

HOSPITAL CLOSURE AND ECONOMIC EFFICIENCY*

Cory Capps
U. S. Department of Justice
600 E St. NW, Suite 10000
Washington, DC 20530

David Dranove
Department of Management and Strategy
Kellogg School of Management
Northwestern University
2001 Sheridan Rd.
Evanston, IL 60208

Richard C. Lindrooth
Department of Health Administration and Policy
Center for Health Economic and Policy Studies
Medical University of South Carolina
19 Hagood Rd
Charleston, SC 29425
lindrorc@musc.edu
843-792-2192

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Abstract: We present a new framework for assessing the effects of hospital closures on social welfare and the local economy. While patient welfare necessarily declines when patients lose access to a hospital, closures also tend to reduce costs. We study five hospital closures in two states and find that urban hospital bailouts reduce aggregate social welfare: on balance the cost savings from closures more than offset the reduction in patient welfare. However, because some of the cost savings are shared nationally, total surplus in the local community may decline following a hospital closure.

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I. Introduction

Communities often spend public funds to attract or retain private businesses, believing that the benefits in jobs and local spending will offset the tax expenditures.¹ It is less common for a community to prop up a local business on the verge of bankruptcy. Hospital closures are an important exception. When a hospital closes, its patients must turn to more distant and less familiar alternatives for care. For these reasons, public outcry typically accompanies the announcement of a pending hospital closures. In contrast with most other industries, the outcry often leads to government intervention to keep ailing hospitals afloat. For example, officials in Quincy, Massachusetts successfully lobbied for a \$12.1 million bailout of Quincy Hospital to facilitate its acquisition by a nonprofit enterprise in 1999; similarly, officials in Tampa, Florida authorized \$3.5 million from local tax revenue to bailout Tampa General Hospital in 2000.

In well functioning markets, insolvency is a clear sign that a firm is inefficient, in low demand, or both. Previous studies indicate that the same applies to hospitals. For example, in a study of closures in the mid-1990s, Lindrooth, LoSasso, and Bazzoli [2003] found that hospitals destined to close were had occupancy rates around 48% versus a rate of over 64% at their non-closing rivals. This suggests that local residents did not place much value on these hospitals and that alternative sources of care were available. Why bail out a hospital under these circumstances?

The notion of bailing out a failing firm would not normally arise in the context of traditional business ventures, except perhaps as a political matter. But the hospital

¹See Black and Hoyt [1989], King, McAfee, and Welling [1993] and others for analyses of the competition between local markets that often accompanies such subsidies.

industry is comprised of large numbers of non-profit and local government-owned hospitals and operates in a market rife with moral hazard and adverse selection. Furthermore, the prices Medicare and Medicaid pay for hospital services are set by fiat, rather than the market. Thus, for a sizable group of patients, prices do not adjust to supply and demand conditions. As a result, “market forces,” such as they are, may not lead to socially optimal closure decisions in this industry.

Consider the distortions created by the absence of the profit motive. We expect for-profit hospitals to exit markets when their costs of remaining in business exceed their ability to translate value creation into revenues [Wedig, et. al 1989]. The same likely does not apply to the nonprofit and government-owned hospitals that dominate the U.S. market.² Lending support to this notion, Bazzoli and Andes [1995] and Duffy and Friedman [1993] show that, in contrast to struggling for-profit hospitals, distressed non-profit hospitals linger in the market despite financial difficulties. Other studies show that for-profit status is a significant predictor of exit (e.g., Ciliberto and Lindrooth, 2006, Succi, et al; Wedig et al 1989; Williams et al., 1992). Taken together, these results suggest that nonprofits may close less often than is socially optimal.

Other market distortions may justify bailouts. Hospital markets are imperfectly competitive, hospitals cannot perfectly price discriminate, and some prices are regulated. Thus, the total social surplus generated by an unprofitable hospital may exceed its costs.³ For example, while Medicaid payments normally meet or exceed variable costs (to

² This might occur because the nonprofit is willing to sacrifice expected profits to sustain patient welfare, or, in a competitive market, because the for-profit does not believe it can outlast a nonprofit in a war of attrition [Ghemawat and Nalebluff, 1990]. Nonprofits are also able to draw upon donors to cover operating shortfalls [Philipson and Posner, 2006].

³ See Philipson et al. [2006] for a discussion of how the gap between total and producer surplus causes under investment in medical research and development.

encourage hospitals to admit Medicaid patients), they often do not cover average total costs of care. As a result, hospitals that rely on Medicaid payments may be hard pressed to generate revenues commensurate with the value they create.

Finally, we note that while the utility loss from a hospital closure is borne entirely by the local community, the cost savings accrue both locally and to the federal government. Most hospitals derive a considerable portion, 30 percent on average, of their revenue from the federal Medicare program. As a result, the cost savings from shutting these hospitals would be shared with federal government, though the local community presumably does not value this portion of the savings. Accordingly, we evaluate the merits of closures from both local and national perspectives.

This discussion suggests that the merit of a particular closure or bailout is an empirical question that requires measuring both cost and utility effects. There is a robust literature on the former, which we employ herein. To measure the utility effects of hospital closures, we build upon the option demand framework from Capps, Dranove, and Satterthwaite (“CDS”, 2003). CDS studied negotiations between hospitals and managed care organizations, and developed an index of a managed care organization’s enrollees willingness to pay for the inclusion of a given hospital or set of hospitals in their network. For that purpose, an index denominated in “utils” was sufficient. In the current context, we require a dollar-denominated estimate of the lost consumer surplus from a hospital closure that we can compare to the attendant cost savings. To achieve this, we develop a method for computing the equivalent variation of the utility effects of a hospital closure.

Our results indicate that, in general, urban hospital bailouts reduce aggregate social welfare: the cost savings from the closures we study more than offset the reduction in patient welfare. However, we also find that because some of the cost savings are shared nationally several of the closures lead to a decline in total surplus in the local community. We conclude with a discussion of the implications of hospital closures for access to care for affected populations.

II. Background

A number of studies have examined the effects of closure on hospital costs, generally finding a positive relationship between inefficiency and closures. Mobley and Frech [1994] find that expected future growth and size were significant determinants of closure. Deily, McKay, and Dorner [2000] find that hospital inefficiency explained a meaningful portion of the probability of closure. Similarly, Ciliberto and Lindrooth [2006] find that inefficiency was a significant predictor of closure. However, they also show that third party payment generosity strongly predicted closures, suggesting that efficient but poorly reimbursed hospitals could close. The generosity of private insurers would likely increase with the value that a hospital brings to the market, because highly valued hospitals can usually negotiate more favorable rates.⁴ However, government payers, especially Medicaid, do not reward valued hospitals in the same way. Thus, hospitals that are dependent upon Medicaid (and to a lesser extent, Medicare) could close in spite of generating positive surplus.

Two recent studies examine the effect of hospital closure on patients. McNamara [1999] used a nested logit model to estimate the welfare effects of rural hospital closures.

⁴ See Capps et al. [2003].

McNamara concludes the rural hospitals brought enough value to the market to warrant a subsidy, though he did not specifically examine hospital costs. Buchmueller et al. [2006] compare outcomes of patients in zip codes that had been affected by closure to those that were unaffected by closure. They find that closures lead to increases in the probabilities of death from Acute Myocardial Infarction (AMI) and from unintentional injuries.

Lindrooth, Lo Sasso, and Bazzoli [2003] find that closure leads to an evolutionary improvement in the efficiency of urban hospital markets. This increase was due mostly to filling beds at neighboring hospitals and the resulting scale economies rather than the baseline inefficiency of the closed hospital. In a different context, several papers have measured the cost of an empty hospital bed and reached conclusions consistent with Lindrooth, Lo Sasso, and Bazzoli (e.g., Gaynor and Andersen, 1995; Keeler and Ying, 1996; and Pauly and Wilson; 1986).

III. Methods

A. Overview

We use a structural demand model and information about actual patient choices to compute the value of each hospital in our sample, as well as the reduction in utility should a hospital close. For reasons explained below, we denominate the change in utility due to closure in hours of driving time. Specifically, we compute the number of additional hours that would need to be driven pre-closure in order to reduce the patient utility by the same amount as the closure did. If we were computing income changes rather than time changes, this would be the “equivalent variation” of the hospital closure. Our measure accounts for differences in quality and other idiosyncratic elements of the

closing hospital beyond simply its location. Finally, by drawing on estimates of the value of driving time, we convert the utility losses from a closure into dollars.

Next, we measure changes in market cost efficiency using the simulation methods of Lindrooth, Lo Sasso, and Bazzoli [2003]. We estimate the aggregate cost changes in the market by combining estimates of where the patients who were treated at the closed hospital would be admitted post-closure with parameter estimates from a multi-product trans-log cost function. Thus, we simulate the costs of treating the closed hospital's patients at other hospitals and compare those to the costs at the closed hospital. Our measure of total welfare changes due to closure is simply the sum of the access and cost effects.

Patient Welfare

To measure the value a hospital brings to a market, we adapt the framework in CDS. While that paper focuses on estimating the value of a hospital in the context of negotiations between hospitals and managed care organizations, the techniques are also well-suited for analyzing hospital closures. In a bargaining context, a hospital commands higher prices in proportion to the reduction in consumers' utility from its withdrawal from the network. In the current setting, we apply a somewhat different interpretation, computing the reduction in consumers' utility when a hospital withdraws completely from a market. To do so, we measure the aggregate difference between patient welfare when a hospital is in operation and when it is not; the difference between the two is the willingness to pay (WTP) to keep that hospital open. We then implement a methodological extension that allows us to assign dollar values to the ordinal WTP measure derived in CDS.

The starting point is a logit model of the utility that patient i derives from being admitted for care at hospital j :

$$U_{ij}(H_j, X_i, \lambda_i) = \alpha R_j + H_j' \Gamma X_i + \tau_1 T_{ij} + \tau_2 T_{ij} \bullet X_i + \tau_3 T_{ij} \bullet R_j - \gamma(Y_i, Z_i) P_j(Z_i) + \varepsilon_{ij}. \quad (1)$$

$H_j = [R_j, S_j]$ is a column vector of hospital j 's characteristics, where the vector of variables in R_j includes features that are common across all patient conditions, such as teaching status, and the vector of variables in S_j includes indicators of service offerings whose value depends on the patient's specific condition, such as delivery rooms. The column vector $X_i = [Y_i, Z_i]$ is patient i 's type and includes both his socioeconomic characteristics Y_i and his clinical attributes Z_i that affect what services he may need. $P_j(Z_i)$ is the out-of-pocket price that patient i with clinical characteristics Z_i pays at hospital j . As in CDS, we assume $\gamma(\cdot)$ is constant.

The variable λ_i is the geographical location of his home and $T_{ij} = T_j(\lambda_i)$ is the approximate travel time from his residence zip code to hospital j . The function $\gamma(Y_i, Z_i)$ converts money to utils; it is the utility value of \$1 to patient i with characteristics $[Y_i, Z_i]$.⁵ Relatively few patients face meaningful or observable cross-hospital variation in their out-of-pocket expense, rendering direct estimation of $\gamma(\cdot)$ infeasible. As detailed below, we instead denominate utils in terms of travel time and rely on other research to translate time into money. The final term in (1), ε_{ij} , represents the personal and idiosyncratic component of patient i 's evaluation of hospital j .

⁵ As discussed above, $\gamma(\cdot)$ is not identified because relatively few patients face meaningful or observable cross-hospital variation in their out-of-pocket expense.

Because we value hospitals in terms of travel time, we make the obvious but important point that patients do not make single one-way trips. Instead each patient makes, or hopes to make, at least one round trip; therefore, at a minimum we should measure T_{ij} as twice the one-way travel time. If the patient has a spouse or family, there may be additional associated trips. We are unaware of any studies that indicate the expected number of round trips associated with a hospital stay. Thus, we estimate the model using an alternative measure of T_{ij} : the *effective driving time*, computed as the actual driving time times the expected length of stay for the patient's DRG. In using our methods to prospectively evaluate a bailout, it would be possible through survey research to more precisely measure the number of trips per day in a hospital stay. Note that a linear transformation of travel time does not affect the prediction of which hospital a patient will choose; it will however affect the utility cost of losing access to a preferred alternative.

Under the logit model of demand, the formula for the utility value of a particular choice set is well established by previous literature. The expected value of the utility-maximizing option to patient i , who can choose from a set of hospitals, $G = \{1, 2, \dots, G\}$, equals

$$\begin{aligned} V(G | Y_i, Z_i, \lambda_i) &= E \max_{g \in G} [U(H_g, Y_i, Z_i, \lambda_i) + \varepsilon_{ig}] \\ &= \ln \left[\sum_{g \in G} \exp(U(H_g, Y_i, Z_i, \lambda_i)) \right]. \end{aligned} \quad (2)$$

Accordingly, i 's utility loss should hospital k close is simply:

$V(G | Y_i, Z_i, \lambda_i) - V(G/k | Y_i, Z_i, \lambda_i)$. Integrating this utility difference over the population distribution of patients and their characteristics yields the community's aggregate utility loss. As shown in CDS, the formula for this integral is

$$\begin{aligned}
\Delta W_k^{EA}(G) &= N \bullet E_{Y,Z,\lambda} \left[\frac{V(G) - V(G/k)}{\gamma} \right] \\
&= N \int_{Y,Z,\lambda} \frac{1}{\gamma} \ln \left[\frac{1}{1 - s_k(G, Y_i, Z_i, \lambda_i)} \right] f(Y_i, Z_i, \lambda_i) dY_i dZ_i d\lambda_i,
\end{aligned} \tag{3}$$

In equation (3), N is the total population in the market, $s_j(G, Y_i, Z_i, \lambda_i)$ is hospital k 's market share of patients with characteristics (Y_i, Z_i, λ_i) , $f(Y_i, Z_i, \lambda_i)$ is the joint density of the demographics, clinical indications, and locations of all consumers who will be sufficiently ill during the next year to cause them to require hospitalization, and $1/\gamma$ is the util-to-dollar conversion factor. Because the constant γ is not identified, (3) gives a util-denominated estimate of the utility loss from the closure of hospital k , up to γ .

B. Assigning a Dollar Value to a Util

Equation (3) allows us to derive the total patient utility loss from a closure, measured in utils. The objective of CDS was to derive an index of market power that could be used to assess hospital mergers, so util-denominated WTP was sufficient. In order to compare the costs and benefits of hospital closures, however, we require a dollar-denominated measure of WTP. As described below, data limitations and the presence of insurance make estimating hospital patients' marginal utility of income difficult at best, thwarting a traditional approach to measuring consumer surplus. Instead, as described below, we develop an algorithm that uses the coefficients on travel time to compute the equivalent variation of a given hospital closure.

Specifically, the travel time coefficients in patients' underlying utility functions are sufficient to express the utility loss from traveling in utils per hour. By combining (1) and (3), we can compute the "travel time equivalent of closure," which is the total time that would have to be added to every patient's travel time to all hospitals so as to generate an equivalent reduction in utility. We then use estimates of the dollar value of travel time from other research to convert this time-denominated figure into dollars.

This indirect approach would not be necessary if we could directly place a dollar value on utils, but this would only be possible if we included out-of-pocket price in the choice model. This is not practical for two reasons. First, there is little if any variation across hospitals in the prices paid by most patients. Second, data on out-of-pocket prices are not available. Patients with fee-for-service insurance, Medicare patients, and Medicaid patients face essentially no variation across hospitals in their out-of-pocket expense for receiving care. Patients in a preferred provider organization (PPO) and

managed care organizations (MCOs) face prices that vary depending on whether the provider is in or out of the insurer's network, which we cannot observe. While the inclusiveness of PPO networks is not known with certainty, based on conversations with industry participants we believe that most PPO networks include most hospitals, thus eliminating virtually all inter-hospital price differences.⁶

Due to this lack of observable and meaningful price-variation, patients' marginal utility of income is not identified and cannot be estimated. While this does not affect the estimates of the other parameters, it does prevent directly mapping utility changes into dollars. As a result, we instead rely on the "travel time equivalent of closure." With the time-denominated equivalent value of each closure in hand, we compute approximate dollar-denominated utility losses by drawing on estimates of the value of travel time from the transportation economics literature.

While the transportation literature gives no single number for the dollar value of an hour of time, the range of estimates is consistently between \$7.00 and \$20.00 per hour. For instance, Small, Winston, and Yan [2002] studied commuters' willingness to pay for the use of congestion-free express lanes in Los Angeles. Using a revealed preference model (preferences are revealed by whether commuters choose to pay for express travel), they found that "the median value of time based on commuters' revealed preferences is \$20.36/hour; at 88% of the average wage, it is toward the top of the range expected from previous work." They also report that the value of time computed from surveys of commuters is \$9.22 per hour. A similar study [Brownstone et al., 2003] of travel patterns

⁶ To our knowledge there is only one direct study of this issue, a study of Connecticut hospital networks [Cogswell, 2002], and it supports our belief. Connecticut provides highly detailed data on hospital participation in managed care networks. Cogswell reports that of the 9 HMOs in the state, 8 contract with at least 87% of the state's hospitals and 5 contract with at least 93%. Of the 15 PPOs, 13 contracted with 87% of the hospitals, and 5 contracted with 93%.

in San Diego found the median value of one hour to be \$15.00.⁷ We present results based on two possible values of time, \$16.00 and \$20.00, loosely reflecting the average and maximum estimates of the value of an hour of travel. Note that hospitals facing closure are likely to serve lower income communities whose residents have below average time costs of money. Thus, our estimates of the benefits of keeping hospitals open may be biased upwards.

To summarize, for a given hospital closure, we derive the change in each patient's driving time to all hospitals that has the same effect on that patient's utility as the closure, and then aggregate to obtain the market-wide valuation. Note that this is not a measure of the change in *actual* drive times due to closure; that factor is captured directly by the reduction of *ex post* utility of all patients who would have chosen the closing hospital. Instead, we compute how much farther away each patient would have to be from *all* hospitals, assuming the closure did not occur, in order to be precisely as worse-off as he is following the closure.

While being farther from all hospitals in a market is physically impossible for most residents, we believe this approach makes intuitive sense. For patients who strongly prefer the closing hospital, we may find that the closure is "just as bad" as having to drive an additional hour to receive inpatient care. If we then arbitrarily assume that the value of time is \$16.00/hour, we can infer that such patients would pay \$16 at the start of the year in order to retain the option of receiving care at the closing hospitals should the need arise.⁸ Other patients may have many options that are nearly as attractive as the closing

⁷ For a methodological overview of the techniques used in the transportation literature, see Gómez-Ibáñez, Tye, and Winston [1999], particularly Chapter 2; also see Small [1992].

⁸ This \$16 is what this hypothetical patient, looking forward and evaluating possible health states (including the possibility of not needing hospitalization), would pay to retain the *option* of receiving care at

hospital. For such patients, the closure might be “just as bad” as having to drive an extra 4 minutes to receive care, implying a willingness to pay of \$1.07 to retain the option of receiving care at the closing hospital. By summing these values, we obtain the aggregate willingness to pay in a market to keep a given hospital open.

Specifically we derive, for each patient i , the Δt^* such that, for the closure of hospital k :

$$\frac{\partial V(G | Y_i, Z_i, \lambda_i)}{\partial t} \Delta t^* \equiv V(G | Y_i, Z_i, \lambda_i) - V(G/k | Y_i, Z_i, \lambda_i) \quad (4)$$

Equation (4) must be integrated over patient diagnoses, demographics, and locations in order to compute a market level estimate. Note, however, that both sides of Equation (4) are denominated in *utils*; the right hand side is the utility loss resulting from hospital k closing – i.e., the WTP for hospital k derived in Equation (3) – and the left hand side is the time increase that has an equivalent effect on utility. The Δt^* that solves Equation (4) has an established translation into dollar values, which we use to translate the utility loss due to closure from *utils* into dollars. Thus, using Equation (3) and integrating over diagnosis, demographics, and location yields the formula that implicitly defines Δt^* :

$$N \int_{Y,Z,\lambda} \left[\frac{\partial V(G | Y_i, Z_i, \lambda_i)}{\partial t} \Delta t^* \right] f(Y_i, Z_i, \lambda_i) dY_i dZ_i d\lambda = \\ N \int_{Y,Z,\lambda} \ln \left[\frac{1}{1 - s_k(G, Y_i, Z_i, \lambda_i)} \right] f(Y_i, Z_i, \lambda_i) dY_i dZ_i d\lambda; \quad (5)$$

or equivalently,

$$\int_{Y,Z,\lambda} \left[\frac{\partial V(G | Y_i, Z_i, \lambda_i)}{\partial t} \Delta t^* \right] f(Y_i, Z_i, \lambda_i) dY_i dZ_i d\lambda = \Delta \bar{W}_j^{EA}(G), \quad (6)$$

the closing hospital. That is, it is the ex-ante value of having the hospital available to provide care. If the patient subsequently draws a condition for which the closing hospital is his preferred choice, his willingness to pay would be much higher.

where $\Delta \bar{W}_j^{EA} \equiv \gamma \bullet \Delta W_j^{EA}$, the WTP for hospital j up to the unknown constant γ . Solving equation (6) for Δt^* gives each patient's drive-time equivalent, in utils, of the utility loss associated with a given closure. We obtain the final formula we use for constructing the equivalent time change for the closure of hospital k by expressing the integral in discrete terms and rearranging terms:⁹

$$\Delta T_k^* = \sum_{i=1}^N \Delta t_{ik}^* = \sum_{i=1}^N \frac{\sum_z -\ln(1-s_{ik}(Y_i, z, \lambda_i)) \bullet \Pr(z_i = z | Y_i, \lambda_i)}{\sum_z \frac{\partial V(G | Y_i, z, \lambda_i)}{\partial t} \bullet \Pr(z_i = z | Y_i, \lambda_i)}. \quad (7)$$

Here, N reflects the entire population. Finally, note that the logit assumption implies that

$\frac{\partial V(G | Y_i, Z_i, \lambda_i)}{\partial t}$ has a closed form solution:

$$\begin{aligned} \frac{\partial V(G | Y_i, Z_i, \lambda_i)}{\partial t} = & \\ & \frac{1}{\sum_{g \in G} \exp(U(H_g, Y_i, Z_i, \lambda_i))} \sum_{g \in G} \left[\exp(U(H_g, Y_i, Z_i, \lambda_i)) \frac{\partial U(H_g, Y_i, Z_i, \lambda_i)}{\partial t} \right] = \\ & \left[\hat{s}_1(H_1, Y_i, Z_i, \lambda_i) \frac{\partial U(H_1, Y_i, Z_i, \lambda_i)}{\partial t} + \dots + \hat{s}_G(H_G, Y_i, Z_i, \lambda_i) \frac{\partial U(H_G, Y_i, Z_i, \lambda_i)}{\partial t} \right]. \end{aligned} \quad (8)$$

Equation (8) measures the reduction in expected utility to a single patient, i , with characteristics (Y_i, Z_i, λ_i) , from a marginal increase in travel time to all hospitals. It implies that changing the drive time to a given hospital will have an effect that is proportional to that hospital's share of patients similar to i (which is an index of the attractiveness of a given hospital to patients like i) and also is determined by how important travel time is within the utility function. The derivatives of $U(\cdot)$ with respect to

⁹ We only integrate over the patients' clinical characteristics, Z , because by summing over all patients in the data we are integrating over the empirical distributions of their locations and demographics.

t in Equation (8) all have analytic solutions that are computable from the estimated coefficients and the observed levels of the H s and X s, as shown in Equation (1).

Note that patients are likely to consider also the drive time of their relatives and friends when choosing a hospital. Thus simply including one-way drive time from the patient's zip code to each hospital will not fully capture the utility cost of being farther from a hospital and lead to over-estimates of Equation (8), resulting in an under-estimate of ΔT_k^* . Therefore, we include *effective travel time*, which we define as the product of one-way drive time and expected length of stay. Whether we include one-way drive time or effective drive time has no consequence on the numerator of Equation (7) because predictions will be unchanged. The final step is to convert the ΔT_k^* implied by Equation (7) into hours and multiply by the dollar value of time to yield our monetary estimates of the value hospital k brings to the community.

C. Change in Operating Costs

Because patients value choice, every hospital closure is associated with some loss in patient utility. However, and particularly if closing hospitals are inefficient, cost savings stemming from the closure may offset this loss. Evaluating the cost effects attributable to the closure of a hospital requires accounting for the direct savings at the closing hospital, as well as the cost increases at other hospitals that absorb patients who would have chosen the closing hospital.

Estimating the cost changes at those other hospitals requires, in addition to cost function estimates, estimating how patients will reallocate themselves across hospitals post-closure. The coefficients from (1) provide just such an estimate. The predicted

probability of a patient with characteristics (Y_i, Z_i, λ_i) of choosing a given hospital j , is given by

$$s_j(G, Y_i, Z_i, \lambda_i) = \frac{\exp[U(H_j, Y_i, Z_i, \lambda_i)]}{\sum_{g \in G} \exp[U(H_g, Y_i, Z_i, \lambda_i)]}. \quad (9)$$

An alternative interpretation of (9) is that it is hospital j 's expected market share among patients with characteristics (Y_i, Z_i, λ_i) .

We use the predicted shares from Equation (9) to estimate the effect of closure on the admissions at other hospitals. Specifically, we first estimate the expected number of admissions for the last year the hospital was in operation, denoted $E(ADM_{Pre})$, and the expected number of admissions at each hospital if the hospital was closed, $E(ADM_{Post})$. We use the same parameter estimates to calculate pre and post closure admissions, obtaining post-closure estimates by eliminating the closed hospital as an option and re-normalizing the predicted probabilities so that they sum to one. For all hospitals, the change in admissions resulting from the closure of hospital k is then calculated as:

$$\Delta ADM_j = E(ADM_{Post})_j - E(ADM_{Pre})_j, \quad (10)$$

where ΔADM_j is the change in admissions at each hospital j in the market. For the hospital that actually closed, $E(ADM_{Post})$ will equal zero. In addition to the change in inpatient admissions, emergency department visits will also increase at surrounding hospitals because a number of patients are admitted through the ED. Thus we also calculate:

$$\Delta ED_j = E(ED_{post})_j - E(ED_{pre})_j \quad (11)$$

Finally, the surrounding hospitals may or may not have the bed capacity to absorb the increase in admissions as measured by ΔADM_j . If $E(ADM_{Post})$ leads the hospital to have a greater than 70% occupancy rate, we add additional beds, ΔBED_j , such that the occupancy rate does not exceed 70%.¹⁰ If the alternative hospital had an occupancy rate greater than 70% prior to closure, then we add beds such that the occupancy rates are unchanged. This leads to lower estimates of the effect of closure on costs because we account for the fact that hospitals will add beds in order to handle the surge in admissions that is a result of closure.

Given the change in admissions, ED visits, and beds at each hospital due to closure, we simulate the change in market costs using the coefficient estimates from the estimation of a hospital cost function:

$$C_{jt} = f(N_{jt}, I_{jt}, PatientMix_{jt}, Wage_{jt}, Hospital_{jt}) + u_j \quad (12)$$

where C_{jt} is total operating cost at time t ; N_{jt} is a vector of hospital outputs; I_{jt} is a vector of quasi-fixed hospital inputs; $Patient Mix_{jt}$ is a vector of variables reflecting the payer and case mix at the hospital; $Wages_{jt}$ is the average payroll expense per FTE; $Hospital_{jt}$ includes variables indicating ownership type and teaching status. Equation (11) is estimated on a national sample of hospitals. Using the coefficients from Equation (11) we then predict hospital costs prior to closure, or \hat{C}_j . To simulate the cost of treating patients after closure, we add the change in expected admissions, ED visits, and beds:

$$\hat{C}_{j,post} = \hat{f}(N_{j,t=Pre} + \Delta N_j, I_{j,t=Pre} + \Delta I_j, PatientMix_{j,t=Pre}, Wage_{j,t=Pre}, Hosp_{j,t=Pre}) + \hat{u}_i \quad (13)$$

The estimated change in market costs stemming from a closure is then

¹⁰ Hospitals face substantial variation in demand, both throughout the year and within a given day. As a result, hospitals' average occupancy rates are well below their maximum occupancy. Our results are insensitive to whether we implement a higher threshold before requiring the alternative hospitals to add beds in response to the post-closure increases in admissions.

$$\Delta Costs = \sum_{j=1}^J \hat{C}_{j,post} - \sum_{j=1}^J \hat{C}_{j,pre}. \quad (14)$$

We only consider general inpatient admissions (and the associated changes in ED visits and beds), so that the estimate of the change in costs is consistent with our estimates of patient welfare. It is possible to extend this approach to consider all types of hospital services including outpatient and skilled nursing visits, but unfortunately data do not exist to estimate the patient welfare effects of such services.¹¹

D. Change in Welfare

The total change in welfare is the dollar-denominated WTP, measured by Equation (6), plus the change in market costs, measured by Equation (14). The total change will be positive if the change in market costs is both negative and larger in magnitude than the WTP reduction.

E. Local versus Social Welfare

If a closure reduces total costs, the benefits are ultimately enjoyed by insurers and, in the case of the government Medicare and Medicaid programs, taxpayers. Medicare is a federal program whose payment rates are based on national averages of hospital costs. Thus, if hospital costs in a local market decline, Medicare rates fall by a tiny amount nationwide. The benefits of reduced taxes are also shared nationwide. A local community would presumably ignore these benefits when assessing the merits of a bailout. A similar argument applies to Medicaid, except that the state government pays the bulk of the program costs. We assume that the local community cares about the

¹¹ In contrast to inpatient care, a hospital is not required for these services. Thus, the value of these services are not relevant to the question of whether a hospital bailout is wise.

state's share of Medicaid savings, but not the federal share. Private insurers normally set their premiums locally, and so the local community cares about all the cost savings as applied to private patients.

Following this discussion, we assume that if the total cost savings at hospital j is ΔC_j , then the local community will consider an amount $(\theta_{pj} + m\theta_{mj})\Delta C_j$, where θ_{pj} is the share of private patient expenses at the hospital, θ_{mj} is the share of Medicaid expenses, and m is the state's contribution percentage for Medicaid. The fact that $\theta_{pj} + m\theta_{mj} < 1$ implies that local communities will underweight cost savings when contemplating a bailout.

IV. Data

The inpatient discharge data are from the State Inpatient Database of the Healthcare Cost and Utilization Project (HCUP-SID). We use two years of data from the Tampa market (1995, 1996), one year from Tucson (1998), and one year from Phoenix (1997). The years were chosen so that we have a full year of data at least two years prior to the closure. We narrow our focus to Tampa, Tucson, and Phoenix for several reasons. First, the closures in these markets all occurred after 1995, a period for which the requisite data are available from HCUP. Second, these are all small to mid-sized MSAs with relatively well-defined geographic market areas.

In the baseline specifications, we estimate the multinomial logit parameters separately for three groups of patients. The first consists of patients who have either Medicare, fee-for-service, or PPO insurance coverage; these patients have access to all or nearly all hospitals in the market. This eliminates potential biases caused by omitting out-

of-pocket prices from the model or by misspecification of the choice set. However, this group of patients accounts for only about 52% of patients. Our second sample consists of patients enrolled in managed care, whether commercial or as part of Medicaid or Medicare (we dummy for the latter two payers in the logit model). These patients generally have less discretion over where they receive care. Our third group consists primarily of patients sometimes viewed by providers as undesirable, or at least, unprofitable: Medicaid patients, indigent patients, self-pay patients, and other patients. Thus, in defining our three sets of patients, we have tried to group patients with similar choice decisions together. We also run separate models, for each payor group, for admissions through the emergency department and non-emergency admissions because we believe the underlying processes for choosing a hospital are fundamentally different for emergency and non-emergency patients. Table 1 contains a summary of how we stratify the samples in each market.

Finally, admissions of patients with DRG's indicating mental health, substance abuse care, rehabilitation care, or psychiatric care are eliminated because these services are not typically performed in general acute care hospitals. Newborns are also dropped to avoid counting a delivery as two admissions.

In the Tampa market we include all of the general hospitals and patients in Hillsborough, Pasco, and Pinellas counties in the analysis. In addition, we added patients from outside of the above counties if more than 60 percent of residents of the zip code sought care in the Tampa-St. Petersburg market. The markets in Tucson and Phoenix are well-defined using 3-digit zip codes. In Phoenix, the following 3-digit zip codes are used: 852, 853, 855, 856, 857, 859, 860, and 865. Over 96 percent of admissions to hospitals in

Phoenix resided in either 856 or 857. In Tucson, we use the following 3-digit zip codes: 850, 852, 853, 855, 856, 859, 860, 863, 864, and 865. Over 95 percent of admissions to Tucson hospitals came from 850, 852, or 853. Maps of each market are in the appendix.

V. Model Specification

The choice model, which we use both to compute the utility loss from a closure and the post-closure patient flows, includes as regressors the logged effective travel time from patient i to hospital j , as well as three other categories of variables.¹² The first category is hospital characteristics: ownership status (for profit, non-profit, and government), teaching status, and nursing intensity, measured as nursing hours per inpatient day. Each of these hospital variables are included in isolation and interacted with logged effective travel time. This allows, for example, the data to reveal whether patients prefer teaching hospitals, or whether patients are willing to travel farther to hospitals that offer higher nurse staffing. The second category of variables consists of interactions between travel time and patient characteristics, both demographic (e.g., age, race, insurer type, median income in the patient's zip code) and clinical (e.g., Major Diagnostic Category, number of procedures, number of diagnoses).

The third set of variables consists of interactions between hospital characteristics and patient characteristics that we expect, based on results in the prior literature, to affect the choice process. For example, for profit hospitals are often hypothesized to selectively refer patients with more remunerative insurance types [Duggan 2000, 2002]; accordingly, we include interactions between the patient's payor type and a dummy for whether the hospital is for profit. Based on the finding in Chernew et al. [2002] that patients are significantly more likely to choose hospitals that treat a higher percentage of patients of their own race, we include interactions between the patient-race variable and hospitals' percentage of discharges of the corresponding race (for example, the hospitals percentage of Hispanic patients interacted with a dummy variable that equals 1 if the patient is

¹² Table A1 in the Appendix contains a summary of all variables used to estimate the utility function.

Hispanic.)¹³ Similarly, we interact the three severity measures with the teaching status and nurse staffing of the hospital, to allow for the possibility that more severely ill patients place higher value on these factors.¹⁴

Finally, we include “service match” dummies for the following conditions: Oncology, HIV, Labor and Delivery, Circulatory, Transplants (non-emergency samples only), and Pediatric care. Patients in each of these categories are unlike to elect to receive care at hospitals without corresponding specialized services. For example, nearly all births occur in hospitals with dedicated labor and delivery rooms, a service typically maintained by 40-60% of hospitals in a market. Similarly, no transplant would ever occur in a hospital that does not offer transplants. If we did not include these match variables, we would underestimate travel aversion for these types of patients because they frequently bypass the closest hospitals for a more distant one with matching services. Table 2 contains descriptive information on the closing hospitals and Table 3 contains summary statistics for hospitals in each market we study.

For the cost side of the model, we use a short-run trans-log specification:

$$\begin{aligned} \ln(\text{TotalCost}_{jt}) = & \alpha + \beta_N \ln(N_{jt}) + \beta_{NN} \ln(N_{jt})^2 + \beta_I \ln(I_{jt}) + \beta_{II} \ln(I_{jt})^2 + \beta_{Nb} \ln(N_{jt}) * \ln(I_{jt}) \\ & + \beta_W \ln(\text{Wage}_{jt}) + \beta_{WW} \ln(\text{Wage}_{jt})^2 + \beta_{WN} \ln(\text{Wage}_{jt}) * \ln(N_{jt}) + \beta_{WI} \ln(\text{Wage}_{jt}) * \ln(I_{jt}) \quad (15) \\ & + \beta_P \text{PatientMix}_{jt} + \beta_H \text{Hospital}_{jt} + \text{Time}_{jt} + \mu_j + \varepsilon_{jt} \end{aligned}$$

¹³ The Arizona HCUP data miscodes the race variable for some hospitals, implausibly indicating that every admitted patient to those hospitals was white. As a proxy, we replaced the miscoded race variables with the percentage of each race in the patient’s zip code and included interactions of those variables with the corresponding hospital-level racial percentages in the Arizona estimation. Also due to this data error, we exclude interactions between travel time and the race variable in the Arizona models.

¹⁴ We experimented with specifications that included more interactions of hospital and patient variables, as well as specifications that included hospital fixed effects, and found little effect on the final results. Thus, we focus on the more parsimonious specification. This approach is supported by preliminary Monte Carlo results in Fournier and Gai [2006], who find that specification changes have small effects on the predicted choice probabilities (which in turn determine willingness to pay).

$Total Cost_j$ is total operating cost; N_j is a vector of hospital outputs (inpatient admissions, skilled nursing facility admissions, ED visits and outpatient visits); I_j is a vector of quasi-fixed hospital inputs (hospital and skilled nursing facility beds); $Wages_j$ is the average payroll expense per FTE; $Patient mix_j$ reflects differences in case-mix (percent Medicare and Medicaid discharges, inpatient surgeries divided by total inpatient admissions and outpatient surgeries divided by total outpatient admissions); $Hospital_j$ includes dummies indicating for-profit or local government ownership, teaching status, and system membership, plus a hospital fixed effect, μ .

Equation (15) treats beds as a quasi-fixed input and allows for flexible substitution through the interactions. We estimate a long-run version of Equation (15) that excludes beds and thus restricts $\beta_I = \beta_{II} = \beta_{NI} = \beta_{WI} = 0$. We also estimate a more parsimonious specification on Equation (15) where we restrict the interactions to be zero, or $\beta_{NI} = \beta_{WN} = \beta_{WI} = 0$.

The variables are from the 1993-2001 American Hospital Association's (AHA) Annual Survey, a census of all US hospitals. The sample is limited to short-term general hospitals in urban (i.e. MSA) markets. The simulations are performed on the subset of hospitals located in the Tampa, Phoenix, and Tucson markets as defined above. The underlying assumption is that hospitals are operating on of the same cost function, allowing for shifts in the cost function by ownership, patient mix, and hospital fixed effects. Thus, any cost changes resulting from the simulations are principally a result of movement along the cost function, or scale. We adjust the predictions from the cost function for heteroskedastic smearing across markets [Manning, 1998] to account for the fact that our estimates are on the log scale but our interpretation is on the unlogged scale.

The smearing adjustments deflate the estimate of change in markets costs from 0% to 3.1%.

VI. Results

A. Assessment of Closures

Tables 4 and 5 display the effect of hospital closure on patient welfare.¹⁵ Table 4 presents results aggregated across all patients, under four different scenarios. On the low end, if we assume that only one person on average travels round-trip to the hospital per day (including the patient's round trip), and an hour of time is valued at \$16.00 per hour, then the dollar equivalents of the utility losses from closure range from just over \$500 thousand to \$1.75 million.¹⁶ On the high end, we assume that two people visit per day on average, and time is valued at \$20.00 per hour. For example, if the patient had a two-night stay, the assumption of two round-trips per day would mean that in addition to the patient's round trip, visitors may an additional three roundtrips during the stay at the hospital. Even under these assumptions, the dollar-equivalents of the utility loss from the five closures we study are relatively small, ranging from \$1.3 to \$4.4 million. In Table 5 we show the effects itemized into the six distinct patient categories (three payor classes, each broken down into emergency and non-emergency admissions) we used in the estimation.

These relatively small, though non-trivial, reductions in patient welfare reflect a combination of two factors. First, in each case a relatively small number of patients viewed the closing hospital as their first choices, as evidenced by those hospitals'

¹⁵ Tables of coefficients from the logit models are in Tables A2 – A5 in the Appendix.

¹⁶ Recall that instead of the actual travel time, we use *effective travel time*, defined as the product of the actual travel time and the patient's expected length of stay. In doing so we assume that the patient will consider not only the distance she must travel to be admitted to the hospital, but also the amount friends and relatives must travel to be visit her during her visit.

comparatively low volumes. In *ex ante* terms, this indicates that in relatively few states of the world would the closing hospital likely be the top choice of a significant number of patients.¹⁷ Second, even among those patients' likely to prefer the closing hospitals, the utility losses from instead receiving care at their second choice hospital are relatively small. In other words, other hospitals are reasonably close substitutes for the hospitals we considered.

Examination of the locations of the closing hospitals reveals why this is not surprising. Each closing hospital has several other proximate hospitals. Both Tampa hospitals that closed were located on the peninsula west of Tampa, which has a high concentration of both hospitals and patients (Figure 1). In Phoenix, Phoenix Regional Medical Center (PRMC) and Community Hospital Medical Center (CHMC) also had nearby substitutes: there are three hospitals within 3-4 miles of CHMC and five hospitals within 2-3 miles of PRMC (Figure 2). Similarly, in Tucson there are a number of alternative hospitals within 2-5 miles (Figure 3). In addition, as Tables 2 and 3 show, the closing hospitals did not offer a particularly unique set of services.

The second step in evaluating the welfare effects of closures is to estimate the cost effects, both the decrease in costs at the closing hospital and the increase in total cost at other hospitals. As described in the previous section, we analyzed both the short run cost function (beds treated as a quasi-fixed input) and the long run cost function (all inputs treated as variable). We also estimated two versions of the short run cost function, a fully interacted translog specification and a more parsimonious quadratic model that includes only factor prices, the vector of outputs, a time trend, and control variables. Nearly all of

¹⁷ However, the utility loss is not necessarily proportional to size. For example, the smallest closure by far involved Tucson General Hospital, and that closure entails the second highest utility loss.

the interactions are significant, so the fully interacted model appears to dominate the quadratic model. However, the predicted cost changes based on the quadratic model are smaller; thus, this specification provides a more conservative estimate of the cost savings from a given closure. The cost changes associated with each closure are in Table 6; the underlying cost function estimates for the three models are in Table A6 in the appendix. We find that each closure led to a decline in market costs.¹⁸

Estimates of the total welfare effects of each closure, under the high-end assumption of two travelers valuing time at \$20.00 per hour, are in Table 7. With one exception, we find that all five closures lead to increases in total welfare. The exception is the closure of PRMC: while estimates based on either short cost function indicate that the cost savings from this closure exceed patients' willingness to pay to retain access to this hospital, the estimates based on the long run cost function are sufficiently lower to render the predicted welfare effect negative. Even in this instance, we only reach this conclusion by applying assumptions that generate the highest utility losses and smallest cost savings.

Thus, our general conclusion is that, despite the many imperfections in hospital markets, and despite the outcry that normally accompanies a hospital closure, closures of financially unviable hospitals are generally welfare enhancing.

B. The Local Community Perspective

Efficiency gains from closures are not fully concentrated within the local community. For every \$1 saved, the local community saves $$(\theta_p + m\theta_m) < \1 in health

¹⁸ Again, scale is not strictly determinative of the relative magnitudes. For example, PRMC is the second largest of the closing hospitals, yet its closure leads entails smaller predicted cost savings than either Tampa hospital. Additionally, as shown below, a closure can also lead to increases in predicted market-wide costs.

care expenditures, where θ_p measures the private insurer share of costs at the hospital, θ_m is the Medicaid share, and m is the state's contribution ratio. We computed these values for each of the affected hospitals and found that $\theta_p + m\theta_m$ ranges from 0.36 to 0.61 for the five closures that we examined.

Table 8 includes calculations of the local welfare effects using the estimates from the long run cost function. The first row contains the local share of the cost savings. Based on the long run cost function estimates, three of the five closures appear to harm the local community, even though two of those same closures are welfare enhancing overall.

C. Hypothetical Closures

To further explore the methodology presented in this paper, we also simulate the closure of hospitals generally viewed as successful, both in terms of their quality of service and financial viability. We examine two non-closing hospitals in each market and year that we study.¹⁹ We did not use any formal criteria to choose these hospitals, selecting instead hospitals that offered a wide range of services and were among the larger, though not necessarily the largest, hospitals in each market. In assessing these hypothetical closures, we assume that no other hospitals are also closing (i.e., we keep the hospitals that actually closed in patients' choice sets.) We base our WTP estimates on the assumption of two travelers, each valuing their time at \$20.00 per hour.

¹⁹ We examine eight rather than ten hypothetical closures because two of the closures occurred in the same year and market, Phoenix, 1998.

The simulation results, in Table 9, vary according to which cost function estimates are used.²⁰ Based on the long run cost function, which treats all inputs as variable, we find that the closure of any of these hospitals would reduce total welfare by a significant amount, between \$3.6m and \$18.3m. When we use either the fully-interacted or quadratic short run cost function to estimate the changes in market cost we find that, with the exception of Tucson, even the closures of these larger, more successful hospitals would increase welfare. As before, the short-run cost function estimates yield larger savings because beds are treated as fixed – there are no adjustment costs at the alternative hospitals that absorb the patients from the closing hospital (in the long-run cost function results, beds are added if the occupancy rates increase over 70%).

Table 10, which shows occupancy rates by market and year, provides some insight into why we find that some of these hypothetical closures may be welfare increasing: each market we study had substantial excess capacity. For example, in 1996, the national average occupancy rate at urban hospitals 62.3%; in contrast, the occupancy rates in Tampa, Phoenix, and Tucson were 55.3%, 58.2%, and 60.0%, respectively. Capacity has a two-sided effect on our estimates of the effects of closures. First, the surplus of beds and hospitals makes it more likely that any given hospital will have reasonably close substitutes, resulting in relatively small utility losses from a closure.²¹ Second, the excess capacity generates large cost savings because the patients treated at the closing hospital can be treated at the remaining hospitals with existing capacity.

²⁰ Due to HCUP data use restrictions, we cannot identify hospitals still in operation.

²¹ This assumes the excess capacity is the result of too many hospitals rather than too many beds per hospital. Hospitals in Phoenix and Tucson averaged 165 and 223 beds, respectively; in Tampa the average hospital size was 270 beds. The US average ranged from 216-222 beds from 1994-2000.

Importantly, however, we examined hypothetical closures in the period *before* the actual closures occurred (i.e., in the same year we used to study actual closures in each market). After the closures occurred, which of course lead to fewer hospitals and beds in each market, the utility losses from further closures would be larger and the cost savings smaller. In addition, the hypothetical closures are large enough that it is possible that they would lead to price effects. If so, then we would underestimate the reduction in patient welfare. Thus, the point of this exercise is not to suggest or conclude that the hospitals we examined *should* close. Instead, the hypotheticals are intended to clarify and further demonstrate how the methodology works in practice. Indeed, as Table 9 shows, by 2000, the occupancy rates in Phoenix and Tucson had nearly reached the levels of other urban markets, suggesting that additional closures in later year could well lead to welfare decreases.²²

D. Access to Care

There are two potential downsides to hospital closures that are not captured by our model. The first is the possibility that a closure could lead to lengthier travel times to emergency departments, possibly worsening outcomes. The second is that uninsured people and many Medicaid enrollees use hospital Emergency Departments, which cannot

²² Capacity utilization in Tampa was essentially flat from 1993-2000, which is somewhat surprising given the two closures in that market. Census data indicate that the Tampa area grew more slowly (16%) in the 1990s than the rest of Florida (23.5%) and a report by the City of Tampa (2005) finds that, compared to the rest of Florida, Tampa has more residents under age 18 and fewer over age 62. Thus, a possible explanation for the flat occupancy rate, particularly given declining lengths of stay and expanding substitution of outpatient care for inpatient care, is that utilization and capacity declined in tandem.

turn patients away, in lieu of primary care physicians, who can and do refuse to treat patients based on ability pay.²³

Due to the density of hospitals in the markets we study, we view the effects of closures on time-to-treatment as relatively small. Nevertheless, Buchmueller et al. [2006] find that closures lead to increases in the probabilities of death from Acute Myocardial Infarction (AMI) and from unintentional injuries. And the magnitudes of their results are surprisingly large: they estimate that a one-mile increase from a given zip code to the nearest hospital increases the AMI mortality rate by 6.5%; the estimated impact on the injury mortality rate is even larger, 11-20%. To explain for the former effect, they cite a report by the American Heart Association claiming that “the survival probability decreases by 7-10% for every minute without treatment.”

Buchmueller et al., however, do not explain the mechanism underlying the effect. Is the causal factor in fact the time to reach a hospital, or is it some related factor that could be ameliorated by measures short of bailing out a hospital? One hint lies in the same American Heart Association report cited by Buchmueller et al. According to the American Heart Association, the key factor determining survival is not the travel time to the hospital *per se*, but rather the time to the start of treatment (p. 32):

A victim’s chances of survival after VF cardiac arrest are reduced by 7 to 10 percent with every minute that passes without treatment. Few attempts at resuscitation succeed after 10 minutes have elapsed.

In-hospital survival after cardiac arrest in heart attack patients improved dramatically when the DC defibrillator and bedside monitoring were developed. Later it also became clear that cardiac arrest could be reversed outside a hospital by properly staffed emergency rescue teams trained to give CPR and to defibrillate. Thus, the problem isn’t the ability to reverse

²³ All hospitals that accept Medicare payments, which virtually every hospital does, are required to treat patients who come to the emergency department. 42 U.S.C. 1395dd(a) [2000].

cardiac arrest, but **reaching the victim in time to do so** [emphasis added].

The time it takes an ambulance to reach the patient is the crucial factor. It need not be the case that a hospital closure leads to lengthened emergency response times. Hospitals are only one source from which ambulances are dispatched. Alternatives include private ambulance services and municipal ambulance services, which are typically operated by the fire department.

To the extent that response time is a concern, it would be more efficient to address this issue directly, rather than by subsidizing an inefficient hospital. Specifically, when a hospital closes, policy makers should carefully evaluate the impact on response times and, where necessary, take appropriate measures to maintain or improve emergency response.

Similarly, it is undoubtedly true that emergency departments are an important source of primary care for many patients, particularly the uninsured. Providing those services in a hospital setting, much less in an inefficient hospital, is surely among the least cost-effective ways to achieve the goal of providing primary care to the uninsured. Public monies would be much better spent addressing the problem directly.

On both accounts, response time and access for the uninsured, care should be taken to maintain access following a closure. However, this is best accomplished head-on, rather than by propping up a hospital that generates more costs than consumer surplus.

VII. Conclusions

We combine cost and demand estimates to evaluate the impact of hospital closures on economic efficiency. Based on the results of studying five closures in three mid-size urban markets in the late 1990s, we conclude that most urban hospital closures increase total welfare. Importantly, this does not imply that most hospitals are not socially valuable. Rather it is a statement about how well market forces select which hospitals to close in a market rife with imperfections, including weak price signals and third party payors, moral hazard, and adverse selection. Our estimates indicate that, despite these imperfections, a hospital that is unable to at least break even is also failing to create more value than cost. The conclusion is that policy-makers should, absent unique circumstances, resist the pressure for a bailout that almost invariably accompanies a closure announcement. However, the fact that reductions in hospital costs are shared between local and federal payers, while access issues are fully local, tilts the local community's calculus in favor of bailouts in several cases.

Several caveats apply. In each of the markets we study occupancy rates varied from 55% to 63%, well below full occupancy. Thus, in the cases we study, there is sufficient capacity at relatively proximate surrounding hospital to absorb the additional patients. The fact that there are low occupancy rates in these markets is not surprising since closure is most likely to occur in precisely those markets that have excess capacity.

We also did not consider changes in hospital prices that might result from closure. We do not think this is an issue in the markets and hospitals we study because the closing hospitals were small and, at least at the time, each market was relatively competitive.

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Table 1. Sample Stratification

<i>Sample:</i>	<i>(1) Free Choice</i>		<i>(2) HMO</i>		<i>(3) Other Payor</i>	
Included Patients:	Traditional Medicare, Private FFS, Private PPO		Private HMO, Risk Medicare, Risk Medicaid		Medicaid, Self Pay/Charity, Other	
Payor Dummies:	1(Private Payor)		1(Medicare), 1(Medicaid)		1(Self/Charity), 1(Other)	
Market	ER	Non-ER	ER	Non-ER	ER	Non-ER
Tampa, 1995	53,063	85,963	15,662	25,621	16,604	19,980
Tampa, 1996	50,956	78,424	19,356	32,165	16,506	20,517
Phoenix, 1997	38,286	59,080	29,610	62,305	16,147	29,228
Tucson, 1998	13,165	16,575	17,253	22,145	6,838	13,885

Table 2. Characteristics of Closed Hospitals

	<i>University Gen. Hosp.</i>	<i>Clearwater Comm. Hosp.</i>	<i>Tucson Gen. Hosp.</i>	<i>Phoenix Regional Med. Center^[*]</i>	<i>Community Hosp. Med. Center</i>
Market	Tampa	Tampa	Tucson	Phoenix	Phoenix
Closure Year	1996	1997	1999	1998	1998
Total admissions (HCUP)	4,271	6,147	4,524	5,079	1,577
Occupancy Rate	37.3%	40.5%	47.4%	35.7%	43.5%
Market share	1.5%	2.3%	3.9%	2.5%	0.8%
Medicare/PPO/FFS Share	74.6%	57.0%	36.7%	48.8%	34.1%
MCO Share, including Medicare & Medicaid	16.0%	33.8%	53.4%	36.5%	46.7%
Medicaid/Self-pay/Charity Share	9.4%	9.2%	9.8%	14.7%	19.2%
Percent Emergency Admissions	50.3%	51.3%	51.5%	31.6%	18.1%
FP/NFP	FP	FP	FP	FP	FP
Beds	152	133	80	174	59
Teaching	0	0	0	0	0
Transplant	0	0	0	0	0
Oncology Services	1	1	1	1	0
HIV Care	0	0	0	0	0
Labor/Delivery	0	0	1	0	0
Cardiac Services	0	0	0	1	0
Pediatric Services	0	1	0	0	0
Trauma Room	0	0	0	1	0

^[*] In 1998 Columbia General Hospital sold to Phoenix Children's Hospital for \$30 million and renamed Phoenix Regional Medical Center (PRMC). Despite the recent purchase, PRMC was closed shortly thereafter. Prior to the sale, Columbia General Hospital had 290 beds and offered kidney transplants; after the sale the new owner reduced beds to 174 and ended transplants.

Table 3. Hospital Characteristics

Variable	Phoenix, 1997 (N=30)		Tucson, 1998 (N=14)		Tampa, 1995 (N= 25)		Tampa, 1996 (N=)	
	Mean	Std. Dev	Mean	Std. Dev.	Mean	Std. Dev	Mean	Std. Dev.
For Profit	0.27	0.45	0.21	0.43	0.56	0.51	0.52	0.51
Non-Profit	0.70	0.47	0.57	0.51	0.40	0.50	0.44	0.51
Government	0.03	0.18	0.21	0.43	0.04	0.20	0.04	0.20
Total Beds	222.87	156.83	164.71	130.71	285.92	208.38	291.92	216.63
Teach	0.10	0.31	0.07	0.27	0.08	0.28	0.08	0.28
Nursing	10.98	3.35	11.66	5.07	13.68	4.95	137.77	49.17
Transplant	0.10	0.31	0.00	0.00	0.08	0.28	0.08	0.28
Oncology	0.73	0.45	0.21	0.43	0.92	0.28	0.88	0.33
HIV	0.40	0.50	0.14	0.36	0.56	0.51	0.52	0.51
Labor/Delivery	0.67	0.48	0.36	0.50	0.48	0.51	0.60	0.50
Cardiac	0.40	0.50	0.21	0.43	0.64	0.49	0.64	0.49
Pediatric	0.10	0.31	0.00	0.00	0.44	0.51	0.44	0.51
Trauma	0.50	0.51	0.14	0.36	0.04	0.20	0.09	0.29

Table 4. Aggregate Effects of Closure on Patient Welfare (\$1000s)

Hospital Closure	Market	Year	Hour-Equivalent of Utility Loss	Roundtrip (1 person)		Roundtrip (2 people)	
				<i>\$16.00 per hour</i>	<i>\$20.00 per hour</i>	<i>\$16.00 per hour</i>	<i>\$20.00 per hour</i>
University Gen. Hosp.	Tampa	1995	18,737.5	-\$599.6	-\$749.5	-\$1,199.2	-\$1,499.0
Clearwater Comm. Hosp.	Tampa	1996	35,901.3	-\$1,148.8	-\$1,436.0	-\$2,297.7	-\$2,872.1
Tucson General Hosp.	Tucson	1998	51,428.8	-\$1,645.7	-\$2,057.2	-\$3,291.5	-\$4,114.3
Phoenix Regional Med. Center	Phoenix	1997	54,711.3	-\$1,750.8	-\$2,188.5	-\$3,501.6	-\$4,376.9
Community Hosp Med. Center	Phoenix	1997	16,512.5	-\$528.4	-\$660.5	-\$1,056.8	-\$1,321.0

Table 5. The Effect of Closure on Patient Welfare (\$1000s), Itemized by Patient Class

<i>2 people at \$20.00 per hour</i>							
Hospital Name	Total Welfare Effect	Non-Emergency Admissions			Emergency Admissions		
		<i>(1) Free Choice</i>	<i>(2) HMO</i>	<i>(3) Other</i>	<i>(1) Free Choice</i>	<i>(2) HMO</i>	<i>(3) Other</i>
University Gen Hosp.	-\$1,499.0	-\$633.8	-\$136.2	-\$71.9	-\$484.2	-\$123.2	-\$49.6
Clearwater Comm. Hosp.	-\$2,872.1	-\$751.6	-\$631.7	-\$164.2	-\$899.0	-\$342.7	-\$82.8
Tucson General Hosp.	-\$4,114.3	-\$1,198.4	-\$1,068.4	-\$218.9	-\$657.1	-\$677.6	-\$293.9
Phoenix Regional Med. Center	-\$4,376.9	-\$2,698.0	-\$655.6	-\$306.1	-\$394.4	-\$213.7	-\$109.2
Community Hosp Med. Center	-\$1,321.0	-\$599.0	-\$452.9	-\$166.9	-\$52.3	-\$49.9	\$0.0

Table 6: Effects of Closures on Market Costs (\$ million)

	Closure				
	University Gen. Hosp.	Clearwater Comm. Hosp.	Tucson General Hosp.	Phoenix Regional Med. Center	Community Hosp. Med. Center
Market Year	Tampa 1995	Tampa 1996	Tucson 1998	Phoenix 1997	Phoenix 1997
<i>Long Run Cost Function</i>	-\$5.311	-\$6.546	-\$5.994	-\$2.833	-\$3.423
<i>Fully Interacted Short-run</i>	-\$9.310	-\$9.917	-\$6.183	-\$7.676	-\$3.897
<i>Quadratic Short Run</i>	-\$6.393	-\$6.842	-\$4.232	-\$5.375	-\$3.117

Table 7: Total Welfare Effects of Hospital Closures (\$ million)

		Closure				
		Univ. Gen. Hosp.	Clearwater Comm. Hosp.	Tucson General Hosp.	Phoenix Reg. Med. Center	Community Hosp. Med. Center
Market Year		Tampa 1995	Tampa 1996	Tucson 1998	Phoenix 1997	Phoenix 1997
<i>Long Run Cost Function</i>	Willingness to Pay (2 @ \$20/hour)	\$1.499	\$2.872	\$4.114	\$4.377	\$1.321
	Change in Cost	-\$5.311	-\$6.546	-\$5.994	-\$2.833	-\$3.423
	Net Change in Welfare	\$3.812	\$3.674	\$1.880	-\$1.544	\$2.102
<i>Fully Interacted Short-run</i>	Willingness to Pay (2 @ \$20/hour)	\$1.499	\$2.872	\$4.114	\$4.377	\$1.321
	Change in Cost	-\$9.310	-\$9.917	-\$6.183	-\$7.676	-\$3.897
	Net Change in Welfare	\$7.811	\$7.045	\$2.068	\$3.299	\$2.576
<i>Quadratic Short Run</i>	Willingness to Pay (2 @ \$20/hour)	\$1.499	\$2.872	\$4.114	\$4.377	\$1.321
	Change in Cost	-\$6.393	-\$6.842	-\$4.232	-\$5.375	-\$3.117
	Net Change in Welfare	\$4.894	\$3.970	\$0.117	\$0.998	\$1.796

Table 8: Total Welfare Effects of Hospital Closures (\$ million)

		Closure				
		Univ. Gen. Hosp.	Clearwater Comm. Hosp.	Tucson General Hosp.	Phoenix Reg. Med. Center	Community Hosp. Med. Center
Market Year		Tampa 1995	Tampa 1996	Tucson 1998	Phoenix 1997	Phoenix 1997
Local Share of Cost Savings		0.609	0.363	0.390	0.410	0.507
<i>Long Run Cost Function</i>	Net Change in Welfare	\$3.812	\$3.674	\$1.880	-\$1.544	\$2.102
	Net Change in Local Welfare	\$1.735	-\$0.496	-\$1.776	-\$3.215	\$0.414
<i>Fully Interacted Short-run</i>	Net Change in Welfare	\$7.811	\$7.045	\$2.068	\$3.299	\$2.576
	Net Change in Local Welfare	\$4.171	\$0.728	-\$1.703	-\$1.230	\$0.655
<i>Quadratic Short Run</i>	Net Change in Welfare	\$4.894	\$3.970	\$0.117	\$0.998	\$1.796
	Net Change in Local Welfare	\$2.394	-\$0.388	-\$2.464	-\$2.173	\$0.259

Table 9: Hypothetical Hospital Closures (\$ million)

	Market	Tampa				Tucson		Phoenix	
	Year	1995	1995	1996	1996	1998	1998	1997	1997
	Hypothetical Closure	H 1	H 2	H 1	H 2	H 1	H 2	H 1	H 2
<i>Long Run Cost Function</i>	Willingness to Pay (\$20)	\$8.79	\$10.11	\$8.59	\$9.12	\$22.13	\$15.21	\$4.85	\$16.96
	Change in Costs	-\$4.57	-\$1.06	-\$3.99	-\$1.45	-\$3.84	-\$6.91	-\$1.18	-\$10.78
	Net Change in Welfare	-\$4.22	-\$9.05	-\$4.60	-\$7.67	-\$18.29	-\$8.30	-\$3.67	-\$6.18
<i>Fully Interacted Short-run</i>	Willingness to Pay (\$20)	\$8.79	\$10.11	\$8.59	\$9.12	\$22.13	\$15.21	\$4.85	\$16.96
	Change in Costs	-\$23.83	-\$24.18	-\$24.04	-\$22.27	-\$11.56	-\$2.85	-\$5.68	-\$23.40
	Net Change in Welfare	\$15.04	\$14.07	\$15.45	\$13.15	-\$10.57	-\$12.36	\$0.83	\$6.44
<i>Quadratic Short Run</i>	Willingness to Pay (\$20)	\$8.79	\$10.11	\$8.59	\$9.12	\$22.13	\$15.21	\$4.85	\$16.96
	Change in Costs	-\$19.75	-\$19.17	-\$20.85	-\$14.14	-\$10.71	-\$3.51	-\$2.50	-\$21.39
	Net Change in Welfare	\$10.96	\$9.06	\$12.26	\$5.02	-\$11.42	-\$11.70	-\$2.35	\$4.43

Table 10. Occupancy Rates by Market and Year

	1993	1994	1995	1996	1997	1998	1999	2000
Tampa	56.91%	57.61%	58.22%	55.30%	53.62%	56.85%	57.29%	54.20%
Phoenix	56.62%	53.79%	55.53%	58.16%	58.07%	59.53%	60.09%	62.58%
Tucson	55.69%	58.26%	55.82%	60.02%	62.22%	62.52%	59.89%	63.89%
Other Markets	65.58%	64.13%	63.57%	62.28%	62.49%	62.94%	63.84%	64.43%

Appendix

Table A1. Choice Model Variables and Interactions

Variable Type	Variable Name	Description	Interacted With:			
			1	Time	Other Variables	
<i>Hospital Characteristics</i>	For Profit	FL: Excluded category is non-profit hosp.	Y	Y		
	Non-Profit	AZ: Excluded category is government hosp.	AZ	AZ		
	Teach	Teaching hospital dummy	Y	Y		
	Nursing	Nursing hours/inpatient days	Y	Y		
<i>Patient Characteristics</i>	Income in Zip	Median income in patient's zip code		Y		
	Male	Male		Y		
	Age: <18; 50-74; 75+	Excluded category is 19-49		Y		
	Race: Black, Hisp., Other	Excluded category is White		FL		
	MDC	Major Diagnostic Category		Y		
	Race Variables	Black	1(Black) in FL; zip code %black in AZ		Y	Hosp. % Black
		Hisp.	1(Hosp.) in FL; zip code %hisp. in AZ		Y	Hosp. % Hisp.
		Other	1(Other) in FL; zip code %other in AZ		Y	Hosp. % Other
	Severity Measures	# Procs.	Number of procedures		Y	Teach, Nursing
		# Diags.	Number of diagnoses		Y	Teach, Nursing
		%Travel	% of patients in DRG who bypass for care		Y	Teach, Nursing
	Payor Dummies	Private Payor	Commercial insurance dummy		FC	For Profit
		Risk Medicare	Medicare HMO dummy		HMO	For Profit
		Risk Medicaid	Medicaid HMO dummy		HMO	For Profit
Indigent/Charity		Indigent/Charity dummy		Other	For Profit	
Other Payor		Other payor dummy		Other	For Profit	
Urgency Measures	Emerg. Cat. 1	Bottom 25% of DRGs based on % emergency		ER		
	Emerg. Cat. 3	Top 10% of DRGs based on % emergency		ER	1(Trauma Hosp.)	
<i>Match Variables</i>	Oncology	Oncology DRG dummy		Y	1(Oncology Hosp.)	
	HIV	HIV DRG dummy		Y	1(AIDS Hosp.)	
	Delivery	Labor/Delivery dummy		Y	1(Labor/Deliv. Hosp.)	
	Circulatory	Cardiac DRG dummy		Y	1(Cardiac Hosp.)	
	Pediatric	Age < 18 dummy		Y	1(Children's Hosp.)	
	Transplant	Transplant dummy		AZ	1(Transplant Hosp.)	
Y	= Interaction included in all models		FC	= Included in "Free Choice" sample only		
AZ(FL)	= Included in Arizona (Florida) model only		HMO	= Included in HMO sample only		
ER	= Included in Emergency Models only		Other	= Included in Other Payor sample only		

Table A2: Phoenix and Tucson Estimates, Non-Emergency Sample

Sample	Phoenix, 1997						Tucson, 1998					
	Free Choice		Managed Care		Other		Free Choice		Managed Care		Other	
	N	J	N	J	N	J	N	J	N	J	N	J
Pseudo R ²	0.3103		0.3218		0.3446		0.3164		0.2958		0.3428	
Var.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
For Profit ≡ “FP”	-1.145	0.053	-0.333	0.056	0.048	0.076	0.232	0.104	-1.289	0.083	-2.075	0.138
Govt.	-2.247	0.158	2.116	0.095	-3.458	0.117	0.852	0.186	-4.132	0.314	2.170	0.130
Teach	0.671	0.052	1.554	0.049	0.849	0.055	-2.677	0.108	-0.353	0.099	-1.746	0.093
Nursing	0.069	0.008	-0.024	0.009	0.187	0.012	-0.010	0.012	-0.230	0.016	-0.080	0.014
Ln(Eff. Time) ≡ “LET”	-0.736	0.050	-1.294	0.054	-0.728	0.096	-0.756	0.083	-0.992	0.096	-1.226	0.122
LET * FP	0.205	0.011	-0.136	0.014	-0.206	0.019	-0.109	0.022	0.062	0.018	-0.092	0.032
LET * Govt.	0.198	0.035	-0.588	0.025	0.264	0.030	-0.564	0.043	0.181	0.072	-0.832	0.032
LET * Teach	0.161	0.012	0.014	0.013	0.081	0.015	0.338	0.019	0.082	0.023	0.175	0.020
LET * Nursing	-0.033	0.002	-0.023	0.002	-0.025	0.003	0.024	0.002	0.041	0.003	0.016	0.003
LET * Median Inc.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LET * Male	0.014	0.016	0.052	0.018	-0.001	0.038	0.046	0.027	0.020	0.033	0.045	0.045
LET * Age: <18	-0.211	0.055	-0.202	0.033	-0.039	0.042	0.211	0.074	0.078	0.054	0.490	0.045
LET * Age: 50-74	-0.186	0.024	-0.128	0.022	-0.315	0.043	-0.005	0.042	-0.259	0.040	-0.070	0.057
LET * Age: 75+	-0.325	0.027	-0.310	0.030	-0.482	0.075	-0.136	0.046	-0.621	0.056	-1.068	0.127
LET * # Procs.	0.042	0.005	0.037	0.006	0.078	0.010	0.067	0.009	0.073	0.010	0.067	0.013
LET * # Diags	-0.011	0.003	-0.002	0.003	0.002	0.006	0.018	0.005	0.002	0.006	0.025	0.009
LET * Pcttrv	1.092	0.055	0.926	0.059	1.037	0.113	0.843	0.091	0.544	0.100	1.267	0.134
LET * Private Pay	-0.032	0.021					-0.071	0.034				
LET * Risk MediCare			-0.039	0.022					0.274	0.040		
LET * Risk Medicaid			-0.015	0.021					-0.386	0.042		
LET * Indig./Char.					0.146	0.038					-0.612	0.057
LET * Other Payor					-0.377	0.036					-0.163	0.042
Teach * # Procs	-0.081	0.008	-0.085	0.008	-0.122	0.011	-0.028	0.015	-0.055	0.016	-0.160	0.018
Teach * # Diags	0.019	0.005	-0.016	0.005	0.030	0.007	0.076	0.009	-0.105	0.010	0.132	0.011
Teach * Pcttrv	-0.154	0.076	0.526	0.071	1.486	0.111	2.922	0.136	-0.173	0.142	2.140	0.154
Nursing * # Procs.	-0.006	0.001	-0.002	0.002	0.021	0.002	0.005	0.002	0.040	0.003	0.024	0.002
Nursing * # Diags	0.002	0.001	0.007	0.001	-0.011	0.001	-0.003	0.001	0.025	0.002	-0.001	0.001
Nursing * Pcttrv	0.104	0.013	0.097	0.016	-0.215	0.023	-0.279	0.016	-0.187	0.021	-0.249	0.020
Hosp. %Black * Black	70.12	6.73	46.20	4.68	93.15	5.42	361.28	25.95	270.86	31.52	240.44	18.47
Hosp. %Hispanic * Hispanic	0.471	0.201	-1.615	0.154	4.310	0.165	-1.148	0.129	-0.825	0.100	-2.771	0.130

Table A2: Phoenix and Tucson Estimates, Non-Emergency Sample (continued)

Hosp. %Other * Other	1.833	0.539	7.615	0.392	-4.842	1.321	1.235	0.255	5.427	0.558	4.821	0.310
Hosp. %White * White	3.683	0.062	3.176	0.060	0.275	0.097	-0.640	0.106	-0.320	0.100	-0.783	0.152
FP * Private Payor	-0.792	0.030					-1.532	0.064				
FP * Risk Medicaid			1.638	0.032					0.667	0.053		
FP * Indig./Char.					0.590	0.065					0.504	0.116
FP * Other					2.092	0.046					1.269	0.078
Match: Oncology	0.628	0.075	0.724	0.086	-0.167	0.128	-0.352	0.130	-1.002	0.119	-0.475	0.180
Match: HIV	0.125	0.213	1.111	0.276	2.021	0.641	1.481	0.467	1.105	0.368	1.844	0.325
Match: Delivery	2.675	0.084	1.744	0.034	1.288	0.053	-0.185	0.061	-0.482	0.033	-1.027	0.038
Match: Circulatory	0.952	0.022	0.571	0.027	0.226	0.051	-0.123	0.046	0.147	0.041	-0.288	0.080
Match: Transplant	3.363	0.314										
Match: Pediatric	1.052	0.065	1.401	0.036	1.447	0.037						
Eye	-0.105	0.188	-0.010	0.202	-0.941	0.345	-0.471	0.414	0.626	0.351	-0.189	0.295
ENT	-0.054	0.071	-0.183	0.074	-0.300	0.130	-0.117	0.124	0.034	0.135	-0.250	0.137
Respiratory System	-0.393	0.035	-0.415	0.041	-0.448	0.081	-0.298	0.060	-0.063	0.086	-0.325	0.095
Circulatory System	-0.309	0.030	-0.390	0.037	-0.513	0.079	-0.146	0.052	0.056	0.074	-0.337	0.100
Digestive System	-0.253	0.035	-0.299	0.040	-0.527	0.086	-0.213	0.060	-0.025	0.081	-0.259	0.099
Liver & Pancreas	-0.356	0.047	-0.373	0.051	-0.675	0.105	-0.362	0.084	-0.197	0.100	-0.407	0.129
Musculoskeletal	-0.108	0.031	-0.307	0.039	-0.121	0.080	-0.166	0.054	-0.014	0.074	-0.293	0.096
Skin & Breast	-0.123	0.049	-0.275	0.059	-0.398	0.110	-0.247	0.089	0.051	0.106	-0.254	0.138
Endocrine & Metabolic	-0.316	0.053	-0.293	0.057	-0.427	0.112	-0.303	0.090	0.092	0.103	-0.339	0.129
Kidney & Urinary	-0.331	0.043	-0.442	0.053	-0.616	0.105	-0.211	0.073	-0.067	0.103	-0.216	0.120
Male Reproductive	-0.102	0.050	-0.429	0.067	-0.783	0.212	-0.158	0.095	-0.141	0.125	-0.356	0.295
Female Reproductive	-0.239	0.040	-0.424	0.043	-0.637	0.097	-0.073	0.072	0.077	0.082	-0.373	0.125
Pregnacy/Childbirth	-0.326	0.039	-0.429	0.038	-0.871	0.074	-0.085	0.072	0.028	0.076	-0.489	0.089
Blood & Pancreas	-0.251	0.079	-0.188	0.089	-0.080	0.160	-0.209	0.137	-0.276	0.194	-0.380	0.176
Myeloproliferative	-0.352	0.059	-0.410	0.066	-0.486	0.171	-0.203	0.096	-0.018	0.123	-0.698	0.152
Infect. & Parasit. Dis.	-0.266	0.060	-0.248	0.064	-0.384	0.125	-0.372	0.103	-0.085	0.140	-0.395	0.146
Injuries/Poisonings	-0.235	0.072	-0.180	0.079	-0.543	0.128	-0.241	0.117	0.162	0.150	-0.693	0.169
HIV	0.007	0.144	-0.354	0.196	-1.286	0.347	0.373	0.269	0.779	0.239	-0.224	0.292

Table A3: Phoenix and Tucson Estimates, Emergency Sample

Sample	Phoenix, 1997						Tucson, 1998							
	Free Choice		Managed Care		Other		Free Choice		Managed Care		Other			
	N	J	Pseudo R ²	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	
	38,286	27	0.4736											
				29,610	27	0.4608				17,253	12	0.3998		
					24	0.3741					11		0.2934	
For Profit ≡ “FP”	-0.191	0.085		0.129	0.093		1.412	0.126	0.868	0.120	-0.132	0.107	-0.530	0.184
Govt.	0.482	0.130		2.362	0.168		-0.814	0.131	-2.315	0.266	-6.558	0.364	-0.835	0.205
Teach	-0.648	0.101		-1.943	0.148		-0.017	0.100	-0.360	0.133	-1.376	0.153	-0.147	0.148
Nrs. Intens.	0.148	0.016		0.247	0.018		0.126	0.023	-0.221	0.024	-0.213	0.021	-0.176	0.031
Ln(Eff. Time) ≡ “LET”	-0.786	0.072		-1.671	0.083		-1.452	0.114	-0.716	0.125	-0.661	0.115	-0.112	0.160
LET * For Profit	-0.079	0.020		-0.205	0.023		-0.538	0.033	-0.175	0.026	-0.069	0.024	-0.280	0.042
LET * Govt.	0.108	0.028		-0.103	0.039		-0.010	0.031	0.024	0.060	0.693	0.079	-0.023	0.045
LET * Teaching	0.310	0.021		0.313	0.034		0.272	0.024	0.041	0.027	0.170	0.035	-0.052	0.033
LET * Nrs. Intens.	-0.046	0.003		-0.043	0.004		-0.017	0.005	0.044	0.005	0.047	0.005	0.033	0.006
LET * Median Inc.	0.000	0.000		0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LET * Male	-0.117	0.020		0.011	0.023		0.216	0.034	-0.023	0.036	-0.058	0.037	0.006	0.054
LET * Age: Under 18	-0.165	0.065		-0.011	0.054		-0.003	0.057	0.068	0.143	0.130	0.080	0.392	0.073
LET * Age: 50-74	-0.388	0.032		-0.176	0.033		-0.199	0.042	-0.295	0.063	-0.213	0.051	-0.087	0.067
LET * Age: 75+	-0.501	0.035		-0.318	0.039		-0.180	0.074	-0.288	0.064	-0.445	0.062	-0.044	0.120
LET * # Procs.	-0.019	0.008		-0.020	0.010		0.024	0.013	-0.028	0.017	0.047	0.016	0.073	0.021
LET * # Diags	0.012	0.005		-0.001	0.005		0.036	0.007	0.033	0.008	-0.005	0.008	0.020	0.012
LET * Pcttrv	1.235	0.088		1.026	0.103		0.450	0.143	0.796	0.170	0.360	0.172	0.351	0.224
LET * Emerg. Cat 1	0.086	0.113		0.277	0.098		0.287	0.137	-0.306	0.225	-0.009	0.135	-0.713	0.212
LET * Emerg. Cat. 3	-0.078	0.033		-0.160	0.041		-0.122	0.053	-0.124	0.065	-0.050	0.063	-0.015	0.092
LET * Private Payor	0.103	0.028							-0.020	0.059				
LET * Risk Medicare				0.367	0.028						0.390	0.046		
LET * Risk Medicaid				0.441	0.036						-0.079	0.064		
LET * Indig./Charity							-0.031	0.040					-0.162	0.075
LET * Other Payor							0.108	0.045					0.080	0.074
Teach * # Procs	0.114	0.013		0.098	0.017		0.038	0.015	-0.057	0.021	-0.017	0.028	-0.114	0.026
Teach * # Diags	-0.016	0.007		-0.020	0.009		-0.065	0.008	-0.001	0.011	-0.230	0.014	0.033	0.014

Table A3: Phoenix and Tucson Estimates, Emergency Sample (continued)

Teach * Pcttrv	0.037	0.138	0.946	0.169	0.685	0.155	1.014	0.214	1.356	0.272	1.539	0.256
Nursing * # Procs.	-0.019	0.003	-0.022	0.003	-0.013	0.004	-0.001	0.004	0.003	0.004	0.024	0.006
Nursing * # Diags	0.013	0.001	0.005	0.002	0.014	0.002	0.024	0.002	0.033	0.002	0.030	0.003
Nursing * Pcttrv	0.115	0.027	0.036	0.030	0.138	0.039	-0.081	0.041	-0.137	0.037	-0.071	0.058
Hosp %Black * Black	25.70	7.15	52.58	6.85	54.39	7.25	509.60	40.71	229.63	40.35	-3.11	38.37
Hosp %Hispanic * Hispanic	2.930	0.238	1.743	0.216	5.333	0.223	0.315	0.173	0.785	0.152	-0.528	0.207
Hosp %Other * Other	-21.65	2.31	-11.70	2.07	-35.37	3.02	1.88	0.46	9.54	1.15	0.90	0.36
Hosp %White * White	5.096	0.087	5.136	0.099	0.138	0.121	-2.128	0.134	-2.079	0.125	-1.192	0.219
FP * Private Payor	-0.509	0.044					-0.978	0.071				
FP * Risk Medicaid			0.339	0.054					0.485	0.072		
FP * Indig./Charity					-0.160	0.081					0.843	0.106
FP * Other					2.503	0.062					1.549	0.090
Match: Oncology	1.187	0.192	1.777	0.256	-0.120	0.223	-0.435	0.245	-0.238	0.188	-0.564	0.309
Match: HIV	-0.007	0.252	1.227	0.280	0.505	0.250	1.600	0.448	0.966	0.389	-0.005	0.365
Match: Delivery	1.670	0.423	0.839	0.194	0.607	0.194	1.521	0.318	1.414	0.135	0.204	0.146
Match: Circulatory	0.202	0.027	0.561	0.030	-0.331	0.050	-0.079	0.042	0.019	0.037	-0.118	0.075
Match: Pediatric	0.945	0.074	2.122	0.056	1.844	0.055						
Match: Trauma	0.530	0.041	0.034	0.040	0.631	0.058	0.402	0.056	0.379	0.056	0.603	0.074
Eye	-0.167	0.249	-0.409	0.253	-0.702	0.280	-0.392	0.449	-0.176	0.476	0.215	0.257
ENT	-0.108	0.104	0.189	0.110	-0.159	0.113	-0.148	0.183	-0.361	0.196	0.006	0.153
Respiratory System	-0.180	0.038	-0.064	0.045	-0.560	0.065	-0.177	0.075	-0.304	0.076	-0.318	0.105
Circulatory System	-0.409	0.036	-0.371	0.045	-0.689	0.065	-0.128	0.070	-0.288	0.069	-0.338	0.103
Digestive System	-0.236	0.041	-0.118	0.049	-0.696	0.070	-0.064	0.081	-0.129	0.075	-0.295	0.108
Liver & Pancreas	-0.286	0.059	-0.276	0.064	-0.773	0.080	-0.107	0.107	-0.082	0.091	-0.525	0.132
Musculoskeletal	-0.040	0.042	0.020	0.056	-0.056	0.068	-0.002	0.082	-0.154	0.086	-0.110	0.106
Skin & Breast	0.281	0.070	0.234	0.086	0.028	0.083	0.000	0.142	-0.326	0.153	-0.228	0.143
Endocrine & Metabolic	-0.059	0.061	-0.108	0.075	-0.452	0.095	-0.008	0.108	-0.168	0.118	-0.622	0.172
Kidney & Urinary	-0.101	0.053	0.029	0.065	-0.464	0.093	0.005	0.094	-0.353	0.102	-0.334	0.148
Male Reproductive	-0.055	0.219	0.010	0.248	-0.843	0.337	0.103	0.387	-1.043	0.452	-0.913	0.494
Female Reproductive	-0.219	0.151	-0.093	0.138	-0.951	0.180	-0.075	0.305	-0.371	0.226	-0.142	0.221
Pregnancy/Childbirth	-0.158	0.144	0.080	0.096	-0.612	0.111	-0.041	0.283	-0.045	0.152	0.078	0.163
Blood & Pancreas	0.020	0.102	0.233	0.116	-0.039	0.149	0.228	0.174	-0.068	0.225	-0.248	0.226
Myeloproliferative	-0.512	0.154	-0.329	0.175	-0.420	0.280	-0.255	0.293	-0.270	0.269	-0.462	0.439
Infect. & Parasit. Dis.	-0.162	0.059	-0.011	0.071	-0.449	0.107	0.101	0.109	-0.403	0.147	-0.079	0.156
Injuries/Poisonings	-0.220	0.073	-0.325	0.088	-0.601	0.082	-0.105	0.150	0.077	0.125	-0.628	0.155
HIV	-0.073	0.184	-0.159	0.192	-0.206	0.182	0.800	0.293	0.437	0.279	-0.590	0.432

Table A4: Tampa 1995 & 1996 Estimates, Non-Emergency Sample

Sample	1995						1996					
	Free Choice		Managed Care		Other		Free Choice		Managed Care		Other	
N	85,963		25,621		19,980		78,424		32,165		20,517	
J	25		22		25		25		21		25	
Pseudo R ²	0.3949		0.3904		0.3985		0.4045		0.3915		0.4198	
Var.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
For Profit ≡ "FP"	-2.600	0.045	-2.231	0.082	-1.693	0.088	-2.585	0.046	-2.430	0.071	-2.457	0.085
Govt.												
Teach	-5.350	0.096	-3.656	0.156	-2.966	0.129	-4.339	0.101	-3.257	0.143	-2.342	0.127
Nursing	-0.670	0.021	0.103	0.034	-0.737	0.031	-0.851	0.022	-0.059	0.033	-0.582	0.032
Ln(Eff. Time) ≡ "LET"	-2.692	0.039	-2.532	0.078	-2.604	0.085	-2.973	0.042	-3.003	0.073	-2.868	0.090
LET * FP	0.428	0.010	0.269	0.019	0.377	0.021	0.420	0.010	0.320	0.017	0.472	0.021
LET * Govt.												
LET * Teach	0.882	0.021	0.593	0.032	0.590	0.027	0.689	0.021	0.465	0.030	0.406	0.026
LET * Nursing	0.049	0.004	-0.038	0.007	0.062	0.006	0.091	0.005	0.015	0.007	0.085	0.007
LET * Median Inc.	-0.001	0.001	0.024	0.003	0.010	0.003	0.010	0.001	0.023	0.002	0.013	0.003
LET * Male	-0.012	0.011	-0.002	0.023	-0.004	0.027	-0.019	0.012	-0.008	0.022	-0.025	0.028
LET * Age: <18	0.128	0.037	0.183	0.040	0.196	0.035	0.170	0.039	0.282	0.038	0.179	0.035
LET * Age: 50-74	-0.101	0.014	-0.073	0.028	-0.132	0.032	-0.213	0.015	-0.105	0.027	-0.161	0.033
LET * Age: 75+	-0.142	0.015	0.031	0.039	-0.250	0.082	-0.249	0.015	-0.153	0.036	-0.282	0.079
LET * # Procs.	0.027	0.004	0.054	0.009	0.014	0.010	0.021	0.004	0.024	0.008	0.044	0.010
LET * # Diags	-0.008	0.002	-0.018	0.005	0.001	0.006	-0.007	0.003	0.014	0.005	0.030	0.006
LET * Pcttrv	0.734	0.032	0.856	0.067	0.623	0.076	0.715	0.035	0.944	0.063	0.494	0.084
LET * Black	-0.118	0.029	-0.119	0.041	-0.184	0.036	-0.002	0.031	-0.053	0.037	-0.118	0.034
LET * Hisp.	-0.144	0.044	0.470	0.059	-0.126	0.051	0.220	0.039	0.459	0.051	0.203	0.041
LET * Other	0.115	0.039	0.037	0.053	0.047	0.054	0.144	0.039	0.084	0.050	0.057	0.054

Table A4: Tampa 1995 & 1996 Estimates, Non-Emergency Sample (continued)

LET * Private Pay	0.037	0.014					0.029	0.014				
LET * Risk MediCare			-0.254	0.031					-0.098	0.028		
LET * Risk Medicaid			-0.144	0.039					-0.066	0.036		
LET * Indig./Char.					-0.172	0.030					-0.162	0.031
LET * Other Payor					0.002	0.032					-0.043	0.032
Teach * # Procs	-0.043	0.012	-0.029	0.023	0.053	0.016	-0.021	0.012	-0.019	0.020	-0.006	0.016
Teach * # Diags	-0.082	0.007	-0.105	0.014	0.034	0.010	-0.047	0.007	0.001	0.012	0.094	0.009
Teach * Pcttrv	1.930	0.084	0.926	0.157	1.196	0.123	1.474	0.088	0.440	0.144	1.353	0.126
Nursing * # Procs.	0.019	0.003	-0.003	0.005	0.019	0.004	0.021	0.003	-0.001	0.005	0.006	0.004
Nursing * # Diags	-0.051	0.002	0.016	0.003	-0.022	0.003	-0.069	0.002	-0.045	0.003	-0.038	0.003
Nursing * Pcttrv	0.558	0.020	0.364	0.034	0.675	0.031	0.763	0.021	0.538	0.033	0.560	0.032
Hosp. %Black * Black	7.340	0.424	6.760	0.553	12.667	0.538	7.444	0.398	5.739	0.466	10.040	0.466
Hosp. %Hisp. * Hisp.	13.898	0.523	11.247	0.828	14.691	0.690	13.573	0.496	12.566	0.629	16.759	0.584
Hosp. %Other * Other	23.699	0.522	17.176	0.766	18.785	0.779	17.363	0.373	10.816	0.492	12.171	0.558
Hosp. %White * White	0.585	0.065	0.506	0.106	-1.420	0.132	0.748	0.061	0.811	0.087	-0.562	0.117
FP * Private Payor	-0.207	0.019					-0.165	0.020				
FP * Risk Medicare			1.596	0.041					0.882	0.033		
FP * Risk Medicaid			-1.158	0.080					-0.688	0.069		
FP * Indig./Char.					-0.513	0.050					-0.184	0.051
FP * Other					-0.660	0.047					-0.169	0.047
Match: Oncology	0.751	0.085	1.708	0.178	1.745	0.416	1.873	0.101	2.200	0.178	3.247	0.442
Match: HIV	1.110	0.154	0.487	0.272	1.102	0.180	1.943	0.196	0.334	0.256	1.369	0.233
Match: Delivery	2.327	0.063	3.599	0.087	2.300	0.056	5.626	0.279	6.234	0.303	4.769	0.146
Match: Circulatory	0.816	0.020	0.227	0.038	0.958	0.074	0.832	0.021	0.251	0.034	0.703	0.070
Match: Transplant												
Match: Pediatric	2.473	0.076	2.598	0.080	2.148	0.065	2.503	0.081	3.099	0.095	2.327	0.071
Eye	0.701	0.104	-0.445	0.264	-0.562	0.250	0.440	0.145	-0.117	0.273	0.137	0.197
ENT	0.020	0.060	-0.096	0.092	-0.146	0.103	0.172	0.061	-0.001	0.098	0.144	0.101

Table A4: Tampa 1995 & 1996 Estimates, Non-Emergency Sample (continued)

Respiratory System	0.052	0.028	-0.120	0.060	-0.019	0.068	0.043	0.030	-0.019	0.056	-0.129	0.072
Circulatory System	-0.036	0.025	-0.067	0.053	-0.147	0.066	-0.061	0.026	-0.098	0.049	-0.143	0.068
Digestive System	0.022	0.028	-0.034	0.058	-0.001	0.069	0.022	0.030	-0.060	0.056	-0.057	0.072
Liver & Pancreas	-0.055	0.041	0.014	0.079	-0.195	0.092	-0.077	0.044	-0.121	0.077	-0.260	0.096
Musculoskeletal	0.165	0.026	-0.061	0.058	0.113	0.063	0.208	0.027	-0.005	0.054	0.223	0.066
Skin & Breast	0.011	0.042	-0.093	0.088	-0.071	0.097	-0.078	0.047	-0.038	0.086	-0.010	0.103
Endocrine & Metabolic	-0.009	0.042	0.086	0.082	0.203	0.094	0.093	0.042	-0.165	0.082	0.073	0.096
Kidney & Urinary	0.096	0.036	-0.164	0.078	-0.068	0.086	0.121	0.037	-0.083	0.069	-0.035	0.095
Male Reproductive	-0.065	0.047	0.001	0.091	-0.004	0.193	-0.042	0.053	0.027	0.090	0.014	0.227
Female Reproductive	-0.071	0.034	-0.186	0.061	0.084	0.077	0.087	0.035	-0.107	0.057	0.076	0.079
Pregnacy/Childbirth	-0.237	0.033	-0.508	0.055	-0.387	0.059	-0.125	0.034	-0.236	0.051	-0.184	0.061
Blood & Pancreas	0.085	0.068	-0.098	0.124	-0.037	0.124	0.006	0.072	0.076	0.113	-0.158	0.133
Myeloproliferative	-0.027	0.049	0.019	0.093	0.024	0.092	0.027	0.052	-0.206	0.086	-0.197	0.109
Infect. & Parasit. Dis.	0.151	0.041	0.044	0.087	0.036	0.095	0.100	0.044	-0.037	0.087	0.044	0.100
Injuries/Poisonings	0.007	0.069	-0.141	0.139	-0.104	0.112	0.040	0.072	-0.360	0.147	-0.439	0.124
HIV	0.339	0.080	0.471	0.144	0.053	0.104	0.563	0.084	0.240	0.158	0.209	0.114

Table A5: Tampa 1995 & 1996 Estimates, Emergency Sample

Sample	1995						1996					
	Free Choice		Managed Care		Other		Free Choice		Managed Care		Other	
N	53,063		15,662		16,604		50,956		19,356		16,506	
J	24		21		24		23		20		22	
Pseudo R ²	0.4639		0.4632		0.5223		0.4781		0.4669		0.5026	
Var	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
For Profit ≡ "FP" Govt.	-2.025	0.062	-2.962	0.118	-1.515	0.120	-2.338	0.062	-2.595	0.102	-1.079	0.114
Teach	-4.499	0.124	-4.228	0.194	-1.636	0.129	-3.575	0.132	-4.274	0.178	-1.703	0.135
Nrs. Intens.	-0.765	0.038	-0.134	0.051	-0.785	0.046	-0.302	0.040	0.224	0.048	-0.460	0.045
Ln(Eff. Time) ≡ "LET"	-3.066	0.057	-3.133	0.105	-2.638	0.100	-3.425	0.060	-3.341	0.096	-2.846	0.105
LET * For Profit	0.285	0.014	0.425	0.027	0.271	0.027	0.292	0.014	0.437	0.024	0.168	0.027
LET * Govt.												
LET * Teaching	0.773	0.026	0.362	0.044	0.140	0.028	0.756	0.027	0.425	0.040	0.120	0.029
LET * Nrs. Intens.	0.119	0.008	0.025	0.011	0.099	0.009	0.132	0.008	-0.011	0.010	0.060	0.009
LET * Median Inc.	0.013	0.002	0.039	0.004	0.012	0.004	0.018	0.002	0.039	0.003	0.004	0.004
LET * Male	-0.014	0.015	0.023	0.029	0.014	0.030	-0.036	0.015	0.017	0.027	-0.002	0.029
LET * Age: Under 18	-0.095	0.058	-0.004	0.064	-0.102	0.047	0.002	0.063	0.142	0.061	-0.289	0.049
LET * Age: 50-74	-0.137	0.019	0.185	0.038	-0.017	0.035	-0.119	0.020	0.017	0.034	-0.229	0.036
LET * Age: 75+	-0.136	0.019	0.460	0.045	-0.384	0.098	-0.109	0.019	0.141	0.039	-0.478	0.085
LET * # Procs.	0.029	0.007	0.064	0.014	0.055	0.012	0.015	0.007	0.035	0.012	0.028	0.013
LET * # Diags	-0.002	0.003	-0.052	0.007	0.001	0.007	0.032	0.003	0.025	0.006	0.037	0.007
LET * Pcttrv	0.432	0.057	0.366	0.113	0.408	0.112	0.363	0.060	0.397	0.101	0.644	0.112
LET * Emerg. Cat 1	-0.034	0.091	-0.023	0.156	-0.170	0.117	0.128	0.093	0.022	0.155	-0.091	0.114
LET * Emerg. Cat. 3	-0.155	0.034	-0.031	0.070	-0.332	0.074	-0.141	0.035	-0.170	0.070	0.051	0.069
Eff. Time * Black	0.040	0.034	0.112	0.049	-0.061	0.040	0.082	0.035	0.106	0.047	-0.072	0.042
Eff. Time * Hisp.	0.601	0.047	0.583	0.085	0.569	0.048	0.642	0.045	0.561	0.068	0.665	0.045
Eff. Time * Other	0.067	0.063	0.160	0.116	-0.034	0.079	-0.128	0.068	-0.065	0.104	0.235	0.075

Table A5: Tampa 1995 & 1996 Estimates, Emergency Sample (continued)

LET * Private Payor	0.023	0.020					0.060	0.020				
LET * Risk Medicare			-0.691	0.039					-0.321	0.033		
LET * Risk Medicaid			-0.169	0.055					-0.065	0.051		
LET * Indig./Charity					-0.293	0.034					-0.255	0.034
LET * Other Payor					0.150	0.037					0.122	0.037
Teach * # Procs	-0.060	0.015	-0.025	0.029	-0.103	0.018	0.006	0.017	-0.075	0.026	-0.095	0.018
Teach * # Diags	-0.116	0.008	-0.037	0.014	0.021	0.009	-0.143	0.009	-0.045	0.013	0.034	0.009
Teach * Pcttrv	3.666	0.111	3.717	0.182	3.203	0.129	3.744	0.129	3.510	0.162	3.269	0.131
Nursing * # Procs.	-0.023	0.006	-0.022	0.008	0.015	0.007	0.022	0.006	0.015	0.007	0.012	0.006
Nursing * # Diags	-0.013	0.003	0.039	0.004	-0.012	0.004	-0.036	0.003	0.003	0.003	-0.006	0.004
Nursing * Pcttrv	0.714	0.046	-0.087	0.050	0.240	0.048	0.686	0.050	-0.245	0.047	0.144	0.045
Hosp %Black * Black	7.475	0.243	6.388	0.332	11.690	0.322	5.338	0.264	5.517	0.296	12.386	0.314
Hosp %Hisp. * Hisp.	19.021	0.649	12.626	0.865	16.330	0.610	10.299	0.523	7.918	0.641	10.990	0.476
Hosp %Other * Other	39.428	1.344	32.816	2.402	43.415	1.819	26.174	1.232	28.715	1.840	32.535	1.478
Hosp %White * White	-0.088	0.066	-0.323	0.108	-3.374	0.110	2.088	0.072	0.418	0.093	-2.464	0.102
FP * Private Payor	-0.088	0.027					-0.113	0.028				
FP * Risk Medicare			1.698	0.051					0.538	0.042		
FP * Risk Medicaid			-0.642	0.100					-0.677	0.088		
FP * Indig./Charity					0.329	0.058					0.150	0.056
FP * Other					-0.908	0.071					-0.494	0.065
Match: Oncology	1.097	0.147	-0.057	0.214	2.109	0.459	1.007	0.148	0.431	0.219	1.565	0.370
Match: HIV	0.730	0.249	0.937	0.468	0.223	0.200	1.025	0.297	0.026	0.385	0.471	0.209
Match: Delivery	2.081	0.161	3.108	0.239	2.572	0.115	3.496	0.459	4.648	0.586	4.779	0.306
Match: Circulatory	0.819	0.023	-0.163	0.038	0.763	0.065	1.183	0.026	0.428	0.037	1.187	0.069
Match: Pediatric	1.775	0.103	2.598	0.117	2.163	0.092	1.963	0.116	2.574	0.112	2.398	0.099
Match: Trauma	0.748	0.068	-0.515	0.159	1.349	0.106	0.369	0.056	0.013	0.112	0.710	0.092
Eye	0.496	0.178	0.743	0.351	-0.166	0.265	0.459	0.224	-0.084	0.335	-0.058	0.286
ENT	-0.167	0.099	-0.033	0.167	-0.651	0.125	0.037	0.100	0.011	0.144	-0.035	0.135
Respiratory System	-0.030	0.032	0.041	0.066	-0.305	0.065	0.025	0.033	-0.069	0.060	-0.006	0.067

Table A5: Tampa 1995 & 1996 Estimates, Emergency Sample (continued)

Circulatory System	-0.363	0.029	-0.051	0.061	-0.557	0.066	-0.290	0.030	-0.242	0.055	-0.351	0.068
Digestive System	-0.089	0.035	0.083	0.069	-0.329	0.069	-0.054	0.036	0.012	0.062	0.063	0.071
Liver & Pancreas	-0.127	0.052	-0.048	0.099	-0.377	0.084	-0.070	0.053	-0.045	0.086	-0.052	0.086
Musculoskeletal	0.095	0.036	0.168	0.084	0.012	0.077	0.164	0.037	0.096	0.076	0.256	0.080
Skin & Breast	0.132	0.069	0.031	0.147	-0.001	0.098	0.035	0.075	0.061	0.151	0.047	0.103
Endocrine & Metabolic	-0.088	0.054	-0.006	0.106	-0.312	0.095	-0.048	0.055	0.027	0.093	0.026	0.098
Kidney & Urinary	0.059	0.047	0.023	0.098	-0.173	0.095	0.103	0.048	-0.066	0.088	-0.060	0.099
Male Reproductive	-0.182	0.202	0.200	0.359	0.070	0.308	-0.214	0.205	-0.147	0.340	0.107	0.280
Female Reproductive	0.039	0.138	-0.044	0.201	-0.217	0.140	-0.018	0.153	-0.283	0.224	-0.260	0.154
Pregnancy/Childbirth	-0.002	0.064	-0.202	0.104	-0.198	0.069	0.077	0.070	0.154	0.092	-0.071	0.072
Blood & Pancreas	-0.295	0.104	-0.039	0.191	0.116	0.126	0.050	0.096	-0.203	0.170	0.333	0.129
Myeloproliferative	-0.371	0.133	0.458	0.223	-0.460	0.257	-0.174	0.132	-0.034	0.217	0.015	0.256
Infect. & Parasit. Dis.	0.056	0.045	0.082	0.107	-0.313	0.101	0.119	0.045	0.128	0.090	0.032	0.108
Injuries/Poisonings	-0.341	0.081	0.035	0.127	-0.531	0.103	-0.299	0.085	-0.333	0.132	-0.570	0.105
Multiple Trauma	0.621	0.102	0.612	0.332	0.141	0.179	0.867	0.094	0.493	0.285	0.359	0.174
HIV	0.356	0.128	0.581	0.179	-0.047	0.118	-0.006	0.164	0.063	0.225	0.413	0.109

Table A6: Parameter Estimates of the Cost Function

All inputs, wages, and outputs are logged	Long Run	Short Run-Fully Interacted	Short Run Quadratic		Long Run	Short Run-Fully Interacted	Short Run Quadratic
Wage	2.022***	1.962***	2.175***	H Bed * SNF Bed		-0.004	-0.017***
Wage ²	-0.070***	-0.069***	-0.097***	H Adm * H Bed		0.011***	
Hosp Adm*Wage	-0.047***	-0.047***		SNF Adm * H Bed		0.006**	
SNF Adm*Wage	-0.013***	-0.018***		Outpatient * H Bed		-0.020***	
Outpatient*Wage	-0.006*	-0.004		ED Visit * H Bed		-0.003*	
ED Visit*Wage	0.006**	0.006**		H Adm * SNF Bed		-0.010***	
Hosp Bed*Wage		0.001		SNF Adm * SNF Bed		-0.005***	
SNF Bed*Wage		0.010*		Outpatient * SNF Bed		-0.006***	
Hosp Adm	0.356***	0.351***	-0.164***	ED Visit * SNF Bed		-0.002	
Hosp Adm ²	0.047***	0.036***	0.034***	% Medicare	0.088***	0.089***	0.085***
SNF Adm	0.209***	0.161***	-0.004	% Medicaid	0.004	0.001	0.002
SNF Adm ²	0.001***	0.004***	0.001*	% Inpatient Surg	0.013***	0.009**	0.008*
Outpatient	0.059*	0.046	-0.020***	% Outpatient Surg	-0.001	-0.001	0.002***
Outpatient ²	0.010***	0.010***	0.003***	For Profit	-0.026***	-0.029***	-0.030***
Ed Visit	-0.057**	-0.046*	-0.031***	Public	-0.020***	-0.016***	-0.023***
Ed Visit ²	0.005***	0.005***	0.004***	Teaching	0.024*	0.020	0.016
Hosp Adm *SNF Adm	-0.006***	-0.005**		System	-0.016***	-0.015***	-0.017***
Hosp Adm *Outpatient	-0.016***	-0.006***		1993	-0.380***	-0.388***	-0.393***
Hosp Adm *Ed Visit	-0.002**	-0.002		1994	-0.346***	-0.353***	-0.358***
SNF Adm *Outpatient	-0.001*	0.003**		1995	-0.309***	-0.314***	-0.317***
SNF Adm *Ed Visit	-0.001**	0.001		1996	-0.270***	-0.273***	-0.275***
Outpatient * ED Visit	-0.003***	-0.003***		1997	-0.226***	-0.228***	-0.229***
Hosp Bed		-0.042	-0.140***	1998	-0.196***	-0.196***	-0.197***
Hosp Bed ²		0.029***	0.029***	1999	-0.161***	-0.161***	-0.162***
SNF Bed		0.044	0.057***	2000	-0.119***	-0.119***	-0.119***
SNF Bed ²		0.017***	0.011***	Constant	2.133***	2.451***	4.044***
N	35,170	35,170	35,170	Notes: All inputs, wages, and outputs are logged. Regressions include hospital fixed effects.			
Overall R2	0.9468	0.9513	0.9463				

Figure 1: Tampa-St. Petersburg Closures
 (Red circles denote closing hospitals)

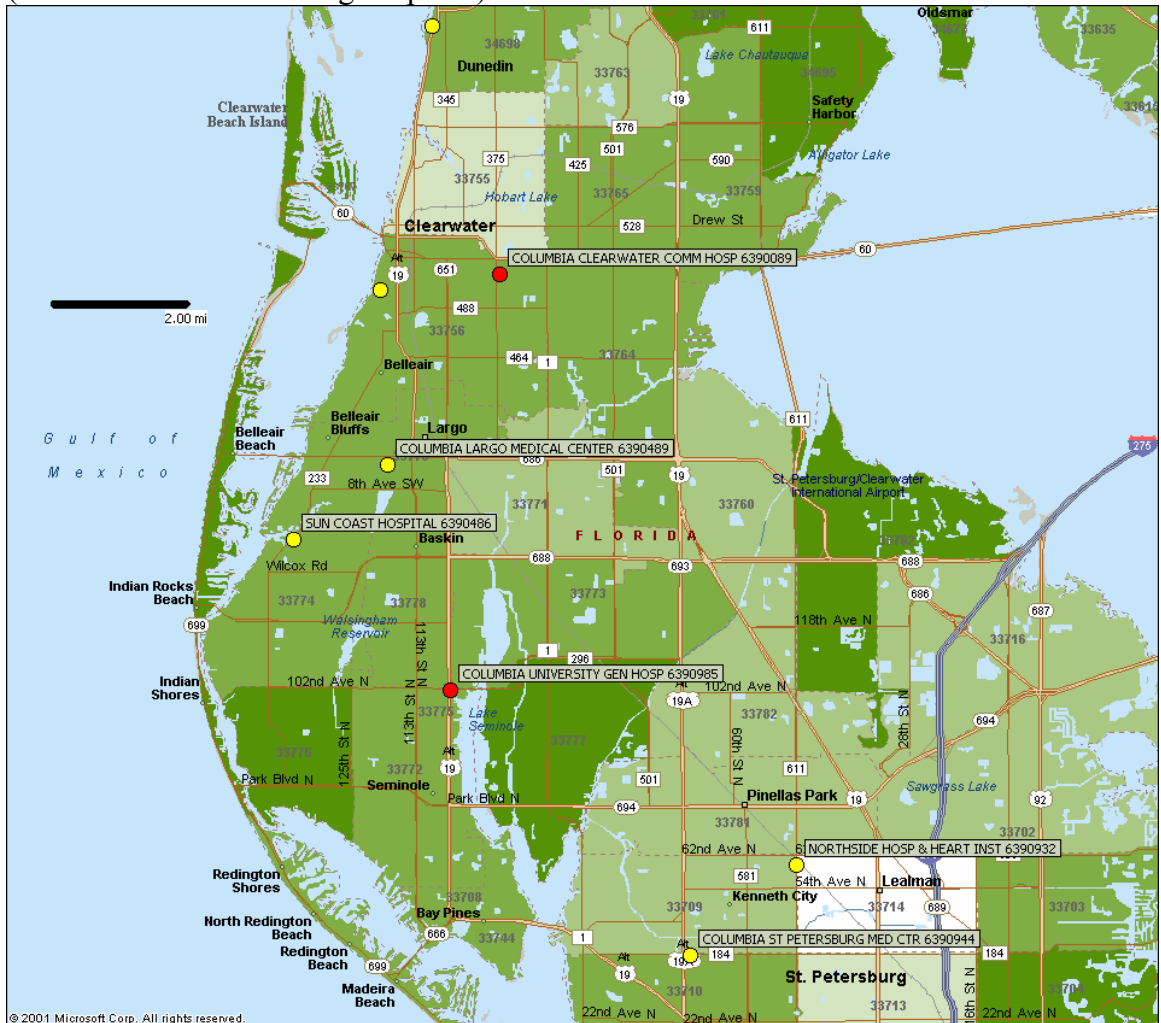
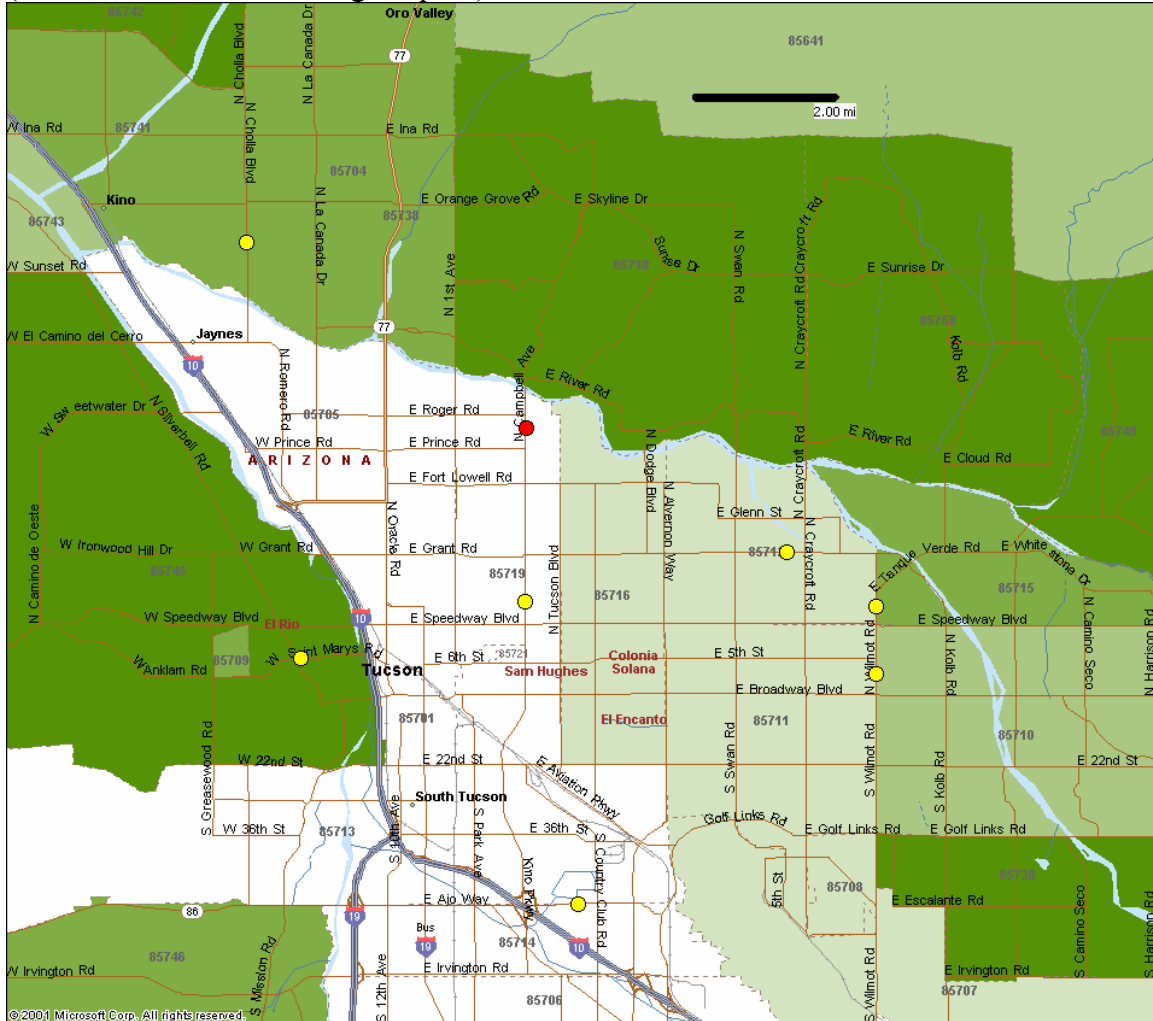


Figure 2: Phoenix Closures
 (Red circles denote closing hospitals)



Note: Not all hospitals in the Phoenix market are shown.

Figure 3: Tucson Closures
 (Red circles denotes closing hospital)



Note: Not all hospitals in the Tucson market are shown.