Concentration and Pricing in the Hospital Sector*

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Abstract

The pricing behavior of non-profit hospitals is an important issue given the size of the non-profit hospital sector in relation to the for-profit sector. It is generally accepted in the literature that for-profit hospitals set higher prices than their non-profit counterparts. However, there is disagreement over the relative behavior of the different types of hospital in the presence of market power. Some authors argue that market power causes hospitals to maintain higher prices regardless of their ownership, while others argue that greater levels of market power are associated with lower prices for non-profit hospitals. Clearly, how market concentration influences the pricing behavior of non-profits has implications for antitrust policy and is an interesting topic for research.

This paper reviews the previous research that identifies the effects of market power on the behavior of hospitals under different forms of control. It then offers a new investigation of the issues using data from a sample of patients suffering from alcohol and drug related disorders. These data have a distinct advantage over those used in previous research in that they examine a more standardized area of treatment and provide more direct control for severity of illness than those used by previous authors. In addition, the model used in this paper avoids some of the specification issues inherent in some of the prior research.

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Summary

The pricing behavior of non-profit hospitals is an important issue given the size of the non-profit hospital sector in relation to the for-profit sector. It is generally accepted in the literature that for-profit hospitals set higher prices than their non-profit counterparts. However, there is disagreement over the relative behavior of the different types of hospital in the presence of market power. Some authors argue that market power causes hospitals to maintain higher prices regardless of their ownership, while others argue that greater levels of market power are associated with lower prices for non-profit hospitals. Clearly, how market concentration influences the pricing behavior of non-profits has implications for antitrust policy and is an interesting topic for research.

This paper reviews the previous research that identifies the effects of market power on the behavior of hospitals under different forms of control. It then offers a new investigation of the issues using data from a sample of patients suffering from alcohol and drug related disorders. These data have a distinct advantage over those used in previous research in that they examine a more standardized area of treatment and provide more direct control for severity of illness than those used by previous authors. In addition, the model used in this paper avoids some of the specification issues inherent in some of the prior research.

Our results substantially contradict those of previous authors: we find that for-profit hospitals charge essentially the same as their non-profit counterparts in comparable markets and, more importantly, neither type of hospital's prices are significantly affected by levels of market concentration.

Introduction

The pricing behavior of non-profit hospitals is an important issue given the relative size of the non-profit sector. In 1996, over 70% of inpatients received care in non-profit hospitals under non-government control, and private and public non-profit hospitals together accounted for 88% of all U.S. hospital admissions. The relative proportion of non-profits and government-controlled hospitals does not seem to be changing very dramatically. In 1986, the percentage of inpatients treated in non-profit and government hospitals was 90%, and the percentage of hospitals and beds in each type of hospital was virtually the same[1] ten years later.

[1] American Hospital Association, AHA Hospital Statistics (1998), table 2.

The growth of managed care and the increased price competition in the hospital sector has led to a significant number of hospital mergers and acquisitions in recent years, (according to Jaspen (1998), over 45% of US hospitals have been involved in mergers, acquisitions, and joint ventures since 1990); and, inevitably, some of the increase in market concentration has involved non-profit hospitals. What does this trend mean to consumers? Will an increase in the market power of non-profits mean that consumers are faced with higher prices, or will the fact that these hospitals are, in theory, non-profit seeking mean that any potential economies of scale and scope will be passed on the consumer? Does ownership make any difference at all? The answers to these questions clearly have implications from an antitrust perspective.

In 1996, a district court refused to grant an injunction against the proposed merger of the two largest hospitals in Grand Rapids, MI which, when combined, accounted for 73% of the market. Basing his decision, at least in part, on a paper in The Journal of Law and Economics by William Lynk (1995), the judge stated that the merging hospitals were unlikely to raise their prices even if they acquired monopoly power.

Since the Grand Rapids court case, authors have revisited the question of whether non-profit hospitals utilize market power in the same way as for-profit hospitals. Keeler, Melnick, and Zwanziger (KMZ) (1999) and Dranove and Ludwick (D&L) (1999)) used similar data to that used by Lynk, together with variations on his model, and were unable to support Lynk's conclusions. Lynk and Neumann (1999), in a response to those criticisms, used a different data set to affirm their original results.[2]

One important omission in all these models is the weakness of controls for severity of illness. Presumably, more severe patients are likely to incur greater use of a hospital's resources that may then be reflected in the price they are charged. If a particular type of hospital systematically admits sicker patients, then the absence of any control for severity would lead to biased results. Although D&L (1999) attempt to address this issue by claiming that the number of secondary diagnoses serves as a better measure of severity than length of stay, they subsequently omit the latter variable from their model – introducing omitted variable bias from a different source (see literature review section for more in depth discussion).

A second limitation of much of the previous research involves the omission of any measure of the type of treatment provided, focusing instead only on the type of illness treated. Different types of hospital may exhibit significantly different styles of treatment for the same illness. This may, in turn, lead to significant price variation between hospitals that is not properly captured within any of the previous models. Lynk (1995), KMZ (1999), and D&L (1999) include an asset-to-expense ratio in their respective models –

[2] "…the general inference from these results is that… higher levels of local hospital concentration in Michigan are not associated with higher non-profit hospital prices. If there is any association at all, it is that higher levels of local hospital concentration are weakly associated with lower prices". L&N (1999), pp. 110.

possibly to account for the differences in operating style (although none of the authors gives an explanation for its inclusion). The usefulness of this variable in accounting for differences in operating style (if this is what it is intended to do) is probably significantly limited (see literature section for further discussion). Our dataset involves closely related diseases (rather than the diverse range used by previous authors), and the specific illnesses we examine are treated with a very limited range of treatments that are largely identified by the disease related group (DRG) into which they are classified. Consequently, not only are we able to avoid the variation introduced by the diverse range of DRGs that are present in other studies, but we are also able to avoid the effect of omitting the intensity of treatment (see 'Hypothesis' section for further discussion).

Because most of the prior research includes multiple DRGs within the data set, the Herfindahl is generally calculated using total hospital admissions.[3] This is somewhat misleading since a hospital that specializes in one particular medical area may have very little market power in a different specialty. Consequently, a general Herfindahl index calculated from total admissions is unlikely to apply to all medical specialties and is likely to provide a distorted view of market concentration. Since this paper concentrates on a very narrow range of illnesses, a more precise measure of Herfindahl index can be calculated based only on hospital admissions pertaining to those specific illnesses. This provides a better measure of the true market structure than is provided by most previous authors.

This paper reviews the methodologies and conclusions of the work done in this area to date and sets up a model that avoids some of the specification problems inherent in the work discussed. The main contributions of the paper concern the selection of a patient level dataset that inherently controls for severity of illness and treatment styles and the inclusion of additional variables to control further for severity. In addition, the model avoids the specification problems inherent in some of the previous work. It omits the share of county admissions as an explanatory variable and, thus, avoids potential simultaneity issues[4] associated with others' work. The model presented here also includes a hospital level measure of wage costs, thus avoiding coefficient bias associated with potentially important variables.[5] As discussed above, it also includes a more appropriate measure of market concentration.

While the nature of the data and the form of the model do not allow direct comparison with the work of previous authors, this paper avoids significant problems inherent in the specifications of previous authors work and is, therefore, more able to shed light on the underlying issue – that of hospital response to market power and whether it is determined by hospital ownership.

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[3] Lynk (1995), Dranove and Ludwick (1999) and Keeler, Melnick and Zwanziger (1999).
[4] Included in Lynk (1995) and Dranove and Ludwick (1999). In Keeler, Melnick and Zwanziger (1999) this variable appears as a hybrid of HHI and SHARE – see literature review for more detail.
[5] Absent from Lynk (1995), and Dranove and Ludwick (1999).

Literature Review.

Non-profit hospitals set lower prices.

There is limited research to show that non-profit hospitals set lower prices than their for-profit counterparts. However, the literature is generally based on fairly old data and therefore has to be treated with caution in today's markets.

Lewin et al. (1981) compare the economic performance of 53 non-profit hospitals with that of 53 similar for-profit hospitals. The non-profit and for-profit hospitals are paired on the basis of location (California, Florida and Texas), size and services offered. Grouping purchasers into two groups – 'charge' payers (private insurance, self-pay, and Blue Cross) and 'cost' payers (primarily Medicare and Medicaid), the authors find that where treatment was paid for by 'charge' payers, investor-owned hospitals are more expensive than their non-profit counterparts. However, when 'cost' payers foot the bill, the authors find that investor-owned hospitals are slightly more expensive on a per day basis but essentially comparable on a per admission basis. Furthermore, a substantial proportion of the difference for Medicare is the return on equity paid only to investor-owned hospitals.

Using a similar methodology to that of Lewin et al. (1981), Watt et al. (1986) examine gross and net revenues of 80 'matched' pairs of investor-owned chain and non-profit hospitals in eight states during 1978 and 1980. (Each investor-owned hospital is matched with a similar non-profit hospital on the basis of location, scale of operation, services offered and average length of stay.) Revenues are adjusted to control for the different case-mixes[6] across hospitals and the total number of admissions, and the authors find that investor-owned hospitals are more expensive than comparable non-profit hospitals in terms of both gross and net revenues. Furthermore, even when the authors adjust the data to allow for the less favorable tax regime facing for-profit hospitals, for-profits remain more expensive.

Pattison (1983), using data from California in 1980, finds that certain ancillary services are generally profitable[7] across all classes of hospital, while others are generally unprofitable[8] and that routine services[9] are generally unprofitable for all classes of hospitals. The mark-ups on the profitable ancillary services are higher at the for-profit hospitals than at non-profit or public hospitals, and per-unit losses on the unprofitable ancillary services are generally smaller in the former type of hospital than in the latter.

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[6] The authors used the Medicare case-mix indexes calculated by the Health Care Financing Administration. These are calculated from a 20% sample of each hospital's Medicare patients.

[7] Clinical laboratories, central services and supply, the pharmacy, and inhalation therapy.

[8] Blood bank, radiology, emergency, and home-health services.

[9] Room and board.

Prices are higher in more concentrated markets.

Research has generally shown that hospitals in more concentrated markets set higher prices. Staten et al. (1988) examine the effect of hospital market structure and insurer market share on the discount rate that hospitals offered to gain acceptance into the newly formed Blue Cross of Indiana PPO. The study finds that hospitals located in less concentrated markets offered greater discounts and that higher Blue-Cross share at either the hospital or market level did not significantly lower the proposed discounts offered by hospitals.

The Staten et al. study uses the initial bid proposed by the hospital as the basis on which to calculate the discount. However, according to Melnick et al. (1992), substantial negotiation takes place between the initial bid and final contractually agreed price. Consequently, the discount calculated may understate the true discount and, therefore, distort the true effect of market concentration on price. Furthermore, Melnick et al. argue that Staten et al.'s use of the county as the measure of the market is likely to overstate the level of competition, particularly in counties with many hospitals where hospitals may actually only compete with a small percentage of other hospitals. To overcome these problems, Melnick et al. use *final* prices paid to hospitals in the Blue Cross of California PPO network, and they derive the size of a hospital's market from patient flow data. Regardless of these refinements, the authors (Melnick et al. 1992, p.227) arrive at the same conclusion as those of Staten et al … "Blue Cross pays higher prices to hospitals located in less competitive markets".

Dranove et al. (1993) study the prices charged to private patients treated in private hospitals in California over the period 1983-1988. During this period, California led the way in relaxing its insurance laws and consequently experienced rapid growth in selective contracting. Consequently, it provided an interesting test site for the rest of the nation. Dranove et al. (1993, p.202) find that hospital profit margins were lower in markets with lower hospital concentration and '…that the degree of concentration in hospital markets can be significant factor in determining the level of prices'.

Connor et al. (1998) study the effects on both costs and prices of 122 hospital mergers during the period 1986 – 1994. The authors find that hospital mergers produced savings in annual operating expenses for the merging organizations and that these savings largely were passed on to consumers as lower prices. However, mergers in markets with higher concentrations (with Herfindahl indices above 0.18) led to price increases instead of price decreases.

Krishnan (2001) examines DRG level data for California and Ohio for 1994-1995 in a pre-post merger event study. Firstly, he compares price changes within the same hospital across DRGs comparing those DRGs that gained substantial market share following a merger with those that did not. This approach allows the author to control for hospital-specific price changes that are unrelated to the merger. He finds that merged hospitals do raise prices in those services in which they have market power.[10]

Krishnan also compares price changes for DRGs from merging and non-merging hospitals in the same market. He selects DRGs where the merging hospital gained more than 20 percentage points in market share and matches these hospitals with a non-merging hospital based on a number of variables.[11] Once again, post-merger prices are higher than those pre-merger.[12] Performing the same examination, but selecting DRGs on the basis of an increase in the Herfindahl index[13] rather than market share, Krishnan (2001, p.222) finds that "…for DRGs where there was an increase of HHI of 2000 or more, the increase in prices was 15.6% in the merging hospitals and 5.7% for the non-merging hospitals".

Finally, Krishnan examines the behavior of merged hospitals relative to all other hospitals in the market in a regression model, controlling for other factors that might influence prices. He includes both market share and Herfindahl index as explanatory variables as do Lynk (1995), D&L (1999) and KMZ (1999). We shall return to the problems inherent in this approach shortly. Regardless, Krishnan finds that merged hospitals once again show higher increases in price relative to other hospitals.

The research on this issue is not, however, unanimous. Noether (1988) fails to find any relationship between concentration and price, but she does find evidence of quality competition – costs are higher in more competitive markets. From our perspective, however, the data in the Noether study are limited in two regards. First, list prices are used rather than net prices. Second, the data are from 1977-78, well before the rise of managed care insurers.

In summary, then, we are fairly sure that non-profits charge less than their for-profit counterparts and that the presence of market power causes hospitals as a whole to maintain higher prices. However, whether non-profit hospitals raise their prices in the same way as do for-profits when market power increases and, conversely, whether they will lower them in the same way as do their for-profit counterparts in the face of competition, is the subject of some debate. The literature is both limited and contradictory.

According to Lynk (1995), there are different styles of non-profit hospital control; at one extreme control resembles a consumer cooperative and, at the other, the motives of the hospital controllers lead to

[10] The relative price increase for the DRGs in which the merging hospitals gained more than 20% market share compared to those DRGs in which the merging hospitals gained less than 5 percent market share was positive and statistically significant at the 1% level.
[11] These variables include location, profit status, size, proportion of Medicare and Medicaid patients, and Case-Mix index.
[12] The mean change in price per patient for DRGs in which hospitals gained a more than 20% market share is 7.4% higher than the mean price change for the control DRGs. This result is significant at the 5% level.
[13] Calculated using DRG level data rather than aggregate hospital admissions – see discussion in Hypothesis section.

similar behavior to that of a for-profit hospital. Lynk's (1995, p.441) hypothesis is that '… market concentration should have a greater effect on price for for-profit hospitals than it does for those non-profit hospitals to whom the consumer cooperative model applies'.

To test his theory, Lynk (1995) uses regression methods to estimate the effect of market share and competition on prices. Using generalized least squares, he regresses average gross and net price against hospital market share and Herfindahl index. He controls for differences in diseases treated and differences in patient characteristics (e.g. proportion of female patients, proportion of black patients, average age, proportion of admissions that were routine, average length of stay, and the share of admissions that died). He also controls for differences in hospitals (e.g. its total number of admissions, its asset-to-expense ratio, whether it is part of a hospital chain, whether it is classified as a teaching hospital, the nature of its ownership, the share of its admissions that are Medicare or Medicaid, and its share of county admissions). Finally, Lynk also controls for differences between counties (e.g. income per capita, population density and county Herfindahl index).

Lynk (1995) explicitly does not take account of differences in cost between hospitals. He claims that although greater market power does imply higher prices for non-profit hospitals, these hospitals pass on the higher prices to interest groups within them and so raise costs. Thus, any regression that uses price-cost margins as the dependent variable might fail to find a relationship between the price-cost margin and concentration. Although he does not explicitly say so, presumably among his reasons for not including cost as an explanatory variable in his model (where price, not price-cost margin, is the dependent variable) is that coefficient estimates would be biased by the endogeneity of hospital costs. Lynk's solution to this problem is to omit hospital costs entirely and, instead, to control roughly for some of the hospital characteristics (e.g., size and capital intensity) and its general factor-cost environment (e.g., local per capita income).

One problem with this approach is that the exclusion of hospital level costs as an explanation of price leads to biased coefficient estimates that could, potentially, lead to completely erroneous conclusions. The variables that Lynk includes as proxies for hospital costs do not provide enough hospital-level variation by themselves to act as effective proxies for hospital level costs. Per capita income applies to all hospitals in the hospital's county regardless of ownership, and hospital sizes and capital intensities do not vary sufficiently between non-profit and for-profit hospitals. Moreover, as suggested by the FTC,[14] the lower labor cost in rural areas and high hospital market concentration in these areas might lead to an observed relationship between high concentration and <u>low</u> prices. Consequently, there is some predictable element of price that is unexplained by Lynk's explanatory variables, and the coefficient estimates are, therefore, biased. Including some measure of hospital level labor costs can effectively eliminate this bias.

[14] Cited in Lynk and Neumann (1999) footnote 19.

Dranove and Ludwick (1999) (D&L) adhere fairly closely to the Lynk (1995) regression formulation – including the latter's cost assumptions. Consequently, the criticism of Lynk's work regarding omitted variable bias also applies to the D&L paper.

D&L point out that bias in coefficient estimates may arise from Lynk's use of share of county admissions as an explanatory variable. They argue (D&L 1998, p.88) that '…the direction of causality between share and price is ambiguous', and that simultaneity bias may result. D&L (1998, p.89) claim they avoid this problem, '…by explicitly examining the prices set by merged hospitals' (although the authors note that this choice may itself introduce self-selection bias). The D&L model introduces a variable called DSHARE that represents the hospital's system share of admissions minus its own share. (DSHARE is positive only when the system has multiple facilities under common ownership, otherwise it is zero). Why the addition of this variable eliminates simultaneity bias is unclear. SHARE remains a right-hand side variable regardless of the addition of the DSHARE variable, so the problem of simultaneity bias still exists.

Regardless of the simultaneity issue, why both Lynk (1995) and D&L (1999) include SHARE as an independent variable at all is unclear. Lynk (1995) cites a paper by Ravenscraft (1983) in the appendix. The Ravenscraft paper examines the relationship between market structure and firm profit, modeling market share as a determinant of profit and finds market share to be a significant predictor of profit. However, in this latter paper, the data consist of line of business profits for non-comparable businesses. The market share variable is used as a proxy for economies of scale with otherwise non-comparable industry data. This problem is not present when modeling a single industry, and, thus, the inclusion of the market share must either have another justification or must be questioned; Lynk and D&L provide no other justification.

The second source of bias in Lynk's work cited by D&L is the omission of a proxy for quality of treatment and a poor choice of proxy for severity of illness. D&L (1999, p.90) argue that 'quality and severity may be positively related to market share if better quality hospitals simultaneously admit more patients and more severely ill patients'. Consequently, they argue, the coefficient on share (one of the keys to Lynk's result) may be positively biased, which would strengthen Lynk's results. However, if more severely ill patients in areas of low hospital concentration travel to hi-tech (high quality) hospitals in more highly concentrated areas, then the relationship between share and the omitted variables may be negative, the coefficient on share may be negatively biased, and this would weaken Lynk's result. D&L do not attempt to control for quality of treatment due to an absence of proxies. This will remain an important issue in this paper.

D&L also argue that Lynk's use of average length of stay as a proxy for the severity of illness may reflect differences in practice style or efficiency rather than the severity of illness. As an alternative to length of stay, D&L choose to use the number of secondary diagnoses, claiming that it is more closely correlated with the severity score provided by the 3M algorithm. This algorithm categorizes patients on the basis of their total medical diagnoses into one of four severity categories that reflect patients' impact on resources.[15] The severity score thus calculated is, therefore, a better measure of severity than either length of stay or number of secondary diagnoses. It was not, however, available for the 1989 data used by Lynk and D&L; nor was it available to Lynk and Neumann (1999), who used discharge data from Michigan. The latter authors argue that average length of stay and number of patient diagnoses are complementary variables rather than substitutes since the correlation between them is only 0.32 and, therefore, they include both variables in their model.

For reasons discussed in the 'Data' section of this paper, I propose to use 1999 data, rather than the 1989 data used by Lynk and D&L. Unfortunately, these data do not allow the 3M severity score to be used as a measure of severity since its provision was discontinued in 1998. However, I largely overcome the problem of variation in severity by selecting pricing and discharge data for a group of patients closely related by type of disease. I also include the location to which the patient is discharged as a further control for severity (see 'Hypothesis' section for further discussion). Like Lynk (1995) and Lynk and Neumann (1999), I include length of stay as an independent variable. However, I do not intend for its inclusion to be as a proxy for severity, but rather as an explanatory variable in its own right.

The third weakness in Lynk (1995) cited by D&L concerns the non-linearity of the price-concentration relationship in the hospital sector. According to Bresnahan and Reiss (1991), beyond a certain threshold number, additional competitors have no influence on price. Consequently, D&L restrict their final regressions to markets that have a Herfindahl greater than 0.10. This restriction was unnecessary in our analysis since no market had a Herfindahl less than 0.11.

Simpson and Shin (1996), also writing in response to Lynk (1995), examine the average price paid per inpatient admission for privately insured patients[16] at general, acute care hospitals in California in 1993. They control for case-mix, length of stay, the ratio of long-term days to total inpatient days,[17] the number of

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[15] Level 1 – Minor severity – little or no impact on resources, Level 2 – Moderate severity – Acute or Chronic diseases with modest impact on resources, Level 3 – Major severity – Acute or Chronic diseases; acute exacerbation; substantial impact on resources, Level 4 – Extreme severity – Serious acute conditions; life threatening; extensive resources required.

[16] Price is computed by multiplying the total net revenues from privately insured patients by the ratio of gross inpatient revenue from privately insured patients over the gross total revenue from privately insured patients. The resulting value was then divided by the number of total discharges of privately insured patients.

[17] Long-term care, which includes skilled nursing care, intermediate care, and sub-acute care is, less expensive per day than is acute care.

licensed beds, and per capita income in the county. Unlike Lynk (1994), however, they also control for wages by using the Medicare Wage Index. In paper 1 of this dissertation I have shown that wages vary between non-profit and for-profit hospitals; consequently, Lynk's approach still suffers from omitted variable bias. In order to correct for this, a measure of hospital costs needs to be included that allows for differences in wages between individual hospitals, or at the very least between the different hospital ownership types. In the model presented herein, the wage variable is calculated at the individual hospital level.

Using the Herfindahl-Hirschman measure of market power, Simpson and Shin find that non-profit hospitals set higher prices in more concentrated markets. Their model also yields a positive and large coefficient on the interaction term between the for-profit dummy and the Herfindahl-Hirschman index, implying that for-profit hospitals maintain higher prices than do non-profits in the presence of market power. However, because the estimate is not statistically significant at any standard level, they cannot reject the hypothesis that the two ownership types behave in the same way.

Keeler, Melnick and Zwanziger (1999) (KMZ) examine the nature of competition across time using data from 1986, 1989, 1992 and 1994. The authors use similar variables to Lynk but utilize a panel data estimation approach. They also use patient-level data rather than aggregating to the hospital level. KMZ find that the effects of non-profit mergers rise from nil in 1986 to more than 7% in 1994 – a result that appears to contradict Lynk's findings. They explain the differences as originating from the more recent data, a larger sample of hospitals, effects of hospital size that are not considered by Lynk (bigger hospitals have higher prices), from their focus on non-Medicare patients, and from their use of individual rather than hospital level data.

Like Lynk, KMZ do not include a hospital-specific wage variable. However, they include the Medicare PPS wage price index that is based on overall staff wages in an area rather than hospital specific wages. The same omitted variable argument used against Lynk (1995) applies to the KMZ paper.

KMZ also argue that Lynk's use of county as the geographic basis from which to calculate Herfindahl index is erroneous. This is because it inherently assumes that all hospitals in a county compete with all others, whereas in urban areas a hospital might only compete with a very few close neighbors. Moreover, a single hospital in a small county near an urban area is not necessarily a monopolist because patients can easily reach the hospitals in the city. As an alternative to a county-defined HHI, KMZ calculate an HHI based on patient flow data calculated from the latter's zip codes of origin; however, the KMZ results are similar regardless of the HHI definition. The more commonly used county definition of HHI will be used in this paper.

KMZ (1999) also argue that SHARE and HHI are collinear and thus that it is difficult to distinguish their effects empirically. For this reason, the authors 'center' the share in each county by subtracting the HHI and claim that the resulting coefficient on this hybrid variable represents the impact of hospital size relative to the market average. They also include HHI as a separate variable, claiming that it shows the impact of concentration independent of size. The addition of the hybrid-centered share variable, however, makes no difference to the problem of multicollinearity. While the variables are empirically collinear (according to KMZ (1999), they have a correlation coefficient of 0.9), the KMZ hybrid variable is not a 'cure' for multicollinearity; it is merely a redefinition of the variables affected by it.

Lynk and Neumann (1999) (L&N) respond to the criticisms of D&L (1999) and KMZ (1999), and stress that the aim of Lynk (1995) paper was to show that the '….ownership-specific price effects are statistically significantly different from each other, not from zero…'.[18] Consequently, the authors argue that the KMZ and D&L papers (which show that non-profit hospitals raise price with increased market concentration) do not, in fact, contradict the essence of Lynk's original findings – that ownership matters with respect to pricing behavior.

L&N (1999) criticize D&L's merger simulation captured by the variable, DSHARE, arguing that it only applies if the merged hospitals retain separate facilities; otherwise, a facility share effect should be included in the regression specification. However, the authors also reject in principle the inclusion of facility share and DSHARE, as well as other 'downstream' variable changes and instead focus on market share and HHI – variables that are generally the focus of the antitrust concept of market power.

L&N (1999) also criticize the KMZ paper for the latter's construction of their market share variable. L&N argue that since KMZ do not attempt to link facility share by ownership, they ignore the defining characteristic of a merger and, therefore, their results do not say anything about mergers per se. This paper will link hospitals under common ownership for the purpose of calculating HHI.

L&N perform regressions using confidential price data provided by two actual payers in Michigan. On the recommendation of the FTC, they include the HCFA hospital wage index – a step that corrects the problem cited at the beginning of this summary. However, the shortcomings of this latest research are that the sample size is relatively small (only 66 and 58 observations per payer); there are no for-profit hospitals in the sample so the null hypothesis now becomes whether non-profits maintain higher prices in the presence of high market concentration rather than whether they behave differently from their for-profit counterparts; and the results are not truly comparable to Lynk (1995) or any of the prior work discussed here since a different geographic region is used and many of the explanatory variables included in Lynk (1995) are excluded.

[18] Lynk 1995 cited in Lynk 1999, pp. 101

Hypothesis

The hypothesis to be tested by the model is the same as that described in the papers above: namely, that non-profit hospitals have the same incentive to maintain high prices in the presence of market power as do their for-profit counterparts. Where this paper will differ from the above described papers, however, is in the following refinements:

1) Data are selected that consist of a closely related group of illnesses that are very similar in nature. The data comprise patients suffering from alcohol and drug related disorders within the major diagnostic category "Alcohol/Drug Use and Alcohol/Drug Induced Organic Mental Disorders" (MDC 20).[19] Within this category, four Disease Related Groups (DRGs) are identified for examination:

- DRG 435 – "Alcohol/drug abuse or dependency, detoxification or other symptoms treated without complications"
- DRG 434 – "Alcohol/drug abuse or dependency, detoxification or other symptoms treated with complications"
- DRG 436 – "Alcohol/drug dependency with rehabilitation therapy"
- DRG 437 – "Alcohol/drug dependency with combined rehabilitation and detoxification therapy".[20]

Because this is such a closely related group of DRGs, severity of illness (and, therefore, resource allocation) can be broadly inferred from the patient's specific DRG treatment category. For example, we would expect DRG 435 – "Alcohol/drug abuse or dependency, detoxification or other symptoms treated without complications" to be less resource intensive than DRG 434 – "Alcohol/drug abuse or dependency, detoxification or other symptoms treated with complications". Similarly, we would intuitively expect that DRG 436 – "Alcohol/drug dependency with rehabilitation therapy" would be less resource intensive than DRG 437 – "Alcohol/drug dependency with *combined* rehabilitation and detoxification therapy". Since severity of illness is potentially a very important explanatory variable in determining the price paid, sample selection in the way described represents a significant improvement on previous work.

An additional benefit associated with these particular narrow selection criteria concerns the limited range of treatments available for dealing with drug/alcohol related diseases. With other types of disease there are various levels of technical sophistication with which patients may be treated. This in turn may

[19] Source: DRGs: Diagnosis Related Groups Definitions Manual, Version 16.0, effective 10/1/1998, developed for the Federal Health Care Financing Administration by 3M Health Information Systems, New Haven.
[20] The remaining DRGs within MDC 20 are omitted due to the diverse range of illnesses they cover (i.e.: DRG 476 -"Prostatic O.R. Procedure Unrelated to Principal Diagnosis", DRG 468 - "Extensive O.R. Procedure Unrelated to Principal Diagnosis", DRG 477 - "Non-Extensive O.R. Procedure Unrelated to Principal Diagnosis") or, as in the case of DRG 433 - "Alcohol/Drug Abuse or Dependence – left AMA", due to a lack of specific information regarding the patient's symptoms.

lead to variation in price due to unobservable differences in methods of treatment. There are no high-tech treatments for drug/alcohol patients, so there is no need to account for this type of variation across hospitals' facilities or style of treatment.

2) Unlike those of any previous authors, this model also includes the location to which a patient is discharged following treatment. There are three main categories: home/jail, skilled nursing care, and other (non-skilled nursing care). The inclusion of this variable serves as an additional severity indicator. Clearly, ceteris paribus, a patient discharged to his own home is likely to be less ill than one who is discharged to a skilled nursing facility, and a patient discharged to non-skilled nursing care is likely to be less severely ill than one discharged to skilled nursing care. Accordingly, with severity proxied by these discharge destinations, we expect prices to be highest for those patients that are sent to a skilled nursing facility, intermediate for patients sent to a non-skilled nursing facility, and lowest for patients that are sent home.

3) There are two additional controls for severity of illness. Firstly, the model includes a variable that identifies whether a patient's admission is scheduled or unscheduled. Presumably, unscheduled admissions are, on the whole, likely to be more urgent in nature and, therefore, require greater resource allocation; this in turn is likely to lead to higher prices. Inclusion of a dummy variable to allow for scheduled admission is similar to the approaches used by Lynk (1995) and by D&L (1998), who include the share of a hospital's admissions that are routine.

4) Like Lynk (1995), but unlike D&L (1998), I include length of stay as an explanatory variable. It can be considered to be a measure of severity (Lynk 1995) and also an explanatory variable in its own right.

5) The model does not include a SHARE variable as per Lynk (1995), D&L (1999), KMZ (1999) and Krishnan (2001) since, as discussed in the literature section above, its inclusion is not warranted and may lead to simultaneity bias.

6) The Herfindahl index is calculated taking into consideration the common control of hospitals. This gives a better measure of market power than does a Herfindahl index based on stand-alone facility share, which might significantly understate a hospital system's true market power.

In addition, the Herfindahl index used in this model is calculated from the number of inpatient drug / alcohol (MDC 20) cases treated at each hospital rather than the hospital's total number of admissions. The approach used here differs from that of Lynk (1995) and D&L (1999), who use total admissions from which to calculate the Herfindahl. KMZ (1999) come closer to this approach by aggregating all DRGs into broader service categories and calculating the Herfindahl index for each service category. (However, the latter authors use patient flows as a measure of market size rather than the more conventional county boundaries.) The use of DRG level data from which to calculate the Herfindahl is a better measure of market concentration than total admissions since hospitals' technical strengths and weaknesses differ between hospitals. For example, a hospital with a particular strength in oncology may not be competing at all in the market for drug / alcohol patients despite being located in the same county.

Econometric Model.

We estimate two models: one model in which the data are utilized in their natural numbers form and a second constant-elasticity model in which the logarithms of the data are utilized.

Model 1

In the first model, all variables are natural numbers and the model is additive.

The variables are as follows:

$P_{ijh}=f(\alpha, X_{ijh}, Y_h, Z_k)$.

Dependent Variable

The dependent variable $\mathbf{P_{ijh}}$ is the estimated net price for patient i categorized as disease related group (DRG) j, at hospital h.

j = 1 – 4. As discussed above, there are 4 types of DRG.

h = 1 – 224. There are 224 hospitals in the sample. These are hospitals that provide comparable drug/alcohol treatment services regardless of the nature of the hospital itself. Acute care, specialist and psychiatric hospitals are included; but due to the nature of their services, state psychiatric health facilities (PHFs) are not. The latter hospitals generally care for indigent people on a very short-term basis. The nature of care provided is therefore fundamentally different from that provided at other more mainstream facilities. Furthermore, Kaiser hospitals are excluded since the insurance plan under which their patients are generally covered restricts them to the use of Kaiser-run hospitals. Consequently, this type of hospital does not compete for patients in the same way as other hospitals. Finally, state hospitals are also excluded since these are mainly for the severely mentally disordered and developmentally disabled who generally have unusually long lengths of stay that make them incomparable with other facilities.

Since actual price paid is unavailable, it was necessary to construct a net price from the list price. The method used to construct net price is described in the Data Section below.

Independent Variables

We turn now to the explanatory variables.

α The regression intercept

The $\mathbf{X_{ij}}$ refer to a group of variables for DRG i at hospital j that are used to control for patient level differences such as disease type, sex, age, length of stay and the nature of admittance to the hospital (i.e.; routine vs. emergency).

SEX Whether the patient is female (1,0)

LOS Length of stay in days.[21]

LOS_SQ Length of stay squared. This variable allows for non-linearity in pricing relating to the length of stay. Previous research has shown that more intense and expensive treatment generally takes place in the early days following a patient's admission, and this variable allows for this phenomenon to be captured.

AGE Age of a patient in years.[22]

NURSE Where a patient was discharged to a care facility with skilled nursing, this dummy variable was coded as 1; 0 otherwise.

NON-NURSE Where a patient was discharged to a care facility without skilled nursing, this dummy variable was coded as 1; 0 otherwise.

The default category of discharge was to either home or jail.[23]

SCHED Whether the patient's admittance was scheduled or emergency. Where the patient was admitted on a scheduled basis, this dummy variable was coded as 1; 0 otherwise.

W_CC If the patient was categorized as DRG 434 – "Alcohol/drug abuse or dependency, detoxification or other symptoms treated with complications", this disease related dummy variable was coded 1; 0 otherwise.

[21] Where a patient was admitted and discharged on the same day, this was coded as 0.5 days
[22] Where a patient was under 4 years old, the data are reported in days and years; thus, we use a fractional number in these cases.
[23] When patients were categorized as having left against medical advice, they were excluded from the sample. This was because the patients' condition was categorized into one of the 4 main categories so treatment type was unavailable.

REHAB If the patient was categorized as DRG 436 – “Alcohol/drug dependency with rehabilitation therapy”, this disease related dummy variable was coded as1; 0 otherwise.

REH_DET If the patient was categorized as DRG 437 – “Alcohol/drug dependency with combined rehabilitation and detoxification therapy ”, this disease related dummy variable was coded as 1; 0 otherwise.

For reasons of collinearity, the default disease type -- DRG 435 -- “Alcohol/drug abuse or dependency, detoxification or other symptoms treated without complications” was omitted.

LOS_REH The LOS variable interacted with the REHAB dummy variable.

LOSS_REH The LOS_SQ variable interacted with the REHAB dummy variable.

LOS_WCC The LOS variable interacted with the W_CC dummy variable.

LOSS_WCC The LOS_SQ variable interacted with the W_CC dummy variable.

LOS_R_D The LOS variable interacted with the REH_DET dummy variable.

LOSS_R_D The LOS_SQ variable interacted with the REH_DET dummy variable.

Inclusion of these last six variables allows us to determine whether the different disease categories are systematically priced differently over different lengths.

I also include 12 dummy variables that represent the expected source of payment and thus reflect differences in pricing structure between payers.[24]

The $\mathbf{Y_h}$ refer to a group of hospital level variables such as ownership, size, teaching status, level of control, cost of service provision, and the proportion of patients who are expected to be paid for from traditional reimbursement plans.

NFP a 1,0 dummy variable indicating whether the hospital is a non-government, non-profit enterprise.[25]

SYS a 1,0 dummy variable indicating whether hospital h is part of a system with any other members in the state.

[24] See Appendix A.
[25] Includes those hospitals classified by OSHPD as ‘nonprofit corp’ and ‘nonprofit – other’. We do not include government hospitals within our sample due to their apparently different operating styles – see Data section for more details. Instead, we examine these data in a slightly modified model and discuss the results separately.

TRAD_TYP the percentage of the hospital's patients who do not receive discounts. This category includes self-paying patients and privately insured patients with traditional reimbursement type insurance. The inclusion of this variable is intended to reflect the relative bargaining power of hospitals versus managed care and other payers. Hospitals with high proportions of traditional type payers are likely to have more scope in setting prices than those with high proportions of government or managed care payers. Clearly, hospitals have little influence over reimbursements from Medicare and Medicaid patients. It is expected that those hospitals that are not characterized by high levels of managed care penetration (and therefore, where managed care payers do not have strong bargaining power) are likely to set prices higher than those where managed care payers have more influence.

BED_LIC Number of licensed beds at the hospital – to control for hospital size.[26]

TEACH a 1,0 dummy variable indicating whether hospital h is involved in teaching.[27]

SPEC a 1,0 dummy variable indicating whether the hospital specializes in drug / alcohol treatment.

PSYCH a 1,0 dummy variable indicating whether the hospital specializes in psychiatric treatment.

WGT_W Average weighted wage at hospital h.[28]

NFP_LOS The interaction of NFP with LOS dummy variable.

LOSS_NFP The interaction of NFP with LOS_SQ dummy variable.

The inclusion of these last two variables allows for the possibility that the category of hospital ownership causes different pricing over the length of a patient's stay.

The $\mathbf{Z_k}$ variables are meant to control for countywide factors such as market concentration and the background cost of living in the area.

HERF County Herfindahl index for hospital h in county k[29] – calculated from the number of inpatient drug / alcohol (MDC 20) cases treated at each hospital, this variable is a

[26] This is the number of licensed beds stated on the hospital's license at the end of the reporting period, excluding nursery bassinets and licensed beds placed in suspense.
[27] Classified by OSHPD as 'teaching' in the Hospital Annual Financial Data – Selected Data File 1999.
[28] The weights are the average wages per hospital. It should be noted at this point that we initially explored a two-stage least squares model to avoid any possible endogeneity of wages and prices. This latter model estimated a hospital level wage variable based on the statistically significant variables in James 2002. The fitted values resulting from this estimation were then used as the measure of hospital wages in the price estimation equation. The results of the two-stage model and those of the model utilizing a simple weighted average wage variable were virtually identical so, for the sake of simplicity, we opted to use the weighted wage variable.

measure of hospital concentration in the county. Where two or more hospitals in the same county were under common control, their combined number of inpatient cases was used to calculate the Herfindahl index.

HERF_NFP The HERF variable interacted with the NFP dummy.

The inclusion of the above two variables allows for non-profit and government controlled hospitals to exhibit different behavior in the face of market power than that exhibited by for-profit hospitals.

RET_WAGE County average retail wage payment to retail workers ($000), Quarter 1 1998 for the county in which hospital h is located. This variable is used as an indication of the general wage (cost) level in the hospital's county.

POP_DEN County population density (people per square km) in 1996[30]. More densely populated urban areas have more hospitals per square km than those in less dense, rural areas. While the presence of more hospitals in an area implies greater hospital concentration (accounted for by the Herfindahl index), greater population density provides a larger potential market. In turn, this larger market might partially mitigate the need for hospitals to compete with their neighbors. We would, therefore, expect the sign of this variable's coefficient to be negative.

PER_CAP Per capita personal income ($000) of people living in county k in 1998. This variable is included in the model in order to control for variation in income-based demand among markets. A higher personal income leads to greater ability to pay, and this in turn may be reflected in hospital's pricing strategies depending on the hospital's philosophy. We would, therefore, expect the coefficient on this variable to be either positive or insignificant.

Model 2

The second, constant elasticity, model contains virtually identical variables to the above model with the exception that the log of all variables (except dummies) is utilized in place of the natural numbers. Due to collinearity issues, all squared terms and variables containing squared terms (i.e., those where the dummy variable is multiplied by a squared term) are omitted.

Data

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[29] Defined as Σs_{hk}^2 where s_{hk} is the share of hospital h of the total MDC 20 cases treated at comparable hospitals in county k.

[30] From the 1998 County and City Extra, Annual Metro, City and County Data Book.

County-specific data were obtained from three sources: per capita income data were obtained from the California Department of Finance,[31] retail wage data were obtained from the US Census Bureau,[32] while population density (1998) was obtained from the 1998 County and City Extra: Annual Metro, City and County Data Book.

Most of the patient and hospital level data were obtained from the Office of Statewide Health Planning and Development (OSHPD) in California. OSHPD's Patient Discharge Data for 1999 provided patient-level variables including the following: patient age, sex, disease related group (DRG), discharge location (home, nursing facility, non-nursing care facility), expected source of payment (enabling the calculation of the 'TRAD_TYP' variable), nature of admission (scheduled versus unscheduled), and the patient's length of stay. These data were also the source of the total number of cases of drug / alcohol patients treated at comparable hospitals in the county. These latter data were used to calculate the Herfindahl index.

OSHPD's Hospital Annual Financial Data Profile[33] provided hospital teaching status, number of licensed beds and type of care classification (specialist, acute care or psychiatric). It also provided the hospital's form of control (investor, non-profit or government[34]) and the name of its owner (from which the SYS variable was constructed).

OSHPD's Individual Hospital Financial Data[35] provided the average hourly wages of 7 types of employee. These were then weighted by the number of hours worked by each category of employee to arrive at the weighted average wage (WGT_W) variable.

Both the OSHPD's Patient Discharge Data and its Individual Hospital Financial Data were used to calculate the net price variable. The Hospital Financial Data categorizes payers as Medicare,[36] Medi-Cal,[37] County Indigent Programs,[38] Other Third Parties[39] and Other Payers,[40] and groups together gross and net

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[31] California Statistical Abstract, Table D-9, "Per Capita Personal Income by County, California 1988-1998", California Department of Finance, published on the Worldwide Web at www.dof.ca.gov.
[32] From County Business Patterns 1998 NAICS Comparison (NAICS 44----) Retail Trade, U.S. Census Bureau on the Worldwide Web at http://tier2.census.gov (CenStats). 1999 data were not available at the time of the analysis so 1998 were used as an estimate.
[33] Hospital Annual Financial Data Profile (1999) published by OSHPD on the Worldwide Web at www.oshpd.cahwnet.gov/hid/infores/hospital/finance/index.htm.
[34] Hospitals labeled as 'District' and 'Government' in the original data were grouped together as 'GOVT' in the analysis.
[35] Individual Hospital Financial Data for California 1998-99, California Office of Statewide Health Planning and Development.
[36] Medicare patients enrolled in Managed Care plans are included in the Other Third Parties payer category.
[37] Otherwise known as Medicaid. Medi-Cal patients enrolled in Managed Care plans are included in the Other Third Parties payer category
[38] Includes all indigent patients for which a county is responsible.
[39] Includes patients covered by a variety of third-party contractual purchasers of health care, as well as indemnity plans. Examples include HMO/PPO contracts, commercial insurance, worker's compensation,

revenues from these categories accordingly. Consequently, a discount factor can be calculated, which represents the discount negotiated between the aggregated payers within a particular payer group and the hospital. There is one discount factor per payer type per hospital – all patients with the same expected source of payment are assigned the same discount factor, regardless of their specific diagnoses.

As with most financial data, the Hospital Financial Data were subject to prior period adjustments and possibly other accounting adjustments. This caused some of the calculated discounts to appear unrealistic.[41] To allow for this, we excluded all hospitals for which the discount factor was less than zero (i.e.; hospitals where prior period adjustments caused the reported contractual adjustment to exceed the reported revenue) or where the discount exceeded 80 percent of gross price. Based on the assumption that it was caused by reporting error, we further excluded patients whose gross price was reported as zero.

The Patient Discharge Data groups patients in a more finely stratified way than the Hospital Financial Data. It assigns expected payers to one of nine payer categories,[42] and further subdivides these categories into one of four types of coverage.[43] The categories into which the Patient Discharge Data are organized enable patients to be assigned to categories that mirror the Hospital Financial Data. Consequently, we were able to group the discharge data into the five payer categories described for the Financial Data and then apply the discount factor calculated from the Hospital Financial Data to the patients' gross price.

Examination of the remaining net price data revealed a very large variance in the average daily price. Because this might also have been caused by the accounting issues identified above, the sample was further restricted to patients whose average daily price was above $50 per day and below $1000 per day. Finally, in order to select patients with similar disease characteristics, and thus better control for severity, patients whose length of stay exceeded 30 days were excluded from the sample.

Since the focus of the paper is whether market structure has the same effect on non-profit prices as for-profit prices, we want to focus on prices that are set by the hospital itself. Thus, we ignore traditional Medicare and Medi-Cal patients whose care is covered by predetermined federal and state government

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TRICARE, Short-Doyle, and any managed care contracts funded by Medicare or Medi-Cal. (The TRICARE program provides HMO/PPO type coverage and reimbursement type coverage to military personnel and their dependents. The Short-Doyle program provides cost-based reimbursement for a broad range of mental health services and a limited range of services for treatment of substance abuse through a contract with the county.)

[40] Includes patients designated as self-pay, those indigent patients who are not the responsibility of the county, and those University of California hospital patients whose care is covered by Clinical Teaching Support Funds.

[41] Leading to extremely small net prices and even negative net prices.

[42] Medicare, Medi-Cal, Private Coverage, Workers' Compensation, County Indigent Programs, Other Government, Other Indigent, Self Pay and Other Pay.

[43] Knox-Keene(HMO) or MCOHS Plan, Managed Care – other (PPO, IPO, POS etc.), Traditional Coverage, No coverage.

formulae respectively. Furthermore, the prices offered to indigent patients may not properly reflect the economic motives of the hospital for two reasons. Firstly, they may be influenced by the charity concerns of the hospital – a factor for which we are unable to control. Secondly, it is unlikely that indigent people (insured by the county or otherwise) are concerned with prices when selecting the hospital from which they request treatment – thus, hospitals are not competing for these patients in the traditional sense. Consequently, the Indigent payer category is also excluded from our analysis. The 'Other Payer' category was also excluded on the grounds of poor data quality. As mentioned previously, this group contains both self-insured patients and all indigents for whom the county is not responsible. Consequently, it is hard to determine what the calculated discount is actually measuring: instead of representing hospital's conscious decision to discount prices to this group, it may be measuring the proportion of indigents in this group who are unable to pay - thus forcing the hospital to 'discount' the price or, alternatively, it may be measuring the hospital's charity behavior.

For all the above reasons, we focus our attention on patients who are covered by private third party payers. This group includes patients covered by a variety of third-party contractual purchasers of health care, as well as indemnity plans (examples include HMO/PPO contracts, commercial insurance, workers' compensation, TRICARE, Short-Doyle, and any managed care contracts funded by Medicare and Medi-Cal). A hospital's policy to discount its prices to these payers (insurance companies, in general) is unlikely to reflect its charitable concerns but rather its economic motives.

Our overall sample consists of a total of 12,719 data points that represent the treatment of this number of patients at 224 hospitals. The distribution of patients and hospitals appears in Appendix A. An interesting feature of the data concerns the average length of stay variable. There are markedly different treatment lengths at the different types of hospital. The average length of stay at non-profit hospitals in our sample is 8.248 days, in for-profit hospital it is 6.067 days, and in government hospitals it is 3.84 days. Why treatment patterns differ in this way is not known. Since the payer category concerned is the same across hospitals, the treatment behavior must be due to some policy (express or implied) of the hospital itself. Perhaps, non-profit hospitals have higher quality service than do for-profit hospitals, and perhaps government hospitals have relatively poor quality – but this is, of course, only speculation.

Another interesting feature of this particular sample concerns the distribution of diseases among hospital ownership types. None of the patients treated at government hospitals fall into DRG 436 (REHAB), while only two patients fall into DRG 437 (REH_DET) category. This appears to reflect different treatment patterns at government hospitals. Because of the dramatically different treatment patterns within our sample (both in terms of length of stay and treatment categories), separate regressions were run for the government and non-profit/for-profit sub-samples of the data. Descriptive statistics for the two sub-samples are presented in **Appendix B**.

Results – Model 1

We examine first at the regression for non-profit and for-profit hospitals (**Appendix C**). Overall, the model appears to fit the data well, having a relatively high adjusted R-squared of 0.808. Moreover, the majority of the coefficients have signs and magnitudes that satisfy intuitive reasoning.

Turning first to the main question of the paper – that of pricing behavior in concentrated markets - we find that the Herfindahl index has a positive and significant sign. As we might expect, for-profit hospitals maintain higher prices in more concentrated markets. Non-profits, on the other hand, actually maintain lower prices in the presence of greater market power: the coefficient on HERF_NFP is negative and greater in absolute magnitude than the positive HERF coefficient.

In terms of the overall magnitude of price changes, however, when changes in market concentration are large (as might accompany mergers), ownership differences make only a small difference to price changes. For example, an increase of 0.1 in the Herfindahl leads to an increase in price in for-profit hospitals of approximately only $33, and a decrease in price of approximately only $19 in non-profit hospitals. Since the average price at for-profit hospitals is approximately $2487 while the average price at non-profit hospitals is approximately $2959[44], this amounts to an increase of 1.3 percent and a decrease of 0.6 percent respectively. Only when market concentration rises by a very large degree does a merger lead to economically more significant price changes. For example, if there were initially only two equal sized for-profit hospitals in a county that then merge (leading to an increase in the Herfindahl from 0.5 to 1.0), the increase in price would be $163 (a 6.5% increase) assuming both hospitals were for-profits, while if both hospitals were non-profits, price would fall by $93 (a 3.1% decrease).

In terms of the absolute price of service, the model predicts that non-profits charge marginally less than their for-profit counterparts; however, the difference is not very large ($11.90 evaluated at the mean Herfindahl and at the more conservative average length of stay of 6.06 days). In terms of the average price of the sample, this result is economically meaningless and is equivalent to saying that non-profits and for-profits are charging the same.

Turning now to the other variables in our model: price is positively related to length of stay both for for-profit and non-profit hospitals. Evaluated for the base case disease and at the average length of stay at for-profit hospitals, an additional day's stay increases the price charged by approximately $389 per day at for-

[44] Not controlling for differences in length of stay or type of DRG.

profits hospitals, and by $352 at non-profit hospitals.[45] Furthermore, as length of stay increases, the rate of increase of price charged declines. Intuitively, this makes sense since we expect more intensive treatment to be provided early in the patient's hospital stay.

As discussed in the Hypothesis section above, there are three severity controls in the model -- the Disease Related Group (DRG) into which a patient is categorized, whether the patient is admitted on a scheduled basis, and the location to which the patient is discharged. Looking at the DRG control first, we see that patients who are admitted suffering from DRG 434 (Alcohol/drug abuse or dependency, detoxification or other symptoms treated *with* complications) are charged more than those who are treated for DRG 435 (Alcohol/drug abuse or dependency, detoxification or other symptoms treated *without* complications).[46] Similarly, those patients who are admitted with DRG 436 (Alcohol/drug dependency with rehabilitation therapy) are charged more than those with DRG 435.[47] Directionally, these results make intuitive sense. The only coefficient that fails to behave as expected is that on REH_DET (DRG 437 – Alcohol/drug dependency with *combined* rehabilitation and detoxification therapy) which, when evaluated at the mean length of stay of the whole sample, is negative[48] implying that these patients are charged less than those treated for DRG 436 and DRG 435.

We turn now to the second control for severity, type of admission. Patients who are admitted on a scheduled basis are expected, on average, to be less seriously ill than those who are admitted without prior scheduling. This is confirmed by our results – scheduled patients are charged $187 less than those who are admitted on an unscheduled basis.

The final control for severity concerns the location to which patients are discharged. Our results reveal that – as expected -- patients who are released to skilled nursing facilities are charged $324 more than those who are sent home. Furthermore, the absolute value of the premium charged to those patients who are sent to facilities offering unskilled care (NON_NURS) is relatively small ($76) compared to that of those who are sent to skilled care facilities.[49] These results indicate that patients who are discharged to skilled care facilities may well be more severely ill (and thus receive more intensive treatment) than those sent home or to non-skilled nursing facilities. This may be further explained by the substitution of skilled nursing care in

[45] The average length of stay at for-profit hospitals was chosen since this was the lower of the two average lengths of stay at 6.07 days compared to 8.25 days at nonprofits. When the average overall length of stay for the combined sample is used (7.36 days), one additional day's stay increases price by approximately $379 at for-profit hospitals and $342 at non-profit hospitals.
[46] Evaluated at the mean length of stay for the whole sample, DRG 434 is charged $472.64 more than DRG 435.
[47] Evaluated at the mean length of stay for the whole sample, DRG 436 is charged $53.39 more than DRG 435.
[48] Evaluated at the mean length of stay for the whole sample, DRG 437 is charged $228.01 less than DRG 435.
[49] The NON_NURS coefficient is only significant at the 90 percentile level.

non-hospital settings for in-hospital treatment. According to Berndt et al. (2000),[50] the use of post-acute care services (such as skilled nursing facilities and rehabilitation units) has increased as hospital lengths of stay have shortened. The implication is of substitution between the two types of treatment. Consequently, those patients who are released to this type of facility are not likely to be fully cured but rather still to be in the course of their treatment. Since the longer the length of stay, the lower the increase in price per day, a patient whose stay is truncated is likely to be charged more for his stay than a patient who is fully cured and discharged to home or an unskilled nursing location after the same length of time.

Teaching hospitals tend to charge more. This result may be a reflection of the quality of care (or of the perceived quality of care) at these hospitals. However, hospital size alone does not appear to affect price. Hospitals that are part of a system[51] charge their patients less, which could possibly be explained by greater economies of scale in chain owned hospitals that are passed on to patients in terms of lower pricing. The negative coefficients on SPEC and PSYCH are also possible further reflections of economies of scale.

One of the shortcomings of Lynk (1995), Dranove and Ludwick (1999) and Keeler, Melnick and Zwanziger (1999) is that these papers omit any hospital level measure of labor cost. The fact that we have a statistically highly significant coefficient on the WGT_W statistic confirms that these papers do, in fact, suffer estimation bias caused by the omission of an important variable. The positive sign on this variable is what we would expect – implying that, where hospitals experience higher costs, they pass them on to patients in the prices they charge. This is further born out in the positive sign of the RET_WAGE variable that measures the underlying cost of doing business in the county in which the hospital is located. Again, higher costs lead to higher prices. The sign on per capita income is somewhat of a mystery since we might expect a positive relationship between price and per capita income.

The coefficient on TRAD_TYP is positive and highly significant: the greater the proportion of traditional fee-for-service or self-payers in a hospital (and, conversely, the lower the proportion of managed care patients), the higher the price charged to all payer types in our sample. This result reflects the stronger bargaining power of managed care providers vis-à-vis the hospital.

The coefficient results on the individual type of payers within the sample are somewhat mixed. Of all the payer types, privately insured individuals with managed care (non-Knox-Keene) type coverage are the most prevalent,[52] and these patients are billed $85.46 less than patients with privately insured, fee-for-service type of insurance. Those patients in the GOV3 category are also charged less – although whether

[50] Berndt, E., Cutler, D., Frank, R., Griliches, Z., Newhouse, J., Triplett, J., (2000) "Medical Care Prices and Output" in Handbook of Healthcare Economics (2000), pg.150.

[51] This result, however, contradicts the findings of Lynk (1995) and those of D&L (1999).

[52] There are 3,675 patients in our sample with this kind of coverage compared to 1,142 with private coverage with fee-for-service type of insurance and 1,007 with some form of non-Medicare, non-Medicaid, non-Indigent, non workers' compensation type of government coverage.

this is to be expected or not is unknown. The sample sizes of most of the other payer groups for which the coefficient results are statistically significant are too small to merit discussion. However, Medicare patients with the two forms of managed care coverage appear to be charged more than privately insured fee-for-service type patients -- intuitively, this is somewhat surprising.

Turning now to government owned hospitals (**Appendix D**), we once again find the model fits the data relatively well having an adjusted R-squared of 0.84. However, these results are substantially different from those of the non-profit / for-profit combined sample. Firstly, the coefficient on Herfindahl is insignificantly different from zero; government hospitals are not influenced by market structure in setting their prices. It is worth noting at this point that when the two samples (non-profit and for-profit hospitals and government hospitals) are combined in one model - with for-profit hospitals being the base case (**Appendix E**) - the HERF_GOV interaction is positive and statistically significant. In other words, government hospitals appear to raise price in an even more aggressive way than do for-profit hospitals when presented with market power. Lynk (1995), using a different model specification, found that government hospitals behaved in a way similar to for-profit hospitals.[53] However, for the reasons described in the 'Data' section above, separating government hospitals from non-profit and for-profits is a more appropriate approach – and the combined sample results presented in Appendix E and Lynk's conclusions are misleading.

Government hospital pricing seems to be largely driven by the length of stay variable. The coefficient on LOS is positive as we would expect, but, unlike the non-government hospital results, that on LOS_SQ is statistically insignificant. It therefore appears that, unlike non-profit and for-profit hospitals, government hospitals charge a flat daily rate.

We again turn to the controls for severity. Like non-government controlled hospitals, government hospitals charge more for patients with DRG 434 (Alcohol/drug abuse or dependency, detoxification or other symptoms treated *with* complications) than for DRG 435 (without complications).[54] However, unlike patients released from non-government hospitals, patients who are discharged to skilled nursing facilities from government hospitals do not appear to be charged higher prices than those who are discharged to either non-nursing care facilities or to their homes. Since only 20 patients in our sample were released to skilled nursing facilities, this result may be an anomaly of this particular data set. The third severity control – the type of admission – also behaves differently in the government sample. It appears that unscheduled

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[53] Lynk (1995) pp. 452.

[54] Evaluated at the mean LOS, DRG 434 patients get charged $184 more. Despite the individual statistical insignificance of the coefficients on W_CC, LOS_WCC and LOSS_WCC, an F-test for the joint significance of these variables revealed that prices are higher for DRG 434 than DRG 435 as we might expect. (The $F_{(3, 1015)}$ value for this test is 10.473)

patients at government hospitals are not charged any differently from those who are admitted on a scheduled basis. Why government and non-government hospitals behave so differently is unknown.

Some similarities do exist between non-government and government hospitals, however. As with non-government hospitals, those government hospitals with greater the proportions of traditional (reimbursement type) payers have higher the prices overall. This result is what we would expect: hospitals with fewer managed care patients are likely to have greater autonomy in setting prices and, therefore, are likely to set higher prices overall. Also, as with the non-profit/for-profit sample, teaching hospitals charge more, while psychiatric hospitals charge less.

Turning to the other variables in the model, the coefficient on WGT_W is positive and significant as it was in the non-government hospital group – once again revealing that the omission of a hospital level wage variable as other authors have done, is incorrect. However, it is strange that the coefficient on RET_WAGE is negative and so large when we would expect this to be either insignificant, or significant and positive.

Results - Model 2

The results for the constant elasticity specification (Model 2) appear in **Appendices F and G**. Looking first at the non-profit and for-profit sample (**Appendix F**), it appears that Model 2 provides a slightly better fit than Model 1 despite the fact that we have imposed the constant elasticity constraint (the adjusted R-squared value for the Model 2 non-government sample is 0.858 versus 0.808 for the same sample in Model 1).

Evaluated at the conservative length of stay of 6.06 days that applies to non-profit hospitals (and the average Herfindahl index for the sample), Model 2 predicts that non-profits charge approximately 1.2% *more* than their for-profit counterparts. However, evaluated at the average length of stay for the entire sample, Model 2 predicts that non-profit hospitals charge 0.26% less than for-profit hospitals. When we apply these percentages to the mean price of hospitals in the sample, we get an increase of $34 or a decrease of $7 – economically insignificant amounts. Therefore, as in Model 1, we can conclude that non-profits and for-profits hospitals effectively charge the same.

More importantly with regard to the aims of this paper, the predicted effect of market power is similar across models. Firstly, the effective signs on the coefficients of L_HERF and NFP_L_HF are the same in Model 2 as those on HERF and NFP_HERF in Model 1. Furthermore, as discussed above, the fact that Model 1 predicts that for-profits hospitals will increase prices by +1.3% ($33) in response to an increase of

10% in market concentration while non-profit hospitals decrease prices by 0.6% ($19) has very little economic significance. In Model 2, neither the L_HERF nor the NFP_L_HF coefficients are statistically significant implying that neither for-profit nor non-profit hospitals take advantage of market power. Although it would have been nice to see the same pattern of statistical significance across models, the two sets of results do not in effect contradict one another since their economic interpretation is the same: regardless of ownership, hospitals do not meaningfully raise prices in more concentrated markets. These results contradict those of all the authors mentioned in the literature section of this paper. However, due to the more recent nature of our data compared to that of the other authors mentioned, we would argue that these results provide evidence of the power of managed care in controlling hospital prices.

We now turn to other variables in Model 2. As we would expect, these results indicate that price increases with the patient's length of stay – and this variable is highly statistically significant. Furthermore, as with Model 1, there is slight concavity in the pricing function due to the length of stay variable – the coefficient on L_LOS is significantly less than 1. This once again confirms our belief that more intensive treatment takes place toward the beginning of a patient's stay.

In terms of the severity results, the relative size of the coefficients on NURSE and NON_NURS are similar to the results on those variables in Model 1: Patients who are released to skilled nursing facilities pay more than those who go home, and those who are released to unskilled care facilities pay more than those who go home but less than those who are sent to non-skilled nursing facilities. Furthermore, those who are admitted on a scheduled basis pay less than those who are admitted on an unscheduled basis. The magnitude of the differences are also fairly similar: Model 1 predicts that the average scheduled patient pays 6% less than an unscheduled patient, while Model 2 predicts that the same scheduled patient pays 10% less.

The relative sizes of the coefficients on the DRG variables in Model 2 vary slightly from those in Model 1. Like Model 1, Model 2 predicts that those patients suffering from DRG 434 (Alcohol/drug abuse or dependency, detoxification or other symptoms treated *with* complications) pay more than DRG 435 (Alcohol/drug abuse or dependency, detoxification or other symptoms treated *without* complications),[55] and we would expect this to be the case. However, Model 2 predicts that patients suffering from DRG 436 (Alcohol/drug dependency with rehabilitation therapy) pay less than those with DRG 435.[56] Furthermore, as with Model 1, those patients suffering from DRG 437 (Alcohol/drug abuse or dependency,

[55] Evaluated at the average length of stay for the whole sample (7.365 days), ceteris paribus, patients suffering from DRG 434 pay 7.6% more than DRG 435.
[56] Evaluated at the average length of stay for the whole sample, ceteris paribus, patients suffering from DRG 436 pay 70% more.

detoxification or other symptoms treated *with combined* rehabilitation and detoxification therapy)[57] appear to be charged less than those with DRG 435. Once again, this is not what we would intuitively expect, and why these coefficients have these magnitudes is unknown. We should not put too much weight on the DRG 436 results, however, since these patients account for only 4% of our sample.

As with Model 1, Model 2 predicts that those hospitals that are part of a system charge less than those that are not, once again indicating the ability of these types of hospitals to pass on economies of scale to payers. Also as in Model 1, we find once again that teaching hospitals charge more than hospitals that do not teach, and we attribute this to the real or perceived quality differences between these two types of hospital.

Specialist and psychiatric hospitals once again tend to charge less than general acute hospitals in both models, and the magnitudes of the differences across are reasonably similar[58] (although why specialist hospitals treat patients so much cheaper than acute hospitals is unknown).

Regarding the expected source of payment, there are only 3 coefficients in this model that are significant. It appears that private payers with managed care insurance, regardless of the type, are charged less than their fee-for-service contemporaries, as are government insured individuals with traditional fee-for-service insurance. Intuitively, this makes sense.

In summary then, despite different structural forms, our two models tend to predict essentially similar results regardless of structural form for the non-government sample. Most importantly it appears that non-profit and for-profit hospitals not only charge approximately the same amount but neither increase prices when presented with reasonably small increases in market power.

The results of the application of Model 2 to the government data appear in **Appendix G**. The fit for Model 2 applied to the government hospital data is significantly worse than that on Model 1 applied to the same data (an adjusted R-squared of 0.68 compared to 0.84), but we will examine the coefficient results nonetheless.

Despite the poorer fit, there are several coefficient results that behave as expected within this model. As with Model 1, the coefficient on the Herfindahl index is insignificant, which implies that government hospital pricing policy is not influenced by the degree of concentration of the market. Furthermore, the

[57] Evaluated at the average length of stay for the sample, DRG 437 (Alcohol/drug abuse or dependency, detoxification or other symptoms treated *with combined* rehabilitation and detoxification therapy) costs 11% less than DRG 435.
[58] Model 1 predicts that specialist hospitals treat patients 48% cheaper than acute hospitals while Model 2 predicts a difference of 33%. Model 1 predicts that psychiatric hospitals treat patients 6% cheaper than acute hospitals while Model 2 predicts a difference of 12%.

length of stay variable is also positive and highly significant, and its magnitude (less than one) allows for the anticipated decline in per diem charges with length of stay. Also as with Model 1, teaching hospitals charge more than non-teaching hospitals, and the higher the proportion of traditional payers in a hospital, the greater the price charged.

There are several coefficient results that cast doubt on the applicability of this model to government hospitals (or on the rationality of government pricing), however. Firstly, since the coefficient on W_CC is insignificant, these results imply that government hospitals do not charge more for patients with DRG 434 (Alcohol/drug abuse or dependency, detoxification or other symptoms treated *with* complications). Similarly, the coefficients on NURSE and NON_NURS are insignificant implying that patients released to follow-up care facilities are not more severe than those who are released to their own homes, and those admitted on a scheduled basis are not less severely ill than those admitted on an emergency basis. These conclusions although possible, are improbable. Finally, the effect of the coefficient on the log of the retail wage is to reduce price charged marginally when we would expect a positive or insignificant coefficient on this variable.

For these reasons, coupled with the deterioration in fit associated with Model 2 over Model 1, we reject the latter model as a reflection of sensible government hospital behavior.

Conclusions

To summarize, the models presented here generally fit the data quite well (with the exception of the application of Model 2 to the government hospital data), and the inclusion of variables not included in previous research – namely, the controls for severity, the weighted wage index and the proportion of traditional payers – appear to be warranted by the sensible coefficient results that they yield.

Our results substantially contradict those of previous authors. While previous authors have shown that non-profits charge lower prices, both our models reveal that there is essentially no difference in the prices charged by non-profit or for-profit hospitals for alcohol / drug dependent treatment. More importantly we find that, for small changes in market concentration (as indicated by a change in the Herfindahl index of the order of 0.1), there is essentially no change in the price charged by either non-profit hospitals or for-profit hospitals. However, Model 1 predicts that when there are large changes in market concentration, and only then, will for-profit hospitals raise their prices by an economically meaningful amount while non-profit hospitals reduce their prices marginally. These latter results are similar to those of Lynk (1995) in terms of the key variables: non-profit hospitals reduce their prices in the presence of increased market power.

Model 2 fits the data better than Model 1 and reveals that the pricing decisions of neither non-profit nor for-profit hospitals are influenced by changes in market concentration. Due to the recent nature of the data used in this sample, it would seem likely that the ability of both types of hospital to raise prices when presented with market power is constrained by the influence of managed care. Furthermore, the similarity of prices between the two types of hospital can be explained by the more careful information gathering procedures adopted by managed care insurers compared to those of fee-for-service insurers.

Finally, it appears that the Government hospitals have substantially different operating styles from those of privately owned for-profit or non-profit hospitals; why this should be may prove an interesting topic for further research. However, as with their private counterparts, these hospitals do not maintain higher prices in the presence of greater market power. Whether this is because of the influence of managed care or a different underlying philosophy of government hospitals is unknown.

Appendix A

Distribution of Hospitals and Patients in the Sample

	Hospitals	Patients
For-Profit	65	4,733
Non-Profit	132	6,950
Government	30	1,036
Total	227	12,719

Expected Source of Payment

The OSHPD Patient Discharge Data assigns codes to Payer Categories and Payer Types – these are replicated below.
(Source: OSHPD Patient Discharge Data Reporting Manual, Third Edition, pg.25).

	Payer Category	
01	Medicare	A federally administered third party reimbursement program authorized by Title XVIII of the Social Security Act. Includes crossovers to secondary payers.
02	Medi-Cal	A state administered third party reimbursement program authorized by Title XIX of the Social Security Act.
03	Private Coverage	Payment covered by private, non-profit, or commercial health plans, whether insurance or other coverage, or organizations. Included are payments by local or organized charities, such as the Cerebral Palsy Foundation, Easter Seals, March of Dimes or Shriners.
04	Workers' Compensation	Payment from workers' compensation insurance, government or privately sponsored.
06	Other Government	Any form of payment from government agencies, whether local, state, federal or foreign, except those listed above and county indigent programs. Includes funds received through California Children's Services (CCS), the Civilian Health and Medical Program of the Uniformed Services (TRICARE), and the Veterans Association.

	Payer Type of Coverage	
1	Managed Care – Knox-Keene/Medi-Cal County Organized Health System	Healthcare service plans, including HMOs, licensed by the Department of Corporations under the Knox-Keene Healthcare Service Plan Act of 1975. Includes Medi-Cal County Organized Health Systems (MCOHS).
2	Managed Care - Other	Healthcare plans, except those listed above, which provide managed care to enrollees through a panel of providers on a pre-negotiated or per diem basis, usually involving utilization review. Includes Preferred Provider Organizations (PPOs), Exclusive Provider Organizations (EPOs), and

		Exclusive Provider Organizations with Point-of-Service option (POS).
3	Traditional Coverage	All other forms of healthcare coverage, including indemnity or fee-for-service plans, or other fee-for-service payers.

Other types of Payer Category/Payer Type included by OSHPD do not appear in our sample**.**

The dummy variables listed below indicate the combination of Payer Category and Payer Type assigned to the individual patient data by OSHPD.

Dummy Variable	**Payer Category**	**Payer Type**
MCRE1	(01) Medicare,	(01) Managed Care – Knox Keene/MCOHS
MCRE2	(01) Medicare	(02) Managed Care – Other
MCAL1	(02) Medi-Cal (Medicaid)	(01) Managed Care – Knox Keene/MCOHS
MCAL2	(02) Medi-Cal (Medicaid)	(02) Managed Care – Other
PRIV1	(03) Private Coverage	(01) Managed Care – Knox Keene/MCOHS
PRIV2	(03) Private Coverage	(02) Managed Care – Other
WC1	(04) Workers Compensation	(01) Managed Care – Knox Keene/MCOHS
WC2	(04) Workers Compensation	(02) Managed Care – Other
WC3	(04) Workers Compensation	(03) Traditional Coverage
GOV1	(06) Other Government	(01) Managed Care – Knox Keene/MCOHS
GOV2	(06) Other Government	(02) Managed Care – Other
GOV3	(06) Other Government	(03) Traditional Coverage

The default category is private, indemnity or fee-for-service type insurance.

APPENDIX B(1):

DESCRIPTIVE STATISTICS – NON-PROFIT AND FOR-PROFIT HOSPITALS ONLY

All results based on nonmissing observations.

Variable	Mean	Std.Dev.	Minimum	Maximum	Cases
All observations in current sample					
NET_P	2767.93904	2487.69749	27.7203947	28119.3455	11683
SEX	.383206368	.486188729	.000000000	1.00000000	11683
LOS	7.36501755	6.80944082	.500000000	30.0000000	11683
LOS_SQ	100.607999	191.629957	.250000000	900.000000	11683
AGE	41.3761023	12.8068607	.273972600E-02	96.0000000	11683
NURSE	.276470085E-01	.163966315	.000000000	1.00000000	11683
NON_NURS	.620559788E-01	.241267521	.000000000	1.00000000	11683
SCHED	.356500899	.478986060	.000000000	1.00000000	11683
NFP	.594881452	.490935984	.000000000	1.00000000	11683
SYS	.566207310	.495618419	.000000000	1.00000000	11683
TRAD_TYP	.108390543	.124229832	.542986400E-02	.717557252	11683
BED_LIC	183.870752	175.121476	16.0000000	1279.00000	11683
TEACH	.290165197E-01	.167859981	.000000000	1.00000000	11683
SPEC	.184284858	.387732920	.000000000	1.00000000	11683
PSYCH	.359667894	.479923551	.000000000	1.00000000	11683
RET_WAGE	4.96269511	.232250616	3.98614776	5.43352762	11683
PER_CAP	29.0475739	6.26255134	15.4920000	52.8690000	11683
WGT_W	18.2968780	3.15562922	11.8964453	26.3057756	11683
POP_DEN	667.416929	728.333570	9.41295337	6419.28099	11683
HERF	.259245905	.200123808	.113855869	1.00000000	11683
HERF_NFP	.146281132	.201125459	.000000000	1.00000000	11683
W_CC	.160917573	.367470632	.000000000	1.00000000	11683
LOS_WCC	.984935376	2.88712716	.000000000	30.0000000	11683

LOSS_WCC	9.30488744	43.2049999	.000000000	900.000000	11683
REHAB	.469057605E-01	.211446062	.000000000	1.00000000	11683
LOS_REH	.681460241	3.67126065	.000000000	30.0000000	11683
LOSS_REH	13.9413892	91.1615461	.000000000	900.000000	11683
REH_DET	.172986390	.378251696	.000000000	1.00000000	11683
LOS_R_D	2.29256184	6.28039961	.000000000	30.0000000	11683
LOSS_R_D	44.6958829	156.529380	.000000000	900.000000	11683
NFP_LOS	4.90691603	7.16002261	.000000000	30.0000000	11683
LOSS_NFP	75.3393606	183.157065	.000000000	900.000000	11683

APPENDIX B(2)

DESCRIPTIVE STATISTICS - GOVERNMENT HOSPITALS ONLY

Descriptive Statistics
All results based on nonmissing observations.

All observations in current sample

Variable	Mean	Std.Dev.	Minimum	Maximum	Cases
NET_P	2497.97665	2096.40662	57.2592900	19580.6820	1036
SEX	.380308880	.485697169	.000000000	1.00000000	1036
LOS	3.84990347	3.09064507	.500000000	28.0000000	1036
LOS_SQ	24.3646236	53.7455038	.250000000	784.000000	1036
AGE	37.8349421	11.9236207	14.0000000	85.0000000	1036
NURSE	.193050193E-01	.137661279	.000000000	1.00000000	1036
NON_NURS	.127413127	.333596226	.000000000	1.00000000	1036
SCHED	.133204633	.339959873	.000000000	1.00000000	1036
SYS	.426640927	.494828044	.000000000	1.00000000	1036
TRAD_TYP	.145285260	.114044920	.254118100E-02	.381489071	1036
BED_LIC	401.268340	218.714380	14.0000000	605.000000	1036
TEACH	.598455598	.490447424	.000000000	1.00000000	1036
PSYCH	.191119691	.393373004	.000000000	1.00000000	1036
RET_WAGE	4.93316313	.260386595	4.02711756	5.37035769	1036
PER_CAP	28.6941718	4.94732943	17.3530000	43.3380000	1036
WGT_W	20.3116194	2.88398424	13.8241301	27.6944590	1036
POP_DEN	547.882138	319.041086	9.41295337	905.310319	1036
HERF	.251723666	.128239469	.113855869	.834710744	1036
W_CC	.152509653	.359687834	.000000000	1.00000000	1036
LOS_WCC	.624517375	1.96894667	.000000000	23.0000000	1036
LOSS_WCC	4.26303089	24.9584089	.000000000	529.000000	1036
MCRE1	.289575290E-01	.167768169	.000000000	1.00000000	1036
MCAL1	.482625483E-01	.214424007	.000000000	1.00000000	1036

MCAL2	.106177606E-01	.102543520	.000000000	1.00000000	1036
PRIV1	.907335907E-01	.287368609	.000000000	1.00000000	1036
PRIV2	.637065637E-01	.244347434	.000000000	1.00000000	1036
GOV1	.193050193E-02	.439162466E-01	.000000000	1.00000000	1036
GOV2	.223938224	.417082496	.000000000	1.00000000	1036
GOV3	.387065637	.487314121	.000000000	1.00000000	1036

APPENDIX C – NON-PROFIT AND FOR-PROFIT HOSPITALS ONLY.

```
+----------------------------------------------------------------------+
| Ordinary    least squares regression    Weighting variable = none    |
| Dep. var. = NET_P    Mean=   2767.939043    , S.D.=   2487.697492    |
| Model size: Observations =   11683, Parameters =  44, Deg.Fr.=  11639 |
| Residuals:  Sum of squares= .1381825625E+11, Std.Dev.=     1089.60425 |
| Fit:        R-squared=  .808865, Adjusted R-squared =          .80816 |
| Model test: F[ 43,  11639] = 1145.47,    Prob value =          .00000 |
| Diagnostic: Log-L = -98261.2939, Restricted(b=0) Log-L = -107927.6546 |
|             LogAmemiyaPrCrt.=   13.991, Akaike Info. Crt.=     16.829 |
| Autocorrel: Durbin-Watson Statistic =   1.21624,   Rho =       .39188 |
+----------------------------------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Constant	-5379.291564	484.69228	-11.098	.0000	
SEX	96.74572068	20.858829	4.638	.0000	.38320637
LOS	437.6048300	10.362473	42.230	.0000	7.3650175
LOS_SQ	-3.995360179	.44318925	-9.015	.0000	100.60800
AGE	1.384101474	.86026166	1.609	.1076	41.376102
NURSE	323.9945728	63.789521	5.079	.0000	.27647008E-01
NON_NURS	76.07135154	42.696197	1.782	.0748	.62055979E-01
SCHED	-187.3937617	28.490333	-6.577	.0000	.35650090
NFP	353.4483589	61.813242	5.718	.0000	.59488145
SYS	-491.2522213	28.181530	-17.432	.0000	.56620731
TRAD_TYP	3295.047935	129.22325	25.499	.0000	.10839054
BED_LIC	-.1579648483	.11266737	-1.402	.1609	183.87075
TEACH	668.5692175	77.564172	8.620	.0000	.29016520E-01
SPEC	-1329.282967	61.394407	-21.652	.0000	.18428486
PSYCH	-166.8404459	37.540633	-4.444	.0000	.35966789
RET_WAGE	960.0487011	114.73728	8.367	.0000	4.9626951
PER_CAP	-56.08224041	4.3437795	-12.911	.0000	29.047574
WGT_W	135.4596528	5.9573668	22.738	.0000	18.296878
POP_DEN	-.6136090813E-01	.19460942E-01	-3.153	.0016	667.41693
HERF	327.6930097	110.81691	2.957	.0031	.25924591
HERF_NFP	-513.9395557	116.77002	-4.401	.0000	.14628113
W_CC	-34.46804686	71.616459	-.481	.6303	.16091757
LOS_WCC	98.05749489	17.891866	5.481	.0000	.98493538
LOSS_WCC	-3.965502001	.84022580	-4.720	.0000	9.3048874
REHAB	-234.0882085	162.86764	-1.437	.1506	.46905761E-01
LOS_REH	49.59572741	27.179468	1.825	.0680	.68146024
LOSS_REH	-1.434449303	.86421750	-1.660	.0969	13.941389
REH_DET	-110.6649742	86.535566	-1.279	.2010	.17298639
LOS_R_D	-23.27262779	15.779098	-1.475	.1402	2.2925618
LOSS_R_D	.9964183023	.53747706	1.854	.0638	44.695883
NFP_LOS	-39.48941256	12.061043	-3.274	.0011	4.9069160

LOSS_NFP	.1925124411	.46805111	.411	.6808	75.339361
MCRE1	295.6560594	62.721483	4.714	.0000	.46734572E-01
MCRE2	187.3092361	75.292827	2.488	.0129	.26448686E-01
MCAL1	-52.51670688	118.06818	-.445	.6565	.84738509E-02
MCAL2	308.8324792	170.79359	1.808	.0706	.37661560E-02
PRIV1	7.075930716	40.880674	.173	.8626	.41521869
PRIV2	-85.46229900	40.649031	-2.102	.0355	.31455962
WC1	-73.89985097	771.91911	-.096	.9237	.17118891E-03
WC2	761.6210851	237.08464	3.212	.0013	.18830780E-02
WC3	305.2451312	141.36453	2.159	.0308	.54780450E-02
GOV1	884.7645545	387.79298	2.282	.0225	.68475563E-03
GOV2	246.7494327	142.15511	1.736	.0826	.54780450E-02
GOV3	-1422.770187	63.854015	-22.282	.0000	.86193615E-01

(Note: E+nn or E-nn means multiply by 10 to + or -nn power.)

APPENDIX D – GOVERNMENT HOSPITALS ONLY.

```
+-----------------------------------------------------------------------+
| Ordinary    least squares regression    Weighting variable = none     |
| Dep. var. = NET_P    Mean=   2497.976650    , S.D.=   2096.406620     |
| Model size: Observations =    1036, Parameters =  29, Deg.Fr.=   1007 |
| Residuals:  Sum of squares= 716092004.5    , Std.Dev.=      843.27588 |
| Fit:        R-squared=  .842574, Adjusted R-squared =          .83820 |
| Model test: F[ 28,   1007] =  192.49,    Prob value =          .00000 |
| Diagnostic: Log-L =  -8435.1503, Restricted(b=0) Log-L =   -9392.8274 |
|             LogAmemiyaPrCrt.=   13.502, Akaike Info. Crt.=     16.340 |
| Autocorrel: Durbin-Watson Statistic =   1.85876,   Rho =       .07062 |
+-----------------------------------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Constant	7866.048882	2056.0392	3.826	.0001	
SEX	32.91175578	54.802531	.601	.5481	.38030888
LOS	599.6263308	23.856673	25.135	.0000	3.8499035
LOS_SQ	-1.220424341	1.3478708	-.905	.3652	24.364624
AGE	-2.467451530	2.5962682	-.950	.3419	37.834942
NURSE	107.4000178	201.98663	.532	.5949	.19305019E-01
NON_NURS	109.7442750	84.884676	1.293	.1961	.12741313
SCHED	116.1327536	85.590254	1.357	.1748	.13320463
SYS	341.4075825	123.63301	2.761	.0058	.42664093
TRAD_TYP	1613.528194	675.20307	2.390	.0169	.14528526
BED_LIC	-.8650319845	.42661195	-2.028	.0426	401.26834
TEACH	539.9318854	178.28655	3.028	.0025	.59845560
PSYCH	-802.9067047	245.51252	-3.270	.0011	.19111969
RET_WAGE	-2329.456330	500.69939	-4.652	.0000	4.9331631
PER_CAP	39.13609136	19.236006	2.035	.0419	28.694172
WGT_W	155.7167913	35.288590	4.413	.0000	20.311619
POP_DEN	-.1048559945	.26734820	-.392	.6949	547.88214
HERF	-819.3428852	562.33678	-1.457	.1451	.25172367
W_CC	-204.5815339	173.45154	-1.179	.2382	.15250965
LOS_WCC	98.85693750	57.615974	1.716	.0862	.62451737
LOSS_WCC	.5884493055	3.2797799	.179	.8576	4.2630309
MCRE1	28.40418568	239.51427	.119	.9056	.28957529E-01
MCAL1	-144.5631467	186.84535	-.774	.4391	.48262548E-01
MCAL2	-462.2558287	290.97546	-1.589	.1121	.10617761E-01
PRIV1	-178.1879595	173.74085	-1.026	.3051	.90733591E-01
PRIV2	-28.59239246	133.80648	-.214	.8308	.63706564E-01

GOV1	-617.8664726	625.65033	-.988	.3234	.19305019E-02
GOV2	-1214.780101	184.05133	-6.600	.0000	.22393822
GOV3	-158.8618229	179.53734	-.885	.3762	.38706564

APPENDIX E – NON-PROFIT, FOR-PROFIT AND GOVERNMENT HOSPITALS COMBINED.

```
+-------------------------------------------------------------------------+
| Ordinary    least squares regression    Weighting variable = none       |
| Dep. var. = NET_P    Mean=   2745.949811    , S.D.=   2459.193222       |
| Model size: Observations =   12719, Parameters =  45, Deg.Fr.=  12674   |
| Residuals:  Sum of squares= .1579773313E+11, Std.Dev.=     1116.45323   |
| Fit:        R-squared=  .794605, Adjusted R-squared =          .79389   |
| Model test: F[ 44,  12674] = 1114.35,    Prob value =          .00000   |
| Diagnostic: Log-L = ***********, Restricted(b=0) Log-L = -117351.6990   |
|             LogAmemiyaPrCrt.=   14.039, Akaike Info. Crt.=     16.877   |
| Autocorrel: Durbin-Watson Statistic =   1.21965,   Rho =       .39017   |
+-------------------------------------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Constant	-4578.442177	462.45267	-9.900	.0000	
SEX	88.62697099	20.481679	4.327	.0000	.38297036
LOS	483.6040637	9.8323544	49.185	.0000	7.0787012
LOS_SQ	-5.285242545	.42969673	-12.300	.0000	94.397751
AGE	1.389343729	.85082433	1.633	.1025	41.087664
NURSE	372.0256956	63.346075	5.873	.0000	.26967529E-01
NON_NURS	42.53176863	40.517262	1.050	.2938	.67379511E-01
SCHED	-265.9516370	27.944867	-9.517	.0000	.33831276
NFP	625.5733049	59.731524	10.473	.0000	.54642661
SYS	-376.4949228	26.210069	-14.365	.0000	.55483922
BED_LIC	-.5291273360	.11032059	-4.796	.0000	201.57843
TEACH	858.0996728	61.320238	13.994	.0000	.75399009E-01
SPEC	-1542.534270	61.362640	-25.138	.0000	.16927431
PSYCH	-285.0756287	36.939765	-7.717	.0000	.34593915
TRAD_TYP	3163.574383	128.52170	24.615	.0000	.11139573
RET_WAGE	755.1935918	109.22290	6.914	.0000	4.9602896
PER_CAP	-52.34787772	4.2113046	-12.430	.0000	29.018788
WGT_W	136.9546137	5.7811012	23.690	.0000	18.460985
POP_DEN	-.5745383475E-01	.19127207E-01	-3.004	.0027	657.68047
HERF	76.03497917	110.37034	.689	.4909	.25863320
HERF_NFP	-404.7321222	116.50130	-3.474	.0005	.13436610
HERF_GOV	1144.295978	165.18527	6.927	.0000	.20503634E-01
W_CC	-90.17652735	69.050082	-1.306	.1916	.16023272
LOS_WCC	105.4295867	17.610420	5.987	.0000	.95557827
LOSS_WCC	-4.260502278	.83580511	-5.097	.0000	8.8942134
REHAB	-160.0977468	166.67704	-.961	.3368	.43085148E-01
LOS_REH	47.79163160	27.783464	1.720	.0854	.62595330
LOSS_REH	-1.384958910	.88228158	-1.570	.1165	12.805822
REH_DET	-56.84169511	88.140131	-.645	.5190	.15905338
LOS_R_D	-35.16112550	16.003416	-2.197	.0280	2.1062977

LOSS_R_D	1.419456633	.54432640	2.608	.0091	41.056687
NFP_LOS	-107.3177988	11.825222	-9.075	.0000	4.5072333
LOSS_NFP	2.361413784	.46249783	5.106	.0000	69.202748
MCRE1	239.4788796	62.471250	3.833	.0001	.45286579E-01
MCRE2	202.3852795	76.353022	2.651	.0080	.24294363E-01
MCAL1	-148.8321904	99.494648	-1.496	.1347	.11714757E-01
MCAL2	185.1539929	156.20543	1.185	.2359	.43242393E-02
PRIV1	53.14978575	40.578401	1.310	.1903	.38878843
PRIV2	-61.44598039	40.253878	-1.526	.1269	.29412690
WC1	-67.42938148	790.83894	-.085	.9321	.15724507E-03
WC2	815.0209943	242.68187	3.358	.0008	.17296957E-02
WC3	307.4448540	144.51551	2.127	.0334	.50318421E-02
GOV1	636.0216505	355.48891	1.789	.0736	.78622533E-03
GOV2	-1299.896947	84.876896	-15.315	.0000	.23272270E-01
GOV3	-929.9441736	57.839582	-16.078	.0000	.11070053

(Note: E+nn or E-nn means multiply by 10 to + or -nn power.)

APPENDIX F – NON-PROFIT AND FOR PROFIT HOSPITALS ONLY – LOG-LOG MODEL

```
+-----------------------------------------------------------------------+
| Ordinary    least squares regression    Weighting variable = none      |
| Dep. var. = L_NET_P  Mean=   7.596976348    , S.D.=   .8131670890      |
| Model size: Observations =   11683, Parameters =  39, Deg.Fr.=  11644  |
| Residuals:  Sum of squares= 1086.436550    , Std.Dev.=         .30546  |
| Fit:        R-squared=  .859354, Adjusted R-squared =          .85889  |
| Model test: F[ 38,  11644] = 1872.25,    Prob value =          .00000  |
| Diagnostic: Log-L =  -2702.5433, Restricted(b=0) Log-L =  -14160.6965  |
|             LogAmemiyaPrCrt.=   -2.369, Akaike Info. Crt.=       .469  |
| Autocorrel: Durbin-Watson Statistic =    .90099,   Rho =       .54950  |
+-----------------------------------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Constant	2.400975852	.15757422	15.237	.0000	
SEX	.2670297181E-01	.58425205E-02	4.570	.0000	.38320637
L_LOS	.9506248060	.66451071E-02	143.056	.0000	1.6463152
L_AGE	-.3295862321E-02	.86464030E-02	-.381	.7031	3.6698516
NURSE	.7483239788E-01	.17747315E-01	4.217	.0000	.27647008E-01
NON_NURS	.4766679231E-01	.11960831E-01	3.985	.0001	.62055979E-01

SCHED	-.1069426141	.79189584E-02	-13.505	.0000	.35650090
NFP	.1535099022	.23006410E-01	6.672	.0000	.59488145
SYS	-.8997522197E-01	.79420224E-02	-11.329	.0000	.56620731
L_TRAD	.4613714188E-01	.49552311E-02	9.311	.0000	-2.5705556
L_BED	-.6191643059E-02	.75761525E-02	-.817	.4138	4.8105673
TEACH	.1158332729	.19123008E-01	6.057	.0000	.29016520E-01
SPEC	-.3933186419	.22155622E-01	-17.753	.0000	.18428486
PSYCH	-.1227077073	.12478805E-01	-9.833	.0000	.35966789
L_RET_W	1.783236927	.16136107	11.051	.0000	1.6008302
L_PR_CAP	-.5547735082	.37901546E-01	-14.637	.0000	3.3473906
L_WGT_W	1.145327476	.29766439E-01	38.477	.0000	2.8904543
L_POPN	-.4556442463E-01	.55119263E-02	-8.267	.0000	5.8974665
L_HERF	-.1904759658E-01	.12190676E-01	-1.562	.1182	-1.5731062
NFP_L_HF	.2084983214E-02	.10540026E-01	.198	.8432	-.97834038
W_CC	.1686640228	.18959665E-01	8.896	.0000	.16091757
W_L_LOS	-.4766071744E-01	.11078952E-01	-4.302	.0000	.25163769
REHAB	-.7885058848E-01	.43041840E-01	-1.832	.0670	.46905761E-01
R_L_LOS	-.3582695783E-02	.17581377E-01	-.204	.8385	.11295779
REH_DET	-.1386207113	.23419809E-01	-5.919	.0000	.17298639
RD_L_LOS	.1077422582E-01	.10550495E-01	1.021	.3072	.39912110
NFP_LLOS	-.7678366769E-01	.78928192E-02	-9.728	.0000	1.0289118
MCRE1	.2794457718E-01	.17314719E-01	1.614	.1065	.46734572E-01
MCRE2	-.3412255258E-01	.20978391E-01	-1.627	.1038	.26448686E-01
MCAL1	-.2394006601E-01	.33053035E-01	-.724	.4689	.84738509E-02
MCAL2	-.1964914833E-01	.47895869E-01	-.410	.6816	.37661560E-02
PRIV1	-.4635871090E-01	.11389535E-01	-4.070	.0000	.41521869
PRIV2	-.6605580717E-01	.11434087E-01	-5.777	.0000	.31455962
WC1	.9253149398E-01	.21638491	.428	.6689	.17118891E-03
WC2	.1213123040	.66354967E-01	1.828	.0675	.18830780E-02
WC3	.1549331342E-01	.39614037E-01	.391	.6957	.54780450E-02
GOV1	.1785987808	.10871612	1.643	.1004	.68475563E-03
GOV2	.1780566158E-01	.39834717E-01	.447	.6549	.54780450E-02
GOV3	-.6166944452	.17459037E-01	-35.322	.0000	.86193615E-01

(Note: E+nn or E-nn means multiply by 10 to + or -nn power.)

APPENDIX G – GOVERNMENT HOSPITALS ONLY -- LOG-LOG MODEL

```
+-----------------------------------------------------------------------+
| Ordinary    least squares regression    Weighting variable = none      |
| Dep. var. = L_NET_P  Mean=   7.510717303    , S.D.=   .8509598911      |
| Model size: Observations =    1036, Parameters =  27, Deg.Fr.=   1009  |
| Residuals:  Sum of squares= 230.5743641    , Std.Dev.=         .47804  |
| Fit:        R-squared=  .692353, Adjusted R-squared =          .68443  |
| Model test: F[ 26,   1009] =   87.34,    Prob value =          .00000  |
| Diagnostic: Log-L =   -691.7000, Restricted(b=0) Log-L =   -1302.3198  |
|             LogAmemiyaPrCrt.=   -1.450, Akaike Info. Crt.=      1.387  |
| Autocorrel: Durbin-Watson Statistic =   1.62021,   Rho =       .18989  |
+-----------------------------------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Constant	7.288532345	1.6187802	4.502	.0000	
SEX	-.2708846316E-01	.31022200E-01	-.873	.3826	.38030888
L_LOS	.8968587095	.25797604E-01	34.765	.0000	1.1124696
L_AGE	-.1010753580E-01	.51386322E-01	-.197	.8441	3.5834182
NURSE	.8162311426E-02	.11484123	.071	.9433	.19305019E-01
NON_NURS	.7494979484E-01	.48067918E-01	1.559	.1189	.12741313
SCHED	.1790624451E-01	.48625898E-01	.368	.7127	.13320463
SYS	.8776103563E-01	.67718999E-01	1.296	.1950	.42664093
L_TRAD	.9356839550E-01	.32376127E-01	2.890	.0039	-2.2770394
L_BED	-.1230052929	.70064694E-01	-1.756	.0792	5.6886616
TEACH	.2999513796	.88852044E-01	3.376	.0007	.59845560
PSYCH	-.9979460831E-01	.12271320	-.813	.4161	.19111969
L_RET_W	-2.915806083	1.3747985	-2.121	.0339	1.5945223
L_PR_CAP	.9622410605	.31189142	3.085	.0020	3.3411317
L_WGT_W	.6582988012	.37660788	1.748	.0805	3.0008742
L_POPN	-.9413423085E-01	.76308514E-01	-1.234	.2174	5.9546202
L_HERF	-.1489344745	.11826352	-1.259	.2079	-1.4918863
W_CC	-.4271040546E-01	.82529869E-01	-.518	.6048	.15250965
W_L_LOS	.8073320358E-01	.60432996E-01	1.336	.1816	.17637959
MCRE1	-.2205156859E-01	.12934142	-.170	.8646	.28957529E-01
MCAL1	-.1043574361E-01	.11491333	-.091	.9276	.48262548E-01
MCAL2	-.3615952171	.17222171	-2.100	.0358	.10617761E-01
PRIV1	-.9923794769E-01	.97175256E-01	-1.021	.3071	.90733591E-01
PRIV2	-.3505078394E-01	.74949519E-01	-.468	.6400	.63706564E-01
GOV1	-.2218750577	.35393496	-.627	.5307	.19305019E-02
GOV2	-.8898582314	.10442030	-8.522	.0000	.22393822

```
GOV3     -.5371286894E-01      .10144567    -.529   .5965     .38706564
(Note: E+nn or E-nn means multiply by 10 to + or -nn power.)
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