	2.14	-3.506**	1.13	-2.845**	1.08	-3.477**	1.09	-2.955**	1.07
12.individual		3.707	1.93	3.521*	1.7	3.608	2.28	3.671	2.17	2.328*	1.12	2.174*	1.08	2.138*	1.09	2.063	1.07
13.individual		-0.839	1.91	0.303	1.68	-0.932	2.27	-0.058	2.17	21.842***	1.23	21.067***	1.16	21.253***	1.19	20.806***	1.15
14.individual		1.271	1.94	1.848	1.71	1.422	2.29	1.8	2.18	-0.501	1.13	-0.736	1.08	-0.662	1.09	-0.831	1.08
15.individual		0.717	1.91	1.123	1.67	0.371	2.27	0.848	2.16	0.662	1.14	-0.095	1.08	0.583	1.11	-0.126	1.07
16.individual										-0.85	1.13	-0.985	1.09	-0.776	1.09	-0.959	1.08
17.individual										-0.126	1.16	-1.006	1.12	-0.278	1.12	-0.965	1.11
18.individual										2.705*	1.13	2.217*	1.09	2.583*	1.09	2.202*	1.08
3.Period						-1.979**	0.71	-0.504	0.72					-0.631	0.57	0.186	0.56
4.Period						-4.758***	0.75	-2.963***	0.74					-1.791**	0.58	-0.644	0.57
5.Period						-4.439***	0.83	-2.695**	0.83					-2.524***	0.59	-1.259*	0.59
6.Period						-4.403***	0.88	-3.060***	0.87					-3.662***	0.6	-2.325***	0.61
7.Period						-4.102***	0.88	-2.966***	0.89					-4.098***	0.61	-2.591***	0.63
Constant		2.333	1.54	2.656*	1.22	6.662***	1.94	6.045***	1.71	1.192	0.84	1.238	0.8	3.747***	0.92	2.799**	0.93
N		1061		1107		1061		1107		1490		1532		1490		1532	

* p<0.05, ** p<0.01, *** p<0.001

Table 4.7: Estimated Coefficients and Marginal Effects of Contributions by Others

		Bonus and Chat		No Bonus but Chat		No Bonus/Chat	
		Estimates	Diff	Estimates	Diff	Estimates	Diff
2.Lagged Other Contribution Between	[5,10)	2.29		2.00		3.01	
3.Lagged Other Contribution Between	[10,15)	3.95	1.66	3.59	1.60	5.34	2.33
4.Lagged Other Contribution Between	[15,20)	4.32	0.36	3.92	0.33	3.34	-2.00
5.Lagged Other Contribution Between	[20,25)	4.94	0.62	9.47	5.55	5.43	2.08
6.Lagged Other Contribution Between	[25,30)	6.75	1.81	16.87	7.40	9.18	3.76
7.Lagged Other Contribution Between	30+	7.41	0.66	7.21	-9.66	7.84	-1.34
Mean			1.02		1.04		0.97
Min			0.36		-9.66		-2.00
Max			1.81		7.40		3.76

		No Bonus but Chat		No Bonus/Chat	
		Estimates	Diff	Estimates	Diff
2.Average Other Contributions So Far Between	[5,10)	2.32		2.66	
3.Average Other Contributions So Far Between	[10,15)	2.97	0.65	3.22	0.56
4.Average Other Contributions So Far Between	[15,20)	7.75	4.78	5.78	2.56
5.Average Other Contributions So Far Between	[20,25)	5.52	-2.23	7.61	1.83
6.Average Other Contributions So Far Between	[25,30)	7.39	1.87	5.88	-1.73
7.Average Other Contributions So Far Between	30+	8.79	1.40	6.00	0.11
Mean			1.29		0.67
Min			-2.23		-1.73
Max			4.78		2.56

Estimates are taken from the AR models.

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Appendix A

Appendix for Second Essay

A.1 Linkliood and GMM Methods for Probit Models

In this section, we show our likelihood method and GMM method that we adopted are not equivalent because we use different objective functions. For the likelihood based probit model, we maximize the following likelihood function:

$$l(\alpha, \beta, \gamma | x_i, x_h) = \sum_{i \in I} \left(D_i \ln \Phi \left(\alpha + x_i \beta + x_h \gamma \right) + (1 - D_i) \ln \left(1 - \Phi(\alpha + x_i \beta + x_h \gamma) \right) \right) \tag{A.1}$$

The maximization problem above is equivalent to a score function
(Note: $\dim([1, x_i, x_h]') = \dim(0)$):

$$\frac{\partial l(\alpha, \beta, \gamma | x_i, x_h)}{\partial [\alpha, \beta, \gamma]} =$$
$$\frac{1}{I} \sum_{i \in I} \left([1, x_i, x_h]' \left(D_i \frac{\phi(\alpha + x_i \beta + x_h \gamma)}{\Phi(\alpha + x_i \beta + x_h \gamma)} - (1 - D_i) \frac{\phi(\alpha + x_i \beta + x_h \gamma)}{1 - \Phi(\alpha + x_i \beta + x_h \gamma)} \right) \right) \tag{A.2}$$
$$E \left(\frac{\partial l(\alpha, \beta, \gamma | x_i, x_h)}{\partial [\alpha, \beta, \gamma]} \right) = 0 \tag{A.3}$$

This objective function is different from the objective function for GMM in equation 3.12.

Appendix B

Appendix for Third Essay

B.1 Proof for Corollary 1

We first assume that there exists an allocation $z < x$ such that $z \succeq x$ for members in a coalition S. This is equivalent to $u_S(z) > u_S(x)$ where $u_S = \sum_{i \in S} u_i$. We further let $x \equiv \{x_S, x_{-S}\}$ and $z \equiv \{z_S, z_{-S}\}$. We also let $u_S(z) \equiv u_S^S(z_S, z_{-S}) + u_{\bar{S}}^S(z_S, z_{-S})$; this reflects that the function u_S is a linear combination of dividends from contributions made by S and $-S$. Similarly, we let $u_S(x) \equiv u_S^S(x_S, x_{-S}) + u_{\bar{S}}^S(x_S, x_{-S})$.

Since $z_{-S} = 0$, $u_{\bar{S}}^S(x_S, x_{-S}) \geq u_{\bar{S}}^S(z_S, z_{-S})$ for any x. If the marginal profit for the coalition S, $N\lambda \leq 1$, then $du_S^S(y_S, y_{-S})/dy_S \leq 0$. Given $\lambda = .5$ and $N = 3$, any coalition S strictly smaller than the grand coalition with $N = 3$ satisfies $N\lambda \leq 1$. Therefore, $u_S^S(x_S, x_{-S}) \geq u_S^S(z_S, z_{-S})$ for any $z < x$. It yields $u_S(x_S, x_{-S}) \geq u_S(z_S, z_{-S})$ contradicting the assumption that x is underblocked by z, which requires $u_S(x_S, x_{-S}) \ll u_S(z_S, z_{-S})$. ■