QUALITY OF CARE, ASYMMETRIC INFORMATION, AND PATIENT OUTCOMES IN U.S. FOR-PROFIT AND NOT-FOR-PROFIT RENAL DIALYSIS FACILITIES

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Abstract

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Economic theory suggests that investor-owned firms exhibit superior performance compared to their not-for-profit competitors due to efficiency gains realized from profit maximization incentives. Others argue that ownership type matters less than the incentives provided by the market in which the facilities operate. This dissertation examines the role of quality in comparative studies of sector performance in the health care industry. Quality variation is then analyzed with a cross-sectional study of almost 200,000 patients receiving renal dialysis treatments at over 2000 dialysis facilities nationwide. Multivariate regression analysis and propensity score analysis revealed higher patient mortality rates among patients treated at for-profit facilities, after adjusting for patient case-mix and market characteristics. Evidence of quality variation across ownership types suggests that researchers studying comparative efficiency of for-profit and not-for-profit health care firms must control for differing patient outcomes. Further testing was performed on a data sub-sample that included variables serving as proxies for patient knowledge. Dialysis facilities were found to treat high-knowledge patients differently than low-knowledge patients, but for-profit firms were not always found to exploit asymmetries of information more than their not-for-profit counterparts.

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The data here have been supplied by the United States Renal Data System (USRDS). The interpretation and reporting of these data are the responsibility of the author and in no way should be seen as an official policy of the U.S. Government.

DEDICATION

I wish to dedicate this dissertation to Jeff Cooper.

INTRODUCTION

The health care sector is one of several industries in the US where both for-profit and not-for-profit firms have substantial market share and power. For-profit ownership of US healthcare organizations has grown tremendously over the last two decades, and recent changes in healthcare payment systems have significantly heightened market competition levels while diminishing industry-wide profit margins. As competition mounts and financing for Medicare and Medicaid tightens, more attention has focused on comparative studies of healthcare performance by ownership type. While many studies have compared expenditures of for-profit and not-for-profit healthcare institutions, few studies have defined output correctly by controlling for quality of care. Thus, these comparative cost studies yield no meaningful results.

Consider two identical patients needing open-heart surgery. The patients are admitted for surgery on day one. Patient X dies on the operating table, while patient Y survives surgery, is hospitalized for one week, then discharged -- and goes on to live another 15 years. In this situation, patient X's hospital may appear more "efficient" because it has taken only one day to treat the patient. Patient Y's hospital is labeled "high cost" and even "inefficient" because the patient spent a week in the hospital for the identical illness. In effect, patient satisfaction or health production is ignored, hospital output is measured as patient-days or number of patients, and the resulting measures of efficiency are nonsensical.

Studies of health care quality have been the domain of the medical researcher, who researches the health outcome effects of one treatment versus another. Medical researchers have rarely included the ownership status of the health care facility in health outcome comparisons. Economists, on the other hand, have focused on comparative financial performance among facilities of differing ownership types and have usually assumed away health outcome variation, or have used a proxy variable as a quality control variable. Common proxy variables for quality in health economics literature include such blunt instruments as hospital accreditation status and medical school affiliation, staffing hours, and market characteristics such as per capita personal income levels. Virtually no health economics research so far has attempted to combine the two domains to study comparative outcome quality by ownership status.

From the economics literature, we know that for-profit health care facilities use different levels of inputs in patient care than their not-for-profit counterparts utilize. For example, Eskoz and Peddecord (1985) and Pattison and Katz (1983) found that for-profit hospitals used more profitable ancillary services. The medical literature points to variations in patient health outcomes when different inputs are employed in the health care process. However, the implication that outcome quality differs by ownership type has not been specifically tested, and should not be assumed. This paper seeks to remedy this gap in the literature by testing outcome quality variation among health care providers of different ownership status.

Patients are said to choose not-for-profit health care providers because of an anticipated higher quality of care given at not-for-profit institutions. This "trust signal" function of the not-for-profit organizational form may aid in mitigating information asymmetries in health care. After two statistical approaches to an empirical study of mortality rates among US dialysis patients, a related study in this paper explores the role of asymmetric information in dialysis treatment inputs.

Chapter 1 provides a discussion of theoretical foundations of quality and ownership status, as well as a description of previous research on possible disparities in quality of health care by ownership type. An intertemporal model of for-profit and not-for-profit managerial utility maximization is introduced in Chapter 2. The US renal dialysis industry is described in Chapter 3 along with a review of pertinent medical and economics literature. Chapter 4 presents an empirical project, whereby almost 200,000 renal dialysis patients nationwide are found, in multivariate regression analysis, to have significantly higher mortality rates at for-profit dialysis facilities. Chapter 5 repeats the analysis for a smaller sample, but uses propensity score methodology to create comparable for-profit and not-for-profit patient sub-samples before analyzing the effect of for-profit versus not-for-profit treatment. A modification to existing propensity score methodology is proposed as part of the empirical analysis in Chapter 5. Chapter 6 introduces a new data set to empirically test differences in treatment for high-knowledge and low-knowledge patients, and constitutes one of the first such investigations of the possible effects of asymmetric information in the health care industry. Discussion of results and conclusions follow in Chapter 7.

CHAPTER 1: QUALITY AND OWNERSHIP STATUS: THEORETICAL FOUNDATION

SECTION 1: FORMATION AND RETENTION OF THE NOT-FOR-PROFIT FORM

PART A: PROVISION OF PUBLIC GOODS

Why donors choose the not-for-profit form over the for-profit form for provision of the public good is straightforward; the donor does not wish to enrich stockholders of the firm, but rather prefers to provide the public good. In the absence of complete monitoring to ensure that the good or service is provided (to a third party or to the community at large) the not-for-profit form with its non-distribution constraint and lack of residual claimants for profits has an efficiency advantage over the for-profit form of organization for donative goods and services (Fama and Jensen, 1983b).

Why donors choose the not-for-profit form over public provision of the public good is not well-researched, however. Considering that governments can obtain tax funding rather than having to rely at least partially on charitable contributions, the not-for-profit form appears to be at a long-term funding disadvantage compared to government. However, as Hansmann (1980) and Frank and Salkever (1994) elucidate, government provision of a public good is most feasible for goods preferred by the majority of the populace, not just a small subset. Furthermore, since not-for-profit firms can be structured more narrowly, they may be more responsive to their donors' intentions, less constrained by bureaucratic restrictions, and more affected by market discipline than government-provided goods.

Weisbrod (1977) proposed that not-for-profit organizations arise when quantity demanded of a public good varies in a population. The voting process results in a level of governmental provision of a public good that is considered inadequate by part of the population, at the current price of the good. When a segment of the unsatisfied population chooses to voluntarily contribute to provide the good, instead of free-riding, the not-for-profit form of organization is chosen.

Since religion is not sponsored by the government in the U.S., churches comprise the largest sub-sector of the not-for-profit sector (Rose-Ackerman, 1996). Many other not-for-profit organizations, from hospitals to universities, were originally founded by religious organizations. Given the particularly heterogeneous religious preferences of the U.S. populace, it is also not surprising that religious organizations in the U.S. are organized as not-for-profits. Nonetheless, to differ with Weisbrod, it is not particularly accurate to characterize religion as a public good.

Not-for-profit hospitals do not necessarily specialize in provision of public goods today. Modern hospitals do provide some collective goods, such as treatment and prevention of communicable diseases. In addition, not-for-profit hospitals in particular provide a substantial amount of uncompensated care for uninsured and underinsured patients. Lewin et al. (1988) and Shortell et al. (1986) showed that not-for-profit hospitals provided more uncompensated care as a percentage of revenues or costs than for-profit hospitals in the 1980's, particularly in competitive markets. Modern healthcare facilities, however, receive most of their compensation from producing private services, and are thus commonly classified as "commercial not-for-profits." This is in contrast to the situation in the early 20th century, when most not-for-profit hospitals were formed and established dominance in the health care industry. Then, as Eli Ginzberg (1991) reports, large urban not-for-profit hospitals funded largely by philanthropists were formed to provided medical care to the poor. Since charitable provision of aid to the needy is often considered a public good, Weisbrod's public good argument aids in explaining the historical foundation of not-for-profit health care in the U.S.

PART B: CONTRACT FAILURE

Hansmann (1980) argues that public goods are only a subset of goods where not-for-profit provision is appropriate. Whenever a purchaser is unable to evaluate the quality of the good (even after purchase), contract failure arises and free-market provision of the good will be inefficient. Public goods markets lead often to contract failure because the purchaser is not necessarily the recipient and is unable to verify if the public good was produced or distributed at all. The profit non-distribution constraint of not-for-profit firms gives some assurance that the funding provided for the good will indeed be used to produce and distribute the good. More importantly, public goods are a subset of goods that are largely consumed by a third party. Charity, which need not be classified as a public good, falls into this category. Aside from the public component of altruism in aiding the needy, charitable goods are difficult to monitor due to third-party consumption, and are subject to contract failure. Thus, for organizations whose output is charitable goods and services, virtually none that rely substantially on donor funding are organized as for-profit firms.

Another type of contract failure arises when the purchaser of the good or service is the consumer, but is still unable to evaluate the delivery or quality of the good. Many cite modern healthcare as an example where some forms of treatment are so specialized that patients cannot judge the quality of care (where the degree of patient sophistication varies by the disease and condition of the patient). Not-for-profit status is said to function as a trust signal for patients seeking some guarantee that the firm will not exploit its information advantage. Hansmann points out that physicians in hospitals serve as "sophisticated purchasing agents" for patients, thus alleviating any contract failure problems caused by the profit status of the hospital (1980, page 867). Physicians are paid by the patient, are not employed by the hospital, and therefore serve as quality control agents for the layman patient. Furthermore, Hansmann (1996) argues, for-profit hospitals are restricted from taking advantage of information asymmetries because they have to maintain their professional reputation. However, when physicians become part owners of the healthcare facility, the purchasing agent role may be altered as partial compensation for physicians comes from facility profits. The empirical portion in Chapter 5 presents evidence that physicians, just as Hansmann theorized, are less affected by financial incentives created by ownership structure than are non-physician staff at renal dialysis facilities.

Two more situations affecting hospitals' incentives to exploit information asymmetries stem from the form of payment for medical care. When the hospital is part of an HMO or when the patient's insurer pays prospectively, rather than on a cost basis, the hospital has an incentive to reduce costs of patient care. Due to explosive growth of HMO medical care in the 1980's and 1990's, and the implementation of Medicare's DRG (diagnostic related group) reimbursement system in the mid 1980's, these two situations are no longer special cases but constitute the majority of hospital care payment mechanisms. Thus, whereas asymmetric information used to be more of a theoretical footnote for the discussions of market failure in the hospital industry, it is now of central concern to those studying physician and hospital staff incentives and performance.

Frank and Salkever (1994) note that the US nursing home industry is one sector of health care where patients are particularly vulnerable, compared to the hospital industry, and contract failure is thus more likely in a free market. The same vulnerability could be ascribed to psychiatric patients in inpatient facilities. One might expect that the not-for-profit organizations in these industries would have a competitive advantage if consumers considered not-for-profit status as a signal of lower incentive to take advantage of the consumer's vulnerability. Notably, however, not-for-profit nursing homes and inpatient psychiatric facilities have a much smaller market share than for-profit facilities, whereas not-for-profit hospitals have a higher market share than for-profit hospitals. Thus, factors other than the "trust signal" role of not-for-profits appear to determine competitive advantage by ownership status in the health care industry.

Contract failure may therefore take two forms that are prevalent in the healthcare industry. First, provision of charitable goods funded by donors is virtually always the role of a not-for-profit organization. Of course, these charitable goods are provided by non-free-riding donors who prefer more of the charitable good than is provided by the public sector. Inability of donors to monitor closely the distribution of charity prompts them to select or create a not-for-profit organization. Thus, charitable donations explain the *foundation* of not-for-profit healthcare, but may not provide sufficient explanation for the *retention* of the not-for-profit form, as donor funding has declined to about 1% of total operating costs and 5% of capital expenditures in 1990 (Ginzberg, 1991), from around 25% of not-for-profit urban hospital income in 1940. The main reasons for the precipitous decline in medical philanthropy were the transformation early in the 20th century of hospital care, from treatment of the poor to fee-for-service care of the general population, the growth of employer-paid medical insurance, and the passage of Medicare and Medicaid in 1965, for medical care of the elderly and impoverished.

Although the passage of Medicare and Medicaid eliminated a source of contract failure by reducing further the role of donor funding, Medicare and Medicaid funding provided not-for-profit hospitals with a substantially stronger financial footing, and hospital expenditure (both not-for-profit and for-profit) subsequently underwent astonishing expansion for about two decades. This lends support to Mark Pauly's belief that healthcare organizational structure is less dependent on managerial objectives than on the prevailing reimbursement environment (1987).

The second form of contract failure prevalent in health care is the patient's lack of information regarding the quality of his treatment. Asymmetric information is not a solid argument for the formation of not-for-profit healthcare facilities, because most not-for-profit hospitals were founded when treatment was simpler. Contract failure due to asymmetric information may be a factor in the retention of the not-for-profit form, as medical knowledge becomes increasingly inaccessible to the layman. On the other hand, in the hospital setting, most physicians are not employees of the facility and are able to mitigate the asymmetric information problem. Whether or not physicians are part owners, the "trust signal" function purportedly performed by the not-for-profit health care facility may be utilized by some knowing patients, but is likely to be a very minor determination of retention of not-for-profit status, compared to other constraints and incentives facing the supply side of health care.

Part C: Benefits to Physicians

In the first two decades of the twentieth century, physicians did not enjoy high incomes, and in particular, did not receive large direct financial rewards for being on staff at large modern (and almost invariably not-for-profit) hospitals. Ginzberg (1991, page 180) reports, "Physicians eagerly sought staff appointments at prestigious hospitals where many of them donated the equivalent of two days of work per week for the privilege of admitting private patients. Young physicians served for years in the hospitals' clinics to earn the right to be considered for a staff appointment." Physicians may have benefited from the prestige afforded by the staff appointment at not-for-profit hospitals, by attracting more patients than a physician at a smaller proprietary facility. It can also be surmised that physicians of some religious groups were instrumental in founding religious not-for-profit hospitals when discriminatory practices limited the physicians' opportunities for staff appointments elsewhere. Remuneration for physician services has improved greatly since then, due in part to successful efforts by the American Medical Association to reduce the supply of graduating medical students (Ginzberg, 1991).

Pauly and Redisch (1973) developed a model of not-for-profit organization whereby, ignoring prestige and leisure effects, staff physicians cooperate to maximize the sum of the money income of all staff members. This seminal paper showed that not-for-profit hospital status can be advantageous for the physician, supporting the claim that physicians themselves can be advocates for retention of the not-for-profit form. Pauly and Redisch's paper also provides insight regarding variation of quality among for-profit and not-for-profit providers. Their model predicts that imperfect cooperation among medical staff members will cause overproduction of hospital services, i.e. quality. Whether or not physicians influence facility quality, it is apparent that to ensure the long-term survival of the health facility, physicians are often granted certain privileges by the facility administration. In an article detailing not-for-profit hospital privileges granted to medical staffs, Sullivan (1992) describes several quasi-legal schemes, such as subsidized office space and recruitment bonuses, undertaken to accommodate doctors' wishes in order to ensure a steady flow of paying patients to the hospital. Hansmann adds (1980, page 867) that doctors in not-for-profit hospitals may have more influence on hospital administration; "For example, a doctor may be able to induce a nonprofit hospital more easily than a for-profit hospital to buy an expensive piece of equipment that will help him increase considerably the size and profitability of his practice, even though the equipment is not cost-justified." Of course, the ability of the hospital to accommodate physicians' equipment desires and of the physician to increase his fees depends to a great extent on the reimbursement scheme in operation.

Thus, it can be concluded that although benefits to physicians may have played a minor role in the founding for not-for-profit healthcare organizations, a more convincing statement is that physicians have a potentially large stake in the retention of not-for-profit healthcare. As Hansmann (1980, page 868) writes, "It is rather as if a foundation, tax-exempt and supported in part by public contributions, were to build office space and then lease it at cost, or less, to Wall Street law firms. One would not expect to see the lawyers in a hurry to have the foundation converted into an ordinary profit-making landlord." Hansmann's analogy is most relevant for the hospital sector, where doctors practicing at for-profit facilities are not as often part owners of the facility. In other sectors of the healthcare industry, such as renal dialysis and inpatient psychiatric care, physicians at for-profit facilities are more often part owners, and therefore are more likely to personally benefit from for-profit facility ownership relative to for-profit ownership.

PART D: MARKET RESTRICTIONS

Entry restrictions and other regulations have affected the strength of the not-for-profit sector over the past century. In health care, the American Medical Association, a not-for-profit organization, was given the authority shortly after the turn of the twentieth century to establish and oversee state regulations for medical schools (Ginzberg, 1991). Partly as a consequence of elimination of many small proprietary hospitals early in the twentieth century, not-for-profit hospitals continue to provide the vast majority of medical teaching programs to this day.

After Medicare was established and it became clear that healthcare costs were consuming ever larger shares of public expenditure, Certificate of Need (CON) programs were introduced by states to limit new investment in health care facilities and equipment (Friedman et al. 1990). Although the intent of CON legislation was to promote economies of scale and thereby reduce local health care expenditures, a significant effect of CON laws was to protect established hospitals from entry of potential competitors. In many cases, CON laws protected not-for-profit facilities from entry by for-profit hospitals. Many, including Sloan (1988) concluded that CON programs failed to reduce the growth of health care expenditures. By the mid-1980's, a majority of states had removed CON regulations and as of 1989, only 15 states had CON programs regulating both hospital-based and freestanding dialysis facilities (Rettig and Levinsky, 1991). In the dialysis industry, Rettig and Levinsky show evidence that when CON regulations were removed in the mid-1980's in some states, significant increases in numbers of for-profit dialysis facilities occurred.

For-profit entry into a few states where rate reviews or budget approval programs are in place has also been slow. These "all-payer" rate review states force hospitals to share in the costs of uncompensated care, which would normally burden a small subset of hospitals. DeLew et al. (1992) report that states with rate-setting regulations successfully controlled hospital cost growth. The regulatory method of rate-setting creates an unfavorable regulatory environment for potential for-profit entrants, according to Friedman et al. (1990).

Market restrictions, whether aimed toward limiting costs of capital expansion, restricting physician licensure, or regulating budgetary processes, have appeared to provide a competitive advantage for existing not-for-profit health care firms. Although the aim of such state regulation is often cost control, the inadvertent consequence, similar to rent control, is that the current market players -- often not-for-profit facilities -- are provided some protection from market entrants.

PART E: TAX EXEMPTION

Not-for-profit organizations are exempt from corporate income taxes and, in most cases, local property taxes. Also, charitable contributions to not-for-profit organizations are deductible, and not-for-profit firms may utilize tax-exempt bond financing. However, Hansmann (1980) and Fama and Jensen (1983b) note that historically, tax benefits conferred to not-for-profit organizations have followed the founding of the not-for-profit sector, not precipitated it. Hansmann concludes in his 1980 article that taxation benefits aid the retention of not-for-profit form, but are not an important determination in the founding of not-for-profit organizations. Later, in an article using 1975 data, Hansmann measured the effect of state and local tax exemption on the market share of not-for-profit firms in the health care and education sectors. He found that the value of the state and local tax exemption was positively correlated with not-for-profit market share (Hansmann, 1987). Despite this finding it can be argued that much of the century's for-profit expansion in health care occurred after 1975.

Friedman et al. (1990) estimate the value of tax exemptions in the US not-for-profit hospital industry is about 5 to 6 percent of total expenses. Even though some authors dismiss the tax exemption's importance in ensuring the survival of the not-for-profit firm, some local governments are beginning to use tax exempt status (and the threat of revocation) as a tool to influence not-for-profit performance. Specifically, some local governments are demanding *quid pro quo* for hospital property tax exemption, in the form of uncompensated care quotas or demonstrated community benefits.[1] Thus, local governments are recognizing that tax exemption affects not-for-profit firm viability.

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[1] *Utah County* v. *Intermountain Health Care, Inc.*, 709 Utah, P.2d, 1985.

Hansmann (1996) supports the revocation of tax exemption for not-for-profit hospitals because he sees little difference between the output of for-profit and not-for-profit hospitals. Hansmann comments further that not-for-profit hospitals are not likely to quickly disappear if taxation is implemented because hospitals have considerable embedded capital and can survive even when their market rate of return is below that of a for-profit hospital. Rose-Ackerman (1996) and Frank and Salkever (1994) argue that tax benefits continue to be granted to not-for-profit healthcare providers because it is recognized that not-for-profit healthcare may consistently provide more goods and services that benefit the community, such as uncompensated care, medical education, research, and so on. The motives of government officials to establish or revoke tax benefits for not-for-profits and to design appropriate reimbursement mechanisms, are explored in the next section.

SECTION 2: US HEALTH CARE: OBJECTIVES BY ACTOR

Many discussions of not-for-profit theory ignore individual incentives in the larger consideration of organizational status. However, it is the individual donor, the hospital CEO, the patient, the physician, the government administrator, and the insurance company executive who faces incentives, maximizes objectives, and makes decisions leading to the production of health care. This section analyses individual decision making by economic actors, and discusses each actor's consideration of quality in his production or consumption decisions. It is not instructive to conclude that not-for-profit firms produce higher quality because quality is in their objective function. In Pauly and Redisch's (1973, page 99) words, "Appropriate choice of the variables to enter the utility function can make almost any observed behavior consistent with utility maximization." Besides the obvious problem of modeling objectives by pulling oneself up by the bootstraps, the definition of the decision maker is unspecified. To whom does this utility function belong?

PART A: THE DONOR OR FOUNDER

The strongest rationale for foundation of not-for-profit health care facilities historically has been the provision of charity. Charitable organizations are usually organized as not-for-profits in order to mitigate agency problems inherent in the acquisition of residual claims by for-profit managers when the recipient of a charitable donation is a third party and monitoring of charity production is incomplete (Fama and Jensen (1983b) and Hansmann (1980)). If the donor wants to purchase charity for others, the not-for-profit form is commonly believed to be the efficient conduit for such a transaction, in that managerial incentives to appropriate the donation as profits are reduced by the nondistribution constraint.

Weisbrod (1977) postulates that donors establish not-for-profit organizations when government provision of the good is inadequate. This provides a possible explanation why a donor would not simply donate to a public institution, whose managers are bound by the same nondistribution constraint as not-for-profit managers. Rose-Ackerman (1996) lists a few other reasons why a donor would select the not-for-profit form over a public agency; the not-for-profits might be easier to monitor than a government organization by a donor, not-for-profits might provide a greater diversity of goods than a government agency (providing public goods for which quantity demanded is very homogenous), and not-for-profits might provide the best operating environment for ideologues -- unconstrained by public agency bureaucracy and from for-profit shareholder demands. In addition, donors' selection of the not-for-profit form is aided by the tax deduction for charitable donations.

Grundfest's (1996) discussion of conversion from the not-for-profit form to the for-profit form suggests another powerful incentive for donors to select the not-for-profit form. Public agencies are more capable than not-for-profits of withdrawing from sectors where public provision is no longer in high demand (Hansmann 1996). Not-for-profits face formidable federal and state legal obstacles when converting from not-for-profit to for-profit status. Usually, the assets of the not-for-profit foundation must be repaid to the government or left within the not-for-profit sector upon conversion. "...(T)he decision to invest capital in the nonprofit form is effectively an irrevocable election of an organizational form, at least as to the current value of that capital." (Grundfest 1996, page 273). Donors wishing to preserve their charitable funding therefore select the not-for-profit firm -- the organizational form with the greatest potential for applying the capital over time to its original intended source.

When donors fund high-quality rather than charity health care, it is often a good that has a *public* component, such as research toward a cure for a disease or construction of an expensive treatment facility to aid those who would otherwise be unable to receive specialized care. Philanthropy, however, is now a small fraction of most not-for-profit health care organizations' revenues, so the motivation for founding not-for-profit institutions for charitable purposes is reduced. Even as early as 1964, philanthropy accounted for only 3.2% of private expenditures on health and medical services (Census Bureau, 1965). Donors played a pivotal role in the establishment of not-for-profit health care in the early part of the 20th century in the US. Other actors however, have been largely responsible for the continued strength of the not-for-profit sector.

PART B: THE BOARD OF DIRECTORS

One of the legal requirements for not-for-profit status is that an organization form a board of directors or trustees to oversee the management of the institution. Boards may often be composed of major donors to the organization. Fama and Jensen (1983a) point out that board members are usually outside agents, because a board composed of internal agents or outsiders chosen by internal agents is too vulnerable to expropriation of donations. Similarly, Callen and Falk (1993) hypothesized that outside board members perform a monitoring role whereas insider board members are more inclined to direct perquisites toward their own domain, causing the firm to have higher costs. Callen and Falk tested this hypothesis with data from 72 health charities, finding no evidence that the makeup of the board has an influence on the technical efficiency of the firm.

Molinari et al. (1995) also studied the influence of insider (medical staff) participation on boards of directors and found that hospitals with medical staff on boards performed better, i.e. had higher net operating margins. Molinari et al. conclude that their findings support a "managerialist" point-of-view -- insiders provide essential knowledge for efficient operation -- rather than the "agency" view of Fama and Jensen (1983 a and b). Molinari et al. did not discuss the possibility that the medical staff's desire to increase hospital profitability might align very closely with their desire to increase patient flow to their own practice, or to increase the prestige of their affiliation with the hospital. Bennett and DiLorenzo (1989) note that unlike boards of directors of private corporations, where board members are elected by shareholders, not-for-profit organization board members are appointed by those who are active in the organization.

Several researchers have noted that board members gain prestige as well as important networking opportunities by serving on boards. Middleton (1987, page 146) reports, "Their reasons for volunteering may also include heightening their own visibility in the community, acquiring an opportunity to mobilize the resources of many organizations on behalf of policies and institutions they favor, and increasing their social and professional connections... Philanthropic work has become a career expectation for managers seeking to advance within corporations." Thus, altruism may play little or even no part in a potential board member's decision to serve on a not-for-profit board.

At the time of founding, a board may be entirely composed of donors, and considerable power, according to Perrow's (1963) study of hospital boards, is wielded by trustees early in the life of the not-for-profit organization. Later, especially if donor financing is minimal, boards of directors perform a less supervisory role. Several studies, according to Middleton (1987), agree that not-for-profit boards in practice usually ratify policy suggested by the organization's management, rather than propose policy changes themselves. Even though the board is the legal ultimate authority, in reality the management controls the flow of information to the board for decision making and the management carries out the recommended policy changes itself.

The give and take of long-term policy negotiations between the board and management varies, of course, by the make-up of the board and the nature of the organization. However, boards of directors all exercise important decision making authority when they hire new executive managers. In the health care industry where donor funding is minimal, the board may simply hire a CEO who appears to be the best candidate for furthering the interests of the board. Not involved in the day-to-day decisions of a not-for-profit organization, the board's contribution to the organization is strongest in the screening process of potential managers, providing a link to external community decision-makers, and ratifying management policies regarding long-term expansion or contraction of facilities.

PART C: THE MANAGER

Regardless of how the not-for-profit manager passed the hurdle of being selected to his position, he now faces incentives uniquely different from a CEO or high-level manager of a for-profit corporation. A CEO of a for-profit firm is a shareholder, and his actions directly and almost immediately affect his wealth. The CEO of the not-for-profit firm, however, has no such direct reward for superior management, due to the non-distribution constraint. It is also instructive to note some of the incentives facing for-profit and not-for-profit managers that are similar. Both managers are fired if their performance is poor -- that is, if the long-term viability of the organization is threatened or if the board members' interests are not being served. Also, both managers may receive future salary enhancement if current job performance is good -- either from the same employer or from another employer. However, a not-for-profit manager's capitalized salary might include recognition for achievements that depart from profit-maximization.

Alchian and Demsetz discussed incentives to shirk facing not-for-profit managers in their 1972 paper. A related article by Alchian and Kessel (1962) discusses similar incentives facing publicly regulated monopolists, who operate within the same nondistribution constraint as not-for-profit managers. Although Alchian and Kessel's notions of desired on-the-job perquisites (i.e. "pretty secretaries") are dated, their central point remains powerful three decades later: Not-for-profit organization provides insufficient incentive for managers to work efficiently, and residual "profits" which would otherwise go to shareholders are consumed on-the-job by utility-maximizing managers as higher costs. Even if managers of not-for-profit hospitals value community health and other lofty ideals, it is also likely that they value also a more pleasant work environment (Young 1987). Since job perquisites are consumed rather than increasing wealth via stock earnings, the compensation system for a not-for-profit manager is inefficient, as cash income always beats in-kind transfers of equal value for utility maximization (Pauly 1987).

Hansmann (1996) contends that the much-maligned operating inefficiency of not-for-profits is usually exaggerated. He notes that for-profit managers commonly don't share significantly in the firm's residual earnings, and not-for-profit managers strive for cost-minimization in order to see their firm grow and prosper. Interestingly and perhaps to Hansmann's credit, empirical studies of comparative hospital costs have not revealed lower costs at for-profit hospitals (Becker and Sloan 1985, Eskoz and Peddecord 1985, Grannemann, Brown and Pauly 1986, Pattison and Katz 1983, and Renn et al. 1985). This may very well be an artifact of the cost-based reimbursement system in place at the time of those studies, when profits were enhanced by maximizing services to patients and receiving reimbursement from third-party payers. Medicare reimbursements changed to a prospective payment in 1984, whereby patients' diseases and severity levels are identified at admission, then reimbursed at a certain level (regardless of inputs utilized). This prospective reimbursement system, similar to prospective capitated payments for HMO patient care, greatly reduces incentives to "overtreat" in order to improve profits. Recent empirical studies with post-1984 data are bound to show a change in comparative cost-control, and if Alchian and Demsetz are correct, we expect for-profit hospitals to have lower costs due to clearer incentives facing managers. Efficiency is not defined over output with unknown differences in quality, however, so it is difficult to claim that not-for-profit managers will act "inefficiently" if they are raising costs by improving the quality of the product. Nevertheless if not-for-profit managers value a pleasant work environment *in addition to* producing a higher quality product, it can be predicted that not-for-profit managers act inefficiently in comparison to their for-profit counterparts.

When not-for-profit organizations are said to have different objectives than for-profit organizations, without specifically identifying the utility maximizing individual, the manager comes closest to the utility maximizer role. In the health care industry, his decisions, within a loose framework of board of directors' wishes, affect capital investments, medical staff satisfaction, and production of health by non-medical staff. Although several authors contend that managers of not-for-profit organizations are "more interested in providing high-quality service and less interested in financial rewards than are most individuals" (Hansmann (1980), page 876), one cannot conclude that not-for-profit status guarantees selection of managers valuing high quality. This is because the not-for-profit form may merely attract managers who value job perquisites more than profit-maximizing managers do. High quality is just one perquisite among many, including a more relaxed work environment, congenial coworkers, or even a sense of nonpecuniary *noblesse oblige*.

Although past studies measuring hospital industry costs have found no significant evidence of comparative efficiency, a few studies of managerial behavior have implied that the non-distribution constraint has measurable effects on managerial decision-making. In his study of hospital management, Clarkson (1972) found some empirical support for four property rights implications: 1) Rules governing not-for-profit management behavior are more extensive than owners' rules for for-profit managers because for-profit manager behavior is partially controlled by linking their income to residual wealth. 2) Not-for-profit managerial effort is directed more toward acquiring on-the-job perquisites than for-profit managerial effort. 3) Not-for-profit managers base decisions on information that is easier to obtain than information used by for-profits in their decisions. 4) Not-for-profit managers vary their input mix more than for-profit managers in producing the same output. In a more recent study, Oswald and Gardiner (1994) purported to show expense preference among not-for-profit hospital managers indicating higher perquisite consumption than their for-profit counterparts. However, the paper's main results could be interpreted as revealing a higher preoccupation with quality of care at not-for-profit facilities (for example, they report average full-time equivalent employees per occupied bed is higher for not-for-profits).

If not-for-profit managers are less interested in financial rewards, empirical studies should show that not-for-profit managers receive lower salaries than their for-profit counterparts. This hypothesis is supported by Preston (1989) in her study of for-profit and not-for-profit sector compensation. She found that average nonprofit wages were 20% lower for managers and 5% lower for clerical and sales workers, even after adjusting for implicit prices of fringe benefits (including job autonomy and flexibility), human capital, industry type and occupation type. Preston's theoretical model of labor donations predicts that the negative wage differential results from not-for-profit workers accepting a lower wage in order to generate positive social externalities in their employment. This hypothesis was not proven by her findings, due to the inconclusive results of self-selectivity bias tests. That is, the not-for-profit worker may simply be of lower quality and may self-select into the less intense not-for-profit sector.

Young (1987) notes that compensation is likely to be comparable across ownership types in the rank and file workers, but that managerial salaries will differ. Preston's results support this claim, and she writes (1989, page 449), "...results...support the prediction that workers less closely tied to social benefit provision in the organization are less likely to donate wages to nonprofit firms." Why workers would be less tied to social benefit provision -- even as they carry out the socially beneficial policies chosen by the manager -- is left unexplained. Young adds an additional angle to consider in top management compensation differentials, reporting that nonprofit agencies pay premium salaries for top administrators in order to maintain their reputation for the highest quality in the profession.

Therefore, a preoccupation with quality in not-for-profit organizations may on one hand justify paying lower salaries to managers and workers (who seek out high-quality firms in which to work), and on the other hand may justify paying top dollar for the highest level administrators. Preston's article appears to support the former notion, while Young's article shows that not-for-profit hospital administrators' salaries top their profession -- supporting the latter justification. Even rank and file hospital and nursing home staff, according to Oswald and Gardiner (1994) and Holtmann and Idson (1991) are paid more at not-for-profit facilities.

Alchian and Demsetz' (1972) view that not-for-profit managers face insufficient incentive to operate efficiently is supported in part by Clarkson (1972) and Oswald and Gardiner (1994). However, others contend that not-for-profit's production of a higher quality product offsets some, if not all of the predicted inefficiency (Pauly 1987). The defining factor appears to be in the screening process and self-selection of managers into their profession. The not-for-profit sector attracts either quality-obsessed ideologues (Rose-Ackerman 1996, Hansmann 1980), perquisite-consuming shirkers (Bennett and DiLorenzo 1989), or managers valuing some unknown combination of high quality and a pleasant workplace. Testing of comparative quality produced by for-profit and not-for-profit firms would aid in determining the nature of differing managerial objectives.

PART D: THE PHYSICIAN

If objectives of donors, board members and managers are difficult to elucidate, physician objectives can appear virtually unapproachable. Conflicting incentives, varying with remuneration form, face the physician, and widely differing physician objectives are modeled in the literature. Pauly and Redisch (1973), on one end of the spectrum, model physicians' efforts to maximize income and find that higher quality at not-for-profit hospitals may be the result of non-cooperative behavior among medical staff members who dominate hospital administration. Young (1987, page 173) lists several other authors agreeing with this premise, stating "nonprofits tend to be domains in which professions and professional thinking dominate, and agendas are shaped by a quest for professional excellence and prestige...(not-for-profit) (h)ospitals compete for patients on the basis of quality reputation as perceived by physicians who seek affiliation." On the other end of the spectrum, Arrow (1963 and 1986) and Hansmann (1980) grant a socially ethical role for doctors whereby they act in the patients' behalf. "Clearly, there is a whole world of rewards and penalties in social rather than monetary form. Professional responsibility is clearly enforced in good measure by systems of ethics, internalized during the education process and enforced in some measure by formal punishments and more broadly by reputations" (Arrow, 1986, page 1194).

Mooney and Ryan (1993) lament the lack of clear separation of patients' and physicians' utility functions in their paper discussing agency theory in health care. Usually it is assumed that the principal and agent utility functions are independent, leading agency theorists to devise complicated incentive-compatible fee structures in markets involving asymmetric information. However, in health care, physicians are said to incorporate their patient's utility into their own utility. If such incorporation is perfect, complicated fee structures are unnecessary. If incorporation is incomplete, physician actions can be predicted to vary according to the remuneration structure. Indeed, many studies note changes in treatment utilization rates when fee structures are changed. Examples are Hughes and Yule (1992), Melnick and Zwanziger (1988), and Custer et al. (1990).

The conditions under which a physician can be expected to provide high quality patient care vary widely. 1) The physician may be more altruistically motivated. 2) The physician may be better trained than his peers. 3) The physician may note that a patient is particularly knowledgeable (Mooney and Ryan, 1993). 4) The physician's compensation may be closely linked to service provided (for example, fee-for-service). 5) High-quality treatment may result in lower malpractice insurance premiums and fewer lawsuits. 6) A reputation for high-quality care may attract more patients to his practice. 7) A reputation for high-quality care may grant him a certain amount of prestige and allow him to have staff privileges at high-quality hospitals. 8) High-quality care prolongs the life of his patients, especially those with chronic diseases, and prolongs the receipt of fees for treatment.

Among the conditions outlined above, only the first presupposes an ethical constraint on treatment behavior. A myriad of external influences can also positively influence quality of care. Since evidence appears to reject the hypothesis that physicians are motivated solely by ethical considerations in choosing treatments for their patients, agency theory can be of use in determining physician reactions to different remuneration schemes and constraints on behavior resulting from the ownership status of the facility in which they practice. Hospital studies with cost-based reimbursement era data by Eskoz and Peddecord (1985) and Pattison and Katz (1983) showed that for-profit hospitals utilized ancillary services more than not-for-profit hospitals, prompting concerns about overutilization. Similarly, McCue et al. (1993) expressed concern that patients at for-profit psychiatric hospitals had longer stays and were possibly 'overtreated.' Physicians have the authority to admit patients, order ancillary services and discharge patients, so some of the blame for possible over- or underutilization must rest on the physician, rather than on the facility's administration. Thus, ownership status of the facility, and in particular any differences in physician compensation stemming from ownership status, may affect physicians' choices of health care inputs for the patients.

PART E: THE GOVERNMENT

It is presumed the objectives of the government or specifically of the government official are to promote social welfare and get reelected. The government pursues these objectives by producing public goods, intervening in markets where goods have production or consumption externalities, and correcting other market failures in the presence of asymmetric information and uncertainty.

Market inefficiencies in health care are abundant, prompting a multi-faceted response from government agencies. Federal and local governments are involved in subsidizing several health goods that have positive externalities, such as medical education and research, immunization, treatment of infectious diseases, and treatment of the indigent and uninsured for reduction of misery in the general population. The market failure cited most often in health care is asymmetric information. Several regulatory approaches established in the early 20th century address information asymmetries; physician licensure, health care facility accreditation, and malpractice liability law. Governments, however, have rarely sought to bridge information gaps by disseminating information on provider quality to health care consumers. Lastly, the Federal government is involved in mitigating uncertainty and moral hazard problems in health care by providing Medicaid and universal Medicare insurance coverage for the poor or elderly, who would otherwise be selected out of the medical insurance market due to their high probability of costly care.

The market inefficiencies described above imply two possible motives for government intervention to subsidize not-for-profit organizations; the public good motive and the asymmetric information motive. Intervention may at times take the form of entry barriers to for-profit facilities or explicit subsidies for not-for-profit capital construction. The most significant intervention influencing not-for-profit viability is exemption from federal and local taxes.

I. Public Good Motive

Very early in the twentieth century, not-for-profit hospitals were exempted from paying taxes to provide some compensation for treatment of large numbers of indigent patients. Not-for-profit hospitals were important providers of charity care to the urban poor. At that time, patients with infectious diseases formed the bulk of the patient population, so charity care was not only important for altruistic purposes, but also for reducing disease in the wealthier population as well.

The inception of Medicaid in 1965 reduced the charitable motivation for not-for-profit and public charitable care of uninsured patients. In addition, by the latter part of the twentieth century hospital care was no longer concentrated on treatment of conditions resulting from infectious diseases, so much of the public component of health care was reduced. A few public good justifications for subsidy of not-for-profit and public providers remain today: Not-for-profit and public health care organizations perform the bulk of the nation's medical education and research. For-profit health care participation in medical education and research per facility is far below that of the other ownership types. Additionally, most studies of uncompensated care report that not-for-profit facilities are providing more unreimbursed care to uninsured patients than for-profit facilities.

Even though not-for-profit organizations are dominant providers of medical education and research, many individual not-for-profit facilities provide no medical education for health professionals or research, so a blanket assumption that not-for-profit tax exemption is justified on the basis of provision of public goods is on shaky ground. So too, is the assumption that not-for-profit health care facilities provide more "community benefit" than their for-profit counterparts. Community benefit is achieved by providing services that not only satisfy patient needs, but also provide a public good by serving the local community as well. An example would be a hospital offering subsidized flu shots for senior citizens at the local mall. One could argue that this service is a form of marketing and thus provides a net benefit to the hospital, not to the community. Perhaps a far stronger contribution to community benefit is from providing not services with a public good component, but private goods efficiently -- higher quality care or lower prices. Thus, not-for-profit advocates would do well to research pricing and quality when calculating comparative social benefits provided by different ownership types.

II. Asymmetric Information Motive

Some advocates of not-for-profit health care attribute not-for-profit tax exemption to a deliberate regulatory strategy to increase quality of care. However, even if not-for-profit providers' objectives lead them to produce a higher quality product, this approach to regulatory quality is as indirect as physician licensure and hospital accreditation. Certainly such indirect methods are cheaper than monitoring quality of care patient by patient. But ultimately, the asymmetric information problem is not entirely solved by quality monitoring in the form of inspections and accreditation procedures because what is monitored are variables most easily measured; physical characteristics of the building, staff education and other health care inputs.

Although promotion of not-for-profit care is another indirect attempt to correct for asymmetric information by improving quality of care, it may be a method nevertheless more likely to enhance quality variables that are hard to measure (patient satisfaction and health outcomes) normally neglected by government programs to monitor and enforce quality. In other words, the managerial behaviors that not-for-profit organization is purported to encourage – devotion to service and high quality -- may convince governments to support not-for-profit health care with tax subsidies in order to improve quality of care and eliminate problems resulting from asymmetric information. Whether intentionally or not, governments' exemption of not-for-profit health care organizations from taxes and related subsidies perpetuates the strength of the not-for-profit sector in US health care. The argument that not-for-profit facilities supply more public goods to the community is true for the industry as a whole (in particular, for medical education and research, and proportionally more uncompensated care), but not necessarily for individual facilities. It is this lack of individual contribution to the public by some not-for-profit facilities that has prompted some local tax authorities to challenge not-for-profit tax exemptions.

Others may argue that government subsidy of not-for-profit health care arises from the government's efforts to control quality problems arising from asymmetries of information. The supposition that governments subsidize not-for-profit health care in order to maintain quality depends on the critical and unproven hypothesis that not-for-profit managers produce a higher quality product and do not merely consume on-the-job perquisites. Furthermore, the government is rarely endorsed by voters to increase an industry's product quality, except in cases involving externalities.

Finally, if provision of medical education, research, and uncompensated care -- as well as asymmetries of information -- are of such a concern to governments, why isn't greater emphasis placed in direct funding of public health care facilities? Medicare and Medicaid funding reduced the government's role as a direct provider, allowing elderly and indigent patients to choose not-for-profit and for-profit facilities for their care. The number of public health care facilities declined notably throughout the 1970s and 1980s, and was largely replaced by growing numbers of for-profit facilities, especially chain hospitals.

With Medicare and Medicaid programs in place, financing of medical care by federal and state governments changed to a voucher system rather than direct provision, and the government essentially subcontracted care. This movement away from direct provision is discussed by Salamon (1987), who notes that support for the not-for-profit sector allows the government to reconcile the public's "hostility to the governmental apparatus" and the desire of the government to increase social welfare. Thus, promotion of not-for-profit health care may be a way for the government to maximize quality and quantity of health care in the community without enlarging the government payroll or sacrificing consumer choice.

If government objectives have appeared to focus on any one aspect of health care since 1965, the likely candidate would not be quality, but costs. State Certificate of Need programs popular in the 1970's and early 1980's were designed to slow expansion in an industry seen as over-capitalized. All-payer rate review regulations in some states were somewhat more successful at restricting health care costs during those decades as well. By the 1980's, though, costs of medical care had increased enough to convince Medicare to replace the inflationary cost-based reimbursement system with the Diagnostic Related Group (DRG) prospective-price reimbursement system. This change produced almost immediate results in the industry -- not only were patients coded to be "much sicker" upon admittance to hospitals to ensure maximum reimbursement from Medicare, but also utilization decreased dramatically. For example, patient lengths of stay decreased significantly (Melnick and Zwanziger, 1988). This important change in financing, affecting hospital costs and utilization, may eventually have an effect on the quality of patient care and patient health outcomes.

Part F: Patients

Patients in the health care industry often differ from consumers of other products because of the presence of third-party payers. Most often, the price the patient pays for health care at one facility or another is identical (zero or a negligible percentage of the total bill as a co-payment). Decisions by the patient regarding prices paid for medical care and quality expected are made in advance of actual purchases. That is, an individual insured at his place of employment chooses an insurer or health maintenance organization based on price and perceived quality of care, or accepts government financing (if over age 65 or indigent). At a later date, the individual falls ill and chooses a facility or doctor for treatment, but does not face further price decisions because the insurer pays according to the pre-arranged agreement.

At the point of consumption, the patient has relatively more choice regarding quality, as several physicians or facilities are usually funded by insurance or Medicare/Medicaid. One would expect *a priori* that patients automatically seek the highest quality provider, since price is no longer a relevant issue However, patients are often incapacitated or not knowledgeable enough to judge the quality of the provider's product before or even after consumption of the product. Patients differ considerably in their ability to judge quality, so at least a portion of the population is unaware of quality of care. For these patients, the choice of provider may be determined by amenities such as location and physical attributes of the facility. Another factor contributing to patient heterogeneity is varying personal discount rates; some patients have a low personal discount rate and a strong desire to remain in good health over a long period, while other patients with higher discount rates are willing to trade survival probability for immediate pain relief or less aggressive treatment of their illness. Patients with high marginal rates of discount may choose facilities similar to those chosen by the patients unaware of quality -- facilities with convenient locations and attractive appearances.

Not-for-profit status may serve as a signal of higher quality in service industries where information on quality is not readily available to the consumer. This trust signal from a not-for-profit organization provides a proxy for patients to evaluate prior to treatment. Hansmann (1980) explains that it is not necessary for all consumers to be aware of an organization's ownership status in order for a not-for-profit to use its trust signal status successfully. There will also be a number of patients who are able to judge quality through research, personal connections, and so forth. For these particularly knowledgeable patients, a provider's ownership status is unimportant next to actual evidence of clinical quality. Thus, the proportion of patients unaware of quality issues but aware of ownership status -- and choosing their provider based on that status -- is likely to be small.

A patient's utility is affected by his quality of health, length of life, and amenities consumed in the course of treatment. The patient's choice of provider does not depend merely on the quality of clinical care. The empirical content of this dissertation measures mortality as the clinical quality variable, and admittedly makes no attempt to measure total patient utility by including amenity variables such as provider location in the empirical analysis. However, for at least a subset of the patient population, health and longevity are dominant variables in utility, and some patients are consequently very aware of the quality of their care. If not-for-profit facilities offer higher quality care because they attract managers or physicians less influenced by cash incentives, one would expect knowledgeable patients to deliberately choose not-for-profit facilities when a choice is possible.

Part G: Objectives by Actor: Conclusion

Examining objectives of individuals in the provision of health care reveals many wordy discussions, but few refutable implications. Certainly, it is clear that not-for-profit health care played a critical role when public and charitable goods were a majority of its output prior to the establishment of Medicare and Medicaid and widespread employer-based health care insurance. Then, the motives for donors, boards of directors, and government officials to promote not-for-profit health care were straightforward. Presently, increasing numbers of uninsured individuals are seeking care at not-for-profit hospitals as public hospitals decline in number, but the volume of charity care at most hospitals is not comparable to the large number of charity patients treated at hospitals a century ago. As a justification for continued subsidy of not-for-profit health care, some now assert that not-for-profit organizations provide comparatively more benefits to the community and provide a higher quality of care to their patients, due to their differing objectives from strict profit maximization.

Government motives for promoting not-for-profit care now sometimes rest on the assertion that the presence of not-for-profit care in a community elevates quality of patient care. Patient motives for choosing not-for-profit providers over for-profit providers rely on the assumption that not-for-profit facilities provide better care, or their not-for-profit status provides at the very least a signal of higher quality care. Physician motives for choosing to be on staff at not-for-profit facilities rather than for-profit facilities depend on compensation systems in place. Differences in physician compensation structures exist in for-profit and not-for-profit organizations, and managers have some influence, especially in for-profit facilities, to alter physician compensation structures in order to encourage quality-enhancing or cost-controlling physician behavior.

However, the assertion that not-for-profit health care facilities provide higher quality care because they are motivated to do so has not been rigorously tested. As discussed in Part C. above, Armen Alchian and colleagues provided perhaps the strongest implication for testing in his examination of not-for-profit managerial objectives. Alchian hypothesized that the not-for-profit organizational form encourages managers to shirk and consume cost-increasing on-the-job perquisites, because managerial effort is not as closely linked to cash income as in for-profit firms. Expressed in a more positive light, Preston adds that the not-for-profit organization is likely to attract managers who are less motivated by cash incentives and more motivated by the opportunity to provide social benefits. Note that provision of social benefit is an on-the-job perquisite, so Preston's research focused on a subset of Alchian's hypothesis. Providing a higher-quality product than that which would maximize profits is another possible on-the-job perquisite for not-for-profit managers, and thus constitutes another subset of Alchian's hypothesis.

A test of Alchian's hypothesis is straightforward: One must compare costs of producing output by the two ownership types, while holding the quality of the output constant across the types. Many studies in health economics have purported to compare "efficiency" of for-profit and not-for-profit health care facilities, but have neglected to measure quality of output; instead assuming that no quality differences existed or that input measures of quality were sufficient controls. Rosko et al. (1995) provide the rare exception. In their study of nursing home efficiency, they utilized data envelopment analysis methodology to compare costs while holding three outcome quality controls constant; pressure ulcer rate, catheter use rate, and use of restraints. They found that although not-for-profit nursing homes produced higher quality outcomes overall, for-profit nursing homes were more efficient, holding quality constant. However, in the nursing home industry, many patients self-pay, and previous studies describe the not-for-profit nursing home sector as occupants of a high-price, high-quality market niche. Thus, results of the Rosko et al. study may be interpreted as mere confirmation that not-for-profits deliver a different product and cannot be compared in efficiency with for-profit nursing homes. Other health care sectors such as hospitals and dialysis centers, for which price is fixed by Medicare or other third-party payers, are better candidates for cross-ownership comparisons of efficiency.

The hypothesis that not-for-profit managers consume more on-the-job perquisites does not posit any preference on the part of the manager for increasing perquisites that accrue just to the manager himself, for producing more output beneficial to the health care facility's community, or for producing output of a higher quality. This paper assumes that Alchian's hypothesis is correct in that managers of for-profit firms will pursue profit-maximizing opportunities more aggressively than their not-for-profit counterparts will. If not-for-profit facilities are indeed producing output of a higher quality when reimbursement is determined by a third party, it can be concluded that not-for-profit managers are not spending all the financial cushion created by preferential tax treatment on personal perquisites, and at least some of the financial cushion accrues to the patient of the facility. This result offers assurance that individual decision making by patients, government officials, and physicians in health care is indeed rational. Patients seeking higher quality base their choice of provider on ownership status, governments subsidize not-for-profits in order to elevate quality or mitigate asymmetric information problems, and physicians choose to affiliate with not-for-profits to provide higher quality care even though compensation may be lower.

The theoretical model in the next chapter shows that over time, the existence of the non-distribution constraint alone induces not-for-profit managers to offer higher quality care, even though for-profit and not-for-profit managers may be equally altruistic, valuing quality of care identically.

SECTION 3: EMPIRICAL EVIDENCE OF QUALITY DIFFERENCES BY OWNERSHIP TYPE

Since the contention exists that not-for-profit firms produce a higher quality product than their for-profit counterparts, it is a worthwhile exercise to examine the medical literature to determine if indeed a disparity in quality exists across ownership types.

PART A: LONG-TERM CARE

Studies of the nursing home sector suggest that for-profit nursing homes use different inputs in the production of long-term care (Davis, 1991, Greene and Monahan, 1981, and Zinn, Aaronson and Rosko, 1993). In one of the few studies focusing on outcome measures of quality, Aaronson, Zinn and Rosko (1994) indicated that quality of care differs by ownership structure in the nursing home industry. However, in the nursing home industry, a significant portion of patients self-pay, and previous research describes the not-for-profit nursing home sector as occupants of a high-price, high-quality market niche (Cohen and Dubay, 1990). Thus, results of the Aaronson, Zinn and Rosko study may be interpreted as mere confirmation that not-for-profits deliver a different product for a different price. Other health care sectors such as hospitals and dialysis centers, for which prices are often fixed by Medicare or other third-party payers, are better candidates for cross-ownership comparisons of quality and efficiency.

PART B: GENERAL ACUTE CARE HOSPITALS

After reviewing studies of hospital performance by ownership, several researchers have come to the conclusion that quality does not differ significantly by ownership type (Gray, 1986, Frank and Salkever, 1994). Comparisons of outcome quality among hospitals are difficult due to the large number of products hospitals produce. Outcomes produced by one department for one type of illness may be very different from the outcomes produced for another department. The best quality comparison would take clinical outcomes by illness type, adjusted for severity of the disease and patient case-mix characteristics, and then compare survival rates across hospitals. The enormity of this task has discouraged researchers from focusing on outcomes. Instead, researchers have often measured inputs as indicators of quality. Outcomes and patient satisfaction research have recently undergone a remarkable transformation, due to significant improvements in computing capacity. We expect that future comparative studies of hospital quality by ownership will focus much more on actual clinical outcomes.

A second reason for the lack of significant results in comparative quality studies across ownership types is the change in reimbursement systems from cost-based to prospective-price financing. Prior to the mid-1980's, hospitals received payment by third-party payers largely on the basis of fee-for-service. Thus, hospitals were encouraged to provide premium care in the form of extensive diagnostic treatment, long hospital stays, and so on. Any firm that pursued profits aggressively found it in their best financial interest to provide the highest quality care at the highest cost. In their study of services provided by for-profit and not-for-profit hospitals, Pattison and Katz (1983) and Eskoz and Peddecord (1985) found that for-profit hospitals provided more profitably reimbursed ancillary services to patients than not-for-profit hospitals. Certainly, the distinctive incentives created by cost-based reimbursement encouraged high cost care which may have resulted in high quality care.

Now, however, prospective price reimbursement systems dominate hospital care financing. Not surprisingly, immediately after Medicare initiated its prospective price Diagnostic Related Group financing in the mid-1980's, average lengths of stay for patients declined (Melnick and Zwanziger,1988). High cost care is still with us, but hospitals are now competing for managed care contracts on the basis of price, and incentives now exist to reduce costs. It is in this new reimbursement environment that we may see distinct quality differences across hospitals arise. Care should be taken, when viewing comparative quality studies, to note whether the financing of the care was fee-for-service or prospective price.

PART C: QUALITY DIFFERENCES: CONCLUSION

For the above reasons, it cannot be concluded from previous research that a significant quality difference exists by ownership type in the hospital industry. Some research points to a quality gap in the nursing home industry, but this may be attributable to the existence of self-pay patients and the availability of a quality decision by patients based on price. The renal dialysis industry, introduced in Chapter 3, offers an ideal alternative laboratory for testing comparative quality across ownership types, due to the homogeneity of patients and treatment protocol and due to its financing, which is almost solely prospective-price.

CHAPTER 2: HEALTH CARE QUALITY AND UTILITY MAXIMIZING MANAGERS

SECTION 1: AN INTERTEMPORAL MODEL OF UTILITY MAXIMIZATION BY HEALTH CARE FACILITY MANAGER/OWNERS

As a formalization of managerial objectives discussed in Chapter 1, this chapter examines the effect of the non-distribution constraint on not-for-profit managerial choice of quality level over time. It is found that when at least some of the patients choose their provider on the basis of quality, the existence of the non-distribution constraint causes not-for-profit managers to select a higher level of patient quality of care than for-profit manager/owners choose. This result holds even though for-profit and not-for-profit providers are assumed to obtain identical amounts of utility from quality of care provided to their patients. This conclusion indicates that at least some of the slack created by preferential tax treatment for not-for-profit firms is used to produce a higher quality product, and therefore not all of the perquisite-consuming behavior predicted by Alchian and Demsetz (1972) is enjoyed solely by the manager.

The following model is a departure from many other models of not-for-profit/for-profit objective functions. It is not assumed that not-for-profit managers seek to break even, since many instances have been observed where not-for-profits have consistently maintained profits and have used their profits in subsequent capital expansion. Nor is it assumed that not-for-profit firm managers derive utility from quality (or number of patients, etc.) more than their for-profit counterparts. Here, identical objective functions are modeled, with only one very fundamental difference between the two ownership forms: The not-for-profit managers take home less cash income from profits than for-profit managers.[2]

The utility-maximizing manager seeks to maximize a combination of cash income and quality. The cash income is modeled as a percentage of profits generated by the firm. For-profit managers receive more cash income tied to the firm's profits than not-for-profit managers. Not-for-profit managers do not explicitly receive cash income as a percentage of profits, but income linked to profitable performance does accrue to not-for-profit managers over time in the form of higher salaries.

Managers maximize $\int_0^\infty e^{-rt}\,\{\alpha[Px - C(u)] + f(u)\}dt$, such that $x' = s(u) + i(u) + E - ax$,

where α is percentage of profits that managers receive as cash;

$$0 \leq \alpha_{NFP} < \alpha_{FP} \leq 1.$$

P is the reimbursement per treatment (or patient) that facilities receive.

x is the firm's number of patients or treatments.

u is quality of care.

C(u) are costs, dependent on quality of care.

f(u) are benefits accruing to the manager (prestige, etc.), dependent on quality.

s(u) is survival, dependent upon quality of care.

[2] It is assumed that managers and owners of for-profit firms are indistinguishable in behavior in this analysis.

$i(u)$ is inflow of patients, dependent upon quality of care.

E is exogenous inflow of patients, regardless of quality.

The manager, caring about the quality of care given and her cash income, seeks to maximize utility over an infinite horizon, discounted by r, the interest rate. The control variable is quality and the number of patients is the state variable. Increased quality of care results in a higher survival rate of current patients, and higher inflows of knowledgeable patients. The distinction between knowledgeable and unknowledgeable patients is relevant to the analysis of asymmetric information and treatment by ownership type in Chapter 6. Inflow of patients is also dependent on the number of patients already being treated.

It is assumed:

costs are increasing and convex in u; $C'(u) > 0$, $C''(u) > 0$
survival, inflow, and prestige benefits are increasing and concave in u;
$s'(u) > 0$, $i'(u) > 0$, $f'(u) > 0$, and $s''(u) < 0$, $i''(u) < 0$, $f''(u) < 0$.

The Hamiltonian is $e^{-rt}\{\alpha[Px - C(u)] + f(u)\} + \lambda(t)[s(u) + i(u) + E - ax]$. The current-value Hamiltonian is

$$H^* = \alpha[Px - C(u)] + f(u) + m[s(u) + i(u) + E - ax], \text{ where } m = e^{rt}\lambda(t).$$

Optimality conditions are:

$$\frac{\partial H^*}{\partial u} = 0: \qquad -\alpha C'(u) + f'(u) + m[s'(u) + i'(u)] = 0 \qquad 1)$$

$$-\frac{\partial H^*}{\partial x} = m' - rm: \qquad -\alpha P + am = m' - rm \qquad 2)$$

$$\frac{\partial H^*}{\partial m} = x': \qquad x' = s(u) + i(u) + E - ax \qquad 3)$$

From 1), $C'(u) = \dfrac{f'(u) + m[s'(u) + i'(u)]}{\alpha}$

The manager chooses quality level u to equate marginal costs with marginal benefits from increased future patient survival and inflow, plus marginal personal benefits from quality, all weighted by the percentage α of profits accruing to the manager as cash income. Similarly,

$$\alpha = \frac{f'(u) + m[s'(u) + i'(u)]}{C'(u)}$$

The for-profit manager with the larger percentage of cash income from profits (α) must utilize a smaller quality of care (u), using the assumptions given above. The important result here is that despite identical manager tastes for quality, the cash income constraint results in the not-for-profit manager providing a higher quality product, with correspondingly higher survival rates of not-for-profit patients.

SECTION 2: AN EXAMPLE SPECIFYING FUNCTIONAL FORM

Letting $C(u) = cu^2$, $f(u) = fu$, $s(u) = su$, and $i(u) = iu$, the optimality conditions are:

$$- 2\alpha cu + f + m(s + i) = 0$$

$$-\alpha P + ma = m' - rm$$

$$x' = su + iu + E - ax.$$

In the steady state when x' and m' = 0, the optimality conditions reveal:

$$m_s = \frac{\alpha P}{r+a}$$

$$x_s = \frac{1}{a}\left[E + \frac{(s+i)f}{2\alpha c} + \frac{(s+i)^2 P}{2c(r+a)}\right]$$

$$u_s = \frac{f}{2\alpha c} + \frac{(s+i)P}{2c(r+a)}$$

Thus, in the steady state, for-profit firms have fewer patients and provide a lower quality of care. Note that in the absence of any altruism on the part of the managers (quality does not enter independently into the utility function), when $f = 0$, managers simply maximize profits and there is no difference between for-profit and not-for-profit managerial behavior, even though the residual earnings constraint differs for not-for-profit managers.

Further analysis with the functional forms specified above produces the Euler equations,

$$x(t) = A_1 e^{\beta_1 t} + A_2 e^{\beta_2 t} + \frac{1}{a}\left[E + \frac{(s+i)f}{2\alpha c} + \frac{(s+i)^2 P}{2c(r+a)}\right]$$

$$m(t) = \left(\frac{(\beta_1 + a)2\alpha c}{(s+i)^2}\right) A_1 e^{\beta_1 t} + \left(\frac{(\beta_2 + a)2\alpha c}{(s+i)^2}\right) A_2 e^{\beta_2 t} + \frac{\alpha P}{r+a}$$

The roots of the equations, β_1 and β_2, are $(r + a)$ and $-a$. Since they are of opposite sign, the model is stable and a steady state can be reached. Assuming that $x(0) = \mathbf{x}$, the path for quality over time is:

$$u(t) = \frac{3f}{4\alpha c} + \frac{E - a\mathbf{x}}{s+i} + \frac{P[1/2 + (s+i)]}{2c(r+a)} \qquad 4)$$

Thus, over time, the for-profit manager chooses a lower level of quality, and survival rates s(u) are lower for patients in for-profit facilities. If quality does not enter the utility function for the managers, they both choose an identical level of quality, regardless of the percentage of income derived from profit generated. Considering that managers who value cash income more than other perquisites will gravitate toward for-profit firms, it is plausible that a utility function of a for-profit manager will contain just the cash income component, while the not-for-profit manager's utility function will contain both cash income and an independent quality variable. In that case, the first term of 4) is absent for the for-profit manager, and the quality produced over time is lower for the for-profit firm. However, this assumption of differing utility functions for for-profit and not-for-profit managers is not necessary for the quality variation result to hold. The opposite assumption -- that not-for-profit managers value cash income more than for-profit managers -- is not plausible given the not-for-profit non-distribution constraint. Managers will self-select into organizations that provide more of their favored form of compensation.

CHAPTER 3: THE US RENAL DIALYSIS INDUSTRY

SECTION 1: DESCRIPTION OF THE DIALYSIS INDUSTRY

To test the effect of the health care provider's ownership status on quality of care, as measured by mortality rates, we utilized Medicare data on US kidney dialysis patients in the End-Stage Renal Disease Program. The US kidney dialysis industry is ideal for studying the effects of ownership status on clinical quality of care for several important reasons:

1) Patients in the US End-Stage Renal Disease (ESRD) program all have the same symptoms and the same need for dialysis or transplant to remain alive. Thus, complex data adjustment to account for case-mix and facility differences is reduced.

2) There are over 2000 dialysis facilities treating over 200,000 patients annually in the US. An adequate sample size of both facility ownership types exists to determine significant differences in clinical quality produced.

3) Mortality, an unambiguous measure of health outcome, is high in dialysis patients; close to 20% annually.

4) Medicare payment for dialysis is a fixed fee per treatment session, regardless of treatment duration and costs. This creates financial incentives similar to incentive created by Medicare's prospective-price Diagnostic Related Groups payments for hospital care. Results can therefore yield insights for the majority of US health care sectors.

5) Since virtually all of the patients with ESRD are eligible to receive Medicare compensation for treatment 90 days after starting treatment, the data set encompasses virtually all patients undergoing dialysis in the U.S.

SECTION 2: HISTORY OF THE U.S. END-STAGE RENAL DISEASE PROGRAM

Dialysis treatment for patients with chronic renal failure was pioneered in 1960 by Dr. Belding Scribner and colleagues at the University of Washington (Rettig, 1976). Dialysis treatments were beyond the financial reach of most renal failure patients then, but were undeniably successful in keeping alive patients who would otherwise not survive. The first dialysis patient, a machinist at Boeing in Seattle, continued to work and lived for eleven years while on dialysis. The Veterans Administration started a dialysis program in its network of hospitals in 1963, and in the late 1960's, the Public Health Service operated several dialysis clinics as a research project (Levinsky, 1993).

By 1972, Congress voted to extend Medicare benefits to some 5,000 patients on dialysis, regardless of age. Thus, renal failure patients, classified as disabled, are the only recipients of Medicare funding who can be under age 65. Health care costs comprised a significantly lower portion of the US gross national product, so the decision to fund a proven life-saving treatment was attractive (Levinsky, 1993). Interesting changes occurred in the average characteristics of patients undergoing dialysis and transplant. In the 1960's, treatment was funded by the patients themselves or by donated funds earmarked for the most worthy of patients. It became clear by the 1980's that the decision to extend Medicare benefits to all end-stage renal disease patients improved the access to treatment for women, minorities, children, and patients over age 55 (Daniels, 1991).

In 1973, reimbursement for dialysis treatment was set at a "reasonable-charge basis" of \$138 per treatment for freestanding dialysis units and somewhat higher cost-based reimbursement for dialysis units in hospitals. In the 1980's the per-treatment reimbursement rates were reduced and adjusted to a composite rate. By 1989, accounting for inflation, the average composite reimbursement rate had declined to \$54 (in 1974 dollars) (Rettig and Levinsky, 1991). Nevertheless, the industry continued to be profitable, and Garella (1997) notes that while the average Medicare composite rate was \$126, the audited average cost per treatment in 1991 was \$107.21, producing an astonishing 18% profit per treatment.

The first for-profit freestanding dialysis facility, named National Medical Care, Inc. (NMC) opened in New York in 1970. Initially the dialysis industry was composed primarily of not-for-profit dialysis facilities in hospitals, but the fastest growth after 1972 was seen in freestanding for-profit facilities. NMC grew rapidly to become the industry's largest provider of dialysis services, and by 1985 operated in 31 states (Daniels, 1991). In 1980, not-for-profit hospital-based providers still treated the most dialysis patients (58.1%) and for-profit freestanding facilities treated 32.4% of the nation's dialysis patients. Phenomenal growth of freestanding for-profit units in the 1980's occurred, and by 1988, freestanding for-profit facilities were treating 51.4% of the nation's dialysis patients, and hospital-based not-for-profit facilities treating only 37% (Rettig and Levinsky, 1991, chapter 6).

Rettig and Levinsky provide further revealing information about the transformation of the dialysis and transplant industry in the 1980's. Besides the growth of for-profit and freestanding dialysis centers, from 1980 to 1988 the total U.S. dialysis patient population increased from 52,364 to 105,958 patients. Not-for-profit facilities also increased during the 1980's, but at a much slower pace. Large multi-unit chains such as NMC grew rapidly during this time as well. Note that the growth of this industry occurred despite the reductions in the composite per-treatment reimbursement rate.

The 1990's have witnessed a continuation of the growth of investor-owned chains, and hospital-based not-for-profit and small physician-owned units are the most common facilities purchased by for-profit chains. At the beginning of 1994, freestanding for-profit facilities treated 55.5% of all U.S. dialysis patients (Garella, 1997). The patient-mix has continued to change, with ever more elderly patients receiving dialysis treatments. Today, over 160,000 patients currently receive Medicare funding for dialysis treatments. Gross mortality rates have declined in the past decade, but when patient age, primary diagnosis, and other case-mix characteristics are controlled for, it is found that overall mortality rates have declined during this period (Rettig, 1996).

Medicare spent approximately $8.9 billion on the end-stage renal disease (ESRD) program in 1995 (Garella, 1997). Although total expenditures for ESRD treatment continue to rise, the increase is due to increases in numbers of ESRD patients treated, rather than increasing expenditures per patient, as is typical of many other health expenditures. Levinsky (1993) noted that in 1990, expenditures per capita for ESRD patients was ten times the average medical expenditure for the U.S. population. Friedman (1996) and others fear that the considerable size of the ESRD program may make it a target for budget cutting in the coming years, as the Medicare fund faces possible future bankruptcy.

Treatment usually consists of three weekly hemodialysis sessions of about three hours duration at an outpatient facility. During these sessions, patients are connected to dialyzing machines that filter waste products from the bloodstream. Nurses and technicians monitor the treatment process and also draw patients' blood and take blood pressure. This time-consuming procedure has its costs for both the patients and the facility, which incurs significant capital and labor expenses. Garella (1997) reports that each dialysis treatment provided requires approximately 2.2 hours of direct patient care. Since facilities are paid a fixed amount per treatment session by Medicare, regardless of the duration or expenses incurred, facilities have an incentive to economize on inputs, especially duration of treatment. With a given amount of dialysis machines and staff, treating patients for a shorter duration can allow a greater volume of patients to be treated weekly, for virtually the same cost. As will be introduced in the next section, duration of treatment may play an important role in outcome quality. Other noted methods of cost-control in dialysis facilities are replacing highly trained nursing staff with less well-trained technicians, reusing dialyzers, and delaying replacement of old equipment (Rettig, 1996).

Medicare compensation for dialysis has two main components. Medicare pays a composite rate fee of approximately \$125-\$130 depending on the geographic region to dialysis centers for each dialysis treatment. Aside from geographic variation, this composite rate is fixed, even though treatment sessions and complications vary from treatment to treatment and from patient to patient. Medicare actually pays 80% of the composite rate, with the remaining 20% coming from additional insurers, Medicaid, or very rarely, the patient himself. The composite rate includes payment for treatments, specified weekly and monthly laboratory tests, and services by dieticians and social workers (Garella, 1997). Other services for medically necessary tests and procedures are reimbursed separately. Recent research by the U.S. General Accounting Office (1997) indicates that some facilities are over-prescribing these separately-billed laboratory tests, but the research did not explore the possibility that the widely varying lab test rates were related to ownership of the facility.

Physicians are also paid a capitated fee per month per dialysis patient of approximately $240, again depending on the geographic region. Physicians affiliated with not-for-profit dialysis centers receive only the capitated fee as compensation. Physicians affiliated with for-profit dialysis centers receive the capitated fee, but may also receive a portion of the dialysis facility's proceeds from the composite rate. Thus, physicians affiliated with for-profit dialysis centers can in some instances receive compensation that is partially linked to the dialysis facility's efficiency, unlike not-for-profit physicians. Note that if this occurs, the distinction between manager objectives and physician objectives are blurred, if not at times nonexistent, because for-profit physicians can own their dialysis centers or serve as part-owners in the organization.

In the dialysis industry, patients rarely select a facility for treatment on their own. Initially, their primary care physician refers them to nephrologists, who then refer patients to the dialysis facility where they are on staff. Once treatment commences, patients seldom switch providers. Lundin (1996) states, "(H)emodialysis patients are the most intimidated and intimidatable of patients, fearing that transfer to another dialysis center may only make their situation worse." On the other hand, conversations with several nephrologists suggested that patients do switch facilities now and then, not only for relocation purposes, but because those patients are dissatisfied with their treatment.

Costs of care vary by treatment modality. Garella (1997) reported the 1991 average annual expense per patient on dialysis as $35,000. Patients receiving a transplant cost

$86,000 in the first year, followed by $7,000 annual costs per patient with a well-functioning transplant and $43,000 annual costs for patients whose previous transplant failed during the year. Since costs over time differ for dialysis and transplant patients, facilities may have incentives to limit or encourage transplants, depending on reimbursement structures.

SECTION 3: EVIDENCE OF QUALITY VARIATION IN THE DIALYSIS LITERATURE

Held et al. (1991) report that dialysis treatments of shorter duration contribute to higher mortality of ESRD patients. Other studies showing a linkage between short duration and higher mortality are Charra et al. (1992); Charra, Calemard and Laurent (1996) and Kjellstrand (1985). Furthermore, Held et al. (1991) indicate that for-profit dialysis centers are more likely to treat dialysis patients with shorter sessions.

The USRDS (US Renal Data System) measured facility average hospital admission and mortality rates, adjusted for patient sex, age, race, and primary disease causing ESRD in the 1995 Annual Data Report. They found that for 1991-1993, not-for-profit dialysis centers had lower hospital admission rates and lower mortality rates than for-profit dialysis centers. However, their results were not adjusted for other factors such as differences in local market competition level, market share, patient income and education level, or geographic region. Hospital admission rates were not measured in this study as an outcome measure because the decision to hospitalize a dialysis patient may be motivated by a concern for quality care for a somewhat sick patient, or may be necessary care for an extremely sick patient. Thus, the hospitalization decision can be measured as an input or a health outcome. Another important distinction between this study and the USRDS measurement of facility-level mortality rates is that here, we consider the possibility of a third element of quality; the opportunity to cease dialysis treatments by receiving a functioning transplant.

Griffiths et al. (1994) studied the US End-Stage Renal Disease program using dialysis facility cost reports in 1990 and determined that for-profit facilities produced more treatments per month than not-for-profit facilities after weighting the data for quantities of capital and labor used in production, and adjusting for facility and patient case-mix characteristics. However, Griffiths et al. did not compare or control for patient outcomes across ownership type, nor did they control for inputs such as duration of treatment. Held et al.'s (1991) results linking shorter treatment sessions with higher mortality imply that Griffiths et al.'s conclusion that for-profit dialysis centers are more efficient may be insupportable due to a differing level of outcome quality between the two ownership types.

Held and Pauly (1983) measured an important quality feature for the dialysis patient; the facility's number of dialysis machines per patient. That is, patients are more able to schedule convenient dialysis sessions (an amenity) at facilities with greater capacity and smaller peak loads. Held and Pauly found that in markets with greater levels of competition, facilities offer more amenities (higher quality). Furthermore, in competitive areas, for-profit dialysis centers offer more amenities than not-for-profit centers. Interestingly, Held and Pauly's amenity results by ownership contrast with USRDS clinical quality results by ownership. One explanation may be that in areas of high competition where patients are able to switch dialysis centers more easily, for-profit dialysis centers may improve quality features that are most apparent to the patient. That is, dialysis facility scheduling, location, music system at the facility, and even duration of treatments may be most important or most visible to the patient, not the facility's comparative mortality and hospitalization rates. Since Held and Pauly did not control for duration of treatment in their study, it is not guaranteed that the facilities with higher machine per patient ratios had more convenient dialysis scheduling available for patients. In addition, convenience of scheduling is only one facet of quality a dialysis patient notices.

In a study of market competitiveness on treatment strategies of facilities, Farley (1993) measured patient outcomes (hospitalization rates and mortality rates) among dialysis-only patients in 1990, for a total sample of 72,445 patients. A sub-sample of 58,437 patients who survived was used in an analysis of patient hospitalization rates. Her results suggested that not-for-profit ownership was linked with lower hospitalization rates. However, this could reflect three phenomena: 1) Not-for-profit firms take better care of their patients, requiring fewer hospitalizations; 2) Patients at not-for-profit firms are healthier, experiencing fewer complications requiring hospitalization; and 3) Not-for-profit firms resist discharging revenue-generating patients to hospitals. Notably, the third reason listed portends very different patient outcomes than the first two reasons. This potential endogeneity of the hospitalization variable makes interpretation of the results as patient outcomes risky.

Farley's multivariate regression analysis of mortality rates included treatment input variables and interactions between competition levels and ownership type. Her analysis was performed on a subset of dialysis-only patients, and did not include outcomes for patients with functioning transplants. Farley's patient case-mix variables were similar with the exception of age, for which she used four discrete groups, rather than a continuous variable. Farley collapsed three measures of competition into one composite variable. This composite variable may have masked different effects on mortality rates of

Herfindahl, market share, and Certificate of Need regulations. In Chapter 4 here, Certificate of Need regulations were found to have different effects on mortality than other measures of competition. Further discussion of Farley's results is provided at the end of Chapter 4.

The research in Chapter 4 analyzes mortality outcomes for a sample 2.5 times as large as Farley's 1990 sample, and includes analysis of transplant status as an independent variable influencing mortality, and transplant status as a possible third (preferred) outcome. Chapter 5 provides a radically different investigation of the estimated causal effect of for-profit ownership on patient mortality. Chapter 6 investigates a new topic – asymmetric information – and provides some evidence that patients' sophistication level may be related to the treatment they receive at dialysis facilities.

CHAPTER 4: OWNERSHIP AND MORTALITY IN THE DIALYSIS INDUSTRY: MULTIVARIATE REGRESSION ANALYSIS

SECTION 1: DATA SOURCES AND ATTRIBUTES

The study described in this chapter is an examination of possible variation in mortality rates by ownership status. Besides controlling for patient case-mix, this study controls for market competition level (using a Hirschman-Herfindahl index), market share of the firm, local income and education levels, entry regulations and geographic region. After controlling for these factors, remaining differences in the quality of care are more likely to originate from differences in objectives of the two ownership types. As facility size is likely to be an endogenous variable, this study does not control for number of patients at each facility, nor does it omit small facilities. Transplant status is examined in two ways – as an independent variable affecting the dependent mortality variable, and as a third dependent variable.

Before the empirical project is described, it is necessary to point out that differing quality of clinical care does not imply greater patient satisfaction, and thus we fall short of specifying the quality of the complete product. For the average patient, renal dialysis consists of three-hour dialysis sessions three times per week. For some patients, the long treatment sessions may seem too great a price to pay for prolonging their lives. Their satisfaction could theoretically be increased by reducing the duration and thus the clinical quality of their treatments.

The sample for the multinomial logistic regression analysis in this chapter consists of 197,710 patients being treated at for-profit and not-for-profit dialysis units nationwide in 1993. This includes all patients who had been on dialysis for three or more months and receiving Medicare benefits as of December 31, 1993. Patients who start dialysis or transplant treatment after age 65 are included in the sample from the beginning of their treatment. Since patients who are under age 65 may be covered by other insurance until Medicare coverage starts after three months of treatment, these patients may be missing from the USRDS database. Therefore, all 4453 patients under age 65 who had less than 90 days of treatment are omitted from the sample. This introduces a possible sample bias toward overrepresentation of patients aged 65 and older, and will limit analysis of very short-term younger patients who died less than three months after starting treatment.

The sample includes all patients receiving dialysis treatments or a transplant in 1993 at dialysis-only facilities, dialysis and transplant and transplant-only facilities (either hospital-based or freestanding). Omitted from the study are patients whose main treatment facility was government-owned, patients whose main treatment modality for dialysis was not center-based hemodialysis or transplant, and patients for whom a treatment facility was unidentifiable. Data programming and regression analysis was performed on mainframe computer with version 6.12 of SAS. Some patients were treated at two or more facilities in 1993. For these patients, their main facility was designated as the facility where they spent the most days during 1993. A related empirical project described in Chapter 6 uses a subset of this data consisting of black and white dialysis patients with hypertension or diabetes as their primary diagnosis, being treated at freestanding facilities only.

The data are from several sources. Patient and facility-level data were from the Patient, Residence, Treatment History, and Facility Standard Analysis Files from the USRDS.

The USRDS is funded by the National Institute of Diabetics and Digestive and Kidney Diseases (NIDDK) of the National Institutes of Health. The Health Care Financing Administration of the US Department of Health and Human Services supplies the NIDDK with the original data. Data by zipcode on education, household income, and urban population are from the 1990 US Census. Data on state Certificate of Need regulations affecting renal dialysis provision were obtained from the National Directory of Health Planning Policy and Regulatory Agencies.

Summary statistics for the data are provided in Tables 1-3. Noteworthy is the very high number of African American ESRD patients. According to the USRDS (1995), among black Americans one person in 399 U.S. residents is an ESRD patient. Among white Americans, one person in 1,672 U.S. residents is an ESRD patient. Another factor explaining the high rates of African Americans in the sample is the choice of treatment modality by black patients and their physicians. Black ESRD patients are less likely to be treated with home hemodialysis than whites (Kendix, 1997). Home hemodialysis patients, as well as continuous ambulatory peritoneal dialysis and continuous cycling peritoneal dialysis patients, comprised 14.4% of US ESRD patients in 1993, but are not included in this study because their treatment is largely performed at home without dialysis center staff assistance. Removal of home dialysis patients from the study may introduce a bias against not-for-profit facilities, since not-for-profit facilities are more likely to place patients on home dialysis than for-profit facilities. Furthermore, home dialysis patients are healthier as a population group than center-based dialysis patients (Kendix, 1997). Thus, removing home dialysis patients from the sample may cause for-profit firms in the sample to have healthier center-based dialysis patients than not-for-profit firms.

Table 1: Patient Characteristics: n = 197,710

Variable	Mean	Std. Dev	Median	5th %	95th %
Age	57.76	16.78	60	28	81
Vintage (days on dialysis)	1519.12	1487.08	1004	116	4780
Household income (by patient's zipcode)	29,119	11,278	27,644	14,016	50,471
Avg. years of schooling (by patient's zipcode)	12.54	.99	12.52	11.07	14.36

Gender: Female (dummy variable = 1): n = 92,377 (46.7%)
Male: n = 105,333 (53.3%)

Race:

Native American:	n = 2,465	(1.2%)
Black:	n = 63,873	(32.3%)
White:	n = 123,741	(62.6%) (omitted reference category)
Asian:	n = 5,209	(2.6%)
Other race:	n = 2,422	(1.2%)

Primary Diagnosis Causing End-Stage Renal Disease:

Diabetic:	n = 57,767	(29.2%)
Hypertension:	n = 52,498	(26.6%)
Glomerulonephritis:	n = 31,057	(15.7%)
Cystic Kidney:	n = 8,238	(4.2%)
Other Primary Diagnoses:	n = 48,150	(24.4%) (omitted reference category)

Transplant Status:

Transplants > or = 1 (dummy = 1):	n = 38,517	(19.5%)
Transplants = 0:	n = 159,193	(80.5%)

Table 2: Market Characteristics[3]

Variable	Mean	Std. Dev.	Median	5th %	95th %
Herfindahl Index of Facility (by county[4])					
	.2561	.1770	.2206	.0431	.6100
Market Share of Facility (in patient's county)					
	.2559	.2576	.1489	.0085	.8061
Percent Urban (in patient's zipcode)					
	69.01%	42.75%	99.10%	0%	100%

Table 3: Facility Characteristics: n = 2,258

South:
Facility in South (dummy = 1): n = 654 Facility not in South: n = 1604

Certificate of Need (CON) entry regulation status:
Facility in state with CON (dummy = 1): n = 868 No CON: n = 1390

Free-standing:
Facility free-standing (dummy = 1): n = 1632 Facility in hospital: n = 626

Ownership:
For-profit facility (dummy = 1): n = 1439 Not-for-profit facility: n = 819

[3] Market information and facility characteristics are attached to each patient observation in the empirical analysis.

[4] The patient origin Hirschman-Herfindahl index (HHI) calculation follows Gruber (1994), p. 209. The HHI is calculated for each county, then a weighted average of the index is created for each county served by a facility. The HHI was also calculated using the first three digits of the zipcode. Regressions using the zipcode-based HHI yielded results similar to those below.

Patient case-mix characteristics that have been noted as important predictors of mortality are age, race, and primary diagnosis. From previous research, it is expected that older patients, patients on dialysis for a long period, white patients (especially when compared to black patients) and patients with a primary diagnosis of diabetes will have a higher mortality rate. The age variable had a distinctly convex shape with respect to mortality, so in the logistic regression analysis discussed below, an additional age term, deviation from the mean age, was added to capture the convexity. Transplant status was also an important indicator of a patient's health, because primarily younger and healthier patients are selected to receive a transplant instead of continuing dialysis. Transplant status enters as an independent variable in the first logistic regression analysis. Later, for the successive cumulative logistic regression analysis, transplant status will be considered as a dependent variable for one of three possible outcomes; death, living on dialysis, and living with a transplant.

Several economic variables were included in the study, but had no *a priori* hypotheses regarding their potential effect on patient mortality. Household income and average years of schooling may be related to patient sophistication level and ability to monitor quality of care. Held et al. (1991) note that higher-income patients had a shorter average duration of dialysis treatment sessions, so higher income may be linked to higher mortality. The Hirschman-Herfindahl index measures the competition level of the facility's market. Stronger competition may induce either greater quality, as facilities compete for patients on the basis of quality, or facilities may cut quality to reduce costs in order to remain viable in a competitive market. Certificate of Need entry regulations affect the level and nature of competition in a market. The market share variable measures the monopoly power a firm may have in a market. Percent urban was included to capture possible urban/rural quality differences, while the south variable may signal regional differences in population besides race, or regional differences in physician practice. A variable indicating freestanding status was also included, due to possible differences in hospital and freestanding patient populations.

Since the populations of patients at for-profit and not-for-profit facilities may differ with respect to variables that affect mortality rates, the data were divided by ownership type to examine the population characteristics separately. Tables 1-3 were repeated for patients at for-profit facilities in Tables 4-6, and for patients at not-for-profit facilities in Tables 7-9 below.

Table 4. Patient Characteristics: n = 108,520

For-profit Facilities Only

Variable	Mean	Std. Dev.	Median	5th %	95th %
Age	61.04	15.53	64	32	82
Vintage (days on dialysis)					
	1249	1295	816	102	4052
Household income (by patient's zipcode)					
	28,004	10,737	26,681	13,630	48,235
Avg. years of schooling (by patient's zipcode)					
	12.44	1.00	12.41	10.92	14.27

Gender: Female (dummy variable = 1): n = 52,796 (48.7%)
Male: n = 55,724 (51.3%)

Race:
Native American: n = 1,328 (1.2%)
Black: n = 41,088 (37.9%)
White: n = 62,126 (57.2%) (omitted reference category)
Asian: n = 2,560 (2.4%)
Other: n = 1,418 (1.3%)

Primary Disease Causing End-Stage Renal Disease:
Diabetic: n = 34,868 (32.1%)
Hypertension: n = 33,982 (31.3%)
Glomerulonephritis: n = 12,999 (12.0%)
Cystic Kidney: n = 3,385 (3.1%)
Other Primary Diagnoses: n = 23,286 (21.5%) (omitted reference category)

Table 4 continues on the next page.

Table 4, continued.

Transplant Status:
Transplants > or = 1 (dummy variable = 1): n = 1,928 (1.8%)
Transplants = 0: n = 106,592 (98.2%)

Table 5. Market Characteristics

For-profit Facilities Only

Variable	Mean	Std. Dev.	Median	5th %	95th %
Herfindahl index of facility (by county)					
	.2443	.1851	.2089	.0330	.6157
Market share of facility					
	.2593	.2641	.1429	.0081	.8046
Percent urban (in patient's zipcode)					
	69.7%	42.3%	99.3%	0%	100%

Table 6. Facility Characteristics: n = 1439

For-Profit Facilities Only

South:
Facility in South (dummy variable = 1): n = 508 (35.3%)
Facility not in South: n = 931 (64.7%)

Certificate of Need (CON) entry regulation status:
Facility in state with CON (dummy variable = 1): n = 446 (31.0%)
No CON: n = 993 (69.0%)

Free-standing:
Facility free-standing (dummy variable = 1): n = 1410 (98.0%)
Facility in hospital: n = 29 (2.0%)

Table 7. Patient Characteristics: n = 89,190

Not-for-Profit Facilities Only

Variable	Mean	Std. Dev.	Median	5th %	95th %
Age	53.79	17.38	54	25	80
Vintage (days on dialysis)					
	1848	1633	1340	142	5298
Household income (by patient's zipcode)					
	30,477	11,761	29,100	14,763	52,305
Avg. years of schooling (by patient's zipcode)					
	12.67	0.97	12.54	11.24	14.44

Gender: Female (dummy variable = 1): n = 39,581 (44.4%)
Male: n = 49,609 (55.6%)

Race:
Native American: n = 1,137 (1.3%)
Black: n = 22,785 (25.5%)
White: n = 61,615 (69.1%) (omitted reference category)
Asian: n = 2,649 (3.0%)
Other: n = 1,004 (1.1%)

Primary Disease Causing End-Stage Renal Disease:
Diabetic: n = 22,899 (25.7%)
Hypertension: n = 18,516 (20.8%)
Glomerulonephritis: n = 18,058 (20.2%)
Cystic Kidney: n = 4,853 (5.4%)
Other Primary Diagnoses: n = 24,864 (27.9%) (omitted reference category)

Transplant Status:
Transplants > or = 1 (dummy variable = 1): n = 36,589 (41.0%)
Transplants = 0: n = 52,601 (59.0%)

Table 8. Market Characteristics

Not-for-Profit Facilities Only

Variable	Mean	Std. Dev.	Median	5^{th} %	95^{th} %
Herfindahl index of facility (by county)					
	.2705	.1655	.2278	.0677	.6099
Market share of facility					
	.2518	.2493	.1535	.0090	.8061
Percent urban (in patient's zipcode)					
	68.2%	43.3%	98.8%	0%	100%

Table 9. Facility Characteristics: n = 819

Not-for-Profit Facilities Only

South:
Facility in South (dummy variable = 1): n = 146 (17.8%)
Facility not in South: n = 673 (82.2%)

Certificate of Need (CON) entry regulation status:
Facility in state with CON (dummy variable = 1): n = 422 (51.5%)
No CON: n = 397 (48.5%)

Free-standing:
Facility free-standing (dummy variable = 1): n = 222 (27.1%)
Facility in hospital: n = 597 (72.9%)

Tables 4-9 reveal important population differences between the samples of for-profit and not-for-profit patients. Because the majority of transplant facilities are not-for-profit, and transplant patients are substantially healthier than the remaining population of patients with end-stage renal disease, the data above show markedly younger patients, fewer diabetic patients at not-for-profit facilities, and many more transplant patients. On the other hand, for-profit facilities have more female patients, patients on dialysis for a shorter length of time, and more African-American patients. If the multivariate regression model is correctly specified, the effects of population bias are eliminated by including independent variables such as age, transplant status, diabetic status, etc. If that is true, the estimate of the effect of for-profit ownership should be correct in its direction and magnitude of effect on the probability of mortality. The confounding influence of transplant status may not be adequately controlled for, however, so after the initial multivariate analysis of ownership and mortality rates, the data are once more examined, using the subset of patients who are treated by dialysis alone. Furthermore, Chapter 5 presents an analysis of data whereby a data sample is created that has no population differences in observable independent variables.

SECTION 2: BINOMIAL LOGIT REGRESSION RESULTS

First, a binomial logistic regression was run, with results shown in Table 10. The continuous and dummy variables above were regressed against a binary variable for death. Parameter estimates were well behaved, with signs following results of previous research. For example, age was the strongest variable, with a strongly positive effect on mortality. The longer the patients had been on dialysis, the higher the mortality risk. Patients with a primary diagnosis of diabetes showed greater mortality rates, while patients with other primary diagnoses showed more favorable mortality results. White patients, the omitted reference group for race variables, had higher mortality results than all other ethnic groups shown. Especially favorable mortality results were shown for African American patients and patients who had received a transplant. Supporting the results of the theoretical model in Chapter 2, the parameter estimate for the effect of a dummy variable indicating for-profit ownership was positive, indicating a higher mortality rate for patients in for-profit facilities. The results linking for-profit ownership with higher mortality rates were robust for a sample excluding patients who started dialysis or transplant treatment during 1993 and for a sample including patients under age 65 who had less than 90 days of treatment.

Economic variables for which no hypothesis existed regarding sign of the effect on mortality were competition (Hirschman-Herfindahl index, market share) and Certificate of Need regulatory status. Interestingly, the results of these economic variables could be considered contradictory. The Hirschman-Herfindahl index, where 1.0 designates no competition and smaller values designate more intense competition, had no effect on mortality. The market share variable, where 1.0 designates full market share and smaller values designate a smaller market share, had a slightly negative effect on mortality. The explanatory power of the Herfindahl and market share variables may be weak because multiple facilities in markets are considered competitors, when in fact they may be owned by the same corporation. Chain ownership status was not available in this data. The presence of Certificate of Need regulations in the facility's state, limiting entry of new dialysis facilities, had a weakly positive effect on mortality. Urban/rural status appeared not to matter, nor did the average years of schooling in the patient's zipcode, yet higher patient income by zipcode seemed to predict lower mortality. Patients treated at facilities in the South and facilities in hospitals rather than freestanding units fared worse.

Table 10: Binomial Logit with Death=1, Living=0 as Dependent Variable

Number of observations: 197,710

Criterion	Intercept Only	Intercept & Covariates	χ^2 for Covariates
-2 ln L	249,668	211,148	38,520 with 22 DF (p=0.0001)
Score			33,896 with 22 DF (p=0.0001)

R^2 = 38,520/249,668 = .1543 (Lemeshow's pseudo-R^2)

Variable	Parameter Estimate	Standard Error	Wald χ^2	Prob. > χ^2	Standardized Estimate
Intercept	-3.2924	0.0931	1251.40	0.0001	.
Age	0.0441	0.0004	12161.30	0.0001	0.4084
Age Deviation^2	0.0003	0.00002	165.62	0.0001	0.050
Transplant	-1.6868	0.0260	4220.50	0.0001	-0.3683
Days on dialysis	0.0001	4.21E-6	368.53	0.0001	0.0663
South	0.0455	0.0139	10.72	0.0011	0.0106
Freestanding	-0.1456	0.0198	54.08	0.0001	-0.0386
Herfindahl index	-0.0043	0.0536	0.01	0.9368	-0.0004
Market share	-0.0579	0.0337	2.95	0.0860	-0.0082
For-profit	**0.1362**	**0.0170**	**64.10**	**0.0001**	**0.0374**
Female	-0.0998	0.0107	86.43	0.0001	-0.0274
Native American	-0.4154	0.0486	72.98	0.0001	-0.0254
Black	-0.3922	0.0128	931.75	0.0001	-0.1011
Asian	-0.5212	0.0359	211.24	0.0001	-0.0460
Other non-white	-0.1538	0.0516	8.88	0.0029	-0.0089
Diabetic	0.4100	0.0151	741.49	0.0001	0.1028
Hypertension	-0.0080	0.0154	0.28	0.5998	-0.0020
Glomerulonephritis	-0.3332	0.0194	295.30	0.0001	-0.0668
Cystic Kidney	-0.6748	0.0335	406.87	0.0001	-0.0743
HH income	-1.96E-6	7.60E-7	6.66	0.0099	-0.0122
Avg. years schooling	0.0096	0.0083	1.32	0.2504	0.0052
Certificate of Need	0.0468	0.0112	17.57	0.0001	0.0128
Percent Urban	-0.0002	0.0002	1.21	0.2718	-0.0039

Logistic regression results are not noted for their particular ease in interpretation because the dependent variable in the regression is the natural log of the odds ratio, where the odds ratio = Probability(death)/[1-Probability(death)]. Since the dependent variable, death, is either 0 or 1, when multiplying β by 100%, the parameter estimates are interpreted as the percentage change in the odds ratio for a one-unit percentage change in the independent variable. At the very least, the parameter estimates are useful because they indicate the direction of effect from a change in an independent variable on the dependent variable. Standardized coefficients are preferred by some in interpreting logistic regression results, but are rarely seen in econometric studies due to the dearth of binary variables in Economics. Standardized coefficients represent the effect on the probability of death for a one standard deviation change in the independent variable. One may rank the standardized coefficients by absolute value of size to obtain a snapshot of the various independent variables' effect on the dependent variable (Table 11). Patient case-mix variables profoundly affect mortality, while economic variables appear less important. The economic variable with the strongest effect on mortality is ownership status of the facility.

Table 11: Independent Variables Ranked by Standardized Coefficient

1. Age
2. Transplant status
3. Diabetic
4. Black
5. Cystic Kidneys
6. Glomerulonephritis
7. Days on dialysis (vintage)
8. Age deviation squared
9. Asian
10. Free-standing facility
11. **For-profit ownership**
12. Female
13. Native American
14. Certificate of Need status
15. Household income
16. South
17. Other non-white race
18. Market share (significant at $p < .10$)
19. Average years of schooling (insignificant)
20. Percent urban (insignificant)
21. Hypertension (insignificant, compared to reference category of "other diagnoses")
22. Hirschman-Herfindahl index of competition (insignificant)

PART A: SELECTED POPULATION PROBABILITY OF DEATH

The parameter estimates can be examined, for selected groups of patients, to determine their effect on death. The logistic equation estimated is

$$\ln [P/(1-P)] = \beta_0 + \Sigma \beta_i X_i ,$$

where $i = 1 - 22$, and P is the probability of death during the year and X_i are independent variables.

As a sample reference case we can enter mean values for all continuous variables and select dummy values of interest to calculate the natural log of the odds. Then, solving for the probability of death in each case, we can determine the effect of a selected dummy variable (ownership) on the probability of death:

For white males, non-South, no transplant, diabetic, treated at a freestanding for-profit facility with no state Certificate of Need entry regulations, with average age, days on dialysis, household income, schooling, percent urban, and average facility Hirschman-Herfindahl index and market share,

$\ln [P/(1-P)] = -0.0746$ solving for the probability of death, $P = .4814$ 1)

For identical patients at not-for-profit facilities,

$\ln [P/(1-P)] = -0.2108$ the probability of death $= .4475$ 2)

Subtracting 2) from 1) we obtain the increase in the probability of death during the year from being treated at a for-profit facility rather than a not-for-profit facility. Here, for the reference group above (white males), that increase is .0339 or 3.39%. Performing a similar operation with the same reference group values but for Black females with hypertension, the increase in the probability of death associated with being treated at a for-profit facility is 2.61%.

PART B: RESULTS FOR DATA SUB-SAMPLES

In the above binomial logistic regression, transplant status of the patient was utilized as an independent variable. The parameter estimate for transplant status was negative, suggesting that patients selected for transplants are healthier than average dialysis patients. Having a functioning transplant is less stressful to the body than long-term dialysis. Patients with cadaveric transplants have adjusted death rates during year 1 of only 9.2%, compared to death rates of 26.4% for patients on dialysis, where the data have been adjusted for age, race, sex, and primary disease causing end-stage renal disease (USRDS, 1995). Since the populations of transplant and dialysis patients are likely to be substantially different, an additional logit regression was run with dialysis-only patients in the sample. For this sample of 159,193 dialysis-only patients shown in Table 12, results showing poorer patient outcomes at for-profit facilities were consistent, with the for-profit ownership variable ranking ninth among the independent variables' effect on the probability of death in 1993 (Table 13). Note that the independent variable parameter estimates and their significance level as reported in Table 12 are virtually identical to the parameter estimates reported in Table 10. Because results showed little change from the dialysis and transplant sample to the dialysis-only sample, this shows some support for the ability of Table 10's regression model to correct for bias in the for-profit and not-for-profit patient populations.

Table 12: Binomial Logit, Dialysis-Only Patients

Number of observations: 159,193

Criterion	Intercept Only	Intercept & Covariates	χ^2 for Covariates
-2 ln L	212,893	194,158	18,735 with 22 DF (p=0.0001)
Score			17,638 with 22 DF (p=0.0001)

R^2 = 18,735/212,893 = .0880 (Lemeshow's pseudo-R^2)

Variable	Parameter Estimate	Standard Error	Wald χ^2	Prob. > χ^2	Standardized Estimate
Intercept	-3.2554	0.0961	1147.69	0.0001	.
Age	0.0433	0.0004	11,003.64	0.0001	0.3729
Age Deviation^2	0.0003	0.00002	183.79	0.0001	0.0479
Days on dialysis	0.0001	4.44E-6	322.65	0.0001	0.0580
South	0.0517	0.0142	13.26	0.0003	0.0124
Freestanding	-0.1506	0.0200	56.83	0.0001	-0.0340
Herfindahl index	-0.0124	0.0553	0.05	0.8221	-0.0013
Market share	-0.0651	0.0347	3.53	0.0604	-0.0097
For-profit	**0.1346**	**0.0172**	**61.15**	**0.0001**	**0.0349**
Female	-0.0904	0.0111	66.80	0.0001	-0.0249
Native American	-0.4261	0.0498	73.19	0.0001	-0.0263
Black	-0.4126	0.0131	992.37	0.0001	-0.1094
Asian	-0.5503	0.0368	223.26	0.0001	-0.0479
Other non-white	-0.1628	0.0527	9.55	0.0020	-0.0096
Diabetic	0.3856	0.0156	612.76	0.0001	0.0990
Hypertension	-0.0054	0.0158	0.12	0.7310	-0.0014
Glomerulonephritis	-0.3416	0.0205	277.92	0.0001	-0.0626
Cystic Kidney	-0.7125	0.0359	393.73	0.0001	-0.0696
HH income	-1.62E-6	7.89E-7	4.22	0.0400	-0.0099
Avg. years schooling	0.0104	0.0086	1.48	0.2243	0.0056
Certificate of Need	0.0541	0.0116	21.94	0.0001	0.0147
Percent Urban	-0.0001	0.0002	0.47	0.4929	-0.0025

Using the same reference groups as noted above to provide a snapshot of the effects of for-profit treatment on mortality, white males in the dialysis-only group with diabetes were 3.34% more likely to die during the year when treated at for-profit facilities (for a probability of death of .4941 at for-profit facilities), while Black females with hypertension were 2.68% more likely to die when treated at for-profit facilities (with a probability of death at for-profit facilities of .2895).

Table 13: Independent Variables Ranked by Standardized Coefficient, Dialysis-Only Patients

1. Age
2. Black
3. Diabetic
4. Cystic Kidney
5. Glomerulonephritis
6. Days on dialysis (vintage)
7. Asian
8. Age deviation squared
9. **For-profit ownership**
10. Freestanding facility
11. Native American
12. Female
13. Certificate of Need status
14. South
15. Household income (significant at $p < .05$)
16. Market share (significant at $p < .10$)
17. Other non-white race
18. Average years of schooling (insignificant)
19. Percent urban (insignificant)
20. Hypertension (insignificant, compared to reference category of "other diagnoses")
21. Hirschman-Herfindahl index of competition (insignificant)

Since the data set size is substantial, it was possible to perform the same logistic regression on sub-samples of the dialysis-only data by population group. Table 14 shows the sub-samples that were used to run the logistic regressions.

Table 14: Binomial Logit by Categorical Subset for Dialysis-Only Patients

Categorical Subset	Number of Observations	For-Profit Coefficient	Wald χ^2	Pr. > χ^2
All Dialysis Patients	159,193	0.1346	61.15	.0001
Age < 55	48,611	0.1117	9.78	.0018
55 <= Age < 75	78,093	0.1555	44.23	.0001
Age >= 75	32,489	0.1067	8.41	.0037
Days on dialysis < 400	42,207	0.1535	18.50	.0001
400 <= Dial. Days <= 1600	77,416	0.1176	23.17	.0001
Days on dialysis > 1600	39,570	0.1636	23.45	.0001
Diabetic	50,588	0.1454	24.36	.0001
Non-diabetic	108,605	0.1392	42.86	.0001
White	93,198	0.1220	28.77	.0001
Black	57,879	0.1668	35.22	.0001
Male	82,210	0.1372	32.32	.0001
Female	76,983	0.1330	29.27	.0001
Freestanding facility	125,394	0.1395	62.88	.0001
Hospital facility	33,799	0.1416	2.22	.1366
Certificate of Need regs.	66,248	0.1822	56.59	.0001
No Certificate of Need regs.	92,945	0.0959	14.88	.0001

Table 14 expresses strong results, suggesting that no matter how the dialysis-only data was subdivided and analyzed with separate multivariate logistic regressions, all groups of patients appeared to fare worse at for-profit facilities. Results of the sub-sample regressions were consistent regarding the effects of for-profit ownership on patient mortality. In all sub-samples except one, the parameter estimate on the for-profit ownership dummy variable was positive and statistically significant at the $p < .01$ level. The one sub-sample that showed no statistically significant effect of ownership on mortality was the subset of 33,799 patients who were treated at hospital-based facilities. The lack of significance for the hospital subset may be caused by the very small number of dialysis patients treated at for-profit hospitals. For-profit ownership effects on mortality were particularly strong (surpassing some patient characteristics in importance) for the following groups; the sub-samples of patients who had been on dialysis for more than 1600 days (about 4 years), non-diabetic patients, white patients, and patients in states with Certificate of Need entry regulations.

PART C: TRANSPLANT STATUS AS A DEPENDENT VARIABLE: SUCCESSIVE CUMULATIVE LOGISTIC REGRESSION

Instead of treating transplant status as an independent variable, one could also consider an ESRD patient with a transplant, off dialysis, to be experiencing a different outcome than those patients still on dialysis. Therefore, three ordered outcomes could be used for dependent variables; death, alive on dialysis, and alive with a transplant. An ordered multinomial logistic regression was run in SAS, and the score test soundly rejected the possibility that outcomes are necessarily ordered as above. To determine the source of unspecified data irregularities causing the rejection of the ordered logistic regression, two successive logistic regressions were run, with the following parameter estimates shown in Table 15.

Table 15: Successive Cumulative Logistic Regression Analysis

Variable	Logit I: Alive = 0, Died = 1 — Parameter Estimate		Wald χ^2	Logit II: Transplant = 0, No Transplant = 1 — Parameter Estimate		Wald χ^2	Note
Intercept	-3.8687	**	1774	-2.4037	**	248	
Age	0.0515	**	17,257	0.0952	**	10,172	
Age Deviation [2]	0.0003	**	130	0.0015	**	2,194	
Days on Dialysis	3.725E-6		.83	-0.00036	**	4,437	•
South	0.0257	*	3.5	0.3875	**	206	
Herfindahl index	-0.2119	**	16	-1.8209	**	463	
Market share	0.3049	**	84	3.5920	**	4,168	
For-profit	0.3501	**	915	3.6088	**	16,409	
Female	-0.0803	**	57	0.1399	**	65	•
Native American	-0.3471	**	52	0.4226	**	31	•
Black	-0.2921	**	523	1.1440	**	2498	•
Asian	-0.4673	**	172	0.4108	**	71	•
Other race	-0.0453		0.8	1.0339	**	160	•
Diabetic	0.4127	**	774	0.3193	**	164	
Hypertension	0.0168		1.2	0.0732	**	7.1	
Glomeruloneph.	-0.3628	**	364	-0.2663	**	127	
Cystic Kidney	-0.7400	**	514	-0.6765	**	341	
HH income	-9.43E-7		1.6	8.296E-6	**	53	•
Avg. yrs. school	-0.0172	*	4.4	-0.2459	**	346	
Cert. of Need	0.0737	**	45	0.3660	**	419	
Percent Urban	0.0004	*	6.1	0.0036	**	234	

* Statistically significant at $p < .05$.

** Statistically significant at $p<.01$

• These parameter estimates switched signs from Logit I to Logit II.

Logit I is the same as the regression reported in Table 10 above, but without the dummy variable for transplant status among the independent variables. Lemeshow's pseudo-R^2 for Logit I is .1330, which is less than the former model's R^2, due to the omission of the important transplant variable on the right-hand side. Logit II tests for explanatory power of the remaining independent variables on the possibility of transplant, and has a high pseudo-R^2 value of .5298. Note that Logit II is ordered such that a positive parameter estimate means that the patient is *less* likely to receive a transplant. This ensures consistency across the two logit regressions, in that a zero value for the dependent variable is favorable to the patient, and a value of one for the dependent variable is an unfavorable outcome for the patient.

The successive cumulative logistic regression results offer interesting insights due to differing rates of transplantation among different population groups: Minorities are more likely to survive (positive parameter estimates in Logit I) but are less likely to have transplants. 13.7% of African American ESRD patients have transplants, whereas 33% of white Americans with ESRD have transplants (USRDS, 1995). The parameter estimate for years of schooling becomes more negative with a transplant vs. non-transplant regression, indicating that the more schooling a patient has, the more likely she is to receive a transplanted kidney. The parameter estimate for household income switches to positive, indicating that there does not appear to be a positive income bias for obtaining transplants.

Market competition may be important, as here we see (contrary to results for the binomial logistic regression above) the higher the market share of the firm, the less likely it is that the patient receives a transplant. The strength of the market share parameter estimate in Logit II might be explained by the fact that transplant patients undergo transplant in facilities located primarily in large cities. Paradoxically, the higher the Herfindahl index of the firm, the higher the transplant rate. Freestanding status of the firm was not included as an explanatory variable in Logit II because no transplants take place at freestanding facilities. The effect of for-profit ownership is steady across the two logistic regressions – that is, patients are less likely to receive transplants at for-profit institutions and are less likely to survive at for-profit institutions. Both regressions suggest that patient outcomes are worse at for-profit facilities. However, the transplant results should be interpreted cautiously, as patients who are ideal transplant recipients are probably referred to the nearest transplant facility, which is usually a not-for-profit facility.

SECTION 3: LOGISTIC REGRESSION ANALYSIS SUMMARY

Multivariate logistic regression supported the hypothesis generated by the theoretical model of managerial utility maximization presented in Chapter 2. In this chapter, we find a positive influence on patient mortality for patients treated at for-profit facilities, compared to the reference group of patients treated at not-for-profit facilities. Binomial logistic regression of twenty-two independent patient, facility, and market characteristic variables on a binary variable indicating death in 1993 revealed statistically significant results of higher for-profit patient mortality. Sample probability statistics for two selected population groups were calculated, indicating that the estimated causal effect (increased probability) associated with for-profit treatment was around three percent. Analysis of various subsets of the population data suggested a consistent theme of higher mortality among patients in for-profit facilities.

Results indicating higher mortality among patients of for-profit facilities were consistent with similar studies by Farley (1993) and the USRDS (1995). Farley included ownership in a logistic regression of treatment inputs, market characteristics, and patient characteristics on the probability of patient mortality. Her model had substantial specification differences than the model discussed in Table 10 here, but her results showed not-for-profit ownership to be a negative influence on patient mortality, statistically significant at the $p <= .001$ level. Given the information in Farley's results, it was not possible to calculate sample probabilities of death for selected patient groups from her logistic regression results because average values for certain variables were not reported.

The USRDS presented standardized mortality ratios (SMRs) only for freestanding facilities with more than 20 dialysis patients. The SMR is obtained by dividing the observed number of deaths for the patient group by the expected number of deaths for that patient group, given age, sex, race, and primary disease characteristics. Although the USRDS did not include adjustments for market characteristics, their facility-level analysis indicated evidence of higher outcome quality at not-for-profit facilities. The SMR for freestanding not-for-profit facilities was .94 and the SMR for freestanding for-profit facilities was 1.01, where an SMR of 1.00 indicates that the same number of patients die during the study period as is statistically predicted by the case-mix characteristics of the patient group. This research suggests a difference in the probability of death due to for-profit treatment of approximately 7%, but note that their facility-level data were not weighted for facility size. In addition, hospital-based patients and transplant patients were not included in the USRDS analysis. The logistic regression results reported in this chapter are therefore consistent with previous literature with respect to the direction of effect that for-profit treatment has on patient outcomes. Here, though, it was possible to present sample probabilities for certain patient groups in order to characterize the magnitude of the effect of for-profit treatment.

There remains a question, however, of whether the logistic models were correctly specified to adjust for baseline differences in the population of for-profit and not-for-profit patients. The next chapter introduces a relatively new technique, propensity score methodology, for correcting differences in the data and avoiding the problem of mis-specification of the model, as well as presenting a clearly-defined measure of the magnitude of the effect of for-profit treatment on patient mortality.

CHAPTER 5: OWNERSHIP AND MORTALITY IN THE DIALYSIS INDUSTRY: PROPENSITY SCORE ANALYSIS

SECTION 1: INTRODUCTION

A common criticism of many empirical research projects, especially in health and social sciences, is that the data are based on observations of subjects non-randomly assigned to treatment and control groups. Baseline differences in important control variables may exist between the treatment and control groups. Multivariate regression analysis with inclusion of the relevant control variables will correct for the existing differences in the treatment and control groups if the model is correctly specified. However, the search for a correctly specified model is often difficult and unrewarding. The multivariate regression analysis in Chapter 4 estimated the causal effect of for-profit ownership for the entire population of patients being treated for end-stage renal disease in the US. Nevertheless, there is no guarantee that the logistic regression models were correctly specified in order to control for possible differences in the populations of for-profit and not-for-profit patients. Furthermore, the logistic analysis produced parameter estimates showing the *direction* of effect of for-profit treatment on mortality of patients, but these parameter estimates could not be used to specify the *magnitude* of that effect, unless specific population groups were targeted for analysis.

One tactic to avoid the lack of randomization would be the use of identical twins in research, because twins have almost identical opportunities and abilities, and they approximate a pair of identically matched observations. Assignment of each identical twin to the treatment and control groups will result in differing effects of the treatment. The causal effect of the treatment can then be calculated by subtracting the dependent variable value (reading score, income, 100-yard dash time, etc.) of the control group twin from the dependent variable value of the treatment group twin. Propensity score methodology provides a way of creating such matched groups without the twins. Observations are evaluated and arranged according to their similarities between treatment and control groups until no statistically significant difference exists between treatment and control group observations for any of the independent variables. Then, the estimated causal effect of the treatment is easily calculated. In the study presented in this chapter, propensity score methodology is employed as an alternative to the multivariate study in the previous chapter. Results from a sample of 15,422 patients showing no discernable differences among for-profit and not-for-profit patients indicate that the estimated causal effect of treatment at a for-profit facility is a 5.86% higher annual mortality rate than the mortality rate experienced by patients at not-for-profit facilities.

The main advantage of propensity score methodology is that it is possible to create treatment and control data subsets that have no discernible differences in the independent variables that affect outcomes. Consequently, there are no lingering concerns about incorrect specification of the model. If the treatment and control groups are proven to have virtually identical characteristics, then the main task is simplified to measuring the difference in outcomes between the treatment and control groups. Another important advantage of propensity score methodology is its ease of interpretation. The difference in outcomes between the treatment and control groups is the estimated causal effect of the treatment. Of course, these propensity score methodology results are dependent on the inclusion of all variables affecting outcome that may differ among treatment and control group observations, but the same dependence exists in multivariate regression models.

SECTION 2: PROPENSITY SCORE METHODOLOGY: THEORETICAL BACKGROUND

When working with a sample, the objective, as Rubin (1974) describes, is to determine the typical causal effect of treatment at a for-profit facility versus the typical causal effect of a patient being treated at a not-for-profit facility, on a dichotomous dependent variable, Y, indicating death during the year of study. However, in attempting to measure Y(for-profit treatment) – Y(not-for-profit treatment), we are unable to observe both simultaneously. Therefore, we observe $y_j(FP)$ - $y_j(NFP)$ in M trials, where the mean causal effect is

$$(1/M)\Sigma_j[y_j(FP) - y_j(NFP)], \text{ where } j = 1 \ldots M$$

As long as patients are randomly assigned to for-profit and not-for-profit treatment, the difference in Y, death, is an unbiased estimate of the average causal effect of for-profit ownership on mortality.

Randomization is impossible in this case, however, so our estimate of ownership type's effect on mortality may be biased. Patients are more or less free to choose their treatment facility, and some patients may be aware of the facility's ownership status. Nevertheless, the lack of randomization would be irrelevant if the two groups of patients at for-profit and not-for-profit facilities were identical for every variable affecting mortality. Rubin and others have suggested that using propensity score methodology might be a viable way to create identical patient sub-groups. Propensity score methodology may even be preferred to analysis using randomized data because perfectly matched groups of patients in for-profit and not-for-profit assignments would guarantee that the estimated causal effect of treatment would be completely unbiased, whereas a random assignment of patients to the treatment group may introduce population bias due to random error. Of course, this claim is predicated on the assumption that the observations matched on observed variables are not influenced by existing bias in unobserved variables. In this chapter, we limit the sample to a population of patients with case-mix similarities. We then find comparable groups of patients using the propensity score methodology and use those matched groups to estimate the average causal effect of ownership on mortality.

SECTION 3: PROPENSITY SCORE METHODOLOGY IN PRACTICE

PART A. CHOOSE SAMPLE AND CHOOSE RELEVANT INDEPENDENT VARIABLES

The first step was to reduce the sample size to hemodialysis patients being treated at freestanding facilities, black and white patients, and patients with either hypertension or diabetes (Table 16). This reduction in the size of the sample was necessary to simplify the process by which sub-samples are identified as "comparable" across ownership types, and to enhance ability to meaningfully characterize average causal effects of ownership for the majority of patients nationwide. Further, it was necessary to eliminate strictly facility-level characteristics from the analysis, since propensity score methodology requires a simple "control versus treatment" assignment with no secondary variables affecting assignment, which, in this case, would mean characteristics of the facility itself that are unrelated to the patient. Therefore, patients being treated at hospital-based facilities were eliminated from the sample so that all facilities remaining were freestanding.

Table 16. Propensity Score Project Sample Characteristics

Total sample size = 77,110.

Variable	Mean	Std. Dev.	Median	5^{th} %	95^{th} %
Age	62.95	14.07	66	36	82
Vintage (days on dialysis)	1045	997	746	97	3082
Household Income (in patient's zipcode)	27,005	10,475	25,786	13,162	46,689
Average Years of Schooling (in patient's zipcode)	12.38	0.98	12.35	10.92	14.20

Gender: Female: n = 38,471 (49.9%) Male: n = 38,639 (50.1%)

Race: Black: n = 34,967 (45.3%) White: n = 42,143 (54.7%)

Primary Diagnosis:
Diabetes: n = 38,536 (50.0%) Hypertension: n = 38,574 (50.0%)

Area:
Patients in South: n = 26,164. Facilities in South: 584.
Patients not in the South: n = 50,946. Facilities not in the South: 1032

Certificate of Need (CON) Status:
Patient's facility in state with CON entry regulations: n = 28,924.
Number of facilities in states with CON entry regulations: n = 550.

Patient's facility in state without CON entry regulations: n = 48,186.
Number of facilities in states without CON entry regulations: n = 1066.

Ownership:
Patients in for-profit facilities: n = 65,825.
Number of for-profit facilities: n = 1395.

Patients in not-for-profit facilities: n = 11,285.
Number of not-for-profit facilities: n = 221.

Table 17: Binomial Logit with Death = 1, Living = 0 as Dependent Variable

(Includes black and white hemodialysis patients with the primary diagnosis of diabetes or hypertension, being treated at free-standing facilities during 1993.)

Number of observations: Died: = 32,435
Living: = 44,675
Total: = 77,110

Criterion	Intercept Only	Intercept & Covariates	χ^2 for Covariates
-2 ln L	104,946	96,762	8183 with 14 DF (p=0.0001)
Score			7772 with 14 DF (p=0.0001)

Logistic Procedure: Analysis of Maximum Likelihood Estimates

Variable	**Parameter Estimate**	**Standard Error**	**Wald χ^2**	**Prob. > χ^2**	**Standardized Estimate**
Intercept	-4.0502	0.1376	866	0.0001	.
Age	0.0461	0.0006	4923	0.0001	0.3573
Age Deviation^2	0.0004	0.00004	122	0.0001	0.0573
Female	-0.0569	0.0157	13	0.0003	-0.0157
Vintage (days on dialysis)	0.0002	8.04E-6	432	0.0001	0.0920
Diabetic	0.3924	0.0164	572	0.0001	0.1082
Black	-0.5803	0.0176	1084	0.0001	-0.1593
South	0.0647	0.0177	13	0.0003	0.0169
Cert. of Need	0.0649	0.0165	16	0.0001	0.0173
HH Income /10,000	-0.0293	0.0117	6	0.0124	-0.0169
Market Share	-0.0746	0.0421	3	0.0767	-0.0136
Avg. Schooling	0.0462	0.0122	14	0.0001	0.0250
Percent Urban	-0.0003	0.0002	2	0.2014	-0.0067
Herfindahl	0.0706	0.0568	2	0.2141	0.0102
For-Profit	**0.1316**	**0.0223**	**34**	**0.0001**	**0.0256**

Table 17 reports the results of the first logistic regression of all the remaining variables (after removing the less common race and primary diagnosis patients) on the dependent variable, death during 1993. Performing this logistic regression was necessary to determine which independent variables have a statistically significant effect on death and should therefore be included in the process of identifying "identical" sub-samples by ownership type. Results of chi-square tests indicate that a Herfindahl index of market competition and the percent urban area in the patient's zipcode are not statistically significant for this sample of 77,110 patients, and thus will not be used in the propensity score analysis. Including irrelevant variables such as these could bias the results in determining the average causal effect of ownership on mortality. Market share of the facility in the patients' zipcode was not significant at the five percent level, so it was also dropped from the analysis. The statistical contribution of the market share variable did not justify the computational requirements of inclusion.

Similar to the results reported in Tables 10 and 12, Table 17 reveals that for-profit ownership is positively associated with higher mortality for patients in this sample. For-profit ownership is ranked sixth among the fourteen covariates listed above, using the absolute value of the standardized parameter estimates, which represent the effect on the probability of death for a one standard deviation change in the independent variable. The independent variables with stronger effects on the probability of death are age, black, diabetic, number of days on dialysis, and deviation from the average age – all of which are important patient case mix characteristics.

After removing the Herfindahl index, percent urban and market share variables, the additional independent variables have effects on the probability of death that are similar to the effects seen in Tables 10 and 12, which described the logistic regression for virtually all patients in the US. Patients in the south have higher mortality rates. Patients in states with Certificate of Need entry regulations appear to have higher mortality rates. Patients in zipcodes with higher income levels have lower mortality rates, yet patients in zipcodes with more years of schooling have a higher probability of death.

PART B. COMPUTE PROPENSITY SCORES AND SEPARATE SAMPLE INTO IDENTICAL FOR-PROFIT AND NOT-FOR-PROFIT STRATA

Following the techniques outlined in Rosenbaum and Rubin (1983) and Dehejia and Wahba (1997), to calculate the propensity of each observation to be a patient treated at a for-profit facility, the independent variables other than ownership were regressed using binomial logistic regression on the ownership dummy variable. The estimates of the dependent variable, propensity score, were retained for each observation. The propensity score thus represents the estimate of the natural log of the odds, where the odds refer to the probability of being a for-profit facility over the probability of being a not-for-profit facility. Then, the observations were ranked by propensity score and divided into strata by propensity score groupings. Separating the data into strata by propensity score enables one to create new smaller data sets whose population of treatment and control observations (for-profit and not-for-profit patients) are comparable. The closer the propensity score for two patients. the more likely it is that their independent variables are identical in distribution.

Before the data are separated into strata, it is necessary to remove any for-profit observations that are substantially different from not-for-profit observations, which is analogous to removing a population of control group observations that are dissimilar to treatment group observations and are therefore irrelevant to the analysis. Here, removing observations substantially different from the rest of the population is accomplished by eliminating for-profit observations that have propensity scores above the highest not-for-profit propensity score observations, and eliminating not-for-profit observations with propensity scores below for-profit observations' propensity scores, where the propensity score refers to the probability of the patient being a for-profit patient. Curiously, in this data set, the observation with the highest propensity score is a not-for-profit patient, and the observation with the lowest propensity score is a for-profit patient. Therefore, all the observations could be considered part of the relevant population. However, the population becomes more homogeneous by eliminating the upper propensity range and the lower propensity range, where for-profit and not-for-profit patients cluster, respectively.

To determine if the for-profit and not-for-profit patients in a strata had identical values for independent variables, a difference in means t-test was performed between the for-profit and not-for-profit subsets of each strata. Strata j had "identical" for-profit and not-for-profit patient observations if the absolute value of the t_α-statistic for strata j was less than 1.645, where $\alpha = .05$ and the null hypothesis is $H_0:(\mu_1 - \mu_2) \neq 0$:

$$t = (y_1 - y_2)/[s(1/n_1 + 1/n_2)^{1/2}] ,$$

where $y_1$and y_2 are the independent variable means for the for-profit and not-for-profit portions, respectively, of the stratum, $n_1$and n_2 are the number of for-profit and not-for-profit observations in the stratum, and s is the independent variable's standard deviation in the stratum (Mendenhall, 1987, page 414). Difference in means t-tests were computed for each independent variable in the stratum. If all t-tests failed to reject the null hypothesis, the for-profit and not-for-profit observations were statistically indistinct and comparable to a completeiy randomized data set.

Rosenbaum and Rubin (1984) and Cochran (1968) assert that separating a data set into five strata of equal sizes results in a 90% reduction in bias between treatment and control group populations. Several conditions must hold for this to be true, such as normality of distribution of the independent variables. For this particular project, separating the sample into five strata by propensity score was not enough to eliminate statistically significant differences in independent variable estimates by ownership. Difference in means t-tests rejected the null hypothesis for several of the independent variables in all five strata, suggesting the need for further subdivision of the data set by propensity score.

The following chart, Table 18, illustrates the process whereby the t-statistics are calculated for each independent variable in each stratum. Table 18 shows these calculations for a stratum that comprises the upper tenth of the data set, when ranked by propensity to be a for-profit facility. The propensity scores in this stratum range from .917 to .979. The standard deviation for each variable is calculated for the entire stratum, while the variable means are calculated for each ownership subset of the stratum. T-tests fail to reject the null hypothesis for the variables age, number of days on dialysis, female, and south, meaning that for-profit patients and not-for-profit patients have essentially identical values for these variables. T-tests reject the null hypothesis, however, for the variables diabetic, black, Certificate of Need (entry) regulations, household income, and average years of schooling. When t-tests fail to reject the null hypothesis, for-profit and not-for-profit patients in this stratum have characteristics that differ substantially from one another.

Table 18. Determining Strata Suitability via Difference in Means t-tests

Stratum Variable	Std. Dev.	F-P Subset Mean (n = 7055)	N-f-P Subset Mean (n = 657)	t-statistic	Reject H°?
Age	13.29	66.56	66.28	0.51	
Days on Dialysis	608.22	691.31	700.72	-0.38	
Female	0.50	0.50	0.48	1.17	
Diabetic	0.49	0.40	0.43	-1.27	
Black	0.47	0.34	0.29	2.56	reject
South	0.32	0.12	0.10	0.83	
Cert. of Need	0.04	0.0014	0.0061	-2.69	reject
Household Income/10,000	1.47	3.69	3.98	-4.97	reject
Avg. Years Schooling	1.38	12.29	12.43	-2.65	reject

If t-tests are rejected for any of the variables, it cannot be claimed that the data set's for-profit patients are the same as the not-for-profit patients, so the sample, or stratum, should be broken into smaller samples by propensity score. However, it can be argued that a stratum is acceptable if variables are biased in the correct direction. For example, the stratum above has more black patients at for-profit units than not-for-profit units. In Table 17, it is clear that black patients have a lower mortality risk than non-diabetic patients. Therefore, it biases the results in favor of for-profit facilities if we accept a stratum where for-profit units have significantly more black patients, as above. If final results indicate that for-profit facilities have a higher death rate, knowledge that for-profit units have more black patients would only serve to strengthen that conclusion. Unfortunately, accepting a stratum where the t-tests are rejected with a bias in favor of for-profits implies that the final estimate of the average causal effect of for-profit ownership on patient mortality becomes not a consistent estimate but a lower limit of the estimated causal effect.

Similar to black race, Certificate of Need regulations and average years of schooling variables also favor for-profit firms in the sample stratum described above. However, household income is a problematic variable. In Table 17, household income (by patient's zipcode) is negatively correlated with patient mortality. Here, however, we see in Table 18 that not-for-profit patients have higher incomes in the featured stratum. Thus, due to the household income variable, results may be biased in favor of not-for-profit facilities. Even though the positive bias exhibited by the three other variables that rejected the t-test may balance out the negative bias from the household income variable, the results are currently indeterminate. Since all of the other strata from the division of the data set into ten subsets have similar t-test problems to those presented in Table 18, the next step is to subdivide the data into yet more strata by propensity score.

Division of the data above into twenty strata instead of ten resulted in slightly fewer t-test rejections and somewhat smaller t-statistics on the rejected variables. In nineteen out of twenty strata, one or more covariates had t-test rejections. Dehejia and Wahba (1997) suggest further stratification, or restructuring of the logistic regression that creates the propensity scores. Further stratification may not yield results until the sample size is down to two digits. If one views the household income variable means for the for-profit and not-for-profit subsets of the stratum showed above in Table 18, it is not clear that further stratification would ever solve the problem of substantially different household income levels in that stratum. At any rate, division of the data set into twenty or more strata requires substantial computing effort, with little promise that certain variables would ever equalize across ownership types. It is also theoretically unsound to divide strata that have substantially different for-profit and not-for-profit subsets into tiny strata just to get good t-test results on the basis of the very small number of observations.

The other option suggested by Dehejia and Wahba is to respecify the logistic regression in obtaining the propensity scores. Rosenbaum and Rubin (1984) describe a process of cycling between reformulating the original propensity score model and checking the composition of the sub-samples. The goal is to specify a logistic equation (using, for example, higher order terms and interactive terms for some variables) which produces propensity scores that aid in equalizing the for-profit and not-for-profit variable means in each stratum. There are no theoretical restrictions on specification of the propensity score regression, since it is simply a tool for ordering the observations in a useful manner. On the other hand, there are few specific guidelines for the ideal specification of the propensity score regression. Thus, this option can be even more labor-intensive than tiny stratification, for it involves respecifying the logistic regression in several ways, and testing the viability of each specification by observing the number of t-tests rejected for various numbers of strata.

The data set used here has a large number of covariates and a fair number of population differences between for-profit and not-for-profit patients, so the problems encountered in finding strata without t-test rejections may be more numerous than with other studies using propensity score methodology. The propensity score ranking of the data described in Table 16 has numerous patterns of variable means. Some variables have an identifiable linear or quadratic trend in their means when the observations are ranked by propensity score. Other variables means show no such discernable pattern. A data set with fewer independent variables would exhibit fewer nonlinear fluctuations in variable means in a propensity score ranking, and creating identical samples of for-profit and not-for-profit observations would require fewer strata. Nevertheless, all of the independent variables used in this analysis have a statistically significant effect on patient mortality, and must be included in the analysis.

However, the data set used here has the advantage of being very large. With a large data set, there is more opportunity to use subsets of the data without much loss of explanatory power. An alternative to propensity score methodology is to break the data down into categories and examine different population groups separately. Thus, it may be instructive to examine only white, male, diabetic patients who do not live in the south. There are 8908 such patients in the U.S. end-stage renal disease program. Unfortunately, with such a division of the population into cells, this ignores the role continuous variables play in the analysis. Household income, length of time on dialysis, and especially age are very important determinants of mortality with dialysis patients. If age, for example, is divided into groups for separation of the population into cells, what sort of division of age groups is needed? It is not certain whether a young-middle-old division is meaningful, or age group divisions by ten or even five years is better. Since there are only 8908 white, male, diabetic, northern patients, division by ten age groups reduces the data to subsets of only 891 patients on average, and still ignores the roles of entry regulations, household income, average years of schooling, and so on. Thus, the propensity score methodology looks more promising in comparison than a simple division of the data into population cell groups, despite the computational difficulties.

The method described above for obtaining identical ownership subsets of strata is summarized as follows:

1. Perform a logistic regression on the ownership variable to obtain propensity scores for each observation.
2. Rank the observations by propensity score.
3. Remove from the data the observations whose propensity scores do not overlap propensity scores from patients in the other ownership group (the very highest and very lowest propensity score observations).
4. Divide the remaining data into strata.
5. Perform t-tests on the means of the for-profit and not-for-profit subsets of each strata for each covariate (age, diagnosis, race, etc.).
6. If no t-tests are rejected for any covariates in a stratum, that stratum has essentially identical for-profit and not-for-profit patient populations.
7. If one or more t-tests are rejected inside a stratum:
    a. Divide the stratum into sub-strata and perform t-tests again. Repeat until no t-tests fail for any variable in any of the sub-strata.

    Or, b. Respecify the variables in the original logistic regression and repeat the stratification process.

The problem with this process is that the original propensity score logistic regression may not be adequate for obtaining for-profit and not-for-profit means of covariates in the strata unless extremely small strata are created. Plus, the removal of the very highest and lowest propensity score observations described in number three above changes the make-up of the data set. The sub-stratification process described in number seven does not take advantage of the new, less extreme characteristics of the smaller data set. Two main improvements in the stratification process can be achieved from utilizing more than one logistic regression to order the data.

PART C. TWO SUGGESTED IMPROVEMENTS OF THE PROPENSITY SCORE STRATIFICATION PROCESS

I. Reduction of the Data Set by Iterative Logistic Regression

For analysis of very large data sets, it could be a computationally expedient option to simply discard more data than the data described in number three. For example, a researcher might save time by dividing the data into five strata and discarding all the data except for the middle (third) stratum. However, the middle stratum is based on the original propensity score ranking of the entire data set, and observations in that middle stratum could still differ substantially, due to the inclusion of extreme covariate values in the original propensity score ordering.

Therefore, if the data set is large, allowing reduction of the data set without too much reduction of explanatory power, it would be better to use an iterative logistic process to arrive at a more successful ranking of observations by propensity score. For example, assume that for-profit facilities have older patients. A propensity score logistic regression would give older patients a higher propensity score (propensity to be a patient in a for-profit facility). The strata with the highest and lowest propensity scores could be discarded, leaving the middle strata remaining with fewer very old and very young patients. Further analysis of the remaining middle strata may not easily yield identical sub-strata because the logistic regression used to order the data was based on the complete data set, which included the extreme observations. It is a simple and intuitively attractive option, then, to perform the logistic regression again, using the new smaller data subset that does not contain the extremely old or extremely young observations. A new ranking of patients by propensity score is obtained from the second logistic regression, and the stratification process will be more successful.

Performing more than one logistic regression in an iterative process is allowable because the intent is merely to find the optimal ordering of observations for groupings into operationally identical for-profit and not-for-profit subsets. An iterative process was very important for analysis of this particular data set, which contained nine covariates. Propensity score rankings differed substantially as different levels of logistic regression were used, each time eliminating the highest and lowest propensity score observations. The following is a summary of the iterative stratification process:

1. Perform a logistic regression on the ownership variable to obtain a propensity score for each observation.
2. Rank the observations by propensity score.
3. Remove from the data the observations whose propensity scores do not overlap propensity scores from patients in the other ownership group (the very highest and very lowest propensity score observations).
4. Divide the remaining data into strata.
5. Remove the highest and lowest strata from the analysis (here, the upper and lower 10% were removed).
6. For the remaining data perform a second logistic regression on the ownership variable to obtain a new propensity score for each observation.
7. Rank the observations by the new propensity score.
8. Divide the data into strata.
9. Perform t-tests on the means of the for-profit and not-for-profit subsets of each strata for each covariate (age, diagnosis, race, etc.).

10. If no t-tests are rejected for a stratum, that stratum has essentially identical for-profit and not-for-profit patient populations.
11. If one or more t-tests are rejected inside a stratum:
    a. Divide the stratum into sub-strata and perform t-tests again. Repeat until no t-tests fail for any variable in any of the sub-strata.

Or, b. Repeat steps 5 through 11a again as needed.

This iterative process reduces the data set size each time a new logistic regression is performed, so the researcher should carefully weigh the advantages of having a large data set against the necessity of dividing the data into extremely small strata to analyze. On the other hand the iteration process provides the researcher with an alternative to the prospect of analyzing hundreds of strata, and provides a methodology for reducing a data set to identical treatment/control subsets without *ad hoc* elimination of observations that have unusual variable values.

II. Recursive Iteration without Reducing Data Set Size

Since successive logistic regression is possible, and in many cases preferred when propensity scores depend heavily on the observations remaining in a data subset, it is useful to re-order the observations within a troublesome stratum by performing the propensity score logistic regression on the observations in that stratum alone. If t-tests fail within a stratum, and further stratification of that stratum appears to yield persistent t-test rejections, another option is to perform the logistic regression again to produce new propensity scores for that stratum alone. The data will then be re-ordered, taking into account the new propensity scores calculated for the stratum alone. Stratification of this stratum alone will yield a more successful ordering of observations in the form of fewer t-test rejections because the ordering did not reflect as many influences from dissimilar observations. This tactic is particularly useful if it is inadvisable to reduce the entire data set further. A within-stratum reordering from a new logistic regression will produce fewer t-test rejections in sub-strata without reducing the size of the overall data set.

PART D. ALTERNATIVES TO SUB-STRATIFICATION BY PROPENSITY SCORE

Several other approaches to propensity score methodology exist. Dehejia and Wahba (1997) describe matching and weighting by propensity score as two such alternatives to sub-stratification of the data. Matching by propensity score entails computing the propensity score, then finding treatment and control observations that have identical or very close propensity scores. To balance the data when propensity scores differ slightly, Connors et al. (1996) ensure that pairs of observations with positive propensity score differences were matched with pairs of observations with corresponding negative propensity score differences. Matching pairs of observations requires that the propensity score regression be correctly specified. The analysis presented above, in contrast, uses the propensity score calculation as a means of ordering and does not assume or require that it is derived from a correctly specified logistic equation. The second alternative to sub-stratification is weighting each observation by the propensity score. If the propensity score regression was correctly specified, weighting the observation by propensity score, then performing the estimation of the causal effect should presumably correct for population bias. Again, however, the same mis-specification argument against multivariate regression analysis holds for matching and weighting observations by propensity score. There is no guarantee that the regression equation to produce the propensity score is correctly specified.

Several others have investigated the feasibility of combining propensity score methodology with stratification based on category response (for example, black or white, diabetes or hypertension). Cook and Goldman (1988) stratified their data in an asymmetric fashion on the basis of category response, finding that the number of strata created were smaller than simple sub-stratification would require, and the strata created were more meaningful in interpretation. Stone, et al. (1995) used first a classification tree method of defining seven major groups of observations, then performed propensity score adjustment. The category divisions reduced the overall number of strata required significantly, but even after propensity score adjustment, Stone et al. found that some data bias remained, and they suggested further regression to control for the remaining bias. Both studies used categorical response (or classification tree) stratification in an advantageous way to reduce the number of strata required. Inasmuch as strata are defined whose data are comparable in treatment and control groups, categorical response methods are useful and intuitively appealing. However, introducing categorical response methods introduces *ad hoc* divisions of strata, and the study loses the objectivity associated with letting the propensity score ordering arrange the strata. If many covariates are involved, categorical response methods may become even more unwieldy than sub-stratification methods. Furthermore, stratification by categorical response requires creating artificial cut-off points for categorical division of continuous variables. Finally, if bias still remain in the data, as Stone et al. experienced, the use of multivariate regression to control for the remaining bias introduces the possibility once more of model mis-specification.

SECTION 4: RESULTS USING PROPENSITY SCORE METHODOLOGY

With the data described in this study, four separate logistic regressions on successively smaller subsets of the data were performed (Section 3.C.I.). Each time the extreme propensity score strata were removed and a new, smaller data set was used, the covariates' chi-square values (influence on the propensity score) reported in the logistic regression results declined. After four such iterations, strata were delineated for the remaining data set of 15,422 observations. Division of the data into five strata yielded "identical" for-profit and not-for-profit independent variable values for two of the five strata, but the other three strata had t-test rejections, so the remaining three strata were each divided into two more strata. Of these new smaller strata, each containing one tenth of the data (1542 observations), three were successful, while the other three strata had t-test rejections. The strata with t-test rejections were re-ordered using a new logistic regression for the propensity scores (Section 3.C.II.), then further subdivided. The flowchart on the following page shows the iteration and subdivision process for obtaining strata with statistically similar for-profit and not-for-profit observations.

From the initial data set of 77,110 observations, four logistic regressions were run in succession, each time eliminating the top ten percent and bottom ten percent of the observations ranked by propensity score. The remaining data set has 15,422 observations.

# Observations	**Strata Descriptions**				
3085	Stratum 1				
		Fifth level logit			
1542		Stratum 2			
			Sixth level logit		
771			Stratum 3		
771			Stratum 4		
1542		Stratum 5			
1542		Stratum 6			
1542		Stratum 7			
			Fifth level logit		
				Sixth level logit	
					7th level logit
289					Stratum 8
289					Stratum 9
					7th level logit
289					Stratum 10
289					Stratum 11
386				Stratum 12	
3085	Stratum 13				

Total Observations = 15,422

Figure 1: Stratification Flow Chart

One of the best features of propensity score methodology is the ease of interpretation of the results. The estimate produced for the expected causal effect of for-profit treatment as opposed to not-for-profit treatment (or treatment versus control), is a consistent, unbiased estimate as long as all the t-tests for each covariate fail to reject the null hypothesis of a zero difference in means between for-profit and not-for-profit patients in each stratum. Once the stratification process is finished, calculation of the causal effect is straightforward. For each ownership subset of a stratum, the mean of the death variable is obtained. The difference in means is calculated for each stratum, and multiplied by the number of observations in that stratum. Then, these weighted differences in means are summed and divided by the total sample size. The estimated causal effect, E, is calculated as follows:

$$E = (1/N)\Sigma\, n_j[d(\mathrm{FP}) - d(\mathrm{NFP})],$$

where $j = 1, \ldots, 13$ strata, n_j are the individual strata sizes, $N = 15{,}422$, and d(FP) and d(NFP) are the stratum means for the probability of death (number of deaths divided by number of patients) at for-profit and not-for-profit facilities.

The estimated causal effect on mortality for patients treated at for-profit facilities, corresponding to the data set used, is 5.86%. That is, operationally identical patients were 5.86% more likely to die in 1993 if they were treated at a for-profit facility rather than a not-for-profit facility. This estimate is quite large – of the thirteen strata in the analysis, only one stratum had a higher death rate at not-for-profit facilities.

Since the sample used in the propensity score analysis was only 15,422 patients, the sample means of all the variables should be noted, so that general differences in the data set sample and the entire US data set can be observed. The iterative process that was used to reduce the data set to one that produced homogenous population characteristics among for-profit and not-for-profit patients had the effect of changing the general make-up of the data set.

Table 19. Propensity Score Project Sample Characteristics, After Reduction by Iteration

Total sample size = 15,422.

Variable	Mean	Std. Dev.	Median	5th %	95th %
Age	63.84	14.39	66	36	84
Vintage (days on dialysis)	1009	1024	699	82	3060
Household Income (in patient's zipcode)	26,225	10,240	24,705	13,162	46,658
Average Years of Schooling (in patient's zipcode)	12.40	0.94	12.36	11.10	14.13

Gender: Female: n = 7,378 (47.8%) Male: n = 8,044 (52.2%)

Race: Black: n = 7,299 (47.3%) White: n = 8,123 (52.7%)

Primary Diagnosis: Diabetes: n = 6,321 (41.0%)
Hypertension: n = 9,101 (59.0%)

Area:
Patients in South: n = 11,351. Facilities in South: n = 390.
Patients not in South: n = 4,071. Facilities not in South: n = 691.

Certificate of Need (CON) Status:
Patient's facility in state with CON entry regulations: n = 1807.
Number of facilities in state with CON entry regulations: n = 248.

Patient's facility in state without entry regulations: n = 13,615.
Number of facilities in state without CON entry regulations: n = 833.
Table 19 continued on next page.

Table 19, continued.
Ownership:
Patients at for-profit facilities: n = 13,481.
Number of for-profit facilities: n = 944.

Patients at not-for-profit facilities: n = 1,941.
Number of not-for-profit facilities: n = 137.

The iterative logistic regression process of eliminating upper and lower strata with extreme propensity scores produced this new, smaller sample resembling the population data of 77,110 observations described in Table 16 for household income, average years of schooling, and days on dialysis. However, comparing Tables 16 and 19, it is clear that the smaller sample has proportionally more patients in the south and patients in states without Certificate of Need entry regulations. Furthermore, the new data set has fewer diabetic patients and slightly more older, white and male patients than the larger population data. Therefore, a drawback to the iterative method of defining a sub-sample with more identical characteristics between for-profit and not-for-profit patients is that the process may create a new sample that does not closely resemble the population.

The advantage of iterative elimination of data with extreme characteristics is shown below in Table 20, where difference in means t-tests are reported for the for-profit and not-for-profit subsets of the large and small data sets. For the larger population of 77,110 patients, t-tests on differences in means for the for-profit and not-for-profit subsets are strongly rejected for seven of the nine independent variables. The smaller data set, however, shows only two t-test rejections. It would be tempting to accept the smaller data set without stratification, noting that the t-test rejection on the south variable indicates a positive bias for for-profit units ("south" is positively associated with higher mortality, as reported in Table 17), and the age variable counters that with a bias in favor of not-for-profit facilities. However, age has the strongest effect on mortality of all the independent variables, so an age discrepancy in the data is a serious flaw, and should not be dismissed because the t-statistic was rather small. Hence, stratification of the data was necessary to achieve an unbiased and consistent estimate of the causal effect of for-profit treatment on mortality.

Table 20. Difference in Means Tests for the Population and Reduced Sample

Variable	Population: n = 77,110 Difference in Means t-test	Reduced Sample: n = 15,422 Difference in Means t-test
Age	4.28 reject: Bias favors NFP	2.20 reject: Bias favors NFP
Days on Dialysis	- 9.53 reject: Bias favors FP	0.07
Female	- 0.24	0.23
Diabetic	- 1.64 (slight bias favoring FP)	- 0.27
Black	- 8.10 reject: Bias favors NFP	- 1.18
South	- 4.11 reject: Bias favors FP	- 2.86 reject: Bias favors FP
Cert. of Need	-44.34 reject: Bias favors FP	0.26
Household Income	12.01 reject: Bias favors FP	0.08
Avg. Years Schooling	- 3.65 reject: Bias favors FP	0.18

It is also instructive to estimate the difference in means for the samples above for the mortality variable in order to gauge how general population differences noted above in Tables 16 and 19 affect average mortality rates. Table 21 below shows that the reduced sample of 15,422 has a somewhat larger proportional number of deaths, despite the fewer numbers of diabetic patients in the sample. Most of the differences in the smaller sample as compared to the population are correlated with higher mortality, such as southern status, older and more white patients. For-profit facilities appear to have higher death rates in the reduced sample, but interestingly, not-for-profit facilities have lower death rates in the reduced sample.

Table 21. Average Number of Deaths for the Population and Reduced Sample

Sample/ Ownership	Population: n = 77,110 For-profit	Not-for-profit	Reduced Sample: n = 15,422 For-profit	Not-for-profit
Number of Deaths	42.5%	39.4%	43.2%	37.0%
Difference in Means	3.17%		6.20%	

The reason that the difference in means calculated for the reduced sample is 6.2%, while the estimated causal effect calculated after the stratification process above is 5.86% is straightforward. The difference in means of death rates for the two ownership subsets is higher in the entire data set before stratification because the data have not been adjusted for the potentially damaging bias due to a slightly older population in the for-profit facilities. Simply reporting the difference in means as presented in Table 21 would overstate the effect on mortality from treatment at a for-profit unit. The stratification process succeeds in eliminating the age bias in each stratum, so the estimated causal effect of for-profit treatment after stratification is smaller and unbiased.

SECTION 5: PROPENSITY SCORE ANALYSIS SUMMARY

The propensity score methodology offers a way to duplicate and perhaps improve upon a completely randomized study by estimating the average causal effect of treatment from trials of closely matched populations. When the initial population is not well-matched in patients characteristics and many significant covariates must be controlled for in the study, such as with this nationwide data of renal dialysis patients, the stratification process suggested by others for achieving identically matched samples of treatment and control group patients is laborious and may not be successful until over 100 subsets of the original data set are separately evaluated.

Two improvements were introduced to aid in creating data subsets with identically matched characteristics. The first proposal is to reduce the data set for analysis in size with an iterative logistic process, repeating a logistic regression for ordering the data by propensity score, and each time removing the upper and lower-ranked strata. As the logistic regression re-ordering and removal of extreme data values progresses, the new sample's treatment and control subsets will have variable means that are progressively closer.

After the final sample size is reached, the second proposed improvement can be employed in the stratification process. Dividing the data into five subsets may reveal some subsets that have no statistically significant differences in means. These strata should be retained as-is for calculation of the average causal effect of treatment later. The other strata with rejected t-tests should be subdivided further. When further subdivision fails to produce identical treatment and control subsets, the second proposed improvement in the stratification process is to first perform a logistic regression to re-order the observations in the strata that failed, then subdivide the data. Performing an additional logistic regression to reorder the observations in a stratum before subdividing greatly increases the likelihood that the new strata will have closely matched population characteristics. These two proposed improvements in the propensity score methodology save computing effort and avoid the intuitively unattractive prospect of basing the calculation of the causal effect of treatment on numerous tiny subsets of the original data set. The variance of the estimated causal effect is inversely related to the sizes of the individual strata from which it was calculated.

Using these two proposed changes to the propensity score stratification process, the final data set size was chosen to be 15,422 observations and the number of strata analyzed was thirteen, with the smallest stratum containing 289 observations. Using strictly sub-subdivision of the data to find adequate strata would have necessitated creating over thirty strata for analysis, so the technique introduced in this chapter significantly reduced the number of strata from which the estimated causal effect was calculated.

The estimated causal effect of treatment at a for-profit facility was calculated to be a 5.86% increase in patient mortality. Although the sample of 15,422 patients had statistically identical independent variable values for for-profit and not-for-profit patients, the overall characteristics of the sample's patients were different than the general population of patients. The sample had more white patients, more patients in the south, fewer diabetic patients, and slightly older patients than the population from which it came. Thus, results are unbiased and consistent for the sample analyzed, but may not easily be generalized to the entire population of patients receiving dialysis for end-stage renal disease in the US. Nevertheless, analysis of the data revealed a persistent pattern of higher mortality rates in for-profit facilities. For this sample of 15,422 patients alone, if all patients had been treated at for-profit facilities, approximately 100 additional patients would have died during the year. If all patients in the sample had been in not-for-profit facilities, roughly 750 more patients would have survived the year.

CHAPTER 6: ASYMMETRIC INFORMATION, OWNERSHIP, AND QUALITY OF CARE IN THE US RENAL DIALYSIS INDUSTRY

SECTION 1: INTRODUCTION

Several theorists have asserted that not-for-profit firms exist to mitigate agency problems in donor-financed charitable organizations (Fama and Jensen, 1983[b] and Hansmann, 1980). This was a strong rationale for the founding of charity hospitals in the U.S. during the late 19th to early 20th centuries. However, since most not-for-profit health care organizations now earn most of their revenue from commercial sources, theorists turn to other reasons for the continued strength of the not-for-profit sector. The 1960's through the mid-1980's saw expansion of both not-for-profit and for-profit health care sectors due to the generous cost-based reimbursement financing of health care from Medicare and employer-provided health insurance. Favorable tax conditions, too, have aided the survival of not-for-profit health care organizations in increasingly competitive times. Occasionally the asymmetric information rationale has been used to explain the existence of not-for-profit firms in commercial health care markets. That is, where consumers have incomplete information about the quality of the product, consumers may seek a not-for-profit firm under the assumption that, due to the non-distribution constraint, not-for-profit managers have less incentive to exploit information advantages by reducing quality to increase profits.

This chapter describes an empirical project using data from the U.S. renal dialysis industry. End-stage renal disease (ESRD) patients are ranked by level of sophistication, then patient treatment data are adjusted for case mix differences and examined to see if treatment patterns differ by patient sophistication level. Evidence indicates that unsophisticated patients receive lower quality care from their dialysis facility in the form of more shortened and skipped dialysis treatments. Also, patients at for-profit facilities have more skipped dialysis treatments than patients at not-for-profit facilities. Physicians appear to prescribe shorter hemodialysis treatments for more sophisticated patients, case-mix adjusted, but the effects of facility ownership on physician hemodialysis prescriptions is indeterminate. Thus, facility ownership may affect patient care at the institutional level, but has no significant effect on care provided by the physician. Results imply that asymmetric information in the renal dialysis industry accounts for a differing quality of treatment provided to patients of differing knowledge levels, but results lend mixed support for the theoreticai proposition that for-profit firms exploit information asymmetries more often than not-for-profit firms.

SECTION 2: THE ASYMMETRIC INFORMATION RATIONALE FOR NOT-FOR-PROFIT HEALTH CARE

Some economists have claimed that patients select not-for-profit health care providers in an effort to alleviate information asymmetries. That is, not-for-profit organizational status serves as a trust signal for patients unable to evaluate quality of care (Frank and Salkever, 1994 and Weisbrod, 1989). The patient assumes that not-for-profit providers have less incentive than for-profit providers to reduce unmonitored quality in order to increase profits. Although this line of reasoning may seem attractive for static analysis, it ignores intertemporal effects on the firm's reputation and ability to attract future customers. Since both for-profit and not-for-profit firms currently co-exist in health care, it appears that asymmetric information problems may be solved by time effects, and therefore, quality should be uniform among for-profit and not-for-profit providers.

Permut (1981) tested the trust signal theory with surveys of customers of not-for-profit organizations and found that very few actually knew the ownership status of the firm, or believed that a not-for-profit organization would provide a higher quality product. We are presented, then, with a possible continuum of patient ability to judge and respond to quality: First, a subset of patients know the quality of care they are receiving and go to the highest quality provider they can, given equivalent prices paid by third-party payers. Second, other patients are unable to judge quality, but do know the ownership status of the firm and select not-for-profit firms on the basis of the trust signal. Third, the rest of the patients can not judge quality and do not know the ownership status of the firm. The second subset is probably very small indeed. Also, the mechanics of hospital selection are probably quite removed from the for-profit versus not-for-profit decision, since patients usually go wherever their physician is on staff.

If the trust signal argument holds, we would expect to see more knowledgeable patients who are aware of ownership status selecting not-for-profit facilities. Assuming equal prices paid by third party payers, sophisticated patients would seek out the highest quality provider and the lower quality firms would leave the market, regardless of ownership status. If not-for-profit firms produced a higher-quality product, for-profit firms would eventually be forced out of the market.

In fact, for-profit health care firms are thriving in the US. One explanation could be that patients are heterogeneous enough in their knowledge levels to allow low-quality firms to exist in the market, serving low-knowledge patients. A second reason for a presence of both low and high-quality providers in the health care market may be that health care firms are competing on the basis of quality that is visible to the patient rather than clinical quality. Thus, parking, appointment scheduling, clinic décor, and waiting room times may be more immediately important to the patient than clinical treatment. Firms providing clinical care of a lower quality may be providing amenities that attract and keep customers. This may be considered a subset of the first reason – that is, patients who place more emphasis on amenities rather than clinical care might be considered by physicians to be less knowledgeable than patients intent on receiving the best clinical care.

A third reason for the co-existence of low and high-quality firms is that some health care sectors such as long term care operate with substantial self-paying patients. In this case, patients may be selecting into separate niches – the higher-priced not-for-profit niche and the inexpensive but lower quality for-profit niche. The comparative absence of fixed payments by third party payers in the nursing home sector makes it impossible to fault providers for providing a level of care that differs from their competitors. Similarly, at the level of insurance and/or managed care plan selection, consumers simply get what they pay for, and a differing level of quality provided may be merely attributable to the different prices paid for premiums. For this reason, the analysis in this paper focuses on one sector where costs of care are paid for almost exclusively by Medicare and virtually no self-pay patients exist. Patients' choice of facility is removed from the price decision in this sector, so firms compete on the basis of quality.

Finally, persistent quality variance by ownership may be attributed to differing preferences of the medical staff. Where physician compensation can be tied to residual earnings, physicians more inclined to favor income may gravitate toward facilities offering higher claims on residual earnings. Physicians with a strong preference for higher quality of care may be on staff at institutions producing high quality clinical care, even though they receive less compensation. Preston (1989) studied the salaries of not-for-profit and for-profit professionals and suggested that employees of not-for-profit institutions trade higher salaries for jobs that produce more social benefits. However, Preston was unable to rule out the possibility that not-for-profit professionals are lower-quality employees self-selecting into lower-paying professions.

Using the mathematical model of managerial utility maximization described in Chapter 2, the notion of high versus low-knowledge patients appears in the form of two separate populations of patients; patients who enter regardless of the quality of the firm (exogenous variable E) and patients who enter higher quality facilities more often (variable i(u)). When results are derived from the model, the existence of no-knowledge patients, as symbolized by E, does not appear as a variable predicting differing behavior between for-profit and not-for-profit firms. However, since the model predicts a higher quality level over time by not-for-profit firms (u(t)), these firms are thus predicted to have a greater population of knowledgeable patients (i(u)).

Since the results in Chapters 4 and 5 suggest lower quality at for-profit firms in the form of higher patient mortality, and since a third party (Medicare) is paying for patients' dialysis treatments, one would expect that patients would avoid for-profit facilities, *ceteris paribus*, because the patients are shopping on the basis of quality, not price. This would eventually lead to the decline of for-profit facilities. In fact, the number of for-profit facilities, especially in states with no Certificate of Need entry regulations, is increasing and the number of not-for-profit facilities is decreasing. The presence of asymmetric information could account for the strength of the for-profit sector despite the outcome quality disparity. If patients have no knowledge about clinical quality, they may be basing their choice of provider on other, more visible aspects of quality such as location and appearance of the facility.

The empirical project described in this chapter has two tiers: First, the project investigates the question of whether facilities are taking advantage of asymmetric information by providing lower quality care to low-knowledge patients. Although this question is not central to the issue of comparative quality by ownership type, it is of very high interest in the health economics field, and needs exploration. Second, the project seeks to determine if for-profit facilities are more aggressive about taking advantage of information asymmetries than their not-for-profit counterparts. If this is true, the asymmetric information (or more generally, the contract failure) rationale for the not-for-profit form of organization is valid as a justification for subsidy of not-for-profit health care.

SECTION 3: PREVIOUS STUDIES OF ASYMMETRIC INFORMATION AND QUALITY OF CARE

Weisbrod and Schlesinger (1986) controlled for price differences and reviewed regulatory violations and consumer complaint data for nursing homes in Wisconsin. They found that for-profit institutions had more consumer complaints but fewer regulatory violations than not-for-profit institutions. They conclude that not-for-profits operate with more organizational slack, leading to more regulatory violations of quality that are easily monitored. Because for-profits were found to have more consumer complaints, they conclude that for-profits are lowering quality attributes that are more costly to monitor by regulatory agencies, but are noticed by the consumers. In their study, for-profits appear to be promising one level of quality to consumers, but delivering another and are thus taking advantage of information asymmetries.

Another study (Holtmann and Ulmann, 1993) used marital status, number of living children, extent of disability, living arrangement, and mental health as independent variables describing transactions costs to monitoring uncertain quality of care. Holtmann and Ulmann predicted that high-cost (that is, low knowledge) patients would choose high-cost, not-for-profit nursing home providers in an effort to avoid future opportunistic behavior by for-profit firms. They found that patients with low-knowledge characteristics, such as those who are not married, are more likely to be in not-for-profit nursing homes. On the other hand, they found that patients with more mental health problems were found in for-profit institutions. Holtmann and Ulmann conclude that low-knowledge patients are selecting into not-for-profit firms because they recognize that they are unable to monitor quality deficiencies, while more knowledgeable patients are selecting the relatively cheaper for-profit nursing homes. Their conclusion rests, however, on the somewhat shaky assumption that patients with lower knowledge levels still are able to recognize their disability and choose their provider strategically.

Scant evidence exists in economics literature to suggest quality differences among for-profit and not-for-profit health care providers, except in the renal dialysis industry, where mortality rates appear to be higher among patients in for-profit facilities. Although a number of empirical studies have explored the relation between ownership status and quality of care as measured by treatment inputs, data are scarce on patient knowledge levels, so virtually no studies have attempted to analyze health care providers' treatment of patients with different knowledge levels by ownership. Rather than analyzing patient choice of provider, the study described in this chapter instead focuses on provider treatments as they differ by patient knowledge levels.

SECTION 4: DATA ANALYSIS AND METHODS

PART A. DATA SOURCES AND DESCRIPTIONS

The sample consists of approximately 4900 patients being treated at for-profit and not-for-profit dialysis units nationwide in 1990-92. This includes all patients who had been on dialysis for three or more months and receiving Medicare benefits during 1990-92. Omitted from the study are patients whose main treatment facility was government-owned, and patients whose main treatment modality for dialysis was not center-based hemodialysis. Data programming and regression analysis was performed on a PC with version 6.12 of SAS for Windows. Least squares and logistic regressions were run in SAS and negative binomial regressions were run in version 6.0 of LIMDEP (MS-DOS).

The data are from several sources. Patient and facility-level data were from the Patient, Residence, Treatment History, and Facility Standard Analysis Files (SAFs) from the US Renal Data System (USRDS), and were from the same data as described in Table 1 of Chapter 4. Sophistication variables and treatment variables were from the USRDS' Case Mix Adequacy SAF. The Case Mix Adequacy SAF, unlike the other files containing patient data nationwide, contained data from a small sample of 7000 patients. Data collection by the USRDS began on April 1, 1992. The purpose of collecting the Case Mix Adequacy data was to examine the relationship between dialysis dose, delivered dialysis therapy, reuse of dialyzers, and patient mortality. The Case Mix Adequacy sample was randomly selected from an incident sample of patients starting dialysis during 1990 and a prevalent sample of hemodialysis patients with onset of ESRD prior to 1990. The facilities were chosen by the USRDS to be representative of the nation. Patients were then chosen from the facilities by random. ESRD regional network offices collected these data in conjunction with their Medical Case Review data abstraction. Included in the data are variables that can be assumed to vary with a patient's knowledge or sophistication level. These variables include patient education level, job status, living situation, and other key predictors of knowledge, as explained later in Table 24. The data also included patient treatment variables, from which we selected number of hemodialysis hours prescribed per week, number of treatments skipped and number of treatments shortened as indicators of physician treatment quality and facility treatment quality, respectively.

The size of the final data sets used in regressions below was determined by the following adjustments: The case mix adequacy file consisted of approximately 7000 patients. 179 patients were lost to follow-up during the study. 347 patients were missing identification numbers, so no case-mix information could be matched to their file from the nationwide databases described above. Patients who were being treated at government-owned facilities, patients who were not receiving center-based hemodialysis, and patients who had missing facility identification numbers (and thus had no information on facility ownership status) were eliminated from the sample. The approximately 4900 remaining patients still had various data missing. As described below for each of the three main data sets created, some observations were excluded for lack of an important missing variable, while others were retained by using sample means.

Summary statistics for the data are provided in Tables 22 and 23. Age, days on dialysis, gender, race, and primary diagnosis were included as they are important patient case-mix characteristics. The variable South was included to catch regional differences in physician and facility staff treatment styles. The Certificate of Need (CON) regulations variable noted the presence of entry regulations in the facility's state. It was included to capture important competitive effects between existing facilities and potential entrants into the market. The effects of competition may show up as an increase in patient treatment quality, since patients do not pay for dialysis treatments themselves and have the incentive to shop for a facility on the basis of quality. On the other hand, competition may induce firms to reduce unmonitored treatment quality to low-knowledge patients. The freestanding variable was included because patient case-mix may differ substantially between freestanding and hospital-based facilities.

Table 22. Patient Characteristics: n = 4939

Variable	Mean	Std. Dev.	Median	5^{th} %	95^{th} %	Missing
Age	61.45	16.09	64	32	84	0
Days on dialysis	1802	1217	1481	413	4399	0
Knowledge Score	6.67	1.20	6.67	4.33	8.67	0
Skipped Treatments	.54	1.45	0	0	3	3245
Shortened Treatments	.90	2.05	0	0	4	3134
Dialysis Hours/week	8.90	2.05	9	6	12	117

Gender: Female (dummy variable = 1): n = 2406 (48.7%) Male: n = 2533 (51.3%)

Race:

Native American:	n = 77 (1.6%)
Black:	n = 1757 (35.6%)
White:	n = 2950 (59.7%) (omitted reference category)
Asian:	n = 102 (2.1%)
Other race:	n = 43 (.9%)

Primary Diagnosis Causing End Stage Renal Disease:

Diabetic:	n = 1542 (31.2%)
Hypertension:	n = 1386 (28.1%)
Glomerulonephritis:	n = 716 (14.5%)
Cystic Kidney:	n = 177 (3.6%)
Other Primary Diagnoses:	n = 1118 (22.6%) (omitted reference category)

Table 23. Facility Characteristics: n = 513

Facility in South (dummy = 1): n = 152 Facility not in South: n = 361

Facility in state with Certificate of Need regulations (dummy = 1): n = 187
Facility in state with no Certificate of Need regulations: n = 326

Facility free-standing (dummy = 1): n = 388 Facility in hospital: n = 125

For-profit facility (dummy = 1): n = 336 Not-for-profit facility: n = 177

PART B. DEPENDENT VARIABLES

The three dependent variables of analysis in this study are introduced in Table 22 as number of treatments shortened and number of treatments skipped during a specified one-month period and the number of dialysis hours prescribed weekly by the patient's physician. The number of treatments shortened skipped offer a perspective on quality of treatment by the dialysis facility. Regardless of physician prescription, facility nurses, technicians, and other staff can affect the level of adherence to the prescribed number of dialysis hours. Staff at a high-quality facility may work closely with patients to ensure that few treatments are skipped or shortened. The skipped variable refers to the number of treatments skipped during December 1-23, 1993, and the shortened variable refers to the number of treatments during December 1993 that were shortened by more than ten minutes, not including skipped treatments. Hemodialysis is a long process, and patients less concerned with their health may seek to skip or shorten the procedure frequently. With effort, facility staff can reduce this behavior to a minimum. Facilities are not compensated for treatments that are skipped, but are compensated for treatments that are shortened.

The main problem with the Skipped and Shortened variables is missing answers to the survey. Over half of the observations for those variables are blank. Data sets with the subset that contains completed surveys were constructed for each of the independent variables. That is, the data set for the sub-sample with non-blank Skipped values contained 1694 observations, while the data set for the sub-sample with non-blank Shortened values contained 1805 observations. Differences in sample case-mix and facility variables (such as age, sex, ownership, etc.) were slight, indicating that the smaller sub-samples had slightly more minorities and fewer white patients, a tighter distribution on the patient knowledge variable, and fewer for-profit firms. Tables 22 and 23 above are repeated for the sub-samples in Appendices A and B. Since proportionally fewer for-profit firms are in the sub-samples, it means that for-profit firms were more likely to leave the Skipped and Shortened survey questions blank. Including the blank answers as zeros introduces a bias in favor of for-profit firms. Therefore, when the regressions were run, a complete set of observations was also tested, whereby all blank answers to Skipped and Shortened were considered zero. Results were consistent for either data set specification.

The dialysis prescription variable can be considered an indicator of quality care stemming from the physician's decisions. Held et al. (1991) report that dialysis treatments of shorter duration contribute to higher mortality of ESRD patients. Other studies showing a linkage between short duration and higher mortality are Charra et al. (1992), Charra, Calemard and Laurent (1996) and Kjellstrand (1985). The duration of treatment is also an important element in facility costs. When patients can be dialyzed for shorter periods, more patients can be scheduled per week and average fixed costs per patient can be reduced. Reimbursement per dialysis treatment is fixed prospectively, regardless of the length of the dialysis session.

Since physician behavior may be influenced by compensation structures, it is necessary to examine financing of dialysis. All of the patients in the study receive Medicare funding to pay for dialysis. Medicare compensation for dialysis has two main components. Medicare pays a composite rate fee to dialysis centers for each dialysis treatment. This composite rate does not vary, even though treatment sessions and complications vary from treatment to treatment and from patient to patient. Physicians are also paid a capitated fee per month per dialysis patient. Physicians affiliated with not-for-profit dialysis centers receive only the capitated fee as compensation. Physicians affiliated with for-profit dialysis centers receive the capitated fee, but may also receive a portion of the dialysis facility's proceeds from the composite rate if they serve as a medical director. Thus, the compensation physicians receive at for-profit dialysis facilities may be partially linked to the dialysis facility's efficiency, unlike not-for-profit physicians. It is hypothesized that for-profit physicians will prescribe shorter dialysis treatment hours per week than their not-for-profit counterparts due to stronger pressure by administration to reduce costs and due to possible income effects from facility profitability if the physician serves as the medical director.

Part C. Constructing the Knowledge Score

Because the data included an unusual number of demographic variables, it was possible to create a composite score roughly indicating the patient's level of sophistication and probable awareness of quality. The following were the knowledge indicators used and the values assigned to survey responses, as well as the methodology used to adjust for missing responses when necessary. Note that variables indicating higher levels of knowledge are assigned higher index scores.

Table 24: Knowledge Score Components

Variable	Survey Response	Index Score
Living Situation	missing or other	2
	Live alone	1
	Live with others	3
	Nursing home, Institution	2
	Homeless	0
Education Level	missing or other	1
	Less than 12 years	0
	High school graduate	1
	Some college	2
	College graduate	3
Number of House-Members	missing	1
	1	0
	2	1
	3	2
	> or = 4	3
Walk Independently	missing	1
	Yes	1
	No	0
Eat Independently	missing	1
	Yes	1
	No	0
Transfer Independently	missing	1
	Yes	1
	No	0
Nutritional Status	missing or other	1
	Obese/overweight	0
	Under-nourished/cachetic	0
	Well-nourished	1

Table 24 continued on next page.

Table 24, continued.

Occupation	missing or other	1
	Clerical	2
	Professional	3
	Tradesperson	2
	Manual labor	1
	Housewife	1
	Student	2
Smoking Status	missing or other	3
	Active smoker	0
	Former smoker	2
	Smoker, time unknown	1
	Non-smoker	3
Employment Status At Start of Study	missing or other	
	use values from another variable indicating highest employment level ever reached	
	still missing or other	1
	full-time work or study	3
	part-time work or study	2
	homemaker	2
	retired	1
	unemployed	0
	disabled	0
Self-hemodialysis	Yes	1
	No	0

Most variables had missing data responses of two to three percent, and were corrected for by inputting the mode value for the missing responses. For example, 2.1% of the Eat Independently survey questions were blank. By far, most patients can eat independently so the missing responses were assumed to be "yes." Less straightforward was the treatment of missing values for the Employment Status variable. A very similar variable, highest employment status ever, was used as a backup to provide responses for missing values. If values were still missing, it was assumed that the patient was retired, or had an employment status comparable to being retired. "Retired" is also the mode for that variable. The self-hemodialysis variable, unlike the others above it, was obtained from data in the nationwide sample of all ESRD patients receiving treatment at facilities in the US. A patient performing self-hemodialysis inserts her own needle to access the graft. Nationwide, the number of patients who do this is less than two percent of those receiving treatment for ESRD.

Most of the variables in the knowledge score could be rejected as true indicators of patient sophistication level, but in general point to a greater or lesser likelihood that the patient has knowledge about her quality of care. Smoking status and nutritional status are probably the least indicative of knowledge. If a person smokes or is very overweight, this could signal not a lack of knowledge, but a lack of desire to adhere to a healthy lifestyle. In effect, smoking and obesity could signal a lack of interest in getting well, and thus a lack of interest in gaining information about the quality of care the patient receives.

The seemingly different index scores given to "housewife" and "homemaker" responses on the occupation and employment status variables were chosen to reflect the lifetime occupation choice as opposed to the current status of the patient. That is, a person whose occupation over her lifetime was that of a housewife might be less knowledgeable than a student, tradesperson, clerical worker, or professional. Conversely, a homemaker was judged to have more ability to judge health care quality than a retired person (a retired homemaker, for example) or an unemployed or disabled person. Clearly, the assignment of index scores required *ad hoc* generalizations about knowledge status with several of the knowledge score variable components.

Index scores for the eleven variables above were then divided by their maximum value so that each index score ranged from zero to one. The calibrated scores were then summed for an overall score, now referred to as the knowledge score. No attempt was made to weight the individual variables for relative importance, as the weighting process would likely be as *ad hoc* as the process above in assigning values to survey responses. The addition of health-related variables such as smoking and nutritional status is thought to capture attitudinal differences among patients. Similarly, variables signaling independence such as Eat Independently are considered strong indicators of frailty and awareness of care being received. Education, occupation, and employment status were fairly straightforward indicators of patient sophistication level. The patient's living situation and number of household members were included on the advice of practicing health care workers, who felt strongly that the presence of partners positively affects the quality of care patients receive.

Part D. Regression Methods

The three dependent variables under study required use of two main regression techniques. The dependent variables stemming from facility care, Skipped and Shortened, were count data truncated at zero. Most of the variable values were zero, but their means were significantly above zero due to higher nonzero observations. These two variables could be analyzed with either Poisson regression or negative binomial regression. OLS regression would not be appropriate in these cases because OLS can produce nonsensical negative predicted values for the dependent variable when used with count data truncated at zero (Roncek, 1998). Poisson regression requires the assumption that the variance of the dependent variable is equal to its mean. Considering the severity of the Poisson requirement, negative binomial regression offers the best choice for analysis of the Skipped and Shortened treatment data (Greene, 1993). The third dependent variable under study, the number of hemodialysis hours prescribed weekly by the patient's physician (shown in Table 25) could be analyzed by ordinary least squares regression, but since the data resembled counts rather than continuous data, polytomous logit was also employed in analyzing the data.

Table 25: Hemodialysis Hours per Week Prescribed

Value	Frequency
0	1
2	5
3	18
4	86
6	910
7	1
8	65
9	2780
10	1
12	940
15	14
16	1

Total Frequency: 4822
(117 observations with missing values were eliminated from the sample.)

SECTION 5: ASYMMETRIC INFORMATION ANALYSIS RESULTS

PART A. SKIPPED TREATMENTS

The results below in Table 26 indicate that case-mix differences in age and length of time on dialysis do have a relationship with number of treatments skipped during the study period. Knowledgeable patients, females, older patients, and patients who had been on dialysis for a long time were all found to have fewer skipped treatments, as indicated by negative values for coefficients. The existence of Certificate of Need (CON) regulations and for-profit ownership was a statistically significant determinant of greater skipped treatments.

Table 26: Skipped Treatments: Negative Binomial Regression
Main sample with no missing observations included as zero values.

N = 1694, Log-likelihood = - 1445.795

Variable	Coeff.	Standard Error	T-ratio	P-value	
Constant	1.0656	0.5959	1.799	.0737	*
Age	-0.0117	0.0048	-2.436	.0149	**
Age Deviation^2	0.0001	0.0003	0.349	.7274	
Days on Dialysis	-0.0002	0.530E-04	-3.865	.0001	***
Female	-0.4005	0.1368	-2.928	.0003	***
Native American	-1.1038	0.7980	-1.383	.1666	
Asian	0.6701	0.4870	1.376	.1688	
Black	0.1265	0.1553	0.814	.4154	
Other race	0.3437	0.6833	0.503	.6149	
Diabetic	-0.1952	0.1775	-1.100	.2715	
Hypertension	-0.0117	0.1815	-0.064	.9487	
Glomeruloneph.	-0.1741	0.2158	-0.807	.4199	
Cystic Kidney	0.2564	0.3589	0.714	.4750	
For-Profit Ownership	**0.7976**	**0.1755**	**4.544**	**.0001**	***
CON Entry Regs.	0.6787	0.1439	4.718	.0001	***
Facility in South	-0.3194	0.1837	-1.739	.0821	*
Free-Standing	0.1648	0.2238	0.737	.4613	
Knowledge Score	**-0.2087**	**0.0548**	**-3.809**	**.0001**	***
α[5]	3.9679	0.3749	10.584	.0001	***

*** = Statistically significant at $p < .01$
** = Statistically significant at $p < .05$
* = Statistically significant at $p < .10$

[5] The parameter α measures overdispersion and is used in computation of negative binomial log-likelihoods (Greene, 1992). This dispersion parameter corrects for the variance of the dependent variable not equaling its mean.

The main results from Table 26 are that for-profit facilities are more likely to have patients with skipped treatments (significant at the $p < .01$ level) and that high-knowledge patients are less likely to have skipped treatments (significant at the $p < .01$ level). While it is worthwhile to know that for-profit ownership is linked to greater numbers of skipped treatments, it is also important to determine if ownership determines different treatment of patients by knowledge level. For-profit facilities are hypothesized to take greater advantage than not-for-profit firms of lower-knowledge patients by providing lower quality care to them. If this were true, we would see a significantly more negative coefficient on the knowledge score variable for for-profit facilities, as compared to not-for-profit facilities. Summarized results in Table 27 are provided for the separate ownership types. The data were separated by ownership type, then a regression of remaining independent variables was run on the dependent variable, number of skipped treatments.

Table 27: Skipped Treatments Regression Results for Knowledge Score Variable By Ownership Type

Main sample with no missing observations included as zero values.

Ownership Type	Sample Size	Coefficient for Knowledge Score	t-statistic for Knowledge Score	p-value for Knowledge Score
For-Profit	N = 957	-0.2129	-3.379	.0007***
Not-for-Profit	N = 737	-0.1534	-1.140	.2543

*** = Statistically significant at $p < .01$

Results indicate support for the hypothesis that for-profit firms are taking advantage of information asymmetry by allowing more skipped treatments for low-knowledge patients. The negative sign of the coefficients indicates that both ownership types have fewer skipped treatments for high-knowledge patients. This result is statistically significant for for-profit firms, but is not statistically significant for not-for-profit firms.

The second set of regressions results, shown below in Table 28, were produced by using the larger data set described in Tables 22 and 23 above, where missing values for Skipped were counted as zero (zero treatments skipped during the study period). Since for-profit firms were more likely to have missing answers, this larger data set may favor for-profits, if their blank answers did not refer to true zero values. Thus, this larger data set is more conservative. Results show that for-profit facilities have statistically significantly fewer skipped treatments for high-knowledge patients, while not-for-profit firms again show fewer skipped treatments, but the result is not statistically significant. These results imply that for-profit firms are taking advantage of information asymmetries and allowing more skipped treatments among low-knowledge patients. Of course, this phenomenon can easily stem from the patient's own determination to persevere with treatment, but effective facility staff can play a large role in exhorting patients to be conscientious about their treatment program. The following passage from Garella (1997) illustrates well the relationship between patient desires and facility staff's role as health care provider:

> "By and large, patients insist on receiving the least possible amount of dialysis, especially as it relates to time spent on treatment. The pressure from patients to receive shorter treatments is great, especially when they observe that their neighbour is staying 'on the machine' for only 2 h, while they are prescribed a longer treatment, and especially when they become aware that a nearby facility (or another nephrologist) tends to prescribe shorter treatment times. To convince patients of the desirability of longer dialysis takes time and effort. In the face of reductions in supporting staff, this important component of quality of care, namely patient education and emotional support, is being progressively shortchanged. An atmosphere of 'let them do what they want' is established, compliance decreases, and smaller dialysis doses are delivered."

Table 28: Skipped Treatments Regression Results for Knowledge Score Variable By Ownership Type
Missing observations included as zero values.

Ownership Type	Sample Size	Coefficient for Knowledge Score	t-statistic for Knowledge Score	p-value for Knowledge Score
For-Profit	N = 2976	-0.2546	-3.334	.0009***
Not-for-Profit	N = 1963	-0.2192	-1.525	.1273

*** = Statistically significant at $p < .01$

PART B. SHORTENED TREATMENTS

The data sub-sample with non-missing values for the number of treatments shortened during the study period was, like the skipped treatment data, count data truncated at zero. Negative binomial regression was the appropriate analytical tool here as well, so Table 29 below shows the results of the negative binomial regression of the independent variables on the number of treatments shortened by ten minutes or more during the study period.

Table 29: Shortened Treatments: Negative Binomial Regression
Main sample with no missing observations included as zero values.

N = 1805, Log-likelihood = - 2166.864

Variable	Coefficient	Standard Error	T-ratio	P-value	
Constant	1.2610	0.4516	2.792	.0052	***
Age	-0.0107	0.0037	-2.913	.0358	***
Age Deviation^2	-0.260E-03	0.184E-03	-1.416	.1567	
Days on Dialysis	-0.106E-03	0.459E-04	-2.313	.0207	**
Female	-0.5473	0.0979	-5.591	.0001	***
Native American	-0.7551	0.4986	-1.514	.1299	
Asian	0.0296	0.3067	0.096	.9232	
Black	0.0636	0.1041	0.611	.5415	
Other race	0.8512	0.3603	2.363	.0181	**
Diabetic	-0.1283	0.1386	-0.926	.3546	
Hypertension	-0.0339	0.1346	-0.252	.8013	
Glomerulonephritis	-0.2724	0.1563	-1.648	.0994	*
Cystic Kidney	0.2159	0.2546	0.848	.3964	
For-Profit Ownership	**0.9714**	**0.1517**	**6.405**	**.0001**	***
CON Entry Regs.	0.3272	0.1015	3.222	.0001	***
Facility in South	-0.2276	0.1185	-1.922	.0547	*
Free-Standing	-0.8319	0.1713	-4.857	.0001	***
Knowledge Score	**-0.0966**	**0.0446**	**-2.164**	**.0305**	**
α	2.7254	0.1832	14.876	.0001	***

*** = Statistically significant at p < .01
** = Statistically significant at p < .05
* = Statistically significant at p < .10

Just like the results from the analysis of skipped treatments, here the main results from the analysis of shortened treatments are that for-profit facilities are more likely to have patients with shortened treatments (significant at the $p < .01$ level) and high-knowledge patients are less likely to have shortened treatments (significant at the $p < .01$ level). Results from the regression of independent variables on the number of treatments shortened by ten minutes or more during the study period have more explanatory power than the Table 26 regression involving skipped treatments because the data set with shortened treatments is somewhat larger and there are more non-zero values for the dependent variable. For-profit ownership is a strong positive influence on the number of shortened treatments, as is the presence of Certificate of Need entry restrictions. As before with skipped treatments, older patients and female patients have fewer shortened treatments, signaling greater compliance among females and the elderly.

To determine if for-profit firms are taking advantage of information asymmetries for high-knowledge patients by allowing more shortened treatments, the sample was divided into for-profit and not-for-profit subsets and the knowledge score and significance was recorded. Summarized results in Table 30 are provided for the separate ownership types. The data were separated by ownership type, then a regression of remaining independent variables was run on the dependent variable, number of shortened treatments.

Table 30: Shortened Treatments Regression Results for Knowledge Score Variable By Ownership Type

Main sample with no missing observations included as zero values.

Ownership Type	**Sample Size**	**Coefficient for Knowledge Score**	**t-statistic for Knowledge Score**	**p-value for Knowledge Score**
For-Profit	N = 1050	-0.0441	-0.758	.4487
Not-for-Profit	N = 755	-0.1527	-1.719	.0856*

* = Statistically significant at $p < .10$

In regression results separated by ownership type we do not find that for-profit firms are taking advantage of information asymmetry to allow more shortened treatments. If anything, not-for-profit providers here appear to be allowing more shortened treatments for low-knowledge patients, as the negative coefficient on the knowledge score shows some statistical significance.

Table 31: Shortened Treatments Regression Results for Knowledge Score Variable By Ownership Type
Missing observations included as zero values.

Ownership Type	Sample Size	Coefficient for Knowledge Score	t-statistic for Knowledge Score	p-value for Knowledge Score
For-Profit	N = 2976	-0.0456	-0.681	.4961
Not-for-Profit	N = 1963	-0.2458	-2.468	.0136**

** = Statistically significant at $p < .05$

For the more conservative data set, where missing observations of the Shortened variable are treated as zero values, not-for-profit firms appear even more likely to allow shortened treatments for low-knowledge patients, since the coefficient for the knowledge score is strongly negative. Although for-profit firms may allow more shortened treatments overall (Table 29), this does not appear to be related to the patients' level of sophistication (Tables 30 and 31).

One may argue that not-for-profit firms, if they are of higher quality, may simply have a larger population of knowledgeable patients who are more conscientious about getting full treatments. To test this, the for-profit and not-for-profit sample mean values for the knowledge score were examined. Slightly more knowledgeable patients are being treated at not-for-profit facilities, as shown in Table 32.

Table 32: Knowledge Score Mean Values by Ownership and Data Set

Ownership	Mean Value for Knowledge	Standard Deviation
Main sample with no missing observations included as zero values:		
For-Profit	6.634	1.165
Not-for-Profit	6.677	1.176
Missing observations included as zero values:		
For-Profit	6.636	1.202
Not-for-Profit	6.726	1.205

For the analysis of number of shortened treatments, therefore, we cannot conclude that for-profit firms are taking advantage of information asymmetries, but do have some evidence that quality of care is higher at not-for-profit facilities.

PART C. HEMODIALYSIS HOURS PRESCRIBED BY PHYSICIAN

The third dependent variable under study is the physician's prescription for hemodialysis. If the physician's income comes at least partially from the facility's earnings in the case of medical directors at for-profit facilities, or if pressure from administration to reduce costs is stronger at for-profit facilities, there may be a stronger incentive for the physician with patients at for-profit facilities to prescribe a shorter duration of treatment so that more patients can be scheduled per dialysis station and average costs per patient can be reduced. Data, as reported in Table 25, are continuous, a product of number of hours prescribed per week and the number of dialysis hours per week. However, the data resemble count data due to the high frequency of certain values. Therefore, in addition to ordinary least squares regression, several forms of logistic regression analysis were also tested for appropriateness. Negative binomial regression was not used with this variable because the data are not truncated at zero. Results of the initial least squares regression are shown in Table 33.

Table 33: Physician Hemodialysis Hours per Week Prescribed by Physician, Ordinary Least Squares Regression[6]

N = 4822, F value = 31.142, Prob.>F = 0.0001.

Variable	Parameter Estimate	Standard Error	T for H_0: Parameter = 0	Prob. > |T|
Intercept	10.6511	0.2530	42.106	0.0001***
Age	-0.0207	0.0021	-9.956	0.0001***
Age Deviation^2	-0.0004	0.0001	-3.779	0.0002***
Days on Dialysis	1.88E-04	2.50E-05	7.525	0.0001***
Female	-0.5537	0.0573	-9.672	0.0001***
Native American	-0.4398	0.2313	-1.901	0.0574*
Asian	-0.8498	0.1980	-4.293	0.0001***
Black	0.2498	0.0638	3.917	0.0001***
Other Race	0.2627	0.3052	0.861	0.3898
Diabetic	0.3662	0.0822	4.457	0.0001***
Hypertension	0.1594	0.0833	1.913	0.0558*
Glomerulonephritis	0.2050	0.0954	2.148	0.0318**
Cystic Kidney	-0.0147	0.1614	-0.092	0.9271
For-Profit Ownership	**0.0632**	**0.0835**	**0.757**	**0.4492**
CON Entry Regulations	0.4774	0.0593	8.053	0.0001***
Facility in South	-0.2391	0.0716	-3.339	0.0008***
Free-Standing Facility	-0.4498	0.0943	-4.770	0.0001***
Knowledge Score	**-0.0798**	**0.0243**	**-3.279**	**0.0010*** **

*** = Statistically significant at p < .01
** = Statistically significant at p < .05
* = Statistically significant at p < .10

[6] 177 observations with missing values for the dependent variable were deleted from this sample. A similar regression was run for a sample with the missing observations equal to 9, the mode. Results from that regression were virtually identical, with the same significance levels of variables.

The clear message from the regression above is that case-mix variables are the deciding factor in the physician's selection of dialysis prescription. Curiously, patients with high knowledge scores have lower hemodialysis prescriptions. The knowledge score elements most related to physical condition (walk, eat, transfer independently as well as weight status) may predominate here, as physicians prescribe the longest hemodialysis hours for the patients who are the most frail. Physicians in CON-regulated states appear to prescribe more dialysis, but freestanding facilities and facilities in the South prescribe shorter treatments. Here, the addition of a geographic variable indicates possible regional differences in physician practice.

The knowledge score may be correlated strongly with the patient's physical condition, which makes interpretation of these results regarding hemodialysis prescription somewhat unreliable. Unlike the Skipped and Shortened variables, which most likely have little relation to patient condition, the physician's hemodialysis prescription is probably longer for patients in poor condition, corresponding to the results presented above.

It was hypothesized that the financial incentives created by for-profit ownership would result in shorter hemodialysis prescriptions among for-profit physicians. However, we fail to accept this hypothesis, since the coefficient on the for-profit ownership parameter is not statistically significant. Therefore, there is no evidence that facility ownership and its differing financial incentives created for the patient's physician have an effect on physician treatment. The least squares regression was repeated above for for-profit and not-for-profit subsets of the data. For-profit firms were not found to prescribe different treatment duration for high-knowledge patients. Not-for-profit firms, however, were found to prescribe significantly shorter dialysis times for high-knowledge patients. These results refute the hypothesis that physicians may be reducing costly dialysis times for low-knowledge patients.

Since the physician prescription variable resembles count data, logistic regression analysis provides an alternative to least squares. Ordered logit was first tried with no success. The score test for the proportional odds assumptions (that the dialysis prescription data are ordered as given) failed for the data as listed in Table 25, and for combined subsets of the data as well. The next step was to try successive cumulative logit, whereby the first logistic regression, Table 34, is between "less than nine" and "more or equal to nine" hours of dialysis. The second logistic regression, Table 35, is between "less than or equal to nine" and "more than nine" hours of dialysis. Breaking the logistic regression into two separate regressions in this fashion allows us to spot changes in parameter estimates as the values of the dependent variable increase.

Table 34: Successive Cumulative Logit for Prescribed Hours of Treatment Logit I: Less than 9 Hours Versus 9 or More Hours Prescribed

N = 4822, Lemeshow's R^2 = .0555, -2 Log L = 5144.428 (intercept only), 4859.108 (intercept and covariates) and χ^2 = 285.320 with 17 df (p = 0.0001).

Variable	Parameter Estimate	Standard Error	Wald χ^2	Prob. > χ^2	Standardized Estimate
Intercept	2.7932	0.3218	75.32	0.0001***	.
Age	-0.0199	0.0026	61.10	0.0001***	-0.1771
Age Deviation^2	-0.0004	0.0001	10.30	0.0013***	-0.0702
Days on Dialysis	1.33E-04	3.4E-05	14.99	0.0001***	0.0887
Female	-0.5095	0.0728	48.93	0.0001***	-0.1404
Native American	-0.4999	0.2677	3.49	0.0619*	-0.3411
Asian	-0.9657	0.2102	21.10	0.0001***	-0.0766
Black	0.2836	0.0835	11.53	0.0007***	0.0748
Other	-0.3293	0.3646	0.82	0.3663	-0.0169
Diabetic	0.4088	0.1033	15.66	0.0001***	0.1045
Hypertension	0.1824	0.1032	3.12	0.0772*	0.0453
Glomerulonephritis	0.2437	0.1221	3.98	0.0460**	0.0470
Cystic Kidney	-0.1146	0.1899	0.36	0.5462	-0.0118
For-Profit Ownership	**-0.0279**	**0.1068**	**0.07**	**0.7937**	**-0.0075**
CON Entry Regs.	0.5566	0.0789	49.71	0.0001***	0.1480
South	-0.2113	0.0892	5.61	0.0178**	-0.0492
Free-Standing	-0.0112	0.1213	0.01	0.9262	-0.0027
Knowledge Score	**-0.0810**	**0.0310**	**6.85**	**0.0089*****	**-0.0539**

*** = Statistically significant at p < .01
** = Statistically significant at p < .05
* = Statistically significant at p < .10

Table 35: Successive Cumulative Logit for Prescribed Hours of Treatment Logit II: Less Than or Equal to 9 Hours Versus 10 or More Hours Prescribed

N = 4822, Lemeshow's R^2 = .0754, -2 Log L = 4802.5 (intercept only), 4400.356 (intercept and covariates) and χ^2 = 362.144 with 17 df (p = 0.0001).

Variable	Parameter Estimate	Standard Error	Wald χ^2	Prob. > χ^2	Standardized Estimate
Intercept	0.4484	0.3425	1.71	0.1904	.
Age	-0.0229	0.0030	56.52	0.0001***	-0.2034
Age Deviation^2	-0.0004	0.0001	7.39	0.0066***	-0.0659
Days on Dialysis	2.26E-04	3.0E-05	55.63	0.0001***	0.1505
Female	-0.6285	0.0780	64.86	0.0001***	-0.1732
Native American	-0.4065	0.3546	1.31	0.2515	-0.0277
Asian	-0.2856	0.3089	0.85	0.3552	-0.0226
Black	0.2647	0.0835	10.06	0.0015***	0.0699
Other	0.4733	0.3648	1.68	0.1945	0.0242
Diabetic	0.3288	0.1113	8.72	0.0031***	0.0840
Hypertension	0.1767	0.1133	2.43	0.1188	0.0439
Glomerulonephritis	0.1373	0.1250	1.21	0.2721	0.0265
Cystic Kidney	0.1798	0.2192	0.67	0.4119	0.0185
For-Profit Ownership	**0.2510**	**0.1201**	**4.37**	**0.0366****	**0.0676**
CON Entry Regs.	0.3191	0.0775	16.95	0.0001***	0.0848
South	-0.2791	0.1025	7.41	0.0065***	-0.0651
Free-Standing	-0.8586	0.1283	44.76	0.0001***	-0.2072
Knowledge Score	**-0.0633**	**0.0326**	**3.78**	**0.0519***	**-0.0421**

*** = Statistically significant at p < .01
** = Statistically significant at p < .05
* = Statistically significant at p < .10

The differences between the least squares regression results in Table 33 and the logistic regression results here in Tables 34 and 35 are small. Coefficients on most parameters are the same sign for either form of regression. Logistic regression coefficients are not interpretable as marginal effects of the variables on the dependent variable, but do indicate the sign and statistical significance of the effect on the dependent variable. If standardized estimates are used, one can rank the absolute value of the variables' standardized effects to obtain a relative ranking of the variables' effect on the dependent variable for a one standard deviation change in the independent variable. Ownership has one of the smallest effects on hemodialysis prescription of any of the independent variables.

An interesting result obtained from the successive cumulative logistic regression analysis is the revealed pattern in the effect of for-profit ownership on hemodialysis prescription. Ownership was one of the few variables to show a change in sign from Logit I to Logit II. Results of Logit I indicate (with no statistical significance) that for-profit firms may prescribe fewer hemodialysis hours, as indicated by the negative parameter estimate. However, Logit II shows a statistically significant positive parameter estimate for for-profit ownership. Therefore, for this data sample, for-profit firms are more likely to prescribe longer hemodialysis hours at higher than average levels (greater than nine hours per week). But this effect is canceled out in the entire data sample due to a somewhat higher likelihood of prescribing fewer than nine hours for for-profit facility patients. It appears, therefore, that the distribution of hours prescribed for for-profit firms is larger than physicians associated with not-for-profit firms.

SECTION 6: DISCUSSION AND CONCLUSION

Little explicit evidence of patient knowledge levels exists in most medical databases. The data set used here, however, had an unusual amount of demographic data that could be combined to fashion a knowledge index score for each patient. This knowledge level was found to be a statistically significant determinant of certain aspects of care. The results that high-knowledge patients have fewer shortened and skipped treatments may depend entirely on the high-knowledge patients' own determination to get the best possible care. However, in an idealized world of perfect health care, treatment should depend entirely on patient health needs, not on socioeconomic status or presence of a relative serving as a patient advocate. Thus, at least some of the differences in treatment by knowledge level are due to a failure of institutional staff to encourage low-knowledge patients to be more conscientious, or conversely due to relatively over-attentive treatment of high-knowledge patients.

Results were mixed, but did show evidence of quality of care differences at for-profit and not-for-profit facilities, as well as quality of care differences in relation to patient knowledge levels. The first variable tested, number of skipped dialysis treatments during the study period, showed that for-profit facilities allow more skipped treatments than not-for-profit firms. Results also showed that more knowledgeable patients have fewer skipped treatments. When tested separately by ownership type, not-for-profit firms did not appear to treat knowledgeable patients better than unknowledgeable patients. For-profit firms, however, showed statistically significantly fewer skipped treatments for high-knowledge patients, indicating that for-profit firms may be taking advantage of information asymmetries and providing more conscientious care to knowledgeable patients.

The second variable tested, number of shortened dialysis treatments during the study period, showed again that for-profit facilities allow more shortened treatments than not-for-profit facilities. In addition, knowledgeable patients experienced fewer shortened treatments. However, these effects were not in evidence when testing ownership types separately. For-profit firms may allow more shortened treatments than not-for-profit firms, but for-profit firms do not appear to allow more shortened treatments specifically for low-knowledge patients. Of the two variables testing treatment of patients by facility staff, Skipped and Shortened, Skipped is more important. That is, Shortened refers to the number of dialysis treatments shortened by 10 minutes or more (a dialysis session lasts usually three hours), whereby Skipped refers to an entire dialysis session skipped on a scheduled day. Held et al. (1996) report that one skipped treatment in a month containing 13 total treatments results in a 14% higher annual mortality risk. So although for-profit facilities do not appear to be taking advantage of information asymmetries in terms of shortened treatments, it is more important to patients' health outcome that the data suggest that for-profit facilities are taking advantage of information asymmetry in terms of skipped treatments.

The numbers of skipped and shortened treatments indicate the ability of the dialysis facility staff to provide quality care and to carry out the prescription ordered by the patient's off-site doctor. The third variable tested, number of hemodialysis hours prescribed weekly by the patient's physician, was included to determine if financial incentives due to ownership differences would affect the duration of the hemodialysis prescription. Results indicate that physicians' dialysis hours prescribed were not affected by ownership type, but that physicians tended to order longer dialysis for low-knowledge patients. Physicians with patients at not-for-profit facilities prescribed significantly fewer hours for high-knowledge patients. Therefore, no evidence exists that physicians affiliated with either ownership type were taking advantage of low knowledge levels among patients to prescribe shorter dialysis treatments.

In summary, though facility treatment quality does appear to differ by ownership type, evidence is mixed that for-profit firms in the renal dialysis industry are specifically taking advantage of information asymmetries in order to reduce costs. Physicians do not appear to be affected by ownership type when prescribing dialysis hours of treatment and also do not appear to be prescribing more dialysis for more knowledgeable patients. Therefore, further studies on this topic should take care to examine not just prescribed treatment differences by the physician, but deviation from prescribed treatment by institutional staff.

CHAPTER 7: QUALITY OF CARE AND OWNERSHIP: FINDINGS AND CONCLUSIONS

SECTION 1: DISCUSSION OF FINDINGS

This dissertation was commenced to correct a perceived lack of both rigorous theoretical models of not-for-profit organizations and proper control of outcome quality in studies of comparative cost efficiency by ownership type. In the process, an improved methodology for an econometric technique was devised, and a study of asymmetric information as a possible cause of health care quality disparity was completed. Contributions to the literature from this dissertation are noted below, in order of their appearance in the dissertation.

PART A. THEORETICAL MODEL

Little effort has gone into the daunting task of modeling not-for-profit objective mathematically. Some theorists have tried a model of maximizing output while breaking even, while others have attempted to model not-for-profit firms as maximizing profit with a break-even constraint. Many have simply assumed that not-for-profit managers value quality or numbers of patients served, as opposed to for-profit managers who merely maximize profits. In Chapter 2, an alternative model is provided, whereby patient survival depends on quality produced over time. The model is attractive in its incorporation of intertemporal effects and also in its conservative assumption that both not-for-profit and for-profit managers are equally altruistic, and both have quality of care in their utility functions. The key feature separating not-for-profit from for-profit managers is the non-distribution constraint: For-profit managers are able to receive a higher percentage of firm profits in the form of income. Of course, not-for-profit firm managers cannot legally have their salary tied directly to residual income, but in practice they do benefit more when the organization is more profitable, so the assumption that they take home some of the profits (albeit indirectly) is sound. The mathematical model is conservative, yet the steady state conditions predict that, over time, for-profit firms will provide care of a lower quality than their not-for-profit counterparts will provide.

PART B: MULTIVARIATE REGRESSION ANALYSIS

The renal dialysis industry provided an excellent opportunity to test whether outcome quality differs by ownership type. The data sets were very large – over 200,000 patients receive care for end-stage renal disease (ESRD) nationwide – and the treatment protocol is straightforward for ESRD. Mortality, the main "quality" variable under scrutiny, is indisputable as a measure of outcome quality, and was frequent enough among ESRD patients that results were easily interpreted. The method of reimbursement for ESRD patients was prospective-price, and thus immediately comparable to prospective-price reimbursement systems used in hospital and other medical care.

Logistic regression analysis in Chapter 4, using virtually all patients undergoing center-based dialysis or transplant in 1993 nationwide, suggested that patients whose main treatment facility was a for-profit firm had higher mortality rates than patients whose main treatment facility was a not-for-profit firm, case-mix and market characteristics adjusted. The increase in mortality appeared to be around three percent, depending on the population group studied. A review of medical literature and discussions with nephrologists indicated that this three percent figure was not at all trivial. A three percent increase in the probability of death translates to roughly five months of life lost for a teenager, whereas a similar increase in the probability of death for an 85-year-old patient reduces life expectancy by approximately two weeks (USRDS, 1995).

The controls for market and firm-level characteristics were found to be an important part of the model's specification, as characteristics such as geographic location and entry regulations were statistically significantly related to higher mortality rates. Certificate of Need regulations' positive influence on mortality was somewhat of a surprise. These regulations restricting the entry of new (primarily for-profit) firms could be inducing current market participants in those areas to treat only the sickest, neediest patients, whereas firms in saturated markets may be starting patients on dialysis who are not yet so debilitated. Further testing of the effect of Certificate of Need regulations on patient mortality would be an interesting future project, but the issue was peripheral to this particular study except for its appearance as a control variable.

PART C: PROPENSITY SCORE ANALYSIS

Several lingering issues remained after performing multivariate regression analysis. First, the data were not randomly generated, and there was no particular guarantee that the data were identical in characteristics of for-profit and not-for-profit patients. Second, the logistic regression models may not have been correctly specified to account for any possible differences in for-profit and not-for-profit patient populations. Third, some independent variables were clearly facility-level covariates, such as freestanding or hospital based status, whereas other independent variables were patient case-mix characteristics such as age, length of time on dialysis, and so on. Neither patient-level regression analysis nor facility-level analysis of patient mortality rates appeared accurate in modeling the effects of these multi-level variables.

Propensity score methodology provided a very different approach to measuring differences in mortality across ownership types. By stratifying the data set on the basis of propensity score (propensity to be a for-profit facility), it was possible to create subsets of data whereby for-profit and not-for-profit patients had comparable characteristics. That is, for-profit and not-for-profit patients in each data subset had means of variables that were not significantly different from each other. These data subsets could be used to calculate the overall mean probability of death for each ownership type. In addition to correcting for biases due to differences in populations of for-profit and not-for-profit patients, propensity score methodology solved the multi-level independent variable problem by reducing the analysis to a subset of patients where facility characteristics were identical (freestanding facilities only). Results for the subset of white or black dialysis patients with diabetes or hypertension indicated that patients being treated at for-profit facilities had a 5.86% greater probability of dying during the year than patients treated at not-for-profit facilities. This figure exceeds that of the approximate 3% difference in mortality rates for dialysis and transplant sample population groups analyzed in Chapter 4, yet falls below the 7% difference in facility average mortality rates suggested by the USRDS study. Since the propensity score methodology model accounted for population bias in not only patient case-mix variables, but also relevant market variables, the 5.86% figure is most likely a better estimate of the causal effect of for-profit treatment for dialysis patients at freestanding facilities.

PART D: IMPROVEMENTS TO THE PROPENSITY SCORE STRATIFICATION PROCESS

Despite the attractiveness of propensity score methodology's ease of interpretation and calculation of causal effects from identical and unbiased subsets of data, the methodology was difficult to implement with this renal dialysis data due to the many number of independent variables to control for and persistent differences in patient populations across ownership types. The data had to be simplified by eliminating observations of non-black and non-white race and uncommon primary diagnoses. Still, though, the stratification methodology used by previous researchers – weighting by propensity score, matching on the propensity score, or sub-sub-stratification – was not adequate to reduce the data to comparable for-profit and not-for-profit subsets unless the data were divided into extremely small subsets. The prospect of basing the estimated causal effect on a myriad of tiny subsets of data, passing the "identical" test on the strength of low numbers of observations alone, was unappealing.

Two alternative methods of stratification were proposed. The first method entails reducing the data to a homogenous subset by recursive formulation of propensity scores and discarding the highest and lowest strata when the observations are ranked by propensity score. This method provided a quick way of creating a data set for analysis whereby the for-profit and not-for-profit subsets are very similar. Remaining differences in for-profit and not-for-profit populations could be easier eliminated by the common stratification, weighting, or matching methods.

The second improvement to the propensity score stratification process may be potentially more attractive to researchers because it does not involve reduction of the overall data set. This second method entails subdividing the data into strata (for example, five initial strata). The strata that have comparable subsets of for-profit and not-for-profit populations are retained for final calculation of the estimated causal effect, while strata rejecting difference in means tests for any of the variables are subdivided again into smaller subsets. They key difference proposed is that the logistic regression creating the propensity score is *repeated* for the strata that failed, creating new "propensity scores" and thus new rankings of observations. It was found that this employment of recursive propensity score regression quickly produced homogenous populations of for-profit and not-for-profit subsets of data and consequently reduced the number of final strata produced significantly. Using this recursive method of logistic regression propensity score ordering, only thirteen strata were needed to estimate the causal effect of for-profit treatment on mortality, while the traditional sub-stratification method would have necessitated creating over thirty strata.

PART E. ASYMMETRIC INFORMATION AND OWNERSHIP

Since the empirical analysis in Chapters 4 and 5 suggested that a disparity in clinical quality exists by ownership type, the question arose as to how this quality gap could exist over time. Chapter 6 investigated the possibility that differences in quality are emanating from the practice of treating low-knowledge patients with low cost, lower quality care than the care provided to high-knowledge patients. It was hypothesized that for-profit facilities would be more likely to exploit information advantages than not-for-profit facilities. Analysis took the form of specifying a knowledge index, composed of responses to variables indicating patient ability to judge quality of care, and analyzing the number of skipped or shortened dialysis treatments during a specified time period. Physician prescriptions of dialysis treatment duration were also examined. Due to the difficulty of obtaining data on patient knowledge levels, this study represents one of the first attempts in the literature to measure differing treatment in response to patient knowledge levels.

Results of the regressions of patient case-mix and market characteristics, ownership, and knowledge scores on the three dependent variables under scrutiny showed the following: First, for-profit providers were found to allow more skipped treatments for their patients than not-for-profit providers. Regardless of ownership type, higher knowledge patients had fewer skipped dialysis treatments. When the results were divided by ownership type, for-profit firms were found to allow significantly fewer skipped treatments for high-knowledge patients, while not-for-profit firms showed no such effect with respect to knowledge level. Therefore, for the variable indicating numbers of treatments skipped, the results could be interpreted to say that for-profit firms are taking advantage of information asymmetry to provide sub-standard care to low-knowledge patients.

Second, when the number of treatments shortened by ten minutes (besides skipped treatments) were examined, it was found that for-profit firms allowed more shortened treatments for their patients than not-for-profit firms allowed. Also, regardless of ownership type, high-knowledge patients had fewer shortened treatments. When the data were separated by ownership type, though, for-profit firms did not show a tendency to allow more shortened treatments for low-knowledge patients. Not-for-profit firms, however, did appear to allow more shortened treatments among low-knowledge patients. In this case, it appeared that not-for-profit firms, rather than for-profit firms, were taking advantage of information asymmetry to provide sub-standard care to low-knowledge patients. Of the two variables under scrutiny, treatments skipped or shortened, the number of skipped treatments has a much greater significance to the patient's health. Treatments last on average a little less than three hours, so a treatment skipped means a substantial reduction in weekly dialysis, whereas a treatment shortened by ten minutes is a relatively minor reduction.

The third variable studied in the asymmetric information analysis was physician hemodialysis prescription. No evidence emerged that physicians prescribe shorter treatment duration for patients in for-profit facilities as opposed to not-for-profit facilities. In addition, physicians appeared not to be influenced by patient sophistication levels, and in fact were found to prescribe longer treatments for low-knowledge patients, which may be caused by patient health conditions' relation to the knowledge score. Results of the asymmetric information analysis imply that differences in clinical quality may be emanating from facility staff rather than physician care. Physicians may be acting as patient advocates to insure that contract failure in health care does not occur, but their advocacy role may not be adequate to overcome differences in facility administration.

SECTION 3: CONCLUSIONS

The theoretical model in Chapter 2 underscored the importance of the non-distribution constraint in observed behavior between not-for-profit and for-profit health care firms. Empirical evidence supported the theoretical hypothesis that quality of care will be higher at not-for-profit facilities, and also provided insight into treatment differences for high- and low-knowledge patients. Further empirical work in Chapter 5 using an innovative method of eliminating population bias also pointed to an outcome quality gap between for-profit and not-for-profit renal dialysis providers. The quality disparity found in this research suggests that outcome quality is a key control variable for future studies of cost efficiency in the health economics literature. In addition, previous theoretical assumptions of a not-for-profit quality advantage in health care, though in the past largely unsubstantiated, may in fact be justified.

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APPENDIX A: "SKIPPED" SMALL SAMPLE DATA

Table A1. "Skipped" Data Patient Characteristics: n = 1694
Observations with missing values for Skipped not included in the sample.

Variable	Mean	Std. Dev.	Median	5th %	95th %
Age	60.93	16.03	64	32	83
days on dialysis	1838	1220	1497	417	4369
Knowledge Score	6.61	1.17	6.67	4.67	8.33
Skipped Treatments	.54	1.45	0	0	3

Gender: Female (dummy variable = 1): n = 823 (48.6%)   Male: n = 871 (51.4%)

Race:

Native American:	n = 36 (2.1%)	
Black:	n = 659 (38.9%)	
White:	n = 933 (55.1%)	(omitted reference category)
Asian:	n = 46 (2.7%)	
Other race:	n = 16 (.9%)	

Primary Diagnosis Causing End Stage Renal Disease:

Diabetic:	n = 555 (32.8%)	
Hypertension:	n = 460 (27.2%)	
Glomerulonephritis:	n = 242 (14.3%)	
Cystic Kidney:	n = 52 (3.1%)	
Other Primary Diagnoses:	n = 385 (22.7%)	(omitted reference category)

Table A2. "Skipped" Data Facility Characteristics: n = 298

Facility in South (dummy = 1): n = 97 Facility not in South: n = 201

Facility in state with Certificate of Need regulations (dummy = 1): n = 106
Facility in state with no Certificate of Need regulations: n = 192

Facility freestanding (dummy = 1): n = 245 Facility in hospital: n = 53

For-profit facility (dummy = 1): n = 217 Not-for-profit facility: n = 81

Table A3: Treatments Skipped

Value	Frequency
0	1318
1	178
2	80
3	52
4	18
5	17
6	8
7	4
8	5
9	1
10	8
11	3
12	1
13	1

Total Frequency: 1694
(Observations with missing variables not included.)

APPENDIX B: "SHORTENED" SMALL SAMPLE DATA

Table B1. "Shortened" Data Patient Characteristics: n = 1805
Observations with missing values for Shortened not included in the sample.

Variable	Mean	Std. Dev.	Median	5^{th} %	95^{th} %
Age	60.65	16.07	64	31	83
Days on dialysis	1886	1240	1540	453	4374
Knowledge Score	6.65	1.17	6.67	4.67	8.33
Shortened Treatments	.90	2.05	0	0	4

Gender: Female (dummy variable = 1): n = 878 (48.6%) Male: n = 927(51.4%)

Race:

Native American:	n = 36 (2.0%)	
Black:	n = 687 (38.1%)	
White:	n = 1023 (56.7%)	(omitted reference category)
Asian:	n = 41 (2.3%)	
Other race:	n = 14 (.8%)	

Primary Diagnosis Causing End Stage Renal Disease:

Diabetic:	n = 564 (31.2%)	
Hypertension:	n = 486 (26.9%)	
Glomerulonephritis:	n = 277 (15.3%)	
Cystic Kidney:	n = 58 (3.2%)	
Other Primary Diagnoses:	n = 420 (23.3%)	(omitted reference category)

Table B2. "Shortened" Data Facility Characteristics: n = 329

Facility in South (dummy = 1): n = 100 Facility not in South: n = 229

Facility in state with Certificate of Need regulations (dummy = 1): n = 113
Facility in state with no Certificate of Need regulations: n = 216

Facility free-standing (dummy = 1): n = 261 Facility in hospital: n = 68

For-profit facility (dummy = 1): n = 231 Not-for-profit facility: n = 98

Table B3: Treatments Shortened

Value	Frequency
0	1169
1	337
2	116
3	64
4	36
5	17
6	12
7	9
8	7
9	6
10	10
11	1
12	6
13	12
14	1
15	1
20	1

Total Frequency: 1805
(Observations with missing variables not included.)

VITA

Renee A. Irvin

University of Washington

1998

EDUCATION

Ph.D., Economics, University of Washington. Seattle, Washington.
Date of completion: August 6, 1998
Fields of specialization: Microeconomics, Health Economics, Public Finance, Natural Resource and Environmental Economics, Not-for-Profit Organizational Theory
Thesis: Quality of Care, Asymmetric Information, and Patient Outcomes in U.S. For-Profit and Not-for-Profit Renal Dialysis Facilities
Thesis Advisor: Dr. Levis Kochin

M.A., Economics, University of Washington. Seattle, Washington, December 1991.

B.A. Magna Cum Laude, German, University of Oregon. Eugene, OR, Dec. 1984.

Additional advanced coursework: Chinese language, creative writing and mathematics
Exchange programs: Studied one year at **Universitaet Stuttgart** (Stuttgart, Germany) and one semester at **Beijing Normal College of Foreign Languages** (Beijing, China).

Academic Honors:

Dissertation Grant Fellowships: 1996, 1997
Ensley Graduate Fellowship for Economic Policy: 1992-93
Economics Graduate Teaching Assistantship: Contract awarded on merit basis, 1990-1996.
Undergraduate Honors: Phi Beta Kappa, Dean's List, and five separate merit scholarships

Languages:

Fluent German, some proficiency in Japanese, Chinese and Spanish.

Software Experience:

SAS (PC and mainframe), SPSS (mainframe), LIMDEP (MS-DOS), Eviews, MS-Word and EXCEL

TEACHING

Primary Teaching Areas:	Classes Taught:
Economics	Introductory Microeconomics(UW, 1990 – 1996) Introductory Macroeconomics (UW, 1990 – 1996) Intermediate Microeconomics (UW, Fall 1993) Intermediate Macroeconomics (UW, Summer 1992)
Public Economics	The Public Economy (UNO, Fall 1997 and Spring 1998)
Health Economics & Finance	Health Care Finance (UNO, Fall 1997 and Fall 1998)
Economics of Not-for-Profit Organizations	Not-for-Profit Firms in a Market Economy (will teach Spring 1999 at UNO)

New Courses Developed:

Health Care Finance (masters-level course)
Not-for-Profit Firms in a Market Economy (masters and doctoral-level course)

PUBLICATIONS

Papers Submitted for Publication:

Quality of Care Differences by Ownership Form: Implications for Cost Efficiency Studies, submitted to ASAIO Journal in June 1998.

Unpublished Reports and Manuscripts:

Quality Differences in For-Profit and Not-for-Profit Renal Dialysis Facilities: An Application of Propensity Score Methodology, June 1998.
Asymmetric Information in Health Care: Treatment of Low-Knowledge Patients, March 1998.
Cost and Efficiency Performance of For-Profit and Not-for-Profit Health Care Providers, December 1995.
The Provision of Community Benefit in an Era of Health Care Competition with Dr. Douglas R.Conrad and Dr. Carolyn Madden, October 1995.
Measuring Up: An Analysis of State and Local Fiscal Policies Affecting Disadvantaged and Vulnerable Populations, (contributor) September 1995.
Regulating Industrial Dischargers of Multiple Pollutants, June 1995.
One Fish, Two Fish...Fiscal Analysis Using Comparison States Methodology, April 1995.

FUNDED RESEARCH

Not-for-Profit Health Care Research:
Dissertation fellowships funded by Belding H. Scribner, M.D. and Northwest Kidney Centers, Seattle, Washington, 1996-1997.

The Impact of Competition on the Provision of Community Benefit:
Critiqued literature pertaining to health care organizations' provision of community benefits, comparative cost efficiency and quality of care. Co-wrote *The Provision of Community Benefit in an Era of Health Care Competition*, for use in aiding national and state-level health care policy discussions, especially with regard to tax exemption of not-for-profit health care providers. Wrote *Cost and Efficiency Performance of For-Profit and Not-for-Profit Health Care Providers*. This research was funded by the Catholic Health Association, June 1995 to September 1995 and the University of Washington Department of Health Services, September 1995 to December 1995.

Institute for Public Policy & Management Fiscal Policy Center:
Assisted faculty in obtaining a two-year, $200,000 grant from the Ford and Annie E. Casey Foundations to establish a fiscal policy study center. Analyzed Washington State fiscal policies by developing own methodology for selecting peer states for comparative analysis. Contributed to two reports, *Measuring Up: Revenue Policy* and *Measuring Up: Spending Policy*, and wrote methodological paper, *One Fish, Two Fish....Fiscal Analysis Using Comparison States Methodology*. March 1994 to May 1995.

PROFESSIONAL ASSOCIATION ACTIVITIES

American Economic Association (AEA)

AEA Committee on the Status of Women in the Economics Profession (CSWEP)
Presented paper at MEA conference as part of CSWEP-sponsored section on the Economics of Information, March 1998.

American Society for Artificial Internal Organs (ASAIO)
Invited and fully funded to present paper, *Quality of Care Differences by Ownership Form: Implications for Cost Efficiency Analysis*, at annual conference in New York City, April 1998.

American Society for Public Administration (ASPA)

ASPA Section on Health and Human Services Administration

Association for Public Policy Analysis and Management (APPAM)
Will present *Quality Differences in For-Profit and Nonprofit Renal Dialysis Facilities: An Application of Propensity Score Methodology* at the October 1998 APPAM national conference in New York City.

Northwest Regional Economics Association (NREA)
Presented paper, *One Fish, Two Fish....Fiscal Analysis Using Comparison States Methodology* at annual conference in Missoula, MT, April 1995.

Midwest Economics Association (MEA)
Presented paper, *Asymmetric Information in Health Care: Treatment of Low-Knowledge Patients* at annual conference in Chicago, March 1998.

Western Economics Association (WEA)
Served as discussant for annual conference in Seattle, July 1997. Presented paper, *Regulating Industrial Dischargers of Multiple Pollutants* at annual conference in San Diego, July 1995. Served as discussant at annual conference in Vancouver, BC, July 1994. Presented paper, *Maximizing Social Net Benefits in Alaska Cod Fisheries* at annual conference in June 1992.

PUBLIC AND UNIVERSITY SERVICE

Recent Seminars Presented:

Does Quality of Care Differ by Ownership in Health Care? Seminar presented to University of Nebraska Medical Center faculty at the Nebraska Center for Rural Health Research, December 1997.

Does Quality of Care Differ by Ownership in Health Care? Seminar presented to University of Nebraska at Omaha College of Business Administration faculty, November 1997.

Served as water resources, waste management, and energy and information systems panelist at Omaha's Integrated Approaches to Infrastructure Issues conference, October 1997.

The Economics of Not-for-Profits Seminar presented to University of Washington Department of Economics faculty and students, November 1996.

Volunteer Experience:

Served as member of the City of Seattle's Citizen's Water Quality Advisory Committee, and chaired its Industrial and Household Hazardous Waste Sub-Committee, 1990-1993.

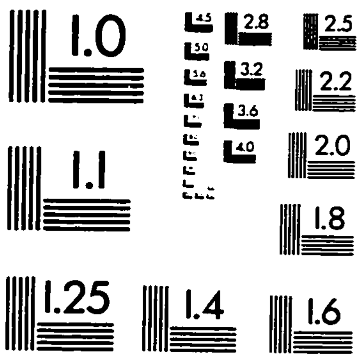
Served as citizen representative for the City of Seattle's Industrial Waste Advisory Board, a group organized to hear appeals from businesses penalized for industrial waste regulations violations, 1991-1993.

PROFESSIONAL EXPERIENCE

Industry Economist: US Department of Commerce, National Oceanic and Atmospheric Administration, National Marine Fisheries Service. Seattle, Washington, June 1991 to October 1992. Wrote benefit-cost analyses for proposed Alaskan fisheries regulations. Research included time series analysis of fisheries catch and bycatch data and vessel costs of operation.

Pre-Graduate School Employment:
Language Specialist, Japan Ministry of Education, Hyogo Prefecture, Japan, 1987-88
Foreign Study Assistant, Oregon State System of Higher Education, Corvallis, OR, 1985-87
Financial Aid Needs Analyst, University of Oregon, Eugene, OR, 1984-85

IMAGE EVALUATION TEST TARGET (QA-3)



150mm

6"

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