DEBUNKING THE COST-SHIFTING MYTH

AN ANALYSIS OF DYNAMIC PRICE DISCRIMINATION IN CALIFORNIA HOSPITALS

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Presented in partial fulfillment of the requirements for
Graduation with Distinction in Economics
in Trinity College of Duke University

Duke University
Durham, North Carolina
2013

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Abstract

Cost-shifting, a dynamic form of price discrimination, is a phenomenon in which hospitals shift the burden of decreases in government-sponsored healthcare reimbursement rates to private health insurers. In this paper, I construct a data set spanning 2007 – 2011 that matches financial metrics of California hospitals to hospital- and market-specific characteristics with theoretical implications in price discrimination. The subsequent analysis is split into three stages. In the first and second stages, I use a fixed-effects OLS model to derive a point estimate of the inverse correlation between private revenue and government revenue that is consistent with recent empirical work in cost-shifting, a body of literature almost entirely reliant upon fixed-effects and difference-in-difference OLS. These types of models are encumbered by the inherent causality loop connecting public and private payment sources. I address this endogeneity problem in the third stage by specifying a fixed-effects 2SLS model based on an instrument for government revenue constructed with data from the California Department of Health Care Services and the U.S. Census. This instrument performed well in canonical tests for relevance and validity. I find that an increase in government payments causes an increase in private payments, and that the relationship is statistically-significant at all reasonable levels. In addition, I comment on properties of the data set that suggest that the original inverse correlation was due to inadequate measurements of market power. I conclude with policy implications and suggestions for future research.[1]

JEL Classification Numbers: L11, L80, I11, I13, I18

Keywords: Market Structure, Price Discrimination, Health Insurance, Medicaid, Medicare

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[1] I am grateful to my advisor, Professor Frank Sloan, for his mentorship through all stages of the writing process. I would like to thank Professor Kent Kimbrough and the rest of my seminar class for their invaluable comments. I would also like to thank Professor Andrew Sweeting for his guidance during the early stages of writing. Finally, I would like to thank my friends and family for their support and encouragement.

Introduction

In the summer of 2008, then-Director of the Congressional Budget Office, Peter Orszag, made the following statement in a testimony before the U.S. Senate's Committee on Finance (Orszag, 2008):

> Future growth in spending per beneficiary for Medicare and Medicaid—the federal government's major health care programs—will be the most important determinant of long-term trends in federal spending. Changing those programs in ways that reduce the growth of costs—which will be difficult, in part because of the complexity of health policy choices—is ultimately the nation's central long-term challenge in setting federal fiscal policy. (p. 3)

Indeed, the growth of government healthcare expenditures was a recurring talking point of the presidential election later that year, with both main candidates advocating the necessity of cost-control over the long run. The conversation continued throughout the next four years, taking center stage following the passage of the Affordable Care Act in 2010 and again during the fiscal cliff saga of late 2012. In the case of the latter, the negotiations were primarily concerned with managing the simultaneous increase in tax rates and decrease in public spending slated to take effect in the early part of 2013. While health care programs were eventually spared from the subsequent curtailment in spending, Congress only narrowly avoided blanket cuts to Medicare and Medicaid reimbursement rates. Among the most vocal opponents of these cuts were health care providers and private insurers, two groups traditionally averse to any reduction in government spending on healthcare. Providers argue that lower government reimbursement rates for medical services leads to lower quality patient care and less investment in technology. Insurers, on the other hand, argue that decreases in government reimbursement rates directly affect their own margins, as hospitals make up lost profit by charging higher prices to private insurers. Consider the following time series of payment-to-cost ratios for government and private insurers based on nationwide data from the American Hospital Association's Annual Survey of Hospitals:

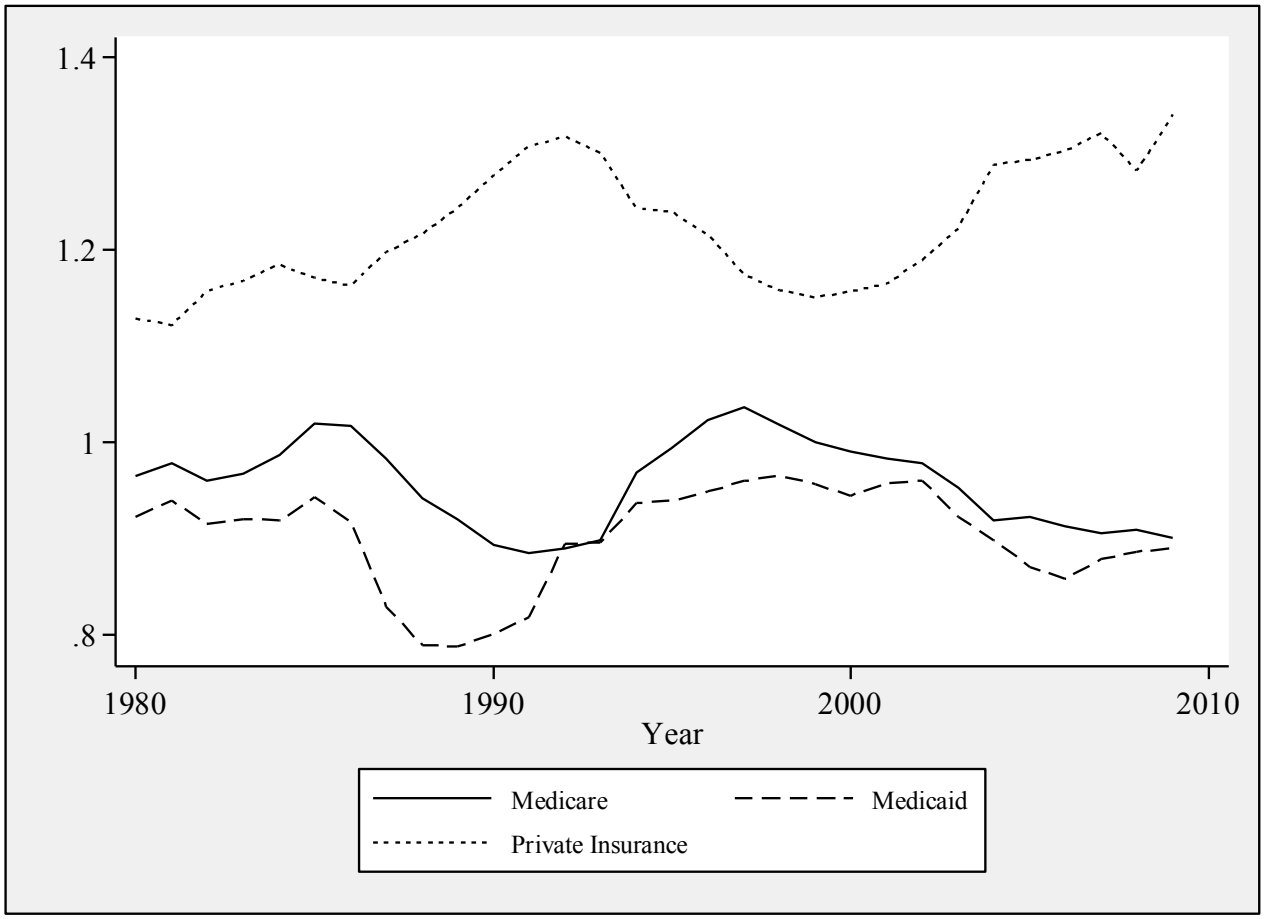

Figure 1: Payment-to-Cost Ratios for Medicare, Medicaid, and Private Insurers, 1980-2009 (American Hospital Association, 2012)

Over the last twenty years, private payment-to-cost ratios were inversely correlated with Medicare and Medicaid payment-to-cost ratios to the tune of -82% and -53%, respectively. It would appear, then, that the claims of private insurers may not be entirely unmerited. This idea that hospitals increase prices for private insurers in response to reductions in government reimbursement rates is known as "cost-shifting". In this paper, I examine the cost-shifting phenomenon and its associated literature in greater detail. The next section provides background information on hospital financing in the United States, especially in the context of cost-shifting. I conclude the section with my research question, my hypothesis, and an outline of the remainder of the paper.

I. Background Information

Medicare is a federally funded program that provides health insurance primarily to Americans aged 65 and older. The program was enacted in 1965 under the Johnson administration as an amendment to the Social Security Act, and has since been revised several times since. Hospitals were initially paid for medical services based on a fixed margin of their reported costs (Weiner, 1977). This system incentivized profligate spending, and costs increased four-fold in the early 1970s alone (Frakt, 2011). The Social Security Amendments of 1983 ended unconditional reimbursements and replaced them with a standardized prospective payment system based on approximately 750 diagnosis-related groups (DRGs) (Mayes, 2007). Patients admitted to a physician practice or hospital are assigned a DRG based on their primary complaint as well as medically-relevant idiosyncrasies, such as age, geographic location, and case severity ("Diagnosis Related Group (DRG) Codes," 2011). The DRGs are mapped to a nationally-standardized reimbursement menu that is frequently updated to incorporate the effects of technological improvement, changes in supply costs, and other exogenous price determinants. Changes to the DRG system are made by Congress in conjunction with The Medicare Payment Advisory Commission an independent advisory agency (MedPAC, 2013).

Medicaid provides healthcare insurance primarily to Americans with low-income backgrounds. Unlike Medicare, the Medicaid payout policy is set jointly between the state- and federal government. States can set their own reimbursement rates within federal requirements. These reimbursements are made to providers in one of three ways: 1) a DRG-based system, (similar to Medicare) 2) per-diem payments, or 3) fee-for-service payments. Although states re-weight the national DRGs to internalize local variation, reimbursements fall notoriously short of full cost. The Medicaid payout for a given DRG is, on average, 34% less than the Medicare payout for the same DRG; in some states, the number is closer to 70% (Kliff, 2012). Not surprisingly, doctors are 8.5 times more likely to turn away a Medicaid patient than a Medicare patient (Roy, 2011).

Payments from Medicare and Medicaid typically make up the largest portion of hospitals' revenue. As argued in the 1995 anti-trust case, *FTC vs. Freeman Hospital*, the result is that Medicare and Medicaid "set their own payment schedules and offer hospitals a "take it or leave it" deal on prices…[which] virtually no hospital can afford to leave" (FTC vs. Freeman Hospital, 2005). In contrast, private insurers negotiate their prices with providers. These prices take the form of either steeply

discounted charges, per diems, or flat-charges per episode similar to Medicare and Medicaid (Austin, 2009). Larger insurers generally favor per-diem arrangements, while smaller insurers typically pay hospitals through discounted charges. Private insurers meet with every hospital in their network to negotiate discounts from the "charge master", or comprehensive list of prices for all procedures performed in a given hospital. Each hospital updates its charge master at least annually (but often more frequently) to reflect changes in supply costs, volume trends, and new technology. Private insurers' plans were primarily fee-for-service until the late 1980s. Even as public payment-to-cost ratios fell to all-time lows, private insurers were paying more than ever for health care. The nearly ubiquitous adoption of managed care in 1992 reversed this trend, causing private payment-to-cost ratios to fall significantly over the following five years (Frakt, 2011) . A wave of state and federal legislation in 1997 shifted leverage away from insurance plans by enforcing less restrictive network contracting (Guterman, Ashby, & Greene, 1996). Although this may have contributed to an increase in payment-to-cost ratios for private insurers, managed care is the dominant model of healthcare delivery in the United States today.

As discussed above, insurers have long argued that they are forced to absorb the payment shortfall caused by decreases in government reimbursement rates. This phenomenon is known as "cost-shifting". The mechanism differs from the more general form of price discrimination only in causality. Price discrimination is exactly that—that is, it is the selective categorization of consumers and the setting of prices as a function of the resulting cohorts (Armstrong, 2006). Cost-shifting, however, is observed when a group of consumers is charged more because another group is charged less, connoting a temporal dynamism absent in classic price discrimination. A considerable body of literature on cost-shifting in healthcare markets has accumulated over the last three decades, coinciding with the transition to DRG-based reimbursement systems for government entitlement programs. Empirical studies of the phenomenon point to the inverse correlation between private and public revenue, even in the presence of hospital- and market-specific controls. Coupled with visuals such as Figure 1, a compelling case can be made that the government systematically exploits the private sector by shifting away its own financial burden. As any student of economics will note, however, conclusions based on correlation are incomplete at best. Conclusive evidence of cost-shifting must rely on more sophisticated econometric techniques, ones that can be used to interpret directionality and, more importantly, causation.

In this paper, I use three fixed effects models based on data from the California Office of Statewide Health Planning and Development, the California Department of Health Care Services, U.S. Census, and the American Medical Association to test the presence and magnitude of cost-shifting in California

hospitals. Economic theoreticians have long argued that because hospitals are profit-maximizing (an assumption accepted ex ante), they cannot offset exogenous shocks to prices for one group of consumers by raising prices for another. A significant body of empirical literature has shown, however, that cost-shifting-like phenomena occur in the presence of a circumscribed set of market-specific conditions. Many of these studies point to the observed inverse correlation between private and public revenue streams as evidence of government malfeasance. I analyze this correlation in three stages. In the first stage of my results, I specify a fixed effects OLS model that predicts private revenue for a given hospital as a function of government revenue, patient volume, and other controls for hospital- and market-specific characteristics. Based on these results, I then modify the model to produce a best point estimate of the implied inverse correlation between government and private revenue. The results of the first and second stage show that, even with a new data set, it is possible to produce results that appear to be cost-shifting using the same models as much of previous literature. In the final stage of my results, I specify a fixed effects 2SLS model using an instrument for government revenue. This model is econometrically-superior to OLS, allowing for interpretations of causation and avoiding the endogeneity trap inherent in previous findings. Using this new model, I show that government revenue and private revenue are in fact positively correlated to a statistically-significant degree. This evidence casts doubt on recent empirical findings of cost-shifting and suggests that the inverse correlation drawn from OLS is due to unobserved or inadequately controlled variables, most likely hospital and insurer market power.

The remainder of this paper is structured as follows. Section II reviews the relevant literature, including recent findings of cost-shifting based on OLS specifications. Section III provides an overview of the theoretical foundations of dynamic price discrimination. Sections IV and V outline the data sources and empirical specification, respectively. The next two sections include the results and discussion of the main findings. I conclude with suggestions for future research and a brief note on policy implications.

II. Literature Review

The lamentations of private insurers have generally found a skeptical audience among academicians. A 2005 national survey of health economists posed the following question: "If a payer negotiates a lower price for hospital services, [will the] hospital raise prices to other payers[?]". Less than half of health economists answered in the affirmative, and nearly a quarter were unsure (Morrisey, 2008). This discord is rooted in a refrain familiar to any student of economics: the theory of the profit-maximizing firm. Assume a hospital in an imperfectly competitive market. If the government suddenly tightens its purse-strings, then, according to cost-shifting theorists, this hospital will charge private insurers more in order to "make up the difference"—that is, to maintain the same profit margin as before. However, this necessarily implies that the hospital was not profit maximizing in the first place (otherwise they would have charged private insurers the higher price to begin with). So either the hospital's real-life counterpart does not maximize profit, or it does not cost shift. For the academic economist, the latter is a much easier pill to swallow.

Yet the profit-maximizing behavior of a firm is more assumption than axiom. In theory, cost-shifting may be observed if a hospital maximizes a different function, such as a mixture of profit and quality. Gowrisankaran and Town (1997) developed a non-linear dynamic model that differentiated for-profit hospitals, which maximize net profits, and non-profit hospitals, which maximize some combination of net profits and qualities (Gowrisankaran & Town, 1997). The authors also accounted for differences in taxation (non-profits have tax-exempt status, for-profits pay corporate tax rates) and cost of capital related to financing constraints on non-profit hospitals. As expected, the application of the authors' dynamic model to the annual American Hospital Association national survey data suggested that cost-shifting is indeed possible for a non-profit-maximizing hospital. Surprisingly, however, Gowrisankaran and Town presented the first model that, when applied to the data, suggested cost-shifting in a rational profit-maximizing setting. Although the mathematics of the paper are beyond the scope of this proposal, it suffices to say that, unlike static models, dynamic models take into account entry, exit, and investment when determining general equilibrium. The authors of this paper also found that incremental changes in quality must be considered as mechanisms for reacting to decreases in public payments, where hospital quality was modeled as a function of physical capital (MRIs, testing labs, etc.), human capital (better physicians and nurses), and an unobserved component.

If hospitals don't maximize profit, then what do they maximize? The answer may depend on the type of hospital. Chang (2011) derived the response of nonprofit hospitals to a large fixed cost shock under each of the following leading theories of nonprofit hospital behavior: 1) "for-profits in disguise," (2) output maximizers, (Gupchup, Wolfgang, & Thomas) welfare maximizers, and (4) perquisite maximizers (Chang, 2011). They tested the predictions of their model by examining data from the retrofitting of California hospitals with equipment to minimize damage from earthquakes. This process is expensive, representing a large fixed-cost shock to the hospital. They found that the behavior of non-profit hospitals was most consistent with output and perquisite maximization. Similar literature on for-profit hospitals does not exist. Rather, assumptions are made *a priori* that for-profit hospitals maximize only profit (Lynk, 1995). However, as mentioned above, there is at least an intuitive reason for why this may not be entirely accurate. Cornell and Shapiro (1987) made the claim that while it is generally unambiguous that investors want to maximize profit, management may not act in a profit-maximizing manner due to different incentives, signaling issues, or asymmetric information (Cornell & Shapiro, 1987). Similarly, while it is likely that for-profit hospitals maximize some form of profit, but they may also maximize other variables, like size, prestige, or volume. I consider this case, grouped as "utility-maximization", in the "Theoretical Foundations" section of this paper.

Frakt (2011) discusses the role that insurance and provider market power play in any analysis of cost-shifting. The basic theory is highly intuitive. If there is a single hospital in a market with many insurers, the hospital can raise prices for its services and it can expect to receive greater income on average. This is because an insurer cannot refuse to pay the higher price; if it does, it will be excluded from the network (because other insurers would be willing to pay the higher price). Furthermore, if a single insurer attempts to shift costs to its enrollees, those individuals will switch to a different insurer. Similarly, if the insurer market is highly consolidated and the hospital market is not, then insurers can pay less for the providers' services, and providers are forced to accept the new payments.

In his 2010 paper, "Hospital prices and market structure in the hospital and insurance industries", Moriya et al. analyzed the relationship between insurer/hospital market concentration and the prices of hospital services (Moriya, Vogt, & Gaynor, 2010). The authors used a proprietary national data set containing transaction prices for over 11 million privately insured Americans. This paper was the first to exclusively consider a "bilateral exercise of market power" by both insurers and hospitals. Previous papers studied the effects of provider concentration on hospital prices, with the majority finding a positive relationship (Dranove & Ludwick, 1999; Dranove, White, & Wu, 1993). Similarly, previous research has

found a positive relationship between insurer market power and discounts on health care services (Sorensen, 2003). Moriya studied the magnitude of the opposing "vectors" of hospital and insurance concentrations, as measured by the Hirschman-Herfindahl Index, on the prices charged for medical services. The authors found that increases in insurance market concentration were correlated with decreases in prices paid for private insurance transactions, while increases in provider concentration were correlated with increases in the same prices. Moriya noted that his paper did not take into account changes in quality of health care due to provider or insurer concentration, or the effect of increased insurance concentration on enrollee premiums. Either of these factors could decrease the consumer surplus gained when larger insurers negotiate for lower hospital prices.

The Moriya paper makes two important contributions to this thesis. The first is that it provides evidence supporting the intuition that an increase in insurer concentration leads to a decrease in actual payments made to healthcare providers. Moriya notes, "our results indicate that increased insurer market is significantly associated with lower inpatient hospital prices per case and increased hospital market concentration is non-significantly associated with higher hospital prices" (Moriya et al., 2010). The opposing forces of hospital and insurance market consolidation are precisely the dynamics that I wish to study. The greater contribution that Moriya makes is the empirical specification that he uses to test the phenomena observed in hospital and insurance market. Moriya uses the structure-conduct-performance framework for his analysis. This approach treats market performance as a function of the conduct of firms, which in turn is the function of market structure. The HHI for insurers and markets are used as proxies for market structure. The model specification is as follows:

$$\begin{aligned}\ln(\text{Price}_{tshi}) = \alpha + \beta(\text{HHI of Insurers})_{ts} + \gamma(\text{HHI of Hospitals})_{ts} \\ + W_{tsh}\zeta + X_{tshi}\delta + \eta_{sh} + \mu_t + \varepsilon_{tshi},\end{aligned} \qquad (1)$$

This equation shows that price is a function of the market structure of insurers (HHI of Insurers), the market structure for providers (HHI of Hospitals), control variables at the HSA (health-service area) and individual levels (W), market effects (η), time effects (μ) and random error (ε). There are a few major considerations that must be made with respect to this model specification. The first is that while the market concentrations of hospitals are calculated at the HSA level, insurer concentration is calculated at the state level. This is purely due to data availability; private insurers are notoriously protective of market share and enrollment plan data. The second is that the assumption of independent and identically distributed regression errors is likely violated. This is because common random effects, such as economic shocks at the state level, would likely induce serial correlation among the regression errors. I encounter

similar issues with my own regression, and I outline my solution in the "Empirical Specification" portion of this paper.

The final portion of this literature review provides an overview of the results of Zwanziger (2000) and Zwanziger (2006), often cited as among the most conclusive evidence of cost-shifting in health care markets. In the first paper, published in the reputable *Journal of Health Economics*, Zwanziger specified a fixed effects OLS model that predicted private revenue (deflated by a volume proxy) as a function of government revenue (also deflated), average cost, for-profit ownership, hospital market concentration, and time period dummy variables. Using data from the California Office of Statewide Health Planning and Development (OSHPD) spanning 1983 – 1991, Zwanziger showed that a 10% decrease in government revenue was correlated with a 1.7% - 5.8% increase in private revenue. Based on these results, Zwanziger noted that "[the hypothesis that] not-for-profit hospitals will increase prices for privately insured patients in response to reductions in payment rates by Medicare or Medi-Cal…has been largely confirmed" (p.221). His controls for showed that, while ownership and competition were likely implicated in this correlation, they were in a "more complex manner" than suggested by his model. Zwanziger followed up on these results with another study in 2006, published in the more policy-oriented journal, *Health Affairs.* Using the same fixed effects OLS specification as his previous paper, and using OSHPD data spanning 1993 – 2001, Zwanziger found that a 10% decrease in government revenue was correlated with a 0.4 – 1.7% increase in private revenue. Though seemingly trivial, Zwanziger noted that these results implied that "cost-shifting from Medicare and Medicaid to private payers accounted for 12.3% of the total increase in private payers' prices from 1997 – 2001" (p. 197).

I use the remainder of this paper to show that the Zwanziger results above should be interpreted with caution. Although I unfortunately did not have access to the California data from 1983 - 2001, I was able to show that a similar magnitude and statistical significance of the inverse correlation could be drawn out of data from 2007 – 2011. Then, using an econometrically-superior fixed effects 2SLS model, I show that the inverse correlation disappears entirely.

III. Theoretical Framework

As described above, cost-shifting is a selective and responsive price-setting behavior by firms. The key distinction between cost-shifting and price discrimination is that price discrimination is a static phenomenon in which a firm takes advantage of consumers' different demand curves, while cost-shifting implies that one cohort of consumers is priced one way *because* other consumers are priced another way. This definition implies that the essence of cost-shifting is the choice of a firm to mitigate increased average costs by increasing prices, thereby keeping margins steady. The economic objection to this phenomenon is immediately discernible. If a hospital can increase prices for a certain cohort of consumers in order to increase profit, then why were prices not set optimally in the first place? On the individual physician level, all research since 1996 has found that cost-shifting does not occur, and that the assumption that physicians maximize profits is likely an accurate representation (Rice et al., 1996; Showalter, 1997)

There are, however, ways that traditional economic foundations can be reconciled with cost-shifting. McGuire and Pauly (1991) derived a model of physician behavior that encompassed two cases: profit maximization and target-income behavior (McGuire & Pauly, 1991). They showed that under the assumption of profit maximization, cost-shifting would not be observed. Instead, their results showed that physicians responded to pay cuts by volume-shifting. Their data set was drawn from a forty-five-month period between 1988 and 1991. This timeframe encompassed a twenty-four-month period prior to a policy-driven reduction in Medicare reimbursement for a basket of surgical procedures. They found that, for some procedures, there was a statistically significant shift in the volume of procedures performed; that is, when Medicare reimbursement rates decreased, a substitution-like behavior towards treating the more lucrative private payers was observed. This is the result of simple supply and demand. An exogenous shift downward in price of Medicare lowers the quantity supplied. This creates spare capacity for a hospital. In order to fill this spare capacity, the providers *lowes* prices for private payers, creating more demand for healthcare services and yielding an outcome antithetical to that which cost-shifting would predict.

The obvious criticism of this approach is that hospitals should not be modeled as profit-maximizers. It may seem that providers of social goods like healthcare are not "firms" in the way that, say, Wal-Mart is. This is likely a shallow intuition more rooted in linguistics than economics—it is possible to envision many scenarios in which non-profits would, in fact, maximize profit. They may maximize their profit so that they can fund capital expenditures or research, for example, or, in the case of the University, to attract

and retain higher quality faculty. A hospital that maximizes profit in this way cannot shift costs. However, if hospitals maximize a different function, or if hospitals maximize a utility function which includes profit along with other characteristics, then cost-shifting is theoretically possible.

Clement (1997/1998) attempted to explain dynamic cost-shifting using data from the California Office of Statewide Health Planning and Development (OSPHD) annual financial reports on all hospitals in the state (Clement, 1997). She specified a utility-based model by noting that, "[since] empirical research has not supported a specific hospital objective function, the hospital is assumed to be a utility-maximizing entity...[where] utility is derived from both profits and the quantity of output". The model was based on a paper by Dranove (1988), which showed that, under assumptions of utility-maximization, hospitals voluntarily raise prices for private paying patients in response to government cuts in hospital reimbursement (Dranove, 1988). Her results indicated that hospitals in California practiced cost-shifting during the 1980s and early 1990s, consistent with a hospital that maximizes utility but underutilizes market power. Similarly, Rosenman, Li, and Friesner (2000) developed a model in which hospitals maximized prestige subject to a cost hurdle (Rosenman, Li, & Friesner, 2000). They showed that California primary care clinics exhibited cost-shifting behavior in 1995. Because cost-shifting was observed, they claimed, clinics are most likely not profit-maximizing.

Cutler (1998) also used a model of utility-maximizing price setting to show that cost-shifting is expected when government reimbursement rates are cut (Cutler, 1998). Similar to those mentioned above, the Cutler paper found empirical evidence of cost-shifting during the 1980s. He also noted, however, that market power is an important variable to consider when testing for cost-shifting. This is discussed in greater detail below.

The ability of a hospital to shift costs depends on whether it can be excluded from insurance plans. If a hospital commands a high degree of market power and cannot be excluded from insurance plans, and assuming a utility-maximizing objective function, then cost-shifting can be observed. Hospitals may be shielded from threats of exclusion if they are prestigious or if they provide services that other hospitals do not. Similarly, a hospital that is geographically isolated from its nearest competitor also possesses the ability to deviate from competitive pricing. Ho (2009) observed that capacity constraints may also be a source of hospital leverage, as hospitals that operate at near-full capacity can command higher prices from insurers (Ho, 2009).

Insurer market power also plays a role in the pricing of hospital services. As alluded to above, an insurance plan that covers a large number of enrollees in a certain geographic area is able to negotiate for lower prices with hospitals. A hospital cannot afford be excluded from a plan that brings in a significant number of patients. Furthermore, such hospitals have a difficult time raising prices without risking the loss of an insurance plan's contract.

Since price discrimination requires market power, and since cost-shifting requires the ability to selectively set a variegated price schedule, cost-shifting is linked in some form to the market power of the provider. The intuition is simple. If government reimbursement rates are cut, a hospital with market power may have the ability to negotiate higher rates from private insurers (assuming a utility-maximizing function, a qualifier I will omit from now on). The ability to cost shift and the extent of the shifting is also dependent on insurer market power. If an insurer wields a high degree of market power, they may be able to resist upward negotiation of prices. Thus, the hospital would be forced to either accept lower revenue or otherwise change operations to compensate for shock.

IV. Data

The primary source of data for this analysis is the Annual Statewide Hospital Financial Trends published by the State of California's Office of Statewide Health Planning and Development. California is a common choice of data in health economics papers due to its state-mandated financial disclosure requirements. Each hospital in the state is assigned an identification number that is consistent over the reporting period, enabling the time-series analysis used below. Due to limitations on insurance and case mix data availability, I restrict my analysis to the five-year period of 2007-2011. Key variables of interest from this data set include: Net Government Revenue, Net Private Insurer Revenue, Government Patient Days, Private Patient Days, Type of Hospital, Type of Care, Severity-Weighted Case Mix, and Beds Available. Government Revenue is segregated by two main program types: Medicare and Medi-Cal, where Medi-Cal is the State of California's analogue to Medicaid.

Net Revenue for both Government and Private Insurer agents is calculated as Gross Patient Revenue plus Capitation Premium Revenue less Deductions from Revenue for each hospital. OSHPD guidelines

note that this amount is "more comparable than gross patient revenue because it indicates the actual amount received from patients and third party buyers" (OSHPD, 2005). In their empirical analysis of cost-shifting, McGuire and Pauly (1991) noted that hospitals might mask revenue shifts with shifts in volume (McGuire & Pauly, 1991). To incorporate these effects into my results, I also include patient days by category of payer as controls for volume. Patient days are defined as the number of census days that all formally admitted inpatients spent in the hospital during the reporting period. By the OSPHD reporting standards, if both admission and discharge occur on the same day, then one patient day is counted. Also important is that Nursery Days and Purchased Inpatient Days are excluded from the total count, presumably to control for non-revenue patient streams (in the case of the former) and non-comparable sources of patient days, such as drug and alcohol rehab (in the case of the latter).

The OSHPD data set includes information on "Type of Hospital" and "Type of Care" for each observation in the data set. Type of Hospital indicates whether "the hospital's report contains comparable data, or if the data are considered non-comparable due to reporting modifications granted by OSHPD or the hospital's unique operating characteristics" (OSHPD, 2005). Figure 2 below outlines the types of hospitals in the OSHPD dataset.

Number	Type
1	State
2	Comparable
3	Psychiatric
4	Kaiser
5	Long-Term Care
6	Non-Comparable

Figure 2: Type of Hospital Legend for OSHPD Data Set

Each category above is characterized by operating idiosyncrasies relevant in determining financial comparability. State hospitals provide care to the mentally disordered and developmentally disabled. Comparable hospitals "includes hospitals whose data and operating characteristics are comparable with other hospitals" (OSHPD, 2005). Psychiatric hospitals are licensed as Psychiatric Health Facilities, which are licensed to provide only mental health services. Kaiser hospitals are operated by the Kaiser Hospital

Foundation, with a funding model incomparable to investor-controlled or non-profit hospitals. Long-Term Care Hospitals tend to be larger facilities that provide palliative, hospice, or supervisory services. The final Type of Hospital, "Other Non-Comparable", includes hospitals with unique operating characteristics that may not charge for services provided, such as Shriner's Hospitals for Crippled Children (OSHPD, 2005).

Due to these differences in funding models, hospitals vary in the degree to which they receive government reimbursement. This variation is displayed in Figure 3 below.

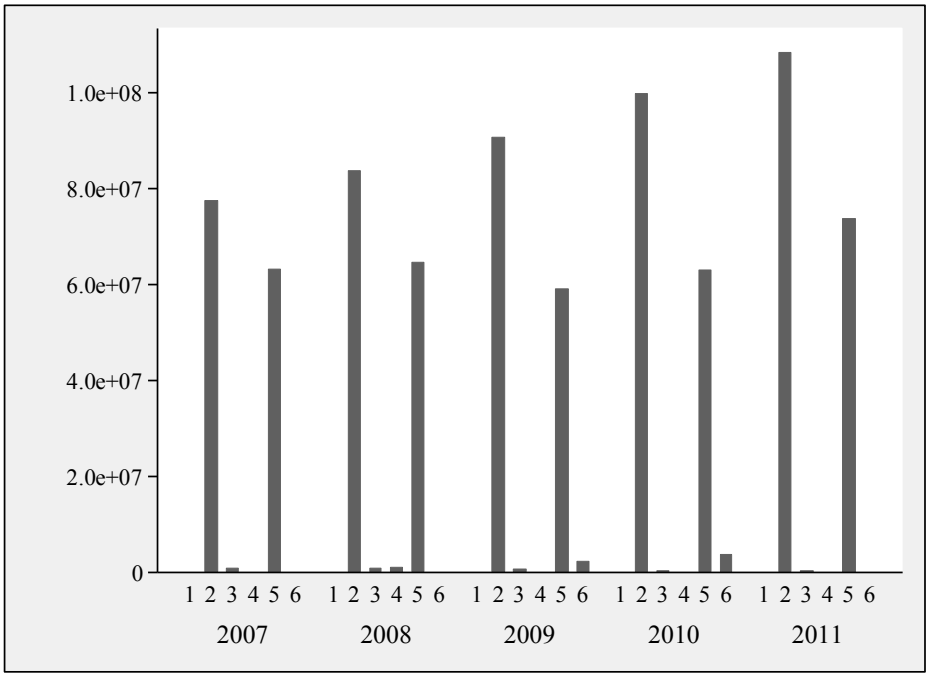

Figure 3: Variation in Government Revenue for Different Types of Hospital, 2007 - 2011

While "Comparable" and "Long-Term Care" hospitals each receive a consistently significant sum of revenue from government entitlement programs, Psychiatric, Kaiser, and Non-Comparable hospitals seem to manage with other arrangements. Curiously, State hospitals appear to receive no revenue from government entitlement programs. The OSHPD Guidelines make no mention of this peculiarity, but a likely possibility is that the hospitals' budgets are set by lump-sum payments from the State rather than a per-patient reimbursement through Medicare or Medicaid. Due to the complications of inter-Type

comparisons, I restrict my analysis of cost-shifting only to those hospitals designated as "Comparable" (i.e. Type 2) by OSHPD Guidelines.

Each hospital in the data set is also categorized by Type of Care, which "indicates the preponderance of care provided at the hospital" in one of four categories. These categories are shown in Figure 4 below.

Number	Type
1	General
2	Children's
3	Psychiatric
4	Specialty

Figure 4: Type of Care Legend for OSHPD Data Set

These delineations are generally intuitive, except for Number 4, which is includes "specialty hospitals, such as chemical dependency recovery hospitals and rehabilitation hospitals" (OSHPD, 2005). Government revenue varies across Type of Care, as shown in Figure 5.

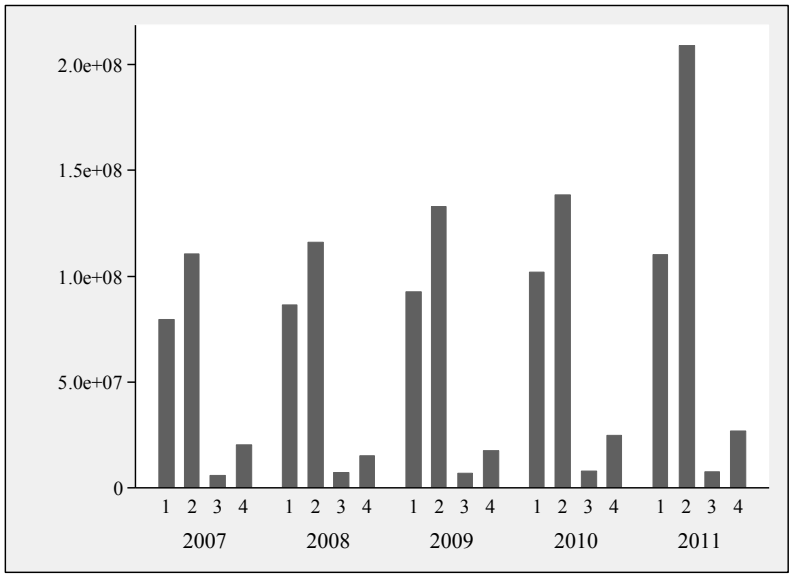

Figure 5: Variation in Government Revenue for Different Types of Care, 2007 – 2011

There is significant variation in average revenue across Type of Care, with the average Children's Hospital consistently generating more revenue than any other Type of Care class, and the average Psychiatric Hospital generating less. With no intuition for excluding any category, all Types of Care were considered in the regression analysis.

My analysis also controls for variation in the average severity and case mix between hospitals. The intuition is that hospitals may react to lower government reimbursement rates by shifting the types of services they offer, or by seeing patients with more or less severe complains. To incorporate these effects into the regression, I analyze the Severity-Weighted Case Mix Index (CMI) for each observation in the data set. As described in the introduction of this paper, DRGs are numerical values assigned to patients based on diagnosis as well as procedures performed, the presence of co-morbidity and/or complications, discharge status, and gender. DRGs can be weighted by severity to assist in budget calculations and financial benchmarking. An example of this weighting system is the Medicare-Severity DRG classification scheme. MS-DRGs are "based on resource consumption by Medicare patients, [but] OSHPD applies them to all patient discharge data reported by hospitals in California during the course of a calendar year. Weightings increase with "average hospital resource consumption", relying on the assumption that resource consumption is a valid proxy for complexity. Previous literature has suggested a relationship between complexity, severity, and average lengths of stay (Berki, Ashcraft, & Newbrander, 1984). Table 1 below compares MS-DRG Weights with arithmetic and geometric average length of stays, as calculated by the Centers for Medicare and Medicaid in 2010 (OSHPD, 2010):

Table 1: MS-DRG Weights are Highly Correlated with Severity and Complexity Metrics

	Weights	Average LOS Arithmetic Mean	Average LOS Geometric Mean
Weights	1.00	-	-
Average LOS Arithmetic Mean	0.33	1.00	-
Average LOS Geometric Mean	0.39	0.28	1.00

These results suggest that the MS-DRG weights are highly correlated with conventional severity metrics. Severity-Weighted Case Mix Index is calculated as the sum of MS-DRGs for all patients in a given hospital and for a given year, divided by the total number of patient days. Since MS-DRGs are

proportional to severity, the Case Mix Index is an increasing function in severity. Figure 6 below describes the Case Mix Index across Types of Care for the data set.

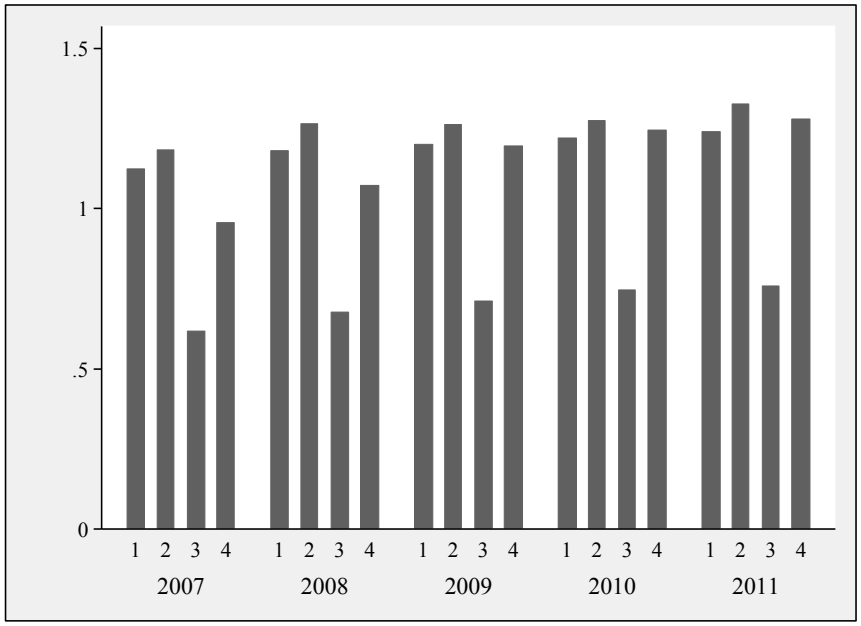

Figure 6: Variation in Severity-Weighted CMI Across Types of Care, 2007 - 2011

The average Case Mix Index across all hospitals is 1.22, with Specialty Hospitals tending to have more complex cases than any other type of hospital. This is expected; we can imagine a burn unit or a microsurgery outpatient center attracting patients with the gravest (and costliest) illnesses.

In theory, hospitals with greater market power may be able to wrestle more money from private insurers in response to decreased government reimbursement rates. However, there is also an entire body of literature concerned with market definition from hospitals. To incorporate these effects, I calculated the Herfindahl-Hirschman Index, or HHI, for each Health Service Area in the data set based on the number of available beds at a hospital. HHI is calculated as the sum of the squared market shares of all competitors in a given market. For example, if Market A has two competitors, each with 50% market share, HHI for that market equals $0.50^2 + 0.50^2 = 0.50$. The maximum HHI for any market is 1, which would indicate that the market is served by a single pure monopolist. Similarly, an HHI of 0 indicates perfect competition. Health Service Areas, or HSAs, are local health care markets for hospital care. They are defined as a collection of zip codes whose residents receive most of their hospitalizations from the

hospitals in that area. Figure 7 below shows the boundaries of the fourteen California HSAs as of 2013 (Dartmouth, 2013):

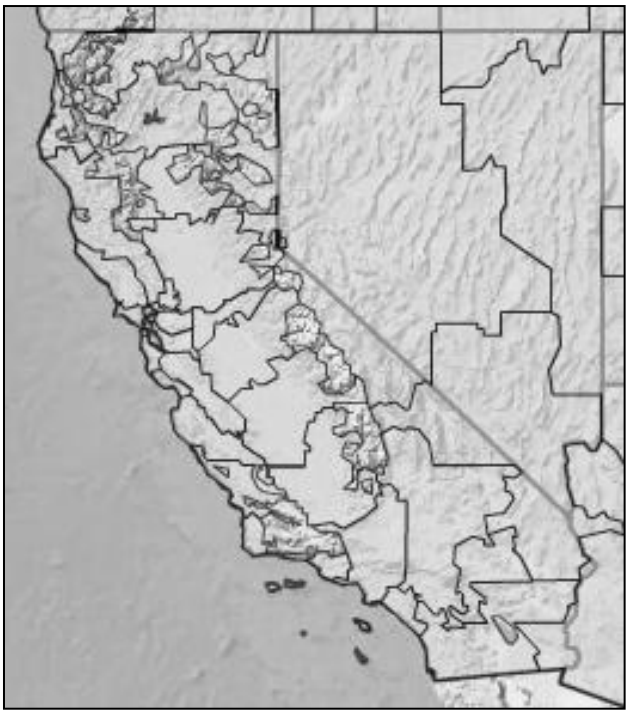

Figure 7: Map of California and Nevada Health Service Areas

The size of HSAs varies across the state, with smaller areas being associated with urban centers of high population density. It should be noted that parts of Northeastern and Southwestern California share HSAs with Oregon and Nevada, respectively. In order to control for state-level variation, these areas were not included in the regression analysis.

To incorporate the effects of market power, I mapped each hospital in a given HSA to the market concentration for that HSA. These HHI values vary significantly between hospitals, as shown in Figure 8.

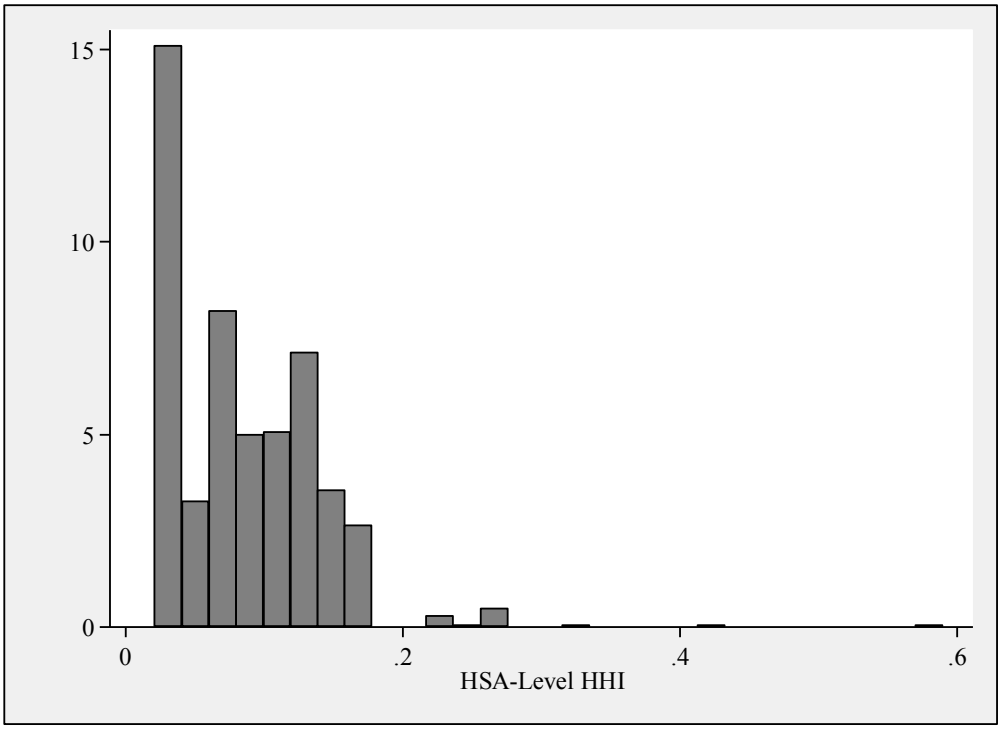

Figure 8: HSA-Level Market Shares for All Hospitals, 2007 – 2011

The majority of hospitals were not located in concentrated areas (i.e. HHI > 0.18), although there were enough to continue with the analysis. While this model satisfies a crude proxy for market share, there are considerable drawbacks. Consider a land mass in the shape of a simple square. Then, consider a vertical line bisecting this square vertically, and another bisecting the square horizontally. Call each square an HSA. Also consider four hospitals, one located in each HSA in the corner furthest away from the perimeter. Using the methodology I have described above, I would conclude that each hospital is in a highly concentrated market, as there are no other hospitals in its HSA. This is clearly not accurate, as there are nearby hospitals that are in different HSAs. This observation motivated additional calculations of market concentration.

For robustness, I calculate market concentration using the variable radius method, a procedure described in Elzinga and Hogarty (1973). I obtained additional data from OSHPD containing the zip code of patient residence and street address of hospital visited for each patient-hospital visit combination in California from 2007 - 2011. With this data, I was able to calculate the circular radius that would be required to encompass 60% of all of the residences of patients that visited a given hospital in a given year.

I then determined the number of hospitals within that variable radius, and then calculated the associated market share based on beds available. Figure 9 displays the distribution of this new market share data.

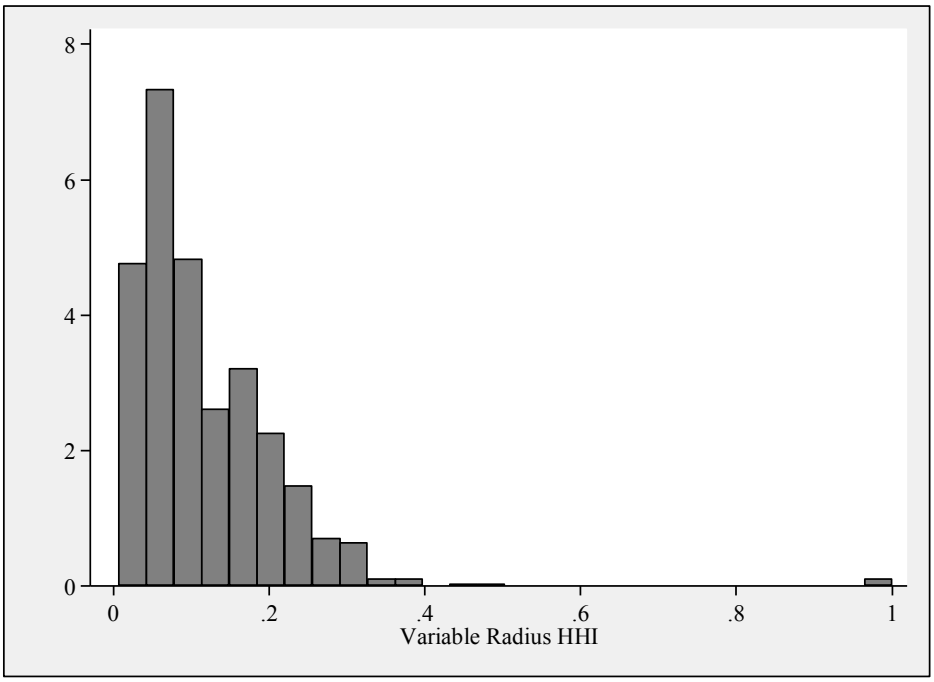

Figure 9: Variable Radius Market Shares for All Hospitals, 2007 – 2011

These results showed a significantly greater proportion of hospitals with higher market concentration. Due to the differences in the distributions between the two methodologies, all results were calculated using market shares derived at the HSA-Level as well as the 60th percentile radius.

In order to control for the effects of insurer concentration on cost-shifting, I utilized data from the American Medical Association's Annual Report on Competition in Health Insurance (AMA, 2007). The AMA calculates county-level HHI by dividing each insurer's individual enrollment into the sum of all insurers' enrollment for each HSA, then summing the squared market shares for each individual county. To derive an HSA-level HHI, I averaged the HHI of counties located within each HSA, as determined by the OSHPD Annual Financial Disclosure Report. This is an admittedly crude measure to calculate market share. The first is that insurance is not a good that is "bought" in the sense that a consumer must travel to a physical location to engage in a transaction. A patient in San Diego may be covered by a health insurance company based out of Sacramento. Secondly, the HHI calculation relies on assumptions about

transferability of goods across arbitrary geographic boundaries. More specifically, to define a county as a "market" implies that there is a certain access to that good for those within the county that is not available to outsiders. Also, I find the OSHPD classification of each county as existing wholly within a single HSA as doubtful. Given that HSAs are determined at the zip code level, the geospatial assumption that is implicitly made in the OSHPD data is likely flawed. However, without data about insurer concentration at the zip code level (a silly metric, given the nature of the insurance "good"), there were little alternatives but to use the OSHPD classification.

Additional limitations to the AMA data have been expounded upon in previous literature. In the Robert Wood Johnson Foundation white paper, "Consolidation in Health Care Markets", authors David Balto and James Kovacs note that the data "does not accurately capture overall enrollment, demonstrates an implausible pattern of volatility over time, and [displays] state-level concentration [that is] significantly higher than other data" (Balto, 2013). Recent research based on proprietary private sector data has overcome many of the limitations to the AMA methodology (Dafny, 2010). Given my lack of access to this proprietary data, I accepted the AMA calculation with its flaws and incorporated insurer market concentration into the regression analysis.

My analysis was further limited by an inability to measure either government reimbursement rates or private prices directly. A more accurate cost-shifting analysis would show how prices themselves changed over time, not revenue with a volume proxy. I addressed this obstacle in two ways. First, I noted that a hospital's ability to increase revenue through volume is naturally limited by its physical capacity. Indeed, I found that patient volume was relatively invariant on average, which enables the interpretation of revenue as a proxy for price. This is displayed in Figure 10 on the next page, which shows the average patient days for all hospitals.

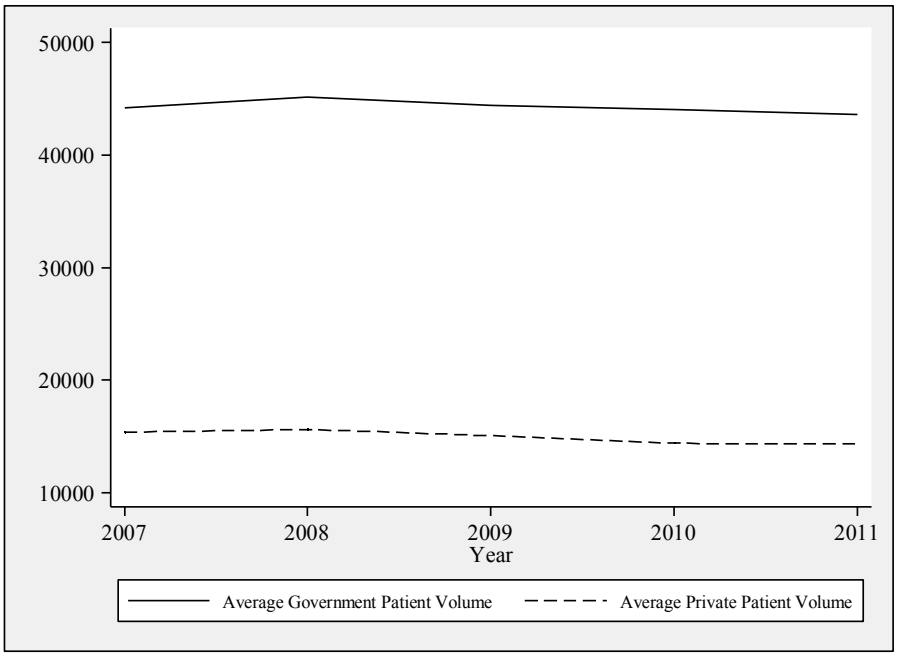

Figure 10: Invariance of Average Patient Days by Payer, 2007 – 2011

To ensure that the stationary mean was due to invariance of measurements for individual hospitals (rather than fluctuating volumes with equal but opposite magnitude that result in a stable aggregate), I regressed Government Patient Days and Private Patient Days separately on the Year variable, including fixed effects at the provider level (results not shown) . In the case of the former, the Year coefficient was less than 0.02% of the constant, with a standard error less than 2% of the Year coefficient. These values were 0.05% and 4.5%, respectively, for the Private Patient Days regressions. These results indicate that Government and Private volume is relatively invariant, even at the individual provider level. However, it is possible that while overall volume does not fluctuate, the mix of government and private payers changes in response to price variation. To internalize these effects in the model, I included the ratio of private payer patient days to public payer patient days (where "patient days" are defined according to the guidelines above) as a covariate.

Finally, to ensure that regressions were comparable, I cleaned the data in the following manner. Hospitals that derived no revenue from either public or private sources (that is, hospitals funded either solely by public funds or by private funds) were excluded from the analysis. Hospitals with missing variables in any year were excluded from the regressions for all years. All county and district hospitals

were excluded from the data. Finally, hospitals with duplicate listings in any single year were also excluded from the regressions for all years. Along with the changes described above, these cuts reduced the raw data set from 2245 observations to 850.

V. Empirical Specification

V.1. Historical Precedent and Current Motivation

Cost-shifting is only possible if hospitals do not maximize profit. Consequently, it is no surprise that claims of shifting are received skeptically by the academic community. Even so, however, empirical findings implying a cost-shifting-like phenomenon have been reported in the literature. Table 2 below provides a summary of recent empirical studies relevant to this paper.

Table 2: Recent Comparable Empirical Work on Cost-Shifting

Author (Year)	Percent increase in private payments for 1% decrease in public payments	Comments on Market Power
Clement (1997/1998)	0.03 (Medicare) , 0.02 (Medi-Caid), decrease over time	Hospital competition did not influence cost shifting
Dranove and White (1998)	No evidence of cost shifting	Employed hospital competition controls, did not test for effect on shifting
Cutler (1998)	1 (i.e. dollar-for-dollar, Medicare)	Urban = proxy for high hospital competition. Effect doubled (i.e. two dollar increase in private prices for every dollar decrease in Medicare reimbursement) when including rural hospitals.
Zwanziger, Melnick, and Bamezai (2000)	0.17-0.58, depending on market concentration	Larger changes for not-for-profit in less competitive markets than those in more competitive markets; other comparisons almost universally insignificant
Friesner and Rosenman (2002)	Non-profits cost shift, for-profits do not, both shift service-intensity	No competition controls
Zwanziger and Bamezai (2006)	0.17 (Medicare), 0.04 (Medicaid)	No significant relationship beween competitiveness of a hospital's market and strength of relationship between prices paid by privately insured patients and those paid by Medicare/Medicaid patients
Wu (2009)	0.37 (Medicare), measured using natural experiment of Balanced Budget Act of 1997	More shifting for more competitive markets and for for-profit hospitals

Note: Table borrows from Frakt (2011) review of cost shifting literature

For those papers that found cost-shifting, the magnitude of the change in the private metric associated with a 10% decrease in the public metric varied widely. For example, while Dranove and White (1998) showed no evidence of cost-shifting in their cross-sectional study of California hospitals, Cutler (1998) showed that hospitals nation-wide shift at least on a dollar-for-dollar basis, an effect that nearly doubles for hospitals with high market power. More recently, Zwanziger (2006) found that California hospitals in the 1990s shifted 1.7% of every 10% cut in government reimbursement. Given that there is much overlap of data (with many studies using OSHPD data from California), the differences in findings are likely a function of control variables and time effects. Theoretical literature on cost-shifting literature suggests that decreases in government reimbursement rates may be confounded by changes in operational characteristics specific to each hospital. Hospital and insurer market power theoretically exacerbate and attenuate the phenomenon, respectively (although the provider effect is inconsistent, as shown in Table 2 above). Even beyond these higher-level hospital characteristics, changes to patient mix may also be affected by decreases in reimbursement rates. The "mix variables" cited most often include volume, quality, cost, case-mix, and severity of patients admitted. The analysis below controls for the majority of these variables, as is discussed in the next sub-section.

As a benchmark case, I used OSHPD data spanning 2007-2011 to show the relationship between revenue from public payers and revenue from private payers for each relevant hospital in California. The results are shown in Figure 11.

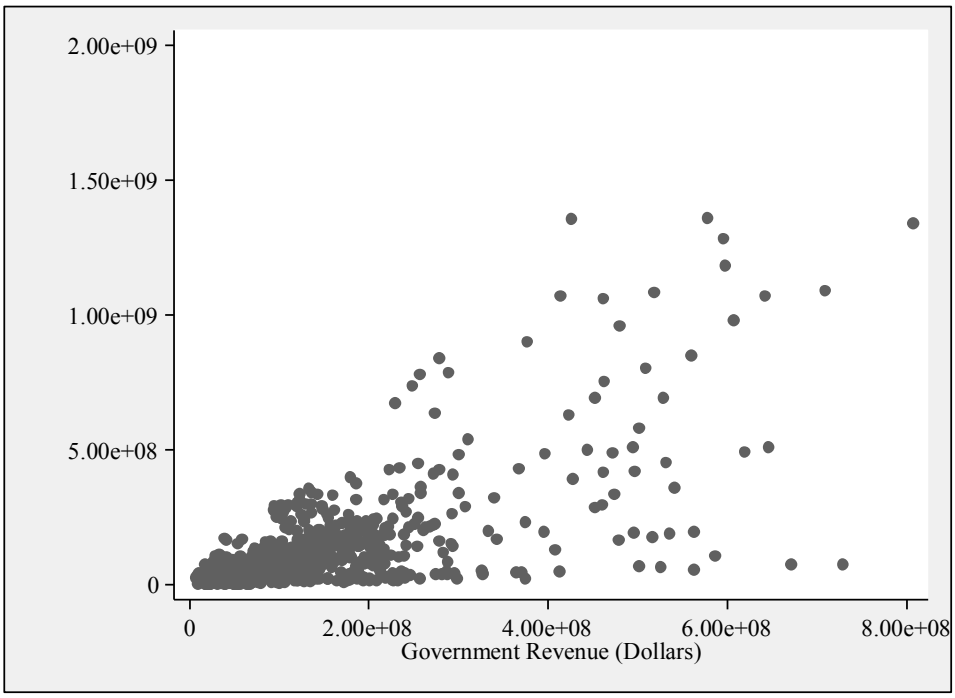

Figure 11: Government Revenue and Private Revenue Have a Weakly Positive Correlation

These results show a clear weakly positive relationship between private revenue and public revenue for each hospital, suggesting that no shifting occurs. It should be noted, however, that the mechanism through which cost-shifting occurs (if at all) is through differential pricing by providers. Phrased differently, cost-shifting occurs if a hospital increases the revenue it takes in from private payers in response to a decrease in the revenue it takes from government payers, controlling for the volume of patients insured by each payer-type, respectively. With this in mind, I qualified the benchmark case by regressing private revenue on government revenue using a logarithmic specification for proportionality, and controlling for the number of patient days for each insurance type. I included no controls other than provider-level fixed effects and the ratio of private patient days to public patient days, with the latter used to provide some context for the change in price (which is ultimately the channel through which cost-shifting occurs). More specifically, an inverse relationship between private revenue and government revenue controlling for changes in volume indicates a similar relationship between private and government prices. The results are shown in Table 3 below.

Table 3: Government and Private Revenue Vary Together, 2007 - 2011

ln(Private Revenue)	Coefficient	Standard Error
ln(Government Revenue)	0.59	(0.05)***
Volume Ratio	1.37	(0.14)***
Constant	6.55	(0.95)***

Note: Volume Ratio defined as (Private Insurer Patient Days / Government Insurer Patient Days)
* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

These results corroborate Figure 10, implying that cost-shifting did not occur in California hospitals from 2007 – 2011. In fact, a 10% decrease in revenue from government healthcare programs was actually associated with a 5.9% decrease in revenue from private insurers, controlling for volume of patients enrolled in each insurance type. Indeed, Zwanziger (2006) predicted that cost-shifting would disappear in the future as hospitals became more competitive, and Cutler (1998) predicted the same result due to an increase in insurer market power. With no further analysis, it would seem that cost-shifting in California hospitals has disappeared, if it even occurred in the first place.

To properly test if these initial results hold true, I specified a model that controls for a number of potentially-confounding variables. I also included fixed effects to control for time and provider level idiosyncrasies. The dependent variable was constructed as the net revenue from privately-insured patients for a given provider h in a given year t. The independent variables are described in detail in the following section.

V.2. Original OLS Model

The regression model described below was constructed using a fixed-effects OLS specification in order to reproduce the cost-shifting results found in previous studies. In order to simplify interpretation of the coefficients, I used natural logarithms to transform all dollar-denominated variables. The resulting empirical model for predicting private revenue is specified as described in Table 4.

Table 4: Independent Variables for LHS, "Hospital Revenue from Private Payers"

(1)	Hospital Revenue from Government Healthcare Programs
(2)	Hospital Revenue from Government Healthcare Programs x Insurer High Concentration Dummy (HHI > 1800)
(3)	Hospital Revenue from Government Healthcare Programs x Provider High Concentration Dummy (HHI > 1800)
(4)	Hospital Revenue from Government Healthcare Programs x For-Profit Status Dummy (1 for For-Profit, 0 Otherwise)
(5)	Hospital Average Cost
(6)	Volume Ratio (Private Patient Days / Public Patient Days by Payer Type)
(7)	Severity-Weighted Case Mix Index
(8)	Type of Care Dummy
(9)	Year Dummy
(10)	Hospital Fixed Effects

The variable that anchors my model is "Hospital Revenue from Government Healthcare Programs". I chose the remaining independent variables by using the literature to selectively compile a list of characteristics that differentiate hospitals from one another. This list was grouped into two categories: variables that have been theoretically shown to affect a hospital's pricing power and those that are simply hospital idiosyncrasies[2]. The latter group encompasses Variables 5 – 10, which were employed as controls to isolate differences in the correlation between government and private revenue across differences in hospital operational characteristics and patient mixes. My analysis is not concerned with the statistical significance or signs of these variables. The remaining variables are discussed in further detail below.

Variables 2 – 4 were created by interacting Variable 1 with those variables deemed as affecting hospitals' pricing power; namely, insurer market power, provider market power, and for-profit status. Insurer and provider market power were represented by dummy variables for "highly concentrated market" as determined by the U.S. Department of Justice (Horizontal Merger Guidelines, 1997).

Similarly, for-profit status was represented by a dummy variable, with 1 denoting a for-profit hospital and 0 denoting a non-profit hospital (county, district, and state hospitals were excluded). I expected that Variable 2 would have a positive sign, attenuating the correlation between government revenue and private revenue. This would indicate that private insurers with more market power are able to resist cost-

[2] I make the implicit assumption that the type of care that a hospital provides does not affect its pricing power. Also, while "hospital average cost" may be taken as a crude proxy for quality, which, in turn, may affect a hospital's pricing power, this relationship is not forced for this analysis.

shifting. Analogously, Variable 3 should have a negative sign, as those providers with more market power should be able to shift costs to a greater extent. I make the assumption that for-profit hospitals are, indeed, profit-maximizing; thus, I expect the coefficient on Variable 4 to be close to zero.

Variables 1-4 are most relevant for testing for the presence of cost-shifting. More specifically, I am interested of the LHS variable, "Hospital Revenue from Private Payers", with respect to "Hospital Revenue from Government Payers". The derivative was evaluated at the mean of each interacted variable (i.e. Insurer High Concentration Dummy, Provider High Concentration Dummy, and For-Profit Status Dummy). A negative value would indicate that there is an inverse correlation between government revenue and private revenue, implying cost-shifting. I determined the joint significance of Variables 1 – 4 with an F-test to validate these results. I also determined the joint significance of Variables 2 – 4 alone, which tests whether the combined effect of hospital market power, insurer market power, and for-profit status has a significant effect on the correlation between government revenue and private revenue. A lack of statistical significance would indicate that these variables have no effect on cost-shifting, or, more likely, the effect is more complex than modeled above.

High multicollinearity between variables would indicate that the model is overspecified and would inflate standard errors. Figure 12 shows correlation coefficients between all variables of interest.

	ln(Government Revenue)	ln(Hospital Average Cost)	Hospital Market Share	Insurer HHI	Case Mix Index	Volume Ratio
ln(Government Revenue)	1.00					
ln(Hospital Average Cost)	0.33	1.00				
Hospital Market Share	-0.06	0.02	1.00			
Insurer HHI	0.06	0.18	0.05	1.00		
Case Mix Index	0.29	0.54	-0.04	0.13	1.00	
Volume Ratio	0.02	0.20	-0.03	-0.01	0.16	1.00

Figure 12: Acceptable Level of Correlation between Covariates of Interest

These results indicate that collinearity is not an issue in the regression model. It should be noted, however, that Severity-Weighted Case Mix Index is modestly correlated with Hospital Average Cost. This makes intuitive sense; sicker patients need more complex procedures, which can be costly. According to Princeton Data and Statistical Services, correlation coefficients higher than 0.7 between any two variables are considered prohibitively collinear for a robust analysis (Abrams, 2007). Given this definition, the model is not overspecified as is, and no variables need to be dropped due to collinearity.

VI. Results and Discussion

VI.1. Initial Results Corroborate Previous Cost-Shifting Literature

Tables 5 and 6 show the regression results of the OLS model specified in Section V.2. The main coefficients of interest were ln(Government Revenue) as well as "All Government Revenue Variables, Derivative Evaluated at Means". I refer to these in the discussion as the individual COI and joint COI (for "coefficient of interest"), respectively. The joint COI indicates the combined effect of Government Revenue and its interaction terms on Private Revenue, while the individual COI indicates the effect of Government Revenue net of interaction terms.

There are two main purposes to this section. The first is to frame my results (where applicable) in the context of previous cost-shifting literature. The second is to use the initial results, particularly regarding the statistical significance of the interaction terms, to explore revisions to the original OLS model. I construct a revised model in Section VI.2 and use it to submit a best point estimate of the correlation between government revenue and private revenue.

Individual and Joint Significance of Cost-Shifting Coefficients

Of the four combined-payer cost-shifting regressions (Tables 5 and 6; R.3, R.6, R.9, R.12), all had individual and joint COIs that were negative and statistically significant. R.3 and R.6 had joint COIs that were consistent across the HSA-level and variable radius method of measuring market share, implying that a 10% decrease in government revenue was correlated with an increase in private revenue of 4.6% and 4.1%, respectively. This magnitude is consistent with Zwanziger (2000) and Wu (2009), both of whom used California data from the 1980s and 1990s, respectively. Furthermore, both coefficients were strongly significant as determined by an F-test.

The COIs in the split-program analysis (R.9, R.12) were consistent with the results above. The joint COI on Medicare implied that a 10% decrease in Medicare revenue was correlated with an increase in private revenue of 1.7% and 1.8% using the HSA- and variable radius methods (R.9 and R.12, respectively). The same regressions show that a 10% decrease in Medi-Cal revenue was

Table 5: Combined Payer OLS Regression

	(1)	(2)	(3)	(4)	(5)	(6)
	HSA-Level Market Share			Variable Radius Market Share (60th Percentile)		
ln(Private Revenue)	Traditional Care (TC)	Managed Care (MC)	Combined	Traditional Care (TC)	Managed Care (MC)	Combined
ln(Government Revenue)	-0.523	-0.084	-0.449	-0.597	-0.080	-0.437
	(0.13)***	(0.07)	(0.08)***	(0.13)***	(0.07)	(0.08)***
ln(Government Revenue) x Insurer High Concentration Dummy	0.005	-0.001	0.005	0.000	0.000	0.005
	(0.00)	(0.01)	(0.00)**	(0.00)	(0.01)	(0.00)
ln(Government Revenue) x Provider High Concentration Dummy	-0.019	0.011	0.002	-0.002	0.003	0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
ln(Government Revenue) x Provider For-Profit Dummy	-0.004	-0.036	-0.005	-0.004	-0.032	-0.002
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
All Government Revenue Variables, Derivative Evaluated at Means	-0.519	-0.094	-0.445	-0.599	-0.088	-0.433
Prob > F (Government Revenue + Interactions)	(0.000)***	(0.328)	(0.000)***	(0.00)***	(0.499)	(0.000)***
Prob > F (Interactions)	(0.359)	(0.398)	(0.169)	(0.980)	(0.530)	(0.282)
ln(Hospital Average Cost)	-0.665	-0.786	-0.650	-0.914	-1.040	-0.797
	(0.27)**	(0.28)***	(0.15)***	(0.29)***	(0.29)***	(0.16)***
Severity-Weighted Case Mix Index	-0.165	0.208	-0.035	1.067	0.505	0.371
	(0.45)	(0.46)	(0.25)	(0.54)	(0.55)	(0.29)
Volume Ratio (Private Patient Days / Payer Patient Days)	2.887	0.010	0.486	2.879	0.009	0.589
	(0.31)***	(0.01)	(0.15)***	(0.32)***	(0.01)	(0.16)***
Constant	-108.162	-273.731	-245.384	-122.638	-276.908	-239.242
	(55.72)*	(56.63)***	(31.72)***	(57.66)**	(57.78)***	(31.43)***
R^2 (within; between; overall)	0.146 ; 0.123 ; 0.067	0.063 ; 0.019 ; 0.009	0.160 ; 0.254 ; 0.209	0.155 ; 0.123 ; 0.062	0.066 ; 0.052 ; 0.031	0.173 ; 0.262 ; 0.212
N=	850	850	855	805	805	810

Note: Parentheses Denote Standard Errors, Except Where Noted. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$
Control Variables Not Displayed in Output: Type of Care Dummy, Year Dummy

Table 6: Split Payer OLS Regression

	(7)	(8)	(9)	(10)	(11)	(12)
	HSA-Level Market Share			Variable Radius Market Share (60th Percentile)		
ln(Private Revenue)	Traditional Care (TC)	Managed Care (MC)	Combined	Traditional Care (TC)	Managed Care (MC)	Combined
ln(Medicare)	-0.256	0.052	-0.220	-0.278	0.089	-0.194
	(0.13)**	(0.07)	(0.08)***	(0.13)**	(0.08)	(0.08)**
ln(Medicare) x Insurer High Concentration Dummy	-0.058	0.017	-0.005	-0.065	0.004	-0.013
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)
ln(Medicare) x Provider High Concentration Dummy	0.095	-0.014	0.065	-0.023	-0.060	-0.019
	(0.44)	(0.07)	(0.21)	(0.06)	(0.04)	(0.04)
ln(Medicare) x Provider For-Profit Dummy	-0.135	0.041	0.132	-0.108	0.011	0.131
	(0.09)	(0.08)	(0.07)*	(0.09)	(0.08)	(0.07)**
ln(Medi-Cal)	-0.228	-0.024	-0.085	-0.245	-0.042	-0.095
	(0.06)***	(0.06)	(0.05)	(0.07)***	(0.07)	(0.05)**
ln(Medi-Cal) x Insurer High Concentration Dummy	0.066	-0.020	0.010	0.068	-0.005	0.018
	(0.04)	(0.04)	(0.03)	(0.04)	(0.05)	(0.03)
ln(Medi-Cal) x Provider High Concentration Dummy	-0.123	0.030	-0.066	0.025	0.066	0.022
	(0.48)	(0.07)	(0.22)	(0.07)	(0.05)	(0.04)
ln(Medi-Cal) x Provider For-Profit Dummy	0.145	-0.076	-0.135	0.120	-0.042	-0.131
	(0.10)	(0.08)	(0.07)*	(0.10)	(0.08)	(0.07)*
All Medicare Revenue Variables, Derivative Evaluated at Means	-0.319	0.075	-0.174	-0.368	0.083	-0.176
Prob > F (Medicare Revenue + Interactions)	(0.009)***	(0.668)	(0.062)**	(0.005)***	(0.495)	(0.067)*
Prob > F (Interactions)	(0.273)	(0.911)	(0.282)	(0.306)	(0.581)	(0.233)
All Medi-Cal Revenue Variables, Derivative Evaluated at Means	-0.161	-0.055	-0.128	-0.148	-0.044	-0.109
Prob > F (Medi-Cal Revenue + Interactions)	(0.009)***	(0.491)	(0.014)**	(0.005)***	(0.497)	(0.013)**
Prob > F (Interactions)	(0.234)	(0.691)	(0.293)	(0.299)	(0.505)	(0.244)
ln(Hospital Average Cost)	-0.684	-0.712	-0.637	-0.960	-0.943	-0.781
	(0.28)**	(0.28)**	(0.16)***	(0.30)***	(0.30)***	(0.16)***
Severity-Weighted Case Mix Index	-0.172	0.157	-0.040	1.078	0.368	0.394
	(0.47)	(0.46)	(0.26)	(0.55)	(0.55)	(0.29)
Volume Ratio (Private Patient Days / Payer Patient Days)	0.308	0.014	0.448	0.637	0.014	0.527
	(0.05)***	(0.01)	(0.15)***	(0.08)***	(0.01)	(0.16)***
Constant	-124.288	-256.678	-231.134	-132.990	-255.925	-223.310
	(57.62)**	(57.98)***	(32.27)***	(58.07)**	(59.23)***	(31.92)***
R^2 (within; between; overall)	0.094 ; 0.217 ; 0.144	0.067 ; 0.0.033 ; 0.036	0.150 ; 0.245 ; 0.194	0.150 ; 0.159 ; 0.086	0.071 ; 0.006 ; 0.010	0.163 ; 0.219 ; 0.169
N=	850	850	855	805	805	810

Note: Parentheses Denote Standard Errors, Except Where Noted. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$
Control Variables Not Displayed in Output: Type of Care Dummy, Year Dummy

correlated with an increase in private revenue of 1.3% and 1.1% using the HSA- and variable radius methods, respectively. The HSA-level coefficients were statistically significant at the 5% level, while those measured by the variable radius method were consistent at the 10% and 5% level for Medicare and Medi-Cal, respectively. These magnitudes are consistent with Zwanziger (2006). While these terms were by and large statistically significant, the F-test for joint significance of only the interaction terms for all regressions R.1 – R.12 failed at any reasonable level of statistical significance. This result is explored in the next sub-section.

As a robustness check, I attempted to determine the predictive power of government revenue on a hospital's volume of patients privately insured as well as its severity-weighted case mix index. A significant negative relationship in the former would contradict the cost-shifting hypothesis, suggesting instead that hospitals engage in dynamic customer acquisition. In other words, a hospital facing lower reimbursement rates may pursue contracts with privately-managed HMOs or PPIs more aggressively in order to secure patients with higher reimbursement and/or capitation rates. In the case of the latter, a hospital may elect to see patients with more severe ailments and who are more likely to require follow-up visits and tack-on procedures. Alternatively, a hospital may admit patients with simpler complaints in order to decrease their costs to stabilize profit margins. Either effect would be captured by the proposed regression, and would provide an alternative interpretation of the cost-shifting coefficients in Tables 5 and 6. Tables 7 and 8 below show the results of these respective tests.

Table 7: Government Revenue Does Not Predict Volume of Privately-Insured Patients

ln(Private Volume)	
ln(Government Revenue)	0.215
	(0.06)***
ln(Hospital Average Cost)	-0.986
	(0.13)***
Hospital Market Share	0.580
	(0.48)
Insurer HHI	0.182
	(0.44)
Case Mix Index	0.708
	(0.23)***
Constant	24.610
	(26.96)
R^2 (within; between; overall)	0.187 ; 0.069 ; 0.073
N=	855

Table 8: Government Revenue Does Not Predict Case-Mix of Privately-Insured Patients

ln(Case Mix Index)	
ln(Government Revenue)	0.016
	(0.01)
ln(Hospital Average Cost)	0.086
	(0.02)***
Hospital Market Share	-0.091
	(0.10)
Insurer HHI	0.059
	(0.06)
Volume Ratio	0.000
	(0.02)
Constant	-34.694
	(3.63)***
R^2 (within; between; overall)	0.513 ; 0.290 ; 0.262
N=	855

Table 7 shows that private volume increases proportionally with government revenue, and the relationship is statistically significant. Table 8 shows that severity-weighted case mix index does not have a statistically significant relationship with government revenue. Combined with Tables 5 and 6, these results suggest that the inverse correlation does occur along financial metrics and not patient-mix metrics (such as volume or case-mix index).

To further validate the results in Tables 5 and 6, I considered the effects of the interaction terms on the cost-shifting coefficients. In the next sub-section, I explore the individual and joint significance of these terms, and the implications the results have on the revised model.

Individual and Joint Significance of Interaction Terms

As described in the empirical specification, a negative coefficient on the hospital market power interaction term would be consistent with cost-shifting. Of the 18 coefficients on the ln(Government Revenue) x Provider High-Concentration interactions in Tables 5-6:R.1 – R.12, ten were negative and eight were positive, and none were statistically-significant. These results indicate that hospital market power has no effect on the correlation between private revenue and government revenue. Adjusting for differences in means, it appeared that the market-share interaction coefficients varied widely between the two methods of measurement (i.e. HSA-level and Variable Radius). A visualization of these differences is shown in Figure 13 below.

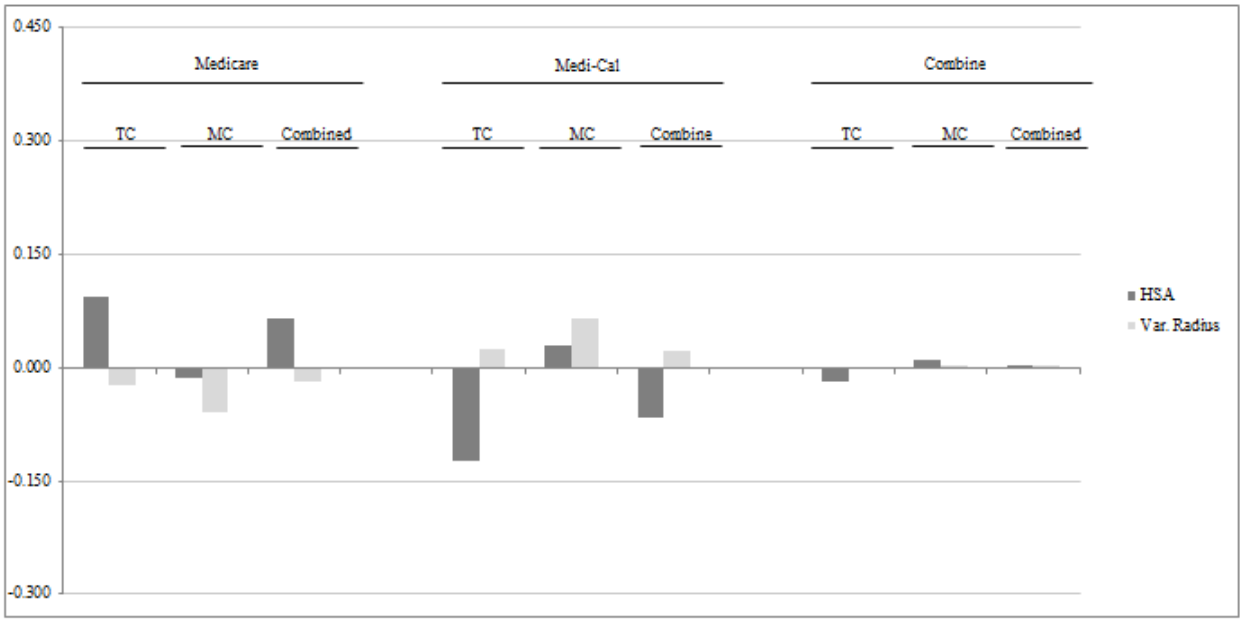

Figure 13: Inconsistent Mean-Adjusted Market Power Coefficients, Irrespective of Provider Market Concentration Measurement Methodology

The inconsistency in coefficient signs and magnitude, as well as the lack of significance discussed previously, indicate that provider market power does not have an effect on the correlation between private and public revenue. Other explanations are more likely. First, it should be noted that the hospital market power may be endogenous to the amount of private revenue generated. For example, a well-to-do hospital generating significant sums of revenue from private insurers may use that money to invest in more beds available for patients. Using the measurement methodology above, this would be recorded as an increase in market power for the hospital. Given this ambiguity in causality, future research should consider measuring market power based on predicted patient admittances to hospitals, using the method described in Kessler and McLellan (2000).

Moriya et al. showed that insurer market power contributed to a decrease in hospital prices, indicating an erosion of hospital negotiating power. As described in the empirical specification, a positive coefficient on the insurer market power interaction would be consistent with cost-shifting, indicating that hospitals with little bargaining power relative to private insurers cannot mitigate decreases in government reimbursement rates by increasing private prices. My results did not support this hypothesis. Of the 18

coefficients on the ln(Government Revenue) x Insurer High-Concentration interactions in R.1 – R.12, seven were negative and eleven were positive. Only one was statistically significant, but only weakly so (R.3). These results indicate that insurer market power has no effect on the correlation between private revenue and government revenue, inconsistent with cost-shifting. A likelier explanation is that the statistical significance was masked by an incorrect measurement of insurers' market power. As described in Section V above, the AMA calculates insurer market power using a method more reserved for vendors of physical goods. A more robust analysis would use the percentage of patients at each hospital enrolled in a given insurance plan. This would be most indicative of insurer pricing power at the hospital level, which is ultimately the variable of interest in examining the inverse correlation between government revenue and private revenue.

Zwanziger (2000) hypothesized that "for-profit hospitals will not increase prices for privately insured patients in response to reductions in [government] payment rates". Since these for-profit hospitals maximize profit, they should not be able to cost-shift. My results were inconclusive regarding this hypothesis. Of the 18 coefficients on the ln(Government Revenue) x For-Profit Status Dummy interaction terms in R.1 – R.12, fourteen were not statistically significant. The remaining four coefficients were calculated for the combined-payer split-program analysis using the HSA-level and variable radius methodologies to measure provider market shares (R.9 and R.12, respectively). There is no economic reason to believe that for-profit hospitals would react differently to Medicare cuts than to Medi-Cal cuts. In fact, if a hospital is truly profit-maximizing, these effects should not be observed. These outliers are likely produced by spurious correlation, and I view the weak statistical significance with skepticism.

All tests for joint significance of only the interaction terms were not statistically significant at any reasonable level of significance. As noted above, many of the underlying variables were also insignificant when considered alone as well. While theoretical studies of cost-shifting have suggested hospital/insurer market power and for-profit status as variables of interest, the empirical support is inconclusive. For example, Moriya (2010) found that hospital market power had a statistically insignificant effect on hospital prices, and Zwanzinger (2000) noted that, except for non-profit hospitals in concentrated markets, competition had an effect that was "almost universally statistically insignificant" (Moriya et al., 2010; Zwanziger, Melnick, & Bamezai, 2000). Wu (2009), however, found that more shifting occurred for hospitals in urban environments, which contradicts traditional theory—that is, more competition equals less shifting. My results suggest that while hospital market power, insurer power, and for-profit status may have a role in cost-shifting, the exact nature is more complex than has been captured by both

this work as well as previous studies. Given these results, I revised the model by dropping the interaction terms (along with the other changes described later in this section). The resulting model is described in greater detail in Section VI.2.

A Comparison of the Traditional Care and Managed Care Regressions

Both the individual and the joint COIs for traditional care were more negative and more significant than those of managed care for all regressions performed. This was consistent with the Zwanziger (2000) hypothesis that "with managed care plans accounting for a growing proportion of patients, and exerting more pressure on hospital revenues, cost-shifting will decline over time in more competitive markets" (p. 215). All joint COIs in R.1 – R.12 were negative and significant at the 1% level. Two of the six Traditional Care individual COIs were significant at the 5% level (the Medicare coefficients for R.7 and R.10); the rest were significant at the 1% level. None of the individual COIs or joint COIs for the Managed Care regressions were significant, and a number were positive, contradicting economic theory.

These results can be explained by the differences in the structure of Traditional Care and Managed Care. Patients enrolled in variations of the former are reimbursed for some fraction of the actual cost of medical care received, regardless of the magnitude of that cost. Alternatively, some enrollees are allotted a per diem expense, constructed such that reimbursement amounts never exceed expenses, but also rarely fall far below them either ("Indemnity vs. Managed Care," 2002-2011). This arrangement offers enrollees agency in their healthcare decisions—at a comparatively steep price. Managed care plans offer enrollees a set menu of healthcare options from which deviations are either penalized (by reimbursing at a discount) or not recognized at all. For example, Health Maintenance Organizations (HMOs) require that enrollees choose a primary care physician, who acts as a gatekeeper to other specialists within the network. This gives private insurers greater leverage in pricing negotiations, as a hospital that is excluded from a network will suffer financially. Thus, proportion of revenue derived from managed care may be taken as a proxy for the insurer pricing power. This is explored in greater detail in Section VI.2.

A Comparison of the Medicare and Medi-Cal Regressions

For those split-payer regressions in which both the Medicare and Medi-Cal cost-shifting variables were statistically significant, the former coefficients were 1.6 - 3.5 times greater in magnitude. This is shown in Table 9 below.

Table 9: Medicare Coefficients as Multiples of Medi-Cal Coefficients

	HSA-Level Market Share			Variable Radius Market Share (60th Percentile)		
ln(Private Revenue)	Traditional Care (TC)	Managed Care (MC)	Combined	Traditional Care (TC)	Managed Care (MC)	Combined
Total ln(Medicare)	-0.487	NA	-0.212	-0.393	NA	-0.177
Prob > χ^2	(0.00)***	NA	(0.01)***	(0.01)***	NA	(0.04)**
Total ln(Medi-Cal)	-0.138	NA	-0.116	-0.142	NA	-0.110
Prob > χ^2	(0.00)***	NA	(0.01)***	(0.04)**	NA	(0.01)**
ln(Medicare) / ln(Medi-Cal)	3.5x	NA	1.8x	2.8x	NA	1.6x

These results were consistent with Zwanziger (2000), who noted that "although responses to Medicare cutbacks were clear, reactions to decreases in [Medi-Cal] cutbacks were more ambiguous" (p.221). Zwanziger did not explore these results further, suggesting that the difference may be due to quality sensitivity. To ensure that no stones were left unturned, I tested two additional hypotheses. First, noting that the regression is in logarithmic form and can thus be interpreted proportionally, a simple explanation is that Medicare revenue is on average 1.6-3.5 times smaller than Medi-Cal revenue at each hospital. The results of this analysis are shown in Table 10 below.

Table 10: Medicare and Medi-Cal Ratios by Payer Types, All Hospitals

	Managed Care	Traditional Care	Total
Medicare Revenue ($ in millions)	40.4	60.5	100.9
Medi-Cal Revenue ($ in millions)	11.8	19.0	30.8
Medicare/Medi-Cal	3.4x	3.2x	3.3x

In fact, the average hospital generated roughly 3 times as much revenue from Medicare as it did from Medi-Cal. Thus, the differences in coefficients were not simply a function of volume.

I also explored the possibility that Medi-Cal had more patients enrolled in managed care plans than traditional care on average. Given the findings above that traditional care was associated with more significant individual and joint COIs, a potential correlation between Medicaid and managed care would also explain the differences in the coefficients. This analysis is shown in Table 11 below.

Table 11: Managed and Traditional Care Ratios by Program, All Hospitals

	Medicare Revenue ($ in millions)	Medi-Cal Revenue ($ in millions)	Total
Managed Care	40.4	11.8	52.2
Traditional Care	60.5	19.0	79.5
Managed Care / Traditional Care	0.7x	0.6x	0.7x

In fact, Medicare had a greater proportion of revenue generated by managed care than did Medicaid. Thus, the difference in the coefficients cannot be attributed to the differences in payer proportion.

Further analysis is needed to determine if the differences between Medicare and Medi-Cal are just statistical anomalies, or if they reveal an underlying economic phenomenon. For example, it may be that Medi-Cal patients, who are from poorer backgrounds by definition, have more limited options for health care due to higher transportation costs in urban environments, and are thus less sensitive to quality shifts. This possibility should be explored in future research. Because these results were largely inconclusive, I omit the Medicare/Medi-Cal distinction in rest of the paper.

Section VI.1 Conclusions

Three salient conclusions emerge from the discussion above. The first is that a fixed effects OLS model can be used to generate a robust inverse correlation between government revenue and private revenue, implying that a 10% decrease in government revenue was correlated with a 4.4% increase in private revenue. This magnitude is consistent with previous cost-shifting literature (see Table 2), and was closest to the Zwanziger (2000) results of 1.7-5.8%. The second conclusion is that, given their nearly-universal lack of statistical significance, the interaction terms were not relevant predictors of private revenue. This suggests that they should be dropped from the revised OLS regression, and that future research is needed to construct more accurate representations of hospital ownership and competition. Finally, it appears that managed care has an important role in the correlation between government revenue and private revenue, likely because it is an indirect measure of insurer pricing power for each hospital.

These conclusions suggest that a revision of the previous model is necessary. The following sub-section discusses the new model in greater detail and displays the results for the corresponding OLS regression.

VI.2. Best Point Estimate of Cost-Shifting Using OLS Model

In light of the conclusions of the previous sub-section, I revised my OLS model for predicting private revenue. The new model is specified as described by Table 12 below.

Table 12: Independent Variables for LHS, "Hospital Revenue from Private Payers"

(1)	Hospital Revenue from Government Healthcare Programs
(2)	Hospital Revenue from Government Healthcare Programs x Proportion of Private Payers Enrolled in Managed Care
(3)	Insurer HHI
(4)	Provider HHI
(5)	For-Profit Status Dummy (1 for For-Profit, 0 Otherwise)
(6)	Hospital Average Cost
(7)	Volume Ratio (Private Patient Days / Public Patient Days by Payer Type)
(8)	Severity-Weighted Case Mix Index
(9)	Type of Care Dummy
(10)	Year Dummy
(11)	Hospital Fixed Effects

The model drops the previous market power and for-profit interaction terms, instead adding the underlying variables as controls in the regression (Variables 3 – 5). Additionally, the market power controls were converted from dummy variables to their continuous variables form.

I also created a new variable to test the hypothesis that the mix of managed care and traditional care patient has an effect on the correlation between private revenue and government revenue. Variable 3 was constructed by interacting Variable 1 with the percentage of private revenue generated by managed care patients for a given hospital. Revenue was chosen instead of volume due to avoid potential differences in per-patient reimbursement rates between managed care and traditional care patients. The results in Section V1.1 suggested that managed care may weaken the correlation between private revenue and government revenue. I hypothesized that this may be because managed care proportion is an indirect measure for insurer pricing power at a particular hospital. Given this hypothesis, I expected the coefficient on Variable 3 to be positive. Table 13 below shows the results of this regression.

Table 13: Best Point Estimate of Correlation between Private and Government Revenue

	(13)	(14)
ln(Private Revenue)	HSA-Level Market Share	Variable Radius Market Share
ln(Government Revenue)	-0.445	-0.435
	(0.09)***	(0.08)***
ln(Government Revenue) x Managed Care Private Revenue Proportion	0.017	0.015
	(0.01)***	(0.01)***
Insurer HHI	0.585	0.720
	(0.52)	(0.51)
Provider HHI	0.649	-0.007
	(0.78)	(0.27)
Volume Ratio (Private Patient Days / Government Patient Days)	0.512	0.629
	(0.15)***	(0.16)***
All Government Revenue Variables, Derivative Evaluated at Means	-0.432	-0.423
Prob > F (Government Revenue + Managed Care Interaction)	(0.000)***	(0.000)***
R^2 (within; between; overall)	0.165 ; 0.179 ; 0.144	0.179 ; 0.187 ; 0.148
N=	845	800

Note: Parentheses Denote Standard Errors, Except Where Noted. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$
Control Variables Not Displayed in Output: Severity-Weighted Case Mix Index, Type of Care Dummy, Year Dummy, Hospital Average Cost, For-Profit Status Dummy

As predicted, the proportion of private revenue generated by managed care patients attenuates the correlation between government and private revenue. The interaction term was individually significant at the 1% level, and was jointly significant at the 1% level when considered with ln(Government Revenue). The joint COI, evaluated at the mean of Managed Care Proportion, implied that a 10% decrease in government revenue was approximately correlated with a 4.3% increase in private revenue. This relationship held true irrespective of the measurement methodology for provider market power.

To determine if the statistical significance was indicative of an economic mechanism, I calculated baseline summary statistics for the managed care proportion continuous variable. Table 14 below evaluates the effect of different proportions of private revenue generated from managed care patients on the joint COI.

Table 14: Effect of Different Managed Care Proportions on Government Revenue

Managed Care Proportion Percentile	25%	50%	75%
Managed Care Proportion	0.72	0.90	0.95
ln(Medicare Revenue) x Managed Care Private Revenue Proportion	-0.43	-0.43	-0.43

Note: Hospital market share measured at HSA Level

Because the magnitude of the coefficient on the interacted term was so small, the joint COI did not change when the derivative with respect to private revenue was evaluated at different percentiles of managed care proportions. Furthermore, the inter-quartile range of managed care revenue proportions was relatively narrow, contributing to the static joint COI. These results suggest that while managed care proportion seems to play a role in the correlation between public and private revenue, the extent and importance of this role is unclear.

Table 13 displays my best point estimate for the correlation between government revenue and private revenue using the OLS model specified in Section V.2 and revised in Table 12. I find that a 10% decrease in government revenue is correlated with a 4.3% increase in private revenue. This result is consistent with previous literature in both significance and magnitude. I also find that while the proportion of private revenue generated from managed care patients weakens the joint COI, the extent and importance of this effect is unclear. I conclude this section with the usual admonition against interpreting correlation as causation. The magnitude of the joint COI only tells us that government revenue and private revenue are inversely correlated. It cannot be concluded that decreases in government revenue cause increases in private revenue. Furthermore, the positive sign of the managed care interaction term may be explained by a number of alternate hypotheses. Percentage of private revenue derived from managed care patients may simply show that private insurers have high bargaining power for hospitals (because they set large fixed contracts). This, combined with the low variances of the managed care proportion term, would also result in a positive sign on the interaction term.

Section VI.2 Conclusions

In the previous two sections, I find that a fixed effects OLS model produced an inverse correlation between government revenue and private revenue for California hospitals in 2007 – 2011. This correlation falls within the predicted range of Zwanziger (2000), and differs only in magnitude (but not directionality or significance) from other previous empirical work on cost-shifting. In Section VI.3, I explore the direction of causality by replacing the OLS model with a two-staged least-squares regression (2SLS) that uses an instrument for government revenue based on the proportion of Medi-Cal enrollees in a given county.

VI.3. 2SLS IV Regression Contradicts Initial Results of Cost-Shifting

The OLS models described in the previous two sections are encumbered by omitted variable endogeneity and simultaneity bias. In their theoretical work on cost-shifting, Glazer and McGuire (2002) argued that Medicare's payment level may depend on factors (such as quality) that are correlated with private payer levels, resulting in omitted variable endogeneity and biased OLS estimates of cost-shifting. Simultaneity bias, on the other hand, results when the explanatory variable is jointly determined with the dependent variable. This is a non-trivial caveat of the OLS model specified in Section V.2 and the subsequent results in Sections VI.1-VI.2. That is, while an increase in government payments may cause a decrease in private payments, it may also be the case that a decrease in private payments causes an increase in government payments. Although hospitals cannot shift costs to Medicare directly, reimbursement rates may be raised in response to exogenous shocks that cause a decrease in private payments, such as recessions. By using a variable that is correlated with private revenue only through its effect on government revenue, I am able to avoid both the omitted variable endogeneity and the simultaneity bias.

In Section VI.3, I attempt to qualify the inverse correlation observed above by instrumenting for government revenue in the specification originally described in Table 4. An ideal instrument is highly correlated with government revenue, and is correlated with private revenue only through its effect on government revenue (i.e. it is not correlated with the unobserved error term). Using data from the California Department of Health Care Services and the U.S. Census, I calculated the percentage of each county's population enrolled in Med-Cal for each year in the sample time period. The distribution of these proportions for 2007 is shown in the histogram in Figure 14.

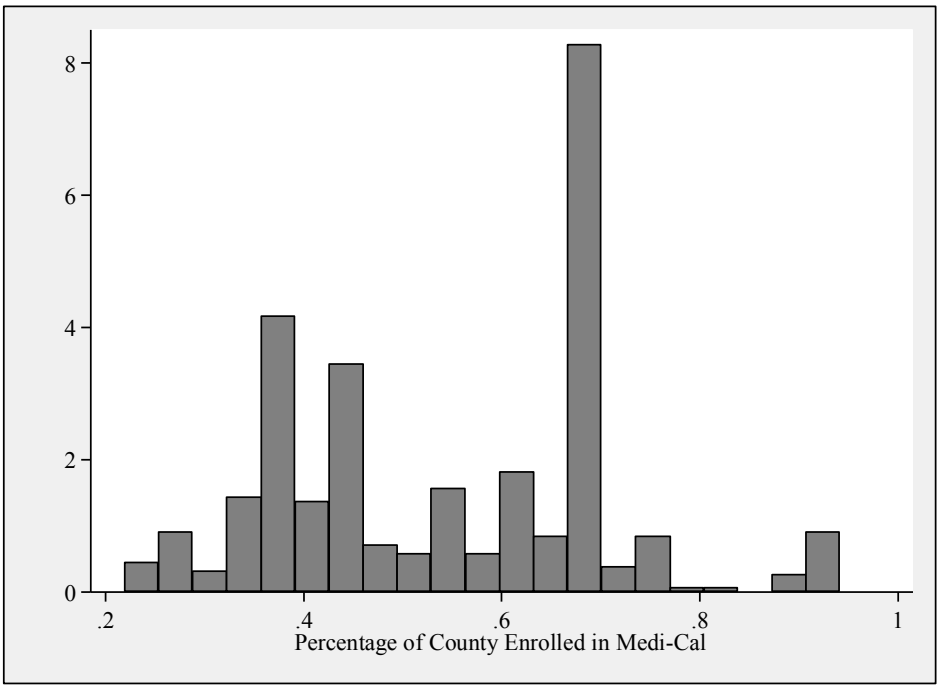

Figure 14: Percentage of County Enrolled in Medi-Cal for all California counties in 2007 (California Department of Health Care Services, 2012)

It is not unreasonable to assume that a significant number of a hospital's patients live in the same county that the hospital is located in. Even though some patients may travel long distances to receive specialized care at large teaching hospitals, convenience and necessity (in the case of ambulance networks) would suggest that hospitals admit a significant amount of patients from within their immediate vicinity. This motivated the use of "Percentage of Medi-Cal Enrollees per County" (MEPC) as an instrument for Government Revenue. Likewise, I instrumented for all of the interaction terms accordingly, replacing "Government Revenue" with MEPC (e.g. ln(Government Revenue) x For Profit Dummy was instrumented with ln(Government Revenue = MEPC) x For Profit Dummy). As before, a natural-log specification for MEPC was used in order to aid with interpretation of the coefficients. Given that the results of the previous section showed no economically significant differences between analogous coefficients for the HSA-Level and Variable Radius methods of measuring market concentration, I only display the results for the HSA-Level regression in this sub-section. The results for same regression carried out with market-shares measured with the Variable Radius Method can be found in Appendix A.3.

The results for the second stage of the 2SLS regression of private revenue on public revenue with HSA-Level market concentrations are shown in Table 15 below.

Table 15: 2SLS Regression of Private Revenue on Instrumented Public Revenue

	(15)
ln(Private Revenue)	HSA-Level Market Share
ln(Government Revenue)	1.914
	(0.63)***
ln(Government Revenue) x Managed Care Private Revenue Proportion	0.007
	(0.01)
ln(Government Revenue) x Insurer High Concentration Dummy	-0.004
	(0.01)
ln(Government Revenue) x Provider High Concentration Dummy	0.003
	(0.01)
ln(Government Revenue) x Provider For-Profit Dummy	0.058
	(0.03)
Volume Ratio (Private Patient Days / Public Patient Days)	1.070
	(0.27)***
All Government Revenue Variables, Derivative Evaluated at Means	1.931
Prob > F (Government Revenue + Interactions)	(0.014)**
Prob > F (Interactions)	(0.223)
ln(Hospital Average Cost)	-0.734
	(0.31)**
Severity-Weighted Case Mix Index	-0.380
	(0.47)
Centered R^2	-0.812 [1]
N=	845
Anderson LM Coefficient for Underidenfication [2]	22.62****
Cragg-Donald Wald F Statistic [3]	4.62
Sargan Statistic for Overidenfication	0.000 [4]
Durbin-Hausman-Wu Statistic [5]	21.86****

[1] Negative value indicates that RSS > TSS for R^2 = (MSS=RSS-TSS)/TSS—i.e. instruments are better predictor for Y than X_b

[2] H_0 = Instrument equation underidentified

[3] H_0 = Weak instruments; critical values derived from Stock and Yogo (2005) "Testing for Weak Instruments in Linear IV Regression"

[4] Equation exactly identified

[5] H_0 = ln(Government Revenue) and associated interaction terms are exogenous

Note: Parentheses denote standard errors, except where noted. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$, **** $p \leq 0.0001$

Control variables not displayed in output: Severity-Weighted Case Mix Index, Type of Care Dummy, Year Dummy, and Hospital Average Cost

The first item worth noting is that the results of the Durbin-Wu-Hausman test indicate that the original regressors were in fact endogenous. This validates the claim that 2SLS is the appropriate form of analysis for the cost-shifting regression. As Table 15 shows, the inverse correlation between government revenue and private revenue from the previous section disappears entirely when an econometrically-superior regression technique was used. In fact, the 2SLS regression above indicated that a 10% increase in government revenue caused a 19% percent increase in private revenue. The ln(Government Revenue) coefficient was highly-significant both individually when considered along with the interaction terms. The positive correlation increased slightly in magnitude when the derivative of the regression was evaluated at the mean of the interaction terms; however, just as in the OLS regressions of the previous

section, the interaction coefficients were almost entirely insignificant both individually and jointly. This contributed to the poor performance of the instruments in the tests for instrumental validity. The F-statistic of instrumental validity was 4.62, indicating that the MEPC instruments were not good predictors of the endogenous regressors. In light of this lack of significance, I revised the 2SLS model above by dropping all of the interaction terms. This new model is nearly identical to that specified in Section VI.2, different only in that, due to its lack of significance in Table 15, the managed care interaction term was also dropped from the regression. Just as before, however, I include hospital concentration, insurer concentration, for-profit status, and managed care proportion as control variables. The results of this analysis are displayed in Table 16 below.

Table 16: Revised 2SLS Regression of Private Revenue on Instrumented Public Revenue

	(16)
ln(Private Revenue)	
ln(Government Revenue)	1.775
	(0.64)***
ln(Hospital Average Cost)	-0.667
	(0.29)
Severity-Weighted Case Mix Index	-0.368
	(0.48)
Volume Ratio	0.986
	(0.26)***
Centered R^2	-0.728
N=	845
Anderson LM Coefficient for Underidenfication [2]	20.10****
Cragg-Donald Wald F Statistic [3]	20.50 [4]
Sargan Statistic for Overidenfication	0.000 [5]
Durbin-Hausman-Wu Statistic [6]	24.93****

[1] Negative value indicates that RSS > TSS for R^2 = (MSS=RSS-TSS)/TSS—i.e. instruments are better predictor for Y than X_b

[2] H_0 = Instrument equation underidentified

[3] H_0 = Weak instruments; critical values derived from Stock and Yogo (2005) "Testing for Weak Instruments in Linear IV Regression"

[4] Implies that IV bias is less than 10% of OLS bias; i.e. strong instruments

[5] Equation exactly identified

[6] H_0 = ln(Government Revenue) is exogenous

Note: Parentheses denote standard errors, except where noted. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$, **** $p \leq 0.0001$
Control variables not displayed in output: Severity-Weighted Case Mix Index, Type of Care Dummy, Year Dummy, Hospital Average Cost, Managed Care Proportion, Hospital Concentration, Insurer Concentration

Although there were slight changes in the government revenue coefficients of the two regressions in Tables 15 and 16 above, the differences were not economically significant. However, the Wald F-statistic increased in magnitude significantly, rejecting the null hypothesis at the 0.1% level and showing that

MEPC is a valid instrument for Government Revenue. More specifically, the test statistic implied that the instrumental variable bias was less than 10% of the OLS bias. The new coefficient on ln(Government Revenue) implies that a 10% increase in Government Revenue yields a 18% increase in private revenue. This result was significant at the 1% level. The Durbin-Hausman-Wu statistic indicated that Government Revenue was indeed endogenous to Private Revenue. This validated the decision to specify the model with an instrumental variable.

While the exogeneity of instruments cannot be directly tested, the Sargan test for overidentifying restrictions can tests whether all instruments are exogenous, conditional upon at least one being exogenous. However, because the first stage equation was exactly identified, the test does not provide useful information about the exogeneity of MEPC. I instead rely on the intuition that the proportion of Medi-Cal enrollees in a hospital's county is correlated with the amount of revenue that it generates from private insurers only through its effect on government revenue.

Section VI.3 Conclusions

Tables 15 and 16 provide evidence that contradicts the claims of recent empirical cost-shifting literature. The results in Sections VI.1 and VI.2 showed a statistically significant inverse relationship between government revenue and private revenue, controlling for a vector of hospital- and market-level effects. However, as has been noted previously in the literature, this result could only be interpreted as correlative, not causative. Furthermore, the endogeneity of government revenue complicates inferences about the directionality of the observed relationship. In Section VI.3, I showed that when government revenue is instrumented for with the percentage of Medi-Cal enrollees in the "home" county of a hospital, the inverse relationship disappears completely.

Assuming that the IV results are an accurate representation of reality, the logical question that follows is, "Where did the inverse correlation go?". First and foremost, it should be noted that all of the OLS regressions had relatively low coefficients of correlation, strongly suggesting the presence of another effect that influences changes in public and private revenue over time. Beyond this, however, the observed inverse relationship between public and private revenue is likely due to weak controls for both insurer and provider market power. A provider's pricing power should increase as its market becomes more concentrated. Similarly, insurers in concentrated markets should be better able to resist price increases than those in competitive markets. This theory is not consistent with my results. There was no

consistent pattern of statistical significance for any of the market power variables in any of the regressions. To examine whether this was economically significant or a function of the data, I examined the change in both of these metrics over time. Figure 15 below shows these results.

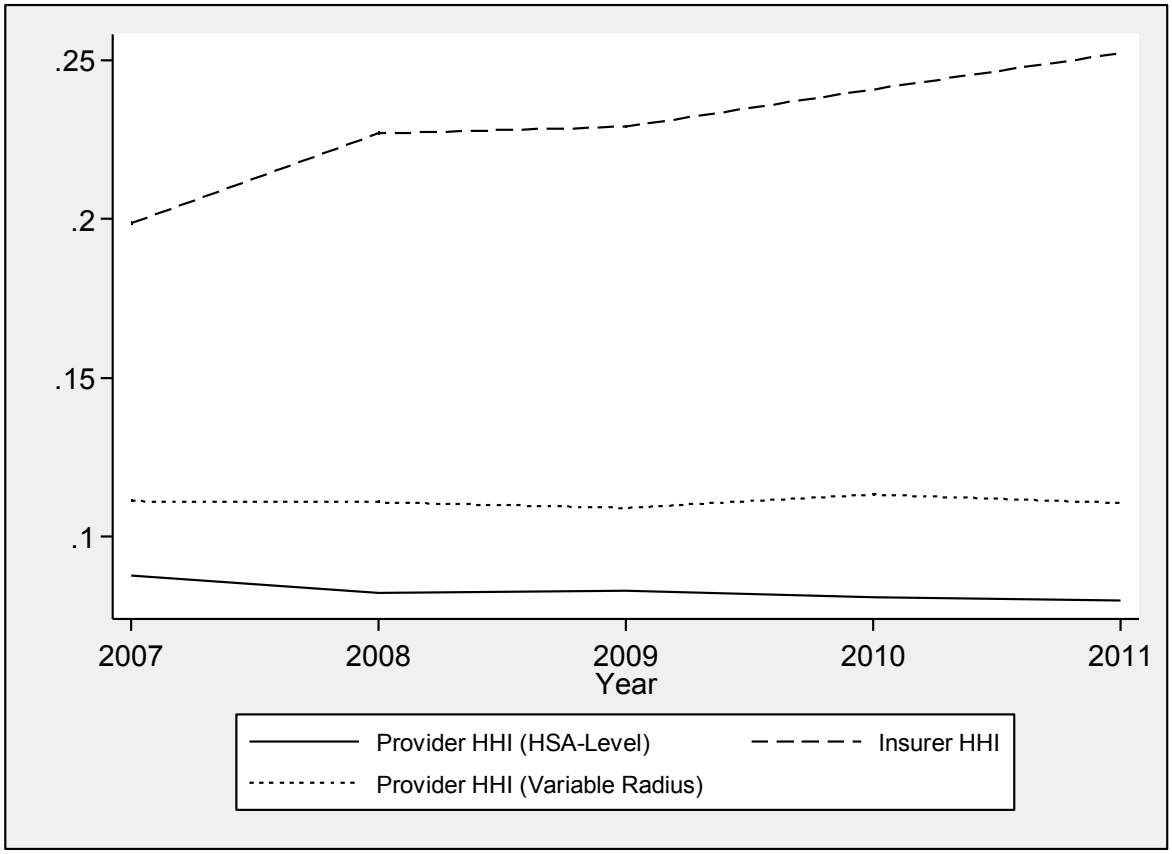

Figure 15: Change in Average Provider and Insurer Market Concentration Over Time

Average insurer market concentration increased during the sample period, while provider market power was relatively invariant. While the results corroborate existing research on insurer consolidation (Melnick, 2011), they diverge from expectations of provider consolidation. Using data from 1990s and early 2000s, Vogt and Town (2006) showed that the number of competing hospital systems in a typical metropolitan statistical area decreased by one third. This trend has continued in recent years; hospital merger and acquisition activity has rebounded from recession lows to the highest levels seen since the late 1990s, driven by lower public program reimbursement rates and reactions to insurer market power (Saxena, 2012). This casts doubt on my measurement of market concentration. I hypothesize that provider market power drives much of the inverse correlation between private revenue and public revenue. As

public revenue decreases, hospitals purchase individual physician practices and other hospitals in order streamline efficiency and maintain margins, resulting in higher prices for insurers. This would result in an inverse correlation mistakenly taken for cost-shifting, when in reality the discrepancy is due to changes in pricing power. To validate these results, future research should measure market power based on patients' expected probability of admission (rather than observed admission, as I do above). This method is described in detail in Kessler and McLellan (2000).

VII. Conclusion

In this paper, I examined the hypothesis that hospitals increase prices for private insurers in response to decreased government reimbursement rates. I first created a data set that mapped financial information from the California Office of Statewide Health Planning and Development (OSHPD) to insurance concentration, severity-weighted case-mix index, and variable-radius market concentration for California hospitals in 2007 – 2011. I then specified an OLS model that elucidated the correlation between government revenue and private revenue, controlling for market- and hospital-level characteristics. Using the results from the initial regression, I revised the model and generated a "best point-estimate" for the correlation between the two revenue sources: a 10% decrease in government revenue was correlated with a 4.4% increase in private revenue. This estimate is consistent with recent cost-shifting literature. Then, using data from the California Department of Health Care Services and the U.S. Census, I created an instrumental variable for government revenue generated by a hospital based on the proportion of the population enrolled in Medi-Cal in that county. Unlike the previous OLS model, this technique allowed for a causative interpretation. The instrument performed well in terms of relevance and validity. Furthermore, there was no reason to believe that the proportion of Medi-Cal enrollees of a hospital's home county was endogenous to private revenue. The results showed that, using the same controls as the original model, a 10% increase in government revenue increased private revenue by 18%. Given that the OLS results showed an inverse correlation consistent with previous literature, the results from the 2SLS regression were more reflective of economic reality rather than temporal idiosyncrasies. I posited that the "lost" correlation from the OLS model was due to an inadequate measurement of market concentration. Insurer market concentration was measured at the HSA-level, which is problematic given that modeling insurance as a physical good with a geographic boundary is not consistent with underlying reality. Average provider market concentration was relatively invariant over the duration of the data set when

measured at the HSA-Level and using the Variable Radius methodology. This indicated that measurements of market power based on geographic boundaries or observed patient flow are not accurate models of pricing power for healthcare providers. As mentioned above, any future related empirical work should measure market power based on expected probability of admission rather than observed admission.

Healthcare expenditures became a prominent fixture of the national conversation on the federal balance sheet in the aftermath of the Great Recession. Universal coverage was a key part of the Obama 2008 Presidential platform, and the passage of the Patient Protection and Affordable Care Act of 2010 was heralded as a defining moment in American history. The 906-page bill contained many provisions designed to expand health insurance coverage and to control the cost of delivery. These methods included the reduction of government reimbursement rates. Hospitals and insurers have typically be outspoken opponents of such measures. However, as my results show, the claim that hospitals shift their financial burden to private insurers is largely unsubstantiated. This suggests that the reduction of government reimbursement rates may effectively help mitigate rising health costs. Such measures must be taken with caution. While it is likely that hospitals do not shift their financial burden between payers, it is possible that physicians provider different quality of care to patients depending on their payer status. This effect would not be absorbed by my regressions above. There are other more structural externalities that may arise from reimbursement reductions. For example, if physicians' salaries decrease due to reimbursement rate cuts, less high-achieving students may elect to study medicine professionally. This would also contribute to a further decline in quality for patients. Such factors should be explored in future research.

As long as the threat of government reimbursement cuts remains, hospitals and insurers will brandish cost-shifting claims as evidence of government malfeasance. My thesis shows that these claims are largely unsubstantiated. Instead, the results suggest that the inverse correlation may be a function of provider market concentration, and that future empirical cost-shifting research should focus on the question of market definition for both insurers and providers.

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Appendix

Table A.1: Combined Payer OLS Regression

	(1)	(2)	(3)	(4)	(5)	(6)
	HSA-Level Market Share			Variable Radius Market Share (60th Percentile)		
ln(Private Revenue)	Traditional Care (TC)	Managed Care (MC)	Combined	Traditional Care (TC)	Managed Care (MC)	Combined
ln(Government Revenue)	-0.523	-0.084	-0.449	-0.597	-0.080	-0.437
	(0.13)***	(0.07)	(0.08)***	(0.13)***	(0.07)	(0.08)***
ln(Government Revenue) x Insurer High Concentration Dummy	0.005	-0.001	0.005	0.000	0.000	0.005
	(0.00)	(0.01)	(0.00)**	(0.00)	(0.01)	(0.00)
ln(Government Revenue) x Provider High Concentration Dummy	-0.019	0.011	0.002	-0.002	0.003	0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
ln(Government Revenue) x Provider For-Profit Dummy	-0.004	-0.036	-0.005	-0.004	-0.032	-0.002
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
All Government Revenue Variables, Derivative Evaluated at Means	-0.519	-0.094	-0.445	-0.599	-0.088	-0.433
Prob > F (Government Revenue + Interactions)	(0.000)***	(0.328)	(0.000)***	(0.00)***	(0.499)	(0.000)***
Prob > F (Interactions)	(0.359)	(0.398)	(0.169)	(0.980)	(0.530)	(0.282)
ln(Hospital Average Cost)	-0.665	-0.786	-0.650	-0.914	-1.040	-0.797
	(0.27)**	(0.28)***	(0.15)***	(0.29)***	(0.29)***	(0.16)***
Severity-Weighted Case Mix Index	-0.165	0.208	-0.035	1.067	0.505	0.371
	(0.45)	(0.46)	(0.25)	(0.54)	(0.55)	(0.29)
Volume Ratio (Private Patient Days / Payer Patient Days)	2.887	0.010	0.486	2.879	0.009	0.589
	(0.31)***	(0.01)	(0.15)***	(0.32)***	(0.01)	(0.16)***
Constant	-108.162	-273.731	-245.384	-122.638	-276.908	-239.242
	(55.72)*	(56.63)***	(31.72)***	(57.66)**	(57.78)***	(31.43)***
R^2 (within; between; overall)	0.146 ; 0.123 ; 0.067	0.063 ; 0.019 ; 0.009	0.160 ; 0.254 ; 0.209	0.155 ; 0.123 ; 0.062	0.066 ; 0.052 ; 0.031	0.173 ; 0.262 ; 0.212
N=	850	850	855	805	805	810

Note: Parentheses Denote Standard Errors, Except Where Noted. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$
Control Variables Not Displayed in Output: Type of Care Dummy, Year Dummy

Table A.2: Split Payer OLS Regression

	(7)	(8)	(9)	(10)	(11)	(12)
	HSA-Level Market Share			Variable Radius Market Share (60th Percentile)		
ln(Private Revenue)	Traditional Care (TC)	Managed Care (MC)	Combined	Traditional Care (TC)	Managed Care (MC)	Combined
ln(Medicare)	-0.256	0.052	-0.220	-0.278	0.089	-0.194
	(0.13)**	(0.07)	(0.08)***	(0.13)**	(0.08)	(0.08)**
ln(Medicare) x Insurer High Concentration Dummy	-0.058	0.017	-0.005	-0.065	0.004	-0.013
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)
ln(Medicare) x Provider High Concentration Dummy	0.095	-0.014	0.065	-0.023	-0.060	-0.019
	(0.44)	(0.07)	(0.21)	(0.06)	(0.04)	(0.04)
ln(Medicare) x Provider For-Profit Dummy	-0.135	0.041	0.132	-0.108	0.011	0.131
	(0.09)	(0.08)	(0.07)*	(0.09)	(0.08)	(0.07)**
ln(Medi-Cal)	-0.228	-0.024	-0.085	-0.245	-0.042	-0.095
	(0.06)***	(0.06)	(0.05)	(0.07)***	(0.07)	(0.05)**
ln(Medi-Cal) x Insurer High Concentration Dummy	0.066	-0.020	0.010	0.068	-0.005	0.018
	(0.04)	(0.04)	(0.03)	(0.04)	(0.05)	(0.03)
ln(Medi-Cal) x Provider High Concentration Dummy	-0.123	0.030	-0.066	0.025	0.066	0.022
	(0.48)	(0.07)	(0.22)	(0.07)	(0.05)	(0.04)
ln(Medi-Cal) x Provider For-Profit Dummy	0.145	-0.076	-0.135	0.120	-0.042	-0.131
	(0.10)	(0.08)	(0.07)*	(0.10)	(0.08)	(0.07)*
All Medicare Revenue Variables, Derivative Evaluated at Means	-0.319	0.075	-0.174	-0.368	0.083	-0.176
Prob > F (Medicare Revenue + Interactions)	(0.009)***	(0.668)	(0.062)**	(0.005)***	(0.495)	(0.067)*
Prob > F (Interactions)	(0.273)	(0.911)	(0.282)	(0.306)	(0.581)	(0.233)
All Medi-Cal Revenue Variables, Derivative Evaluated at Means	-0.161	-0.055	-0.128	-0.148	-0.044	-0.109
Prob > F (Medi-Cal Revenue + Interactions)	(0.009)***	(0.491)	(0.014)**	(0.005)***	(0.497)	(0.013)**
Prob > F (Interactions)	(0.234)	(0.691)	(0.293)	(0.299)	(0.505)	(0.244)
ln(Hospital Average Cost)	-0.684	-0.712	-0.637	-0.960	-0.943	-0.781
	(0.28)**	(0.28)**	(0.16)***	(0.30)***	(0.30)***	(0.16)***
Severity-Weighted Case Mix Index	-0.172	0.157	-0.040	1.078	0.368	0.394
	(0.47)	(0.46)	(0.26)	(0.55)	(0.55)	(0.29)
Volume Ratio (Private Patient Days / Payer Patient Days)	0.308	0.014	0.448	0.637	0.014	0.527
	(0.05)***	(0.01)	(0.15)***	(0.08)***	(0.01)	(0.16)***
Constant	-124.288	-256.678	-231.134	-132.990	-255.925	-223.310
	(57.62)**	(57.98)***	(32.27)***	(58.07)**	(59.23)***	(31.92)***
R^2 (within; between; overall)	0.094 ; 0.217 ; 0.144	0.067 ; 0.0.033 ; 0.036	0.150 ; 0.245 ; 0.194	0.150 ; 0.159 ; 0.086	0.071 ; 0.006 ; 0.010	0.163 ; 0.219 ; 0.169
N=	850	850	855	805	805	810

Note: Parentheses Denote Standard Errors, Except Where Noted. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$
Control Variables Not Displayed in Output: Type of Care Dummy, Year Dummy

Table A.3: 2SLS Regression with Variable Radius Provider Market Concentration

ln(Private Revenue)	Variable Radius Market Share
ln(Government Revenue)	1.704
	(0.75)**
ln(Government Revenue) x Managed Care Private Revenue Proportion	0.003
	(0.01)
ln(Government Revenue) x Insurer High Concentration Dummy	-0.004
	(0.01)
ln(Government Revenue) x Provider High Concentration Dummy	-0.022
	(0.06)
ln(Government Revenue) x Provider For-Profit Dummy	0.054
	(0.03)
Volume Ratio (Private Patient Days / Public Patient Days)	1.053
	(0.31)***
Prob > F (Government Revenue + Interactions)	(0.024)**
Prob > F (Interactions)	(0.224)
ln(Hospital Average Cost)	-0.747
	(0.33)**
Severity-Weighted Case Mix Index	-0.084
	(0.59)
Centered R^2	-0.789 [1]
N=	800
Anderson LM Coefficient for Underidenfication [2]	3.86*
Cragg-Donald Wald F Statistic [3]	0.76
Sargan Statistic for Overidenfication	0.000 [4]

[1] Negative value indicates that RSS > TSS for R^2 = (MSS=RSS-TSS)/TSS—i.e. instruments are better predictor for Y than X_b

[2] H_0 = Instrument equation underidentified

[3] H_0 = Weak instruments; critical values derived from Stock and Yogo (2005) "Testing for Weak Instruments in Linear IV Regression"

[4] Equation exactly identified

Note: Parentheses denote standard errors, except where noted. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$, **** $p \leq 0.0001$

Control variables not displayed in output: Severity-Weighted Case Mix Index, Type of Care Dummy, Year Dummy, and Hospital Average Cost

Table A.4: Summary Statistics for Beds Available by Health Service Area, 2007-2011

Health Service Area	Number of Hospitals	Mean	Standard Deviation	Min	Max
1	1	469.4	281.4	226	797
2	12	3179.2	126.4	3051	3417
3	4	942.4	73.2	825	1009
4	9	3804.2	96.4	3699	3936
5	11	3193.6	121.0	3038	3360
6	8	2397	246.5	2029	2674
7	7	2397.4	20.3	2364	2422
8	7	1109.4	88.4	999	1203
9	10	3613.6	496.3	2956	4318
10	4	1525.8	357.1	878	1803
11	50	18084.8	436.5	17718	18795
12	22	5360.4	265.7	4905	5658
13	16	4464	316.3	3939	4764
14	9	3973.8	617.9	3296	4768