Medicaid Eligibility Expansions and Privately Insured Patients

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Abstract

This paper examines how the price and quantity of treatment for privately insured patients are related to expansions in Medicaid eligibility. A theoretical model shows that when hospitals face an increasing number of Medicaid patients, the quantity of private treatment will decrease. When new Medicaid patients previously did not have insurance, private prices theoretically increase. The predictions of the model are tested using hospital level data in California. Between 2000 and 2013, California implemented county level health insurance programs aimed at increasing health insurance coverage for low-income, uninsured individuals. First stage regressions show that the county health insurance programs significantly increase the treatment of county insured patients. The increase in county insured patients increase the average revenue from private patients received at for-profit hospitals. The results provide insight as to how the current Medicaid expansion, spearheaded by the Affordable Care Act, will impact private patients. More generally, the analysis shows that increasing the quantity of fixed marginal revenue consumers leads to higher prices for consumers facing market prices.

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1 Introduction

In February 2014, over 62 million individuals were enrolled in Medicaid and the Children’s Health Insurance Program (CHIP). Over the next twelve months, enrollment in these programs increased by over 8 million. By 2023, the Centers for Medicare and Medicaid Services expect Medicaid and CHIP enrollment numbers to reach approximately 79 million and cost the government over $800 billion per year (CMS, 2014). The increase in enrollment is primarily driven by states taking advantage of the Patient Protection and Affordable Care Act feature that temporarily provides federal funding for costs associated with increasing Medicaid eligibility. In 2012, the first of thirty-one states began providing Medicaid coverage to all individuals with effective incomes under 138 percent of the Federal Poverty Line.

Recent research finds that health care providers change their behavior following expansions in Medicaid eligibility to specific population groups such as individuals with a disability (Wagner, 2015a) and children (Garthwaite, 2012). Because the current Medicaid expansion applies to all low-income individuals, not just those with disabilities or children, hospitals and physicians may be facing the largest increase in Medicaid patients since the early years of the program. If the change in the insurance composition of patients leads to a large reduction in revenue, providers may turn to privately insured patients in order to make up for the lost revenue.

This paper explores the relationship between the treatment of Medicaid patients at a hospital and financial outcomes for privately insured patients. A theoretical model is derived from the Sloan et al. (1978) two-market model, which is typically used to explore situations where private patients are charged higher prices when Medicaid reimbursement rates fall. The Sloan et al. (1978) cost-shifting framework is adapted to the current Medicaid expansion by allowing the quantity of Medicaid treatment to increase and introducing uninsured patients to the analysis, effectively creating a three-market model. Theoretically, an increase in Medicaid patients is associated with a reduction in the amount of privately insured treatment. Private prices increase when a Medicaid expansion is driven by previously uninsured patients, but the change in private price is ambiguous when a Medicaid increase is driven by patients that were privately insured before an expansion.

Empirically testing the implications of the model requires a situation where health insurance coverage for government insured patients increase exogenously. Between 2000 and 2013, California
implemented two separate, but continuous county-level programs that provided federal funding to counties that increased health insurance coverage for low-income, uninsured individuals ineligible for California’s Medi-Cal program. Variation in the implementation of the health insurance programs is used to test how privately insured patients are impacted by a significant increase in county-insured patients.

Using the subset of counties that implement a health insurance program, first-stage regressions show that county health insurance programs significantly increase the amount of county-insured treatment at hospitals. The increase in county-insured patients is associated with a reduction in the quantity of privately insured patients and an increase in the average revenue hospitals receive from each private patient. Additional regressions show that the results are driven by for-profit hospitals giving fewer discounts to private health insurance companies. The findings are consistent with a theoretical model where Medicaid expansion is driven by previously uninsured patients.

The analysis in the current paper suggests that the ACA promoted growth in Medicaid enrollment may cause hospitals to reduce treatment for privately insured patients. For-profit hospitals in particular may increase prices for private patients in response to an increase in Medicaid patients. It is possible that hospitals will seek out other ways to cover lost revenue as the number of Medicaid patients increase in the near future, such as differentially treating patients based on their health insurance status. In the event that hospitals happen to decrease private quantity and change private prices in response to the recent increase in Medicaid enrollment, the analysis below provides a framework that can help explain hospital behavior.

The results in the paper can also be used to explain how private consumers in other markets are affected by changes in the quantity of low-income, fixed marginal revenue consumers. Eriksen and Ross (2015) show that the price of rental housing does not change when housing vouchers increase. Assuming that at least some of the new voucher recipients were previously paying market rents, the empirical findings of Eriksen and Ross (2015) can be explained by the theoretical model in the current paper. The three-market model developed below can also explain variation in out-of-state tuition at public universities when faced with pressure to lower admission standards for in-state applicants (Groen and White, 2004).
2 Background

2.1 Medicaid Eligibility Expansion and the Affordable Care Act

The Patient Protection and Affordable Care Act (ACA) was signed into law on March 23, 2010 with the overarching goal to increase health insurance coverage and reduce health care costs. A number of significant health care reforms were part of the ACA, including a requirement that all individuals become covered by health insurance, the formation of health insurance exchanges and eliminating coverage denial for pre-existing conditions (HHS, 2015).

The initial writing of the ACA expanded Medicaid eligibility to include families with effective incomes of less than 138 percent of the Federal Poverty Level, beginning January 1st, 2014. In order to receive federal funding for Medicaid, states have historically had to meet minimum coverage standards and offer Medicaid to low-income children, parents, pregnant women and elderly, as well as adults with disabilities (Gruber, 2003). Coverage for low-income, non-disabled adults has not been required to receive federal funding for Medicaid and the Medicaid eligibility reform in the ACA was expected to increase Medicaid enrollment by up to 20 million individuals (Sommers et al., 2012).

In the National Federation of Independent Business (NFIB) v. Sebelius ruling in 2012, the Supreme Court deemed much of the ACA constitutional. However, the Medicaid eligibility expansion was not upheld and states are currently not required to change their Medicaid eligibility requirements in order to receive federal Medicaid funding. Despite the ability to opt-out, 28 states have expanded Medicaid eligibility since the 2012 ruling. In California, individuals with effective incomes under 138 percent of the Federal Poverty Level are eligible for Medi-Cal (California’s Medicaid program), beginning in 2014. California expects 2 million citizens to become newly eligible for Medi-Cal by June, 2015 as a result of the eligibility expansion (Graves, 2015).\footnote{Medi-Cal and Medicaid are used interchangeably throughout the paper.}

Medicaid has a low reimbursement rate relative to both Medicare and private insurance (Zuckerman and Goin, 2012) and hospitals may alter their behavior in response to the increase in Medicaid enrollment. If hospitals and physicians observe an increase in low-paying Medicaid patients, they may seek out ways to generate more revenue from other patients that do not have a fixed reim-

\footnote{Medi-Cal and Medicaid are used interchangeably throughout the paper.}
bursement rate, such as privately insured patients. In the following sections, hospital level data are used to explore the potential relationship between the changes in the treatment of low-income, fixed marginal revenue patients and quantities and prices for privately insured patients.

2.2 Related Literature

The current paper adds to the extensive literature exploring the consequences of expansions in Medicaid eligibility. The Medicaid program expanded in the 1980s to include low-income pregnant women and young children. Cutler and Gruber (1996) use these early expansions targeting women and children to estimate a roughly 50 percent crowd out rate. Dave et al. (forthcoming) potentially explain the source of the crowd out and observe that the probability of a young mother being employed decreases as Medicaid eligibility increases. The eligibility expansions for children are associated with increases in visits to physicians (Currie and Gruber, 1996) and rates of hospitalization (Dafny and Gruber, 2005). Garthwaite (2012) uses a similar theoretical approach as the current paper and finds that physicians spend less time with Medicaid patients after the creation of the State Children’s Health Insurance Program. Goodman-Bacon (2015) studies an earlier time period and shows that infant mortality for non-whites decreased after the inception of the Medicaid program.

A separate but related literature explores whether hospitals charge privately insured patients higher prices when the reimbursement rates of Medicaid patients are reduced, a phenomenon known as cost-shifting. The theoretical predictions surrounding cost shifting are ambiguous. Sloan et al. (1978) develop a mixed-economy model and provide empirical support for the prediction that participation in the Medicaid program is positively related to Medicaid fee schedules. Dranove (1988) shows that when hospitals maximize a utility function that includes the quantity of patients, hospitals may find cost-shifting utility maximizing. Showalter (1997) shows that profit-maximizing hospitals should not cost shift and will reduce private prices when Medicaid reimbursement rates fall. Given the theoretical uncertainty about hospital behavior, it is not surprising that empirical

Supplier-induced demand (Gruber and Owings, 1996; Yip, 1998; Shigeoka and Fushimi, 2014) is another way for hospitals to increase revenue, but the available hospital-level data cannot be used to disentangle whether this behavior is taking place.

Bitler and Zavodny (2014) and Buchmueller et al. (2015) both present comprehensive reviews of the empirical work examining the effects of the Medicaid program.
support for cost-shifting is mixed.\textsuperscript{4}

Past Medicaid eligibility expansions have been relatively small compared to the recent change in eligibility and few papers have focused on whether a relationship exists between charges to private patients and the number of Medicaid patients a hospital treats. Recent work by Wagner (2015b) does explore this potential connection. She exploits changes in Medicaid eligibility for individuals with disabilities and finds that the expansion in eligibility decreases charges for privately insured patients. Her results (Wagner, 2015a; Wagner, 2015b) are consistent with a model where Medicaid expansion completely crowds out private insurance.

The theoretical model below does not assume that a Medicaid expansion will result in complete crowd out. There is evidence that the recent Medicaid expansion in California has reduced the uninsured rate significantly (Shinkman, 2015). In order to accurately depict a Medicaid expansion that reduces the number of uninsured individuals, a theoretical model must consider the consequences of less than complete crowd out. The model below shows that when a Medicaid expansion is driven by uninsured patients, hospitals will optimally increase charges to private patients.

3 Three-Market Model for Hospital Services

In order to understand how hospitals will respond to an expansion in Medicaid eligibility, assume that a hospital faces three types of patients: privately insured patients, Medicaid patients and uninsured patients. Following Sloan et al. (1978), privately insured patients follow a downward sloping inverse demand curve, $p^P(q^P, \gamma^M, \bar{A})$. The price charged to privately insured patients, $p^P$, is a function of the quantity of private patients, $q^P$, and other factors, $\bar{A}$, such as hospital reputation, quality, local competition, patient quality and whether the hospital is for-profit or non-profit. The term, $\gamma^M$, captures Medicaid eligibility and increases as the fraction of the population that is eligible for Medicaid rises.

Hospitals receive a fixed payment, $p^M$, for each Medicaid patient that is treated. Because hospitals cannot control the Medicaid price, they cannot influence the number of Medicaid patients through price changes. An increase in $\gamma^M$ increases $q^M$ as more patients become eligible to receive

\textsuperscript{4}Morrisey (1996) and Frankt (2011) have detailed and complete reviews that summarize the conflicting empirical evidence on cost shifting.
Medicaid. Hospitals also treat uninsured patients, $q^U$. The average uninsured patient increases hospital revenue by $p^U$, where $0 < p^U < p^M$, and the quantity of uninsured patients at a hospital will decrease as $\gamma^M$ increases.

Dranove (1988) characterizes a non-profit hospital by including a parameter that is positively related to the number of patients treated.\footnote{It is possible that some for-profit hospitals also make decisions based on factors other than profit, such as the quality of treatment or reputation, but the available hospital data cannot separate which for-profit hospitals act in a similar fashion to non-profit hospitals.} Equation (1) defines the utility function of a non-profit hospital that faces private, Medicaid and uninsured patients:

$$
U^{NP} (p^P, p^M, p^U, \gamma^M, \bar{A}, q^P, q^M, q^U) = p^P (q^P, \gamma^M, \bar{A}) \cdot q^P + p^M \cdot q^M (\gamma^M) + p^U \cdot q^U (\gamma^M) + B^P (q^P) + B^M (q^M) + B^U (q^U) - c (q^P + q^M + q^U). \tag{1}
$$

The first term in equation (1), $p^P \cdot q^P$ is the revenue a hospital receives from private patients. The inverse demand function follows the standard assumptions, $p_q < 0$ and $p_{qq} \geq 0$. The second source of revenue for a hospital are Medicaid patients, $q^M$. Each of the $q^M$ Medicaid patients increase the hospital’s revenue by $p^M$; both Medicaid parameters are fixed from the point-of-view of the hospital. Assuming that the average uninsured patient pays for some portion of treatment, hospitals receive $p^U \cdot q^U$ in revenue from uninsured patients. The term $p^U$ is the average amount paid by an uninsured patient.

Hospitals also can increase utility in non-monetary ways. This possibility is captured by $B^P (q^P)$, $B^M (q^M)$ and $B^U (q^U)$, which corresponds to the non-monetary benefits a hospital receives from treating private, Medicaid and uninsured patients, respectively. The hospital receives a positive non-monetary benefit for every patient treated, $B^i_q > 0$, but there is a diminishing non-monetary return from treating additional patients, $B^i_{qq} < 0$.

The cost function is determined by the number of total patients treated, $q^T = q^P + q^M + q^U$. In equation (1), the marginal cost does not change based on insurance status. Hospitals may attempt to provide lower quality treatment to patients based on their insurance status, but Medicaid patients expect to receive the same quality treatment as privately insured patients (Sloan et al., 1978). Assuming that uninsured patients receive the same type of treatment simplifies the analysis and incorporating a specific cost structure for uninsured patients does not change the implications of
the model. The cost function is increasing in \( q^T \), \( c_q > 0 \), and the marginal cost is non-diminishing, \( c_{qq} \geq 0 \).

A hospital cannot choose \( q^M \) or \( q^U \), but will choose the level of \( q^P \) that maximizes utility. Taking the first-order condition of equation (1) with respect to \( q^P \) yields:

\[
\frac{\partial U^{NP}}{\partial q^P} = p_q^P \cdot q^P + p^P + B_q^P - c_q q^M = 0.
\]  

(2)

Equation (2) shows that a non-profit hospital maximizes utility at \( q^{P*} \), where the marginal benefit of \( q^{P*} \) equals the marginal cost of treatment, given the hospital treats \( q^M \) and \( q^U \) Medicaid and uninsured patients, respectively. In the case that a hospital is only concerned about profit, the marginal non-monetary benefit term, \( B_q^P \), drops out of equation (2) and the for-profit hospital sets marginal revenue equal to marginal cost.

In order to show how a non-profit hospital will optimally respond to an increase in Medicaid eligibility, begin with a non-profit hospital that is treating the utility maximizing number of private patients, \( q^{P*} \). When Medicaid eligibility expands, the eligibility term, \( \gamma^M \), increases. Intuitively, the expansion will increase the number of Medicaid patients a hospital faces. The increase can come from previously uninsured patients or privately insured patients. Because the hospital treats more patients without private insurance, the hospitals will respond by reducing the number of private patients treated. The optimal change in the quantity of private patients is found by taking the total derivative of equation (2) and solving for \( \frac{dq^P}{d\gamma^M} \):

\[
\frac{dq^P}{d\gamma^M} = \frac{c_{qq} \left[ q_\gamma^M + q_\gamma^U \right] - \left[ p_q^P q^P + p^P + p_q^P \right]}{p_q^P q^P + 2p^P + B_q^P - c_{qq}}.
\]  

(3)

According to equation (3), an increase in Medicaid eligibility will change the optimal number of private patients treated through four channels. The term, \( c_{qq} \left[ q_\gamma^M + q_\gamma^U \right] \), represents the change in the marginal cost of non-privately insured patients as a result of the expansion. The term will be zero when marginal cost is constant or a Medicaid expansion is completely driven by previously uninsured patients who do not exhibit moral hazard. In this extreme case, \( q_\gamma^M = -q_\gamma^U \). If any moral hazard exists, the term is positive when marginal cost is increasing.\(^6\)

The expansion may cause some privately insured patients to switch to Medicaid, changing the

\(^6\)There is an implicit assumption that previously uninsured patients do not reduce their levels of treatment after enrolling in Medicaid and \( q_\gamma^M + q_\gamma^U \) will never be negative.
marginal revenue curve by \( p_q^P q^P + p_q^P + p_\gamma^P \). As patients move from private insurance to Medicaid, the demand and marginal revenue from private patients will decrease, and the term is negative. In the case where there is no crowd out, a Medicaid expansion will not affect the private marginal revenue curve and \( p_q^P q^P + p_q^P + p_\gamma^P \) will be zero. The non-positive value of \( p_q^P q^P + p_q^P + p_\gamma^P \) is subtracted from the non-negative term, \( c_{qq} [q_\gamma^M + q_\gamma^U] \), and the numerator of equation (3) is non-negative.

The denominator reflects the condition that marginal benefit of private patients must remain equal to marginal cost. The marginal revenue decreases when there is an increase in private patients, \( p_q^P q^P + 2p_q^P \), and the term \( B_{qq}^P \) is negative at non-profit hospitals by assumption. Taken together, the term, \( p_q^P q^P + 2p_q^P + B_{qq}^P \), is strictly negative. The last term in the denominator, \( c_{qq} \), reflects the change in marginal cost from treating more private patients and is non-negative by assumption, making the denominator in equation (3) strictly negative.

Under most scenarios, an increase in Medicaid eligibility will be associated with a decrease in the quantity of private patients treated, \( \frac{dq^P}{d\gamma^M} < 0 \). It is possible for \( \frac{dq^P}{d\gamma^M} = 0 \) when there is no crowd out and either marginal cost is constant, or uninsured patients do not increase health care treatment when they receive Medicaid coverage. If there is no crowd out, the magnitude of the reduction in private patients from a Medicaid expansion will grow as the moral hazard exhibited by uninsured patients, \( q_\gamma^M + q_\gamma^U \), increases. In this scenario, fewer private patients are treated, but the private demand curve is unchanged and the price charged to private patients will increase.

The case of no crowd out at a for-profit hospital is seen visually in figure 1. The for-profit hospital faces uninsured and Medicaid patients before deciding the optimal number of private patients to treat (uninsured patients are not depicted in the figure). The Medicaid expansion increases the treatment of non-private patients at the hospital, depicted by the dashed black line. The private demand curve shifts from \( D \) to \( D' \), but the slope of the demand curve remains the same. Hospitals will continue to optimally set marginal cost equal to marginal revenue, treat fewer private patients and charge a higher price.

As the rate of crowd out increases, the term \( q_\gamma^M + q_\gamma^U \) increases because \( q_\gamma^M \) is increasing without a equally sized reduction in \( q_\gamma^U \). An increasing rate of crowd out will increase the numerator of equation (3) further as the private marginal revenue curve decreases by \( p_q^P q^P + p_q^P + p_\gamma^P \). With fewer private patients, the marginal benefit decreases, which is represented by the term, \( p_q^P q^P + 2p_q^P + B_{qq}^P \). Overall, increasing levels of crowd out increase the magnitude of the decrease in private patients
The marginal cost will also determine the magnitude of the change in private patients following a Medicaid expansion. Hospitals where marginal costs are increasing at a higher rate will reduce private patients more than hospitals with flatter marginal cost curves. For-profit hospitals that do not receive a non-monetary benefit from treating patients will drop the term $B_{qq}^P$, and reduce private patients more than at comparable non-profit hospitals following a Medicaid expansion.

The effect of the Medicaid expansion on private charges is ambiguous when there is crowd out. The optimal number of private patients unambiguously decreases, but the nature of the private demand curve also changes since there are now fewer privately insured patients. Depending on the nature of the expansion and the change in the elasticity of private demand, it is possible for private charges to rise or fall after an expansion.

Figure 2 shows the unique situation where a for-profit hospital faces a linear private demand curve and there is perfect crowd out. Perfect crowd out occurs when the increase in marginal cost from treating additional non-private patients, $c_{qq} \left[ q_r^M + q_r^U \right]$, is completely offset by the reduction in marginal revenue from the expansion, $p_{q}^P q^P + p_{q}^P + p_{q}^P$. In this case, the reduction in private patients is exactly equal to the increase in Medicaid patients and the total number of patients treated is unchanged. The linearity of the private demand curve causes the price to remain the same before and after the expansion. This unique situation also suggests that it is possible for non-profit hospitals to reduce private prices after an expansion, but a comparable for-profit hospital could optimally raise prices.

If the parameters of the model above are known, the predictions about quantity and price are straightforward. However, finding a suitable way to measure hospital prices is less clear. The revenue amount reported in inpatient data do not necessarily reflect the actual amount a hospital is reimbursed after negotiations with insurance companies (Reinhardt, 2006). The actual amount received by a hospital for a service depends on their market power, the number of subscribers in the insurance group, the intensity of treatment and patient outcomes.

Negotiating for a higher reimbursement rate comes at the risk of the insurance carrier dropping the hospital from their network. According to the theoretical model, hospitals facing more Medicaid patients are willing to lose private patients as long as the remaining patients are treated at a higher reimbursement rate.
4 Empirical Analysis

4.1 California County Health Insurance Programs

Randomly assigning Medicaid patients to hospitals is not a feasible way to empirically test the implications of the model in the previous section. Without randomization, institutional changes in government health insurance programs must be used to estimate the relationship between Medicaid treatment and private outcomes. In 2007, then again in 2010, California established county-level programs that provided health insurance coverage to hundreds of thousands of low-income, uninsured individuals that were not eligible for the state’s Medi-Cal program. The variation in the timing of the program across counties provides an opportunity to test the predictions of the model by exploring how large increases in county-insured patients are related to outcomes for privately insured patients.

In 2005, the Centers for Medicare and Medicaid Services approved California’s proposal to provide hospital financing waivers through the Health Care Coverage Initiative (HCCI). The funding was made possible by Section 1115 of the Social Security Act that provides assistance with projects that promote the objectives of the Social Security Act. The financing waiver provided $180 million in federal funding annually between 2007 and 2010, with the goal of expanding health insurance coverage to low-income, uninsured individuals in California (DHCS, 2010). Sixteen counties and California’s consortium of thirty-five rural counties (CMSP) applied for HCCI funding. The ten counties that received funding became known as "legacy" counties and received between $7.5 and $54 million annually for HCCI program between 2007 and 2010.

Patients that were insured through the HCCI were considered "county insured" patients by California’s Office of State Health and Planning Development (OSHPD). Using OSHPD data, the solid line in figure 3 shows how the number of county insured inpatient days per hospital change between 2000 and 2010 in legacy counties. The dotted line shows how the average changed at hospitals located in the six counties that applied for HCCI funding, but were rejected. The CMSP counties are omitted. According to figure 3, there was a slight increase in the average number of

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7 The legacy counties are: Alameda, Contra Costa, Kern, Los Angeles, Orange, San Diego, San Francisco, San Mateo, Santa Clara and Ventura.
8 The rejected counties are: Fresno, Merced, Riverside, San Bernardino, Santa Cruz and Tulare.
county insured inpatient days prior to the implementation of the HCCI in hospitals located in legacy and rejected counties. After the HCCI began in 2007, there was a significant increase in the average number of county patients in legacy hospitals, but a minimal decrease in the average in hospitals located in rejected counties. The aggregate information in figure 3 suggests that the HCCI led to a significant increase in county insured treatment.

Before the HCCI funding expired at the end of 2010, the federal government encouraged states to began preparing for the expansion in Medicaid to all low-income individuals, originally set to begin nationally on January 1, 2014. In November, 2010, California’s Low Income Health Program (LIHP) was approved by the Centers for Medicare and Medicaid Services. The LIHP was similar to the HCCI in that the overarching goal was to provide health insurance coverage for low-income, uninsured individuals. The main difference between the LIHP and HCCI was that unlimited federal funding was available under the LIHP for costs associated with providing coverage for individuals with effective incomes under 138% of the FPL.

Another important feature of the LIHP is that the program was introduced in counties at different points in time between 2011 and 2013. The ten HCCI legacy counties transitioned to the LIHP in 2011. In 2012, Riverside, San Bernardino, Santa Cruz, San Joaquin, Placer and Sacramento counties implemented the LIHP, as did the CMSP. Monterey and Tulare counties enacted the LIHP in 2013. An estimated 660,000 individuals received county insurance through the LIHP. When the LIHP ended in December 2013, over 90 percent of the enrollees immediately transitioned to Medi-Cal, while the remaining enrolled for health insurance through the state’s health insurance marketplace or decided not to continue with health insurance coverage (Thomason and Long, 2014).

Figure 4 shows the growth in county insured patients between 2011 and 2013 as a result of the LIHP. The solid line depicts the average county insured inpatient days per hospital in legacy counties. There is an increase in inpatient days in 2011 when the legacy counties began the LIHP. The dashed line shows the average inpatient days at hospitals in adopting counties. Average inpatient days in adoption county hospitals significantly increased in 2012 and 2013. In 2014, the average county insured inpatient days fell significantly as many county insured patients began receiving health insurance coverage through Medi-Cal.

Table 1 provides empirical support for figures 3 and 4. In the table 1, the number of county insured patients and total patients are regressed on time period dummy variables, a binary variable
representing whether a hospital is in a legacy county, interactions between the time period and legacy binary variables and hospital fixed effects. The regressions in table 1 only include hospitals in legacy and adopting counties and the first column shows that the number of county insured inpatient days increase significantly more in legacy hospitals, relative to the LIHP adopting hospitals, during HCCI years and the first year of the LIHP.

When adopting counties implemented the LIHP in 2012 and 2013, the number of inpatient days in hospitals in adopting counties increased significantly. Similar results are seen in the second column when county insured inpatient discharges are used as the dependent variable. The third column shows that the difference in outpatient visits between hospitals in legacy and adopting counties did not change significantly when counties implemented the HCCI and LIHP.

The last three columns of table 1 use thousands of inpatient days, inpatient discharges and outpatient visits for all patients in a hospital as the dependent variable. Implementation of the HCCI or LIHP did not differentially increase treatment of all patients in legacy counties compared to adopting counties. The results show that inpatient treatment may have relatively decreased in legacy counties after the LIHP started. Overall, there does not appear to be a strong relationship between changes in the treatment of all patients and the HCCI and LIHP.

4.2 Hospital Financial and Utilization Data

The empirical analysis uses the change in county insured patients driven by the HCCI and LIHP to explore how hospitals respond to an increase in low-income, fixed marginal revenue patients. The Office of State Health Planning and Development (OSHPD) in California publishes utilization, financial and ownership information for every licensed hospital in California. The data is publicly available from 2000 to 2014. One of the primary benefits of the data is that each year, the net revenue is reported by insurance type. The net revenue is the actual amount hospitals receive from patients, government programs and third party payers. The data also includes information about hospital operating expenses, gross revenue, total patients, licensed beds and hospital competition to control for hospital characteristics that potentially influence the prices charged to privately insured patients.

Table 2 shows the averages for the hospital level variables used in the analysis between 2000 and 2013. The averages are separated by legacy and adoption counties and whether the years coincide
with the HCCI or LIHP. In legacy counties, hospitals received $165.8 million in net revenue from private patients before the HCCI. The private net revenue increased to $242.2 million during HCCI years and then to $263.9 million during the LIHP years. The average net revenue per private patient increased in a similar fashion, although the number of private patient days (inpatient days plus outpatient visits) decreased over the same time period. Consistent with figure 3, the net revenue from county insured patients and county insured patient days increased in legacy counties.

Averages for privately insured variables in hospitals located in adoption counties tend follow a similar pattern as legacy counties. Net revenue and average net revenue for private patients in adopting counties increase and private patient days decrease between the HCCI period and the LIHP period. County insured net revenue decreases in adopting county hospitals between the HCCI period and the LIHP period, but the number of county insured patient days per hospital does increase. The averages for privately insured and county insured patients in table 2 are consistent with the implications of the theoretical model showing that increases in county insured patients could lead to an increase in prices for privately insured patients.

The remaining variables in table 2 show that hospitals in adopting and legacy counties tend to follow similar patterns, with two exceptions. The average total patient days in legacy county hospitals decreased over time, while adoption county hospitals increased patient days. The last row shows the average Herfandahl-Hirshman Index (HHI) using gross revenue in a health facility planning area to construct the HHI. The HHI for both legacy and adoption county hospitals suggest that the average hospital has market power and the HHI has increased over time. However, the HHI in adoption county hospitals are noticeably greater than legacy county hospitals, which is consistent with legacy counties being located in highly populated areas. Licensed Beds, Gross Revenue and Total Operating Expenses are qualitatively similar across the county types.

### 4.3 Empirical Specification

The summary statistics in table 2 show that the average net revenue hospitals received from private patients increase as the number of county insured patients increase. Table 2 is consistent with the theoretical predictions from the model in the previous section, but there are a number of hospital characteristics that can increase private prices and county insured patients simultaneously that must be controlled for.
Using the price of private patients as a dependent variable requires the quantity of private patients to be a regressor. Not only is the coefficient for private quantity biased, but if there is a systematic relationship between the quantity of private and county insured patients, the county insured coefficient will also be biased. Equation (4) begins to mitigate the concerns surrounding the simultaneous relationship between private price and quantity by using the private net revenue \( (p^P \times q^P) \) and private net revenue per private patient day \( \left( \frac{p^P \times q^P}{q^P} \right) \) as dependent variables:

\[
\ln Y_{ht}^P = \alpha + \beta \ln q_{ht}^{CNTY} + \phi Z_{ht} + \theta_h + \pi_t + \varepsilon_{ht}. \tag{4}
\]

The coefficient of interest in equation (4), \( \beta \), reports the percentage change in private net revenue or average private net revenue in hospital \( h \) when the quantity of county insured patients, \( q_{ht}^{CNTY} \), increases by one percent. The regression includes hospital and year fixed effects and the matrix of controls, \( Z_{ht} \), includes the natural log of a hospital’s gross revenue, operating expenses, patient days, licensed beds and HHI in year \( t \).

In order for the results to be consistent with the theoretical predictions, the net revenue per private patient (private price) is expected to increase when the increase in county insured patients is driven by previously uninsured individuals. The expected relationship between private net revenue and county insured patients is less clear. Assuming that the private price increases in response to an increase in county insured patients, the change in net revenue will depend on the relative reduction in the quantity of privately insured patients. A relatively small decrease in private patients, combined with an increase in private prices, will lead to an increase in private net revenue. If the reduction in private patients is large relative to an increase in the private price, it is possible for the net revenue to decrease.

The endogeneity concerns from using the private price and quantity as dependent variables are reduced by using the private net revenue and net revenue per private patient as outcomes. A significant concern remains in equation (4) if the quantity of county insured patients are related to unobservable hospital characteristics that influence private price or quantity. If a hospital gains a reputation for providing high-quality treatment, the hospital may observe an increase in all types of patients and use their improved reputation to negotiate higher prices with private insurance companies. In this scenario, the coefficient of interest in equation (4) would show that county patients and private prices are positively related, but the coefficient would be capturing the unobservable
reputation effect.

To remove some of the bias caused by regressing the private outcomes on the quantity of county insured patients, a first stage regression predicts the natural log of county insured patients treated in hospital $h$ in year $t$ with the implementation of the HCCI and LIHP. In equation (5),

$$\ln q_{ht}^{CNTY} = \lambda CountyProgram_{ht} + \delta Z'_{ht} + \varphi_{h} + \sigma_{t} + \nu_{ht},$$

the natural log of county insured patients is regressed on a binary variable that captures whether year $t$ is a year that coincides with the active dates of the HCCI and LIHP, CountyProgram. The CountyProgram dummy variable is equal to one in 2007 through 2013. The regression only includes legacy and adopting counties and variable of interest in the first stage shows how the quantity of county insured patients change when the HCCI or LIHP are implemented.

After the first stage, the predicted value of $\ln q_{ht}^{CNTY}$ is used in equation (4). The coefficient of interest, $\beta$, then shows how changes in county insured patients driven by HCCI and LIHP are related to private net revenue and private net revenue per patient. The coefficient $\beta$ is unbiased under the assumption that changes in county insured patients generated from the HCCI and LIHP are unrelated to unobservable determinants of private patient outcomes, $\varepsilon_{ht}$. An increase in demand for hospital services that coincides with the implementation of the HCCI and LIHP can lead to an increase in county patients and private prices, but county patients will not be causally related to private outcomes. In the event that a demand shock is driving the results, the quantity of private patients should also increase. To more accurately explore the prevalence of private demand shocks, the the natural log of private patient days will also be used as a dependent variable.

### 4.4 Regression Results

Table 3 presents the regression results of the two-stage regressions described in equations (4) and (5). The first column shows how the implementation of the HCCI and LIHP are related to changes in county insured patient days in a hospital. When the county health insurance programs are enacted, county-insured patient days in a hospital increase by 38 percent. The relationship is highly significant and has an F-stat of 9.30, nearing the conventional F-stat cutoff of 10.

The second column shows that a ten percent increase in county insured patient days in a hospital
is associated with a 1.8 percent increase in the net revenue the hospital receives from private patients, but the relationship is insignificant. In the third column, the results show that the increase in net revenue is driven by an increase in net revenue per private patient. Although the third column may suffer from endogeneity because the natural log of private patients are used as the dependent variable, there is a relatively small, negative and insignificant relationship between private patient days and county insured patient days within a hospital. The last three columns of table 3 support the theoretical predictions of the model.

Another prediction derived from the theoretical model is that for-profit hospitals will respond more strongly to changes in fixed marginal revenue patients, compared to similar non-profit hospitals. Table 4 provides support for that prediction. In the first three columns, the county insured patient day coefficient is reported for unique two-stage regressions corresponding to equations (4) and (5). The natural log of the private net revenue, private net revenue per patient day and private patient days in all hospitals, non-profit hospitals or for-profit hospitals are used as dependent variables.

The main results from table 3 are reported in the first three columns of the first row in table 4. The bottom two rows show the results when non-profit and for-profit hospitals are examined separately. In non-profit hospitals, increases in county insured patients are positively, but insignificantly, related to private net revenue, private net revenue per patient day and private patient days.

At for-profit hospitals, there is a significant increase in private net revenue per patient day when county insured patients increase. There is a large, but insignificant, reduction in private patient days as county insured patients increase. The decrease in private patient days partially offsets the increase in private price and causes the relationship between private net revenue and county insured patients at for-profit hospitals to be positive, but insignificant.

To better understand how hospitals are altering the prices charged to privately insured individuals, the last four columns of table 4 explore how contractual adjustments and capitation revenue from private patients change when county insured patients increase. Contractual adjustments capture the reduction in a private patient’s bill due to an agreement with the insurance company. A higher contractual adjustment, all else held equal, suggests that hospitals receive less from insurance companies.

Two-stage regression results using the contractual adjustment amount as the dependent variable
are reported in the fourth column table 4. Increases in county insured patients are associated with larger discounts for private insurance companies when all hospitals are included in the regression, but the results are insignificant. At for-profit hospitals, increasing the number of county insured patients is associated with a significant reduction in contractual adjustments. Results using non-profit hospitals are insignificant.

The next column shows how county insured patients are related to the average contractual adjustment per private patient. The coefficients mirror the nominal contractual adjustment regressions, but the county insured patient coefficient is only significant in the non-profit hospital regression. The last columns of table 4 explore whether capitation revenue from private managed care patients are related to county insured patients. The amount of capitation revenue per patient decreases as county insured patients increase, but the coefficient is only marginally significant when all hospitals are used in the regression. All other regressions using capitation as the dependent variable are insignificant.

The results in table 4 suggest that non-profit hospitals may be experiencing an increase in private demand that coincides with increases in county insured patients. Point estimates suggest that there is an increase in private patient days and discounts to insurance companies at non-profit hospitals when county insured patients increase. At for-profit hospitals, increases in net revenue from private patients do not appear to be driven by an increase in private patients.

If hospitals that experience an increase in county insured patients are attempting to attract all types of patients to the hospital, then increases in county insured patients should be related to outcomes for Medicaid or Medicare patients. Table 5 shows that net revenue for all patients is positively related to county insured patients, but the coefficient is only marginally significant. County insured patients are unrelated to the net revenue, net revenue per patient day or total patient days for both Medicaid and Medicare patients. These falsification regressions do not rule out the possibility of private demand increasing during the HCCI and LIHP years, but there does not appear to be an increase in Medicare and Medicaid when county patients increase.
5 Discussion

The theoretical predictions in section 3 show that when there is no crowd out, an increase in the number of Medicaid, or fixed marginal revenue, patients will reduce the number of private patients treated. The reduction will be larger at for-profit hospitals compared to non-profit hospitals with similar attributes. Prices for privately insured patients will rise when there is no crowd out. If there is crowd out when Medicaid patients increase in a hospital, the theoretical change in prices for private patients is ambiguous. The implications of the model are tested using county insured health insurance programs in California, which provided health insurance for previously uninsured individuals.

The behavior of for-profit hospitals is consistent with the theoretical predictions. Increasing county insured patients through the HCCI and LIHP is associated with a significant increase in average net revenue per private patient, an insignificant reduction in the quantity of private patient days and an insignificant increase in net revenue from private patients. The increase in revenue per patient at for-profit hospitals appear to be driven by a reduction in contractual adjustments. Non-profit hospitals do not respond to the increase in county insured patients in the same way as for-profit hospitals as the quantity of private patients are positively related to county insured patients.

There are a number of possible reasons as to why non-profits behave differently than for-profits in the results above. The non-profit results may be because private demand increased when the HCCI and LIHP are implemented at non-profit hospitals, but not at for-profits. Assuming that a non-profit hospital is not capacity constrained, any increase in private demand that occurs during the HCCI and LIHP can lead to an increase in both county insured and private patients, as well as an increase in the net revenue and average net revenue from private patients.

Another potential explanation for the difference in results by hospital type may be the relatively weak first stage regression for non-profit hospitals. The strong first stage results reported in the last column of table 4 are driven by for-profit hospitals. A relatively weak correlation between county insured patients and the implementation of the HCCI and LIHP at non-profits will bias the coefficient of interest. A final reason that non-profit hospitals may not act according to theoretical predictions is that non-profit hospitals could have a different utility function than the one described
in equation (1). Non-monetary benefits may enter into the utility function in a unique way or non-profit hospitals may differentially treat patients based on their insurance status. Non-profit hospital results may be influenced by unidentified factors, but the theoretical predictions above suggest that it is possible for non-profits and for-profits to react differently to an increase in county insured patients.

Between 2000 and 2013, county insured patients increased by 21 percent in legacy counties and 10.5 percent in adopting counties. Unreported first stage regression results suggest that 50 percent of the 10.5 percent difference in county insured treatment between legacy and adopting counties is driven by the county health insurance programs. A 5 percent increase in county insured patients in a hospital is associated with a 1.5 percent increase in net revenue from private patients and a 1.75 percent increase in the average net revenue per private patient. Over the same time period, the average net revenue per private patient increased by 45 percent in legacy counties and 33 percent in adopting counties. According to the empirical results above, roughly 13 percent of the difference in the growth in net revenue per private patient between the legacy and adopting counties is explained by the implementation of the HCCI and early years of the LIHP.

The magnitude of the coefficients in table 3 are larger, but comparable to previous cost shifting studies. Zwanzinger and Bamezai (2006) use California OSHPD data and show that when Medicaid prices decrease by 10 percent, there is a 0.40 percent increase in private prices between 1997 and 2001. They also show that cost shifting from Medicare and Medicaid to privately insured patients are responsible for 12.3 of the increase in private prices, which is nearly the same as the current paper. Wagner (2015b) uses HCUP data and finds that a 10 percentage point increase in Medicaid eligibility for individuals with disabilities is associated with a 1.2 percent reduction in charges for privately insured individuals with at least one chronic condition. Although private prices are negatively related to a Medicaid expansion in her analysis, the results are consistent with the model presented in this paper where Medicaid completely crowds out private insurance at non-profit hospitals. Approximately 80 percent of Wagner’s (2015b) patients were treated at non-profit hospitals and the behavior at non-profit hospitals likely drive the negative relationship in her paper.

Cost shifting estimates from reductions in Medicare reimbursements are considerably larger than estimates generated by changes in Medicaid prices. Cutler (1998) finds a dollar-for-dollar shift between Medicare and private patients in the early 1980s, although there is no evidence of cost
shifting in the early 1990s. Wu (2009) shows that increases in private prices recover 21 cents of every dollar lost in Medicare revenue in 1996 and 2000. The difference in cost shifting estimates between Medicaid and Medicare suggest that hospitals may rely more on Medicare to bolster revenue than Medicaid.

The relationship between county insured patients and private quantity and prices found above does not necessarily imply that the current Medicaid expansion will impact private patients in a similar manner. The county level health programs, the HCCI and LIHP, had a finite time horizon and were considerably smaller than the current Medicaid expansion. The significant and sustained increase in Medicaid patients can impact the behavior of hospitals in ways not discussed above. Hospitals may become more diligent about reducing costs or alter the wage structure of health care workers. Garthwaite (2012) finds that physicians see more Medicaid patients, but for a shorter amount of time, following the implementation of the CHIP program.

The differential response of non-profit and for-profit hospitals to an increase in county insured patients is a potentially important finding for policy makers that are working to minimize negative consequences associated with the ACA. According to the theoretical model and empirical results, non-profit hospitals appear to value the potential loss from treating fewer private patients more than for-profit hospitals. Providing incentives for new Medicaid patients to seek out treatment at non-profit hospitals, as opposed to for-profit hospitals, can potentially mitigate negative outcomes for private patients. A significant fraction of hospitals are non-profit, so it is possible to provide this type of incentive without restricting the availability of health care for most Medicaid patients. Policy makers would also need to ensure that treatment quality did not suffer if the majority of new Medicaid patients were treated at non-profit hospitals.

6 Conclusion

Motivated by states following the ACA and expanding Medicaid eligibility to include all low-income individuals, this paper explores how the quantity and price charged to privately insured patients changes when the number of low-paying, government insured patients in a hospital rise. There is a significant literature examining the consequences of changes to the Medicaid program, but before the recent expansion, there has been a limited incentive to study how large scale increases
in eligibility affect private patients. After adding uninsured patients to a mixed-economy model, it is shown that hospitals optimally reduce treatment to private patients and increase charges when there is an increase in Medicaid enrollment driven by previously uninsured patients. The magnitude of the changes are larger at for-profit hospitals, compared to similar non-profit hospitals. When new enrollment in Medicaid crowds out private insurance, there is still a reduction in private treatment, but the predicted change in prices to private patients is ambiguous.

The predictions of the model are tested using hospital level data from California hospitals and exploiting the variation in the timing and location of county programs that increased health insurance coverage for low-income, uninsured individuals. The empirical results are largely consistent with the theoretical predictions and show that the average net revenue per private patient increases when the treatment of county insured patients increase through the HCCI and LIHP. There is a small, insignificant reduction in the quantity of private patients associated with the county insured increase, leading to an overall increase in private net revenue when county insured patients rise.

Additional regressions show that behavior at for-profit hospitals is more consistent with theoretical predictions that non-profit hospitals. The private price increase at for-profit hospitals appears to be driven by fewer discounts to private insurance companies during the billing process. The non-profit results that do not align with theory may be because non-profit hospitals are experiencing a continual increase in demand from privately insured individuals, the effect of the HCCI and LIHP is not as strong at non-profit hospitals or non-profit hospitals have a complex utility function that is not captured in the theoretical model.

The theoretical implications of the three-market model potentially explain behavior in other markets. Past research has examined how consumers facing market prices in housing (Eriksen and Ross, 2015) and education (Groen and White, 2004) are influenced by an increase in low-paying, subsidized consumers. The theory could also be applied to the market consequences of pro-bono work in the legal industry or the reaction of market prices in the shipping industry when companies such as Amazon provide quick delivery at no marginal cost for those who pay an annual membership fee.

Overall, the findings may have important implications for the recent Medicaid expansion. One of the selling points of the ACA has been the Congressional Budget Office estimate that the government will save nearly $1.4 trillion between 2014 and 2023 (CBO, 2013). However, if hospitals increase
private prices as Medicaid enrollments grow, the government savings from the ACA may come at the expense of privately insured patients and the total savings of the ACA may be overstated.

References


Table 1: County Patients, HCCI and LIHP, 2000-2013

<table>
<thead>
<tr>
<th></th>
<th>County Insured Patients</th>
<th>All Patients (1000s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Inpatient Days</td>
<td>Inpatient Discharges</td>
</tr>
<tr>
<td>Legacy Hospitals</td>
<td>1,268**</td>
<td>65.8</td>
</tr>
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<td></td>
<td>(612)</td>
<td>(50.9)</td>
</tr>
<tr>
<td>HCCI Years</td>
<td>-107</td>
<td>3.59</td>
</tr>
<tr>
<td>(2007 – 2010)</td>
<td>(67.0)</td>
<td>(13.0)</td>
</tr>
<tr>
<td>LIHP Years</td>
<td>-128</td>
<td>14.2</td>
</tr>
<tr>
<td>(2011 – 2013)</td>
<td>(142)</td>
<td>(26.8)</td>
</tr>
<tr>
<td>Adoption Years</td>
<td>199**</td>
<td>64.9***</td>
</tr>
<tr>
<td>(2012 – 2013)</td>
<td>(81.1)</td>
<td>(13.8)</td>
</tr>
<tr>
<td>Legacy × HCCI</td>
<td>575***</td>
<td>95.5***</td>
</tr>
<tr>
<td></td>
<td>(192)</td>
<td>(27.0)</td>
</tr>
<tr>
<td>Legacy × LIHP</td>
<td>587**</td>
<td>95.8**</td>
</tr>
<tr>
<td></td>
<td>(291)</td>
<td>(41.8)</td>
</tr>
<tr>
<td>Legacy × ADOPT</td>
<td>-430**</td>
<td>-47.5*</td>
</tr>
<tr>
<td></td>
<td>(218)</td>
<td>(26.2)</td>
</tr>
<tr>
<td>Pre-HCCI Adoption</td>
<td>821***</td>
<td>176***</td>
</tr>
<tr>
<td>Hospitals (Constant)</td>
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<td>(30.5)</td>
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<tr>
<td>Observations</td>
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</tr>
<tr>
<td>R-squared</td>
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<td>0.027</td>
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</table>

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Regressions only include hospitals located in legacy or LIHP adopting counties that treated at least one county insured patient. All regressions include hospital fixed effects.
<table>
<thead>
<tr>
<th></th>
<th>All Counties</th>
<th>Legacy Counties</th>
<th>Adoption Counties</th>
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<tr>
<td></td>
<td>All Years</td>
<td>Pre-HCCI</td>
<td>HCCI</td>
</tr>
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<td>Private Net Revenue (mil.)</td>
<td>178.5</td>
<td>165.8</td>
<td>242.2</td>
</tr>
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<td></td>
<td>(210.4)</td>
<td>(181.8)</td>
<td>(252.2)</td>
</tr>
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<td>Average Private Net Revenue</td>
<td>1427.4</td>
<td>1034.2</td>
<td>1710.4</td>
</tr>
<tr>
<td></td>
<td>(915.1)</td>
<td>(577.4)</td>
<td>(755.7)</td>
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<td>Private Patient Days (thousands)</td>
<td>137.6</td>
<td>159.9</td>
<td>150.7</td>
</tr>
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<td></td>
<td>(160.7)</td>
<td>(181.7)</td>
<td>(167.1)</td>
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<td>County Insured Net Revenue (mil.)</td>
<td>3.82</td>
<td>2.51</td>
<td>4.40</td>
</tr>
<tr>
<td></td>
<td>(6.55)</td>
<td>(4.14)</td>
<td>(7.06)</td>
</tr>
<tr>
<td>County Insured Patient Days</td>
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<td>1793.6</td>
<td>2258.7</td>
</tr>
<tr>
<td></td>
<td>(3335.9)</td>
<td>(3942.8)</td>
<td>(3575.4)</td>
</tr>
<tr>
<td>Total Patient Days (thousands)</td>
<td>86.7</td>
<td>97.2</td>
<td>92.4</td>
</tr>
<tr>
<td></td>
<td>(55.8)</td>
<td>(59.9)</td>
<td>(46.1)</td>
</tr>
<tr>
<td>Licensed Beds</td>
<td>380.4</td>
<td>421.5</td>
<td>405.1</td>
</tr>
<tr>
<td></td>
<td>(237.7)</td>
<td>(251.5)</td>
<td>(212.6)</td>
</tr>
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<td>Gross Revenue (mil.)</td>
<td>1301.0</td>
<td>1047.3</td>
<td>1633.6</td>
</tr>
<tr>
<td></td>
<td>(1330.7)</td>
<td>(974.7)</td>
<td>(1406.4)</td>
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<tr>
<td>Total Operating Expenses (mil.)</td>
<td>352.4</td>
<td>324.0</td>
<td>445.0</td>
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<td></td>
<td>(359.0)</td>
<td>(311.6)</td>
<td>(409.4)</td>
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<td>Health Facility Planning Area HHI</td>
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<td>(2397.4)</td>
<td>(1961.4)</td>
<td>(2253.5)</td>
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<td>Observations</td>
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<td>265</td>
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</table>

Cells report annual means and standard deviations, weighted by the average inpatient days per year.
Table 3: County Insured Patients and Private Outcomes

<table>
<thead>
<tr>
<th></th>
<th>ln County Insured Patient Days</th>
<th>ln Private Net Revenue</th>
<th>ln Private Net Revenue per Patient</th>
<th>ln Private Patient Days</th>
</tr>
</thead>
<tbody>
<tr>
<td>County Program</td>
<td>0.39***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.13)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln County Insured</td>
<td></td>
<td>0.18</td>
<td>0.27*</td>
<td>-0.088</td>
</tr>
<tr>
<td>Patient Days</td>
<td></td>
<td>(0.13)</td>
<td>(0.16)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>ln Total Patient Days</td>
<td>0.65***</td>
<td>-0.0018</td>
<td>-0.25</td>
<td>0.23</td>
</tr>
<tr>
<td></td>
<td>(0.22)</td>
<td>(0.15)</td>
<td>(0.18)</td>
<td>(0.15)</td>
</tr>
<tr>
<td>ln Licensed Beds</td>
<td>-0.14</td>
<td>-0.0093</td>
<td>0.11</td>
<td>-0.10</td>
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<td></td>
<td>(0.32)</td>
<td>(0.13)</td>
<td>(0.22)</td>
<td>(0.15)</td>
</tr>
<tr>
<td>ln Gross Revenue</td>
<td>0.15</td>
<td>0.25*</td>
<td>0.21</td>
<td>0.046</td>
</tr>
<tr>
<td></td>
<td>(0.28)</td>
<td>(0.13)</td>
<td>(0.15)</td>
<td>(0.15)</td>
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<td>ln Operating Expenses</td>
<td>0.08</td>
<td>0.75***</td>
<td>-0.41*</td>
<td>1.14***</td>
</tr>
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<td></td>
<td>(0.33)</td>
<td>(0.14)</td>
<td>(0.21)</td>
<td>(0.21)</td>
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<td>ln HHI</td>
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<td>-0.15</td>
<td>-0.092</td>
<td>-0.061</td>
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<tr>
<td></td>
<td>(0.28)</td>
<td>(0.15)</td>
<td>(0.18)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>F – Stat</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>1,868</td>
<td>1,868</td>
<td>1,868</td>
<td>1,868</td>
</tr>
<tr>
<td>R²</td>
<td>0.073</td>
<td>0.503</td>
<td>0.374</td>
<td>0.377</td>
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</table>

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors clustered by hospital in parentheses. All regressions include hospital and year fixed effects and are weighted by the average number of patient days between 2000 and 2013. Columns (1) through (3) use the predicted value of county insured patient days as the variable of interest. The first stage regression results are reported in column (4).
Table 4: Effect of County Insured Patients in Non-Profit and For-Profit Hospitals

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>0.18</td>
<td>0.27*</td>
<td>-0.088</td>
<td>123</td>
<td>234</td>
<td>-5.50</td>
<td>-74.1*</td>
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<tr>
<td>Hospitals</td>
<td>(0.13)</td>
<td>(0.16)</td>
<td>(0.13)</td>
<td>(75.2)</td>
<td>(310)</td>
<td>(3.65)</td>
<td>(40.5)</td>
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<td>Non-Profit Hospitals</td>
<td>0.23</td>
<td>0.11</td>
<td>0.12</td>
<td>279</td>
<td>600</td>
<td>-11.7</td>
<td>-155</td>
</tr>
<tr>
<td></td>
<td>(0.20)</td>
<td>(0.24)</td>
<td>(0.19)</td>
<td>(212)</td>
<td>(592)</td>
<td>(8.93)</td>
<td>(107)</td>
</tr>
<tr>
<td>For-Profit Hospitals</td>
<td>0.093</td>
<td>0.32**</td>
<td>-0.23</td>
<td>-17.2**</td>
<td>-147</td>
<td>-0.14</td>
<td>6.81</td>
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<td></td>
<td>(0.13)</td>
<td>(0.16)</td>
<td>(0.15)</td>
<td>(7.41)</td>
<td>(291)</td>
<td>(0.36)</td>
<td>(14.7)</td>
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</table>

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the hospital in parentheses. Each cell reports the coefficient of the natural log of county insured patient days for a unique two-stage regression. The dependent variable corresponds with the variables described in the columns and the regressions are stratified based on whether the hospital is a non-profit or for-profit hospital. All regressions include controls and hospital and year fixed effects and are weighted by the average number of patient days.

Table 5: Falsification Regressions

<table>
<thead>
<tr>
<th>Dependent Variables</th>
<th>ln Net Revenue</th>
<th>ln Net Revenue per Patient</th>
<th>ln Patient Days</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>0.068*</td>
<td>0.017</td>
<td>0.051</td>
</tr>
<tr>
<td>Patients</td>
<td>(0.036)</td>
<td>(0.049)</td>
<td>(0.049)</td>
</tr>
<tr>
<td>Medicaid Patients</td>
<td>0.073</td>
<td>0.18</td>
<td>-0.079</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(0.15)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>Medicare Patients</td>
<td>-0.048</td>
<td>-0.021</td>
<td>-0.027</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.089)</td>
<td>(0.12)</td>
</tr>
</tbody>
</table>

* p<0.1. Standard errors clustered at the hospital in parentheses. Each cell reports the coefficient of the log of county insured patient days for a unique two-stage regression. The dependent variable corresponds to variables in the columns and rows. All regressions include controls, hospital and year fixed effects and are weighted by the average number of patient days.
Figure 1: For-Profit Hospital, No Crowd Out

Figure 2: For Profit Hospital, Complete Crowd Out