# HOSPITAL CLOSURE AND ECONOMIC EFFICIENCY*

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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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## HOSPITAL CLOSURE AND ECONOMIC EFFICIENCY

### 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

[1]See 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 they 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 in the mid- to late 1990s. 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. McNamara concludes the rural hospitals brought enough value to the market to warrant a

[4] See Capps et al. [2003].

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 by extending the 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 γ(.) is constant.

The variable $\lambda_i$ 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 γ(.) 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), $\varepsilon_{ij}$, represents the personal and idiosyncratic component of patient *i*'s evaluation of hospital *j*.

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

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

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, …, *G*}, equals

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

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

$V(G \mid Y_i, Z_i, \lambda_i) - V(G / k \mid Y_i, Z_i, \lambda_i)$. 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

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

In equation (3), N is the total population in the market, $s_j\left(G,Y_i,Z_i,\lambda_i\right)$ is hospital *k*'s market share of patients with characteristics $(Y_i,Z_i,\lambda_i)$, $f(Y_i,Z_i,\lambda_i)$ 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 utils need to be converted into dollars in order to compare the costs and benefits of hospital closures.[6] The standard approach is to directly place a dollar value on utils using the estimated price coefficient from the choice model. However, this is not possible in the hospital industry because there is little, if any, variation across hospitals in the price paid by most patients. The out-of-pocket expense is generally the same across hospitals for patients with fee-for-service, Medicare, and Medicaid coverage. Patients in preferred provider organizations (PPO) and managed care organizations (MCOs) face prices that vary depending on whether the provider is in or out of the insurer's network, but we observe the neither the networks nor the out-of-pocket expense faced by these patients. While the inclusiveness of PPO networks is not

[6] 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.

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.[7]

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 derive the "travel time equivalent of closure." Specifically, for each patient *i*, we calculate the $\Delta t^*$ given the closure of hospital *k* that solves:

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

Equation (4) can then be integrated over patient diagnoses, demographics, and locations to compute a market level estimate. 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. Using Equation (3) and integrating over diagnosis, demographics, and location yields the formula that implicitly defines $\Delta t^*$:

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

or equivalently,

[7] 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%.

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

where $\Delta\overline{W}_j^{EA}\equiv\gamma\bullet\Delta W_j^{EA}$, the WTP for hospital *j* up to the unknown constant γ. Solving equation (6) for $\Delta t^*$ 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: [8]

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

where *N* reflects the entire population. Note that the logit assumption implies that $\frac{\partial V(G\,|\,Y_i,Z_i,\lambda_i)}{\partial t}$ has a closed form solution:

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

Equation (8) measures the reduction in expected utility to a single patient, *i*, with characteristics $(Y_i,Z_i,\lambda_i)$, 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

[8] 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.

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*(.) with respect to *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).

Patients are likely to consider the drive time of their relatives and friends when choosing a hospital, in addition to their own travel. 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 $\Delta T_k^*$. Therefore, we use *effective travel time*, which we define as the product of one-way drive time and expected length of stay.

The final step is to convert the $\Delta T_k^*$ 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. 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 in San Diego found the median value of one hour to be

$15.00.[9] 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 $\Delta T_k^*$ 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, $\Delta T_k^*$ measures 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. We obtain the aggregate willingness to pay in a market to keep a given hospital open by multiplying $\Delta T_k^*$ by the dollar value of time.

*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.

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[9] 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].

First, we estimate the admission patterns across hospitals post-closure based on the coefficients from (1). The predicted probability of a patient with characteristics $(Y_i, Z_i, \lambda_i)$ of choosing a given hospital *j*, is given by

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

An alternative interpretation of (9) is that it is hospital *j*'s expected market share among patients with characteristics $(Y_i, Z_i, \lambda_i)$. Using (9) we 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, the post-closure estimates are derived 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:

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

where $\Delta ADM_j$ 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 increased at surrounding hospitals because a number of patients are admitted through the ED. Thus we also calculate:

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

Finally, the surrounding hospitals may or may not have the bed capacity to absorb the increase in admissions as measured by $\Delta ADM_j$. If $E(ADM_{Post})$ leads the hospital to have a greater than 70% occupancy rate, we add additional beds, $\Delta BED_j$, 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:

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

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:

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

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

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

[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.

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 state's share of Medicaid savings, but not the federal share. Private insurers normally set

[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.

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 $\Delta C_j$, then the local community will consider an amount $(\theta_{pj} + m\theta_{mj})\Delta C_j$, where $\theta_{pj}$ is the share of private patient expenses at the hospital, $\theta_{mj}$ 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'

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

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 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 mores 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:

[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).

$$\ln(TotalCost_{jt}) = \alpha + \beta_N \ln(N_{jt}) + \beta_{NN} \ln(N_{jt})^2 + \beta_I \ln(I_{jt}) + \beta_{II} \ln(I_{jt})^2 + \beta_{Nb} \ln(N_{jt}) * \ln(I_{jt})$$
$$+ \beta_W \ln(Wage_{jt}) + \beta_{WW} \ln(Wage_{jt})^2 + \beta_{WN} \ln(Wage_{jt}) * \ln(N_{jt}) + \beta_{WI} \ln(Wage_{jt}) * \ln(I_{jt}) \qquad (15)$$
$$+ \beta_P PatientMix_{jt} + \beta_H Hospital_{jt} + Time_t + \mu_j + \varepsilon_{ji}$$

*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, $\mu$.

Equation (15) treats beds as a quasi-fixed input and allows for flexible substitution though 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.

[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.

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' 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

[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.

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 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.

[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.

*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 care expenditures, where $\theta_p$ measures the private insurer share of costs at the hospital, $\theta_m$ 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

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

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.

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]

[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.

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.

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]

**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

[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.

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.

There is also a possibility that a closure could lead to lengthier travel times to emergency departments, and in doing so, worsen outcomes. 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 in Los Angeles led to increases in the probabilities of death from Acute Myocardial Infarction (AMI) and from unintentional injuries. The magnitude of their results is quite large: a one-mile increase from a given zip code to the nearest hospital increases the AMI mortality rate by 6.5% and the injury mortality rate by 11-20%. They cite a report by the American Heart Association which states the survival probability for cardiac arrest decreases by 7-10% for every minute without treatment. Specifically, the American Heart Association's report states that (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 cardiac arrest, but **reaching the victim in time to do so** [emphasis added].

Thus, the time it takes an ambulance to reach the patient is the most important 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. This is best accomplished by targeting response times, rather than propping up a hospital that generates more costs than consumer surplus.

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**Table 1. Sample Stratification**

| *Sample*: | *(1) Free Choice* | | *(2) HMO* | | *(3) Other Payor* | |
|---|---|---|---|---|---|---|
| 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**

| | *University Gen. Hosp.* | *Clearwater Comm. Hosp.* | *Tucson Gen. Hosp.* | *Phoenix Regional Med. Center*[*] | *Community Hosp. Med. Center* |
|---|---|---|---|---|---|
| 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)** *$16.00 per hour* | *$20.00 per hour* | **Roundtrip (2 people)** *$16.00 per hour* | *$20.00 per hour* |
|---|---|---|---|---|---|---|---|
| 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**

| | | *2 people at $20.00 per hour* | | | | | |
|---|---|---|---|---|---|---|---|
| | | Non-Emergency Admissions | | | Emergency Admissions | | |
| Hospital Name | Total Welfare Effect | *(1) Free Choice* | *(2) HMO* | *(3) Other* | *(1) Free Choice* | *(2) HMO* | *(3) Other* |
| 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 | Tampa | Tampa | Tucson | Phoenix | Phoenix |
| Year | 1995 | 1996 | 1998 | 1997 | 1997 |
| *Long Run Cost Function* | -$5.311 | -$6.546 | -$5.994 | -$2.833 | -$3.423 |
| *Fully Interacted Short-run* | -$9.310 | -$9.917 | -$6.183 | -$7.676 | -$3.897 |
| *Quadratic Short Run* | -$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 | Tampa | Tampa | Tucson | Phoenix | Phoenix |
| | Year | 1995 | 1996 | 1998 | 1997 | 1997 |
| *Long Run Cost Function* | 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** |
| *Fully Interacted Short-run* | 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** |
| *Quadratic Short Run* | 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 | Tampa | Tampa | Tucson | Phoenix | Phoenix |
| | Year | 1995 | 1996 | 1998 | 1997 | 1997 |
| Local Share of Cost Savings | | 0.609 | 0.363 | 0.390 | 0.410 | 0.507 |
| *Long Run Cost Function* | 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 |
| *Fully Interacted Short-run* | 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 |
| *Quadratic Short Run* | 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 |
| *Long Run Cost Function* | 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** |
| *Fully Interacted Short-run* | 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** |
| *Quadratic Short Run* | 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 |
|---|---|---|---|---|---|---|
| *Hospital Charac-teristics* | 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 | |
| *Patient Charac-tersitics* | 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.) |
| *Match Variables* | 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
AZ(FL) = Included in Arizona (Florida) model only
ER = Included in Emergency Models only
FC = Included in "Free Choice" sample only
HMO = Included in HMO sample only
Other = Included in Other Payor sample only

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

| | Phoenix, 1997 | | | | | | Tucson, 1998 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sample | Free Choice | | Managed Care | | Other | | Free Choice | | Managed Care | | Other | |
| N | 59,080 | | 62,305 | | 29,228 | | 16,575 | | 22,145 | | 13,885 | |
| J | 29 | | 28 | | 24 | | 13 | | 12 | | 12 | |
| 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. %Hisp. * Hisp. | 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**

| | Phoenix, 1997 | | | | | | Tucson, 1998 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sample | Free Choice | | Managed Care | | Other | | Free Choice | | Managed Care | | Other | |
| N | 38,286 | | 29,610 | | 16,147 | | 13,165 | | 17,253 | | 6,838 | |
| J | 27 | | 27 | | 24 | | 11 | | 12 | | 11 | |
| Pseudo $R^2$ | 0.4736 | | 0.4608 | | 0.3741 | | 0.3043 | | 0.3998 | | 0.2934 | |
| Var. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. |
| 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 %Hisp. * Hisp. | 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 |
| Pregnacy/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**

| | 1995 | | | | | | 1996 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sample | 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**

| | 1995 | | | | | | 1996 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sample | 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” | -2.025 | 0.062 | -2.962 | 0.118 | -1.515 | 0.120 | -2.338 | 0.062 | -2.595 | 0.102 | -1.079 | 0.114 |
| Govt. | | | | | | | | | | | | |
| 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 |
| Pregnacy/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 | | | | |
| Overall R2 | 0.9468 | 0.9513 | 0.9463 | | | | |

**Notes: All inputs, wages, and outputs are logged. Regressions include hospital fixed effects.**

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

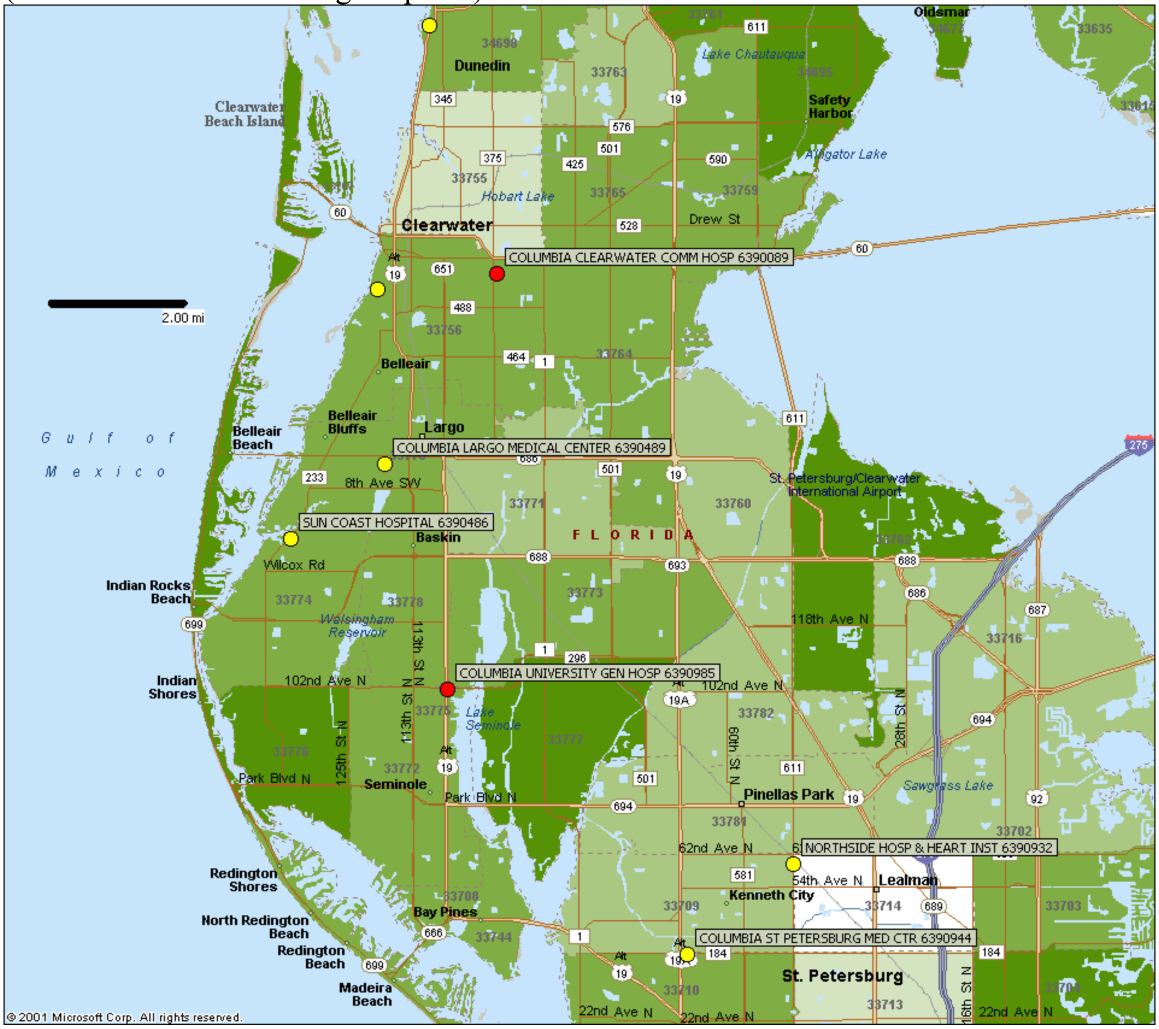
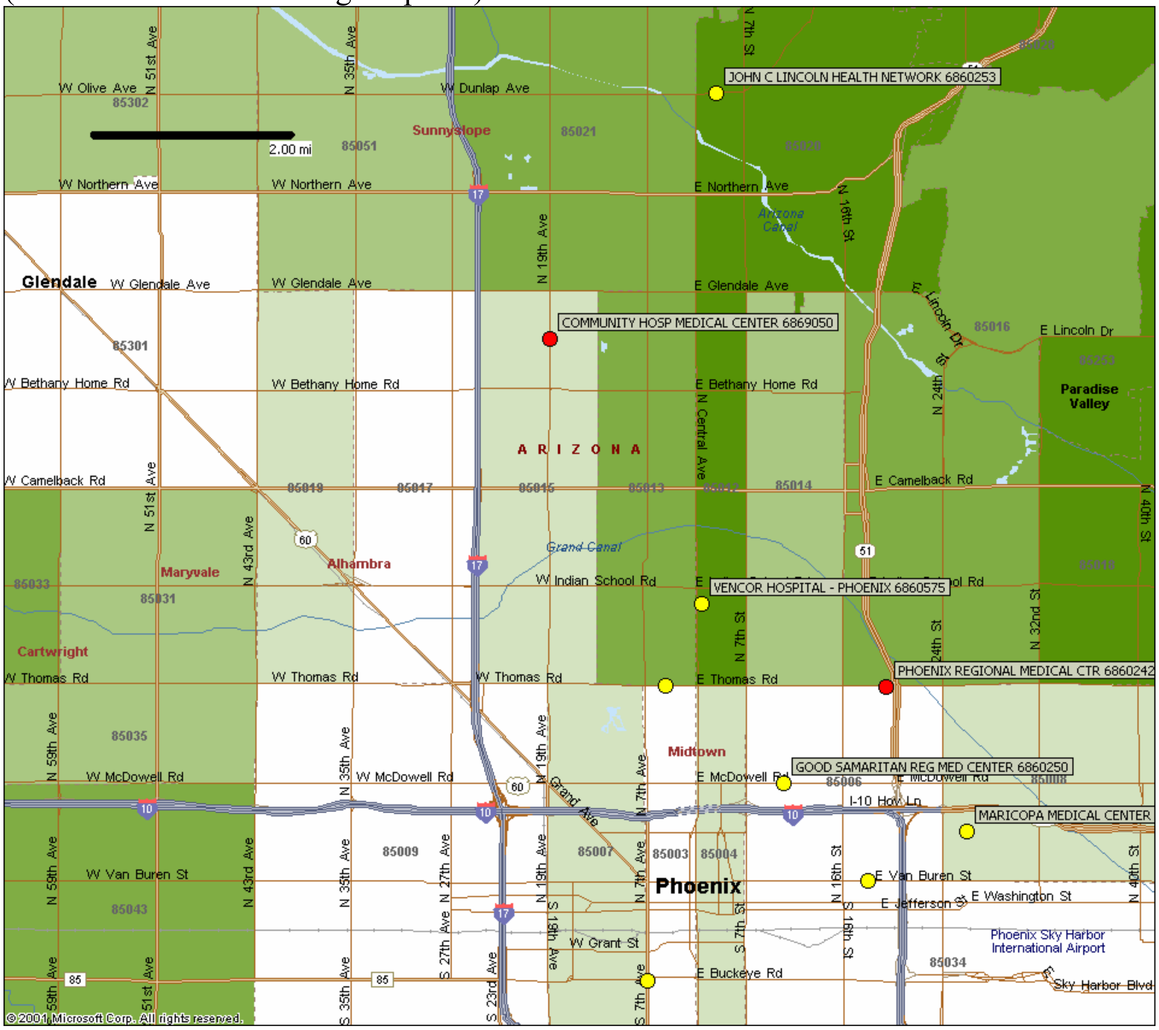


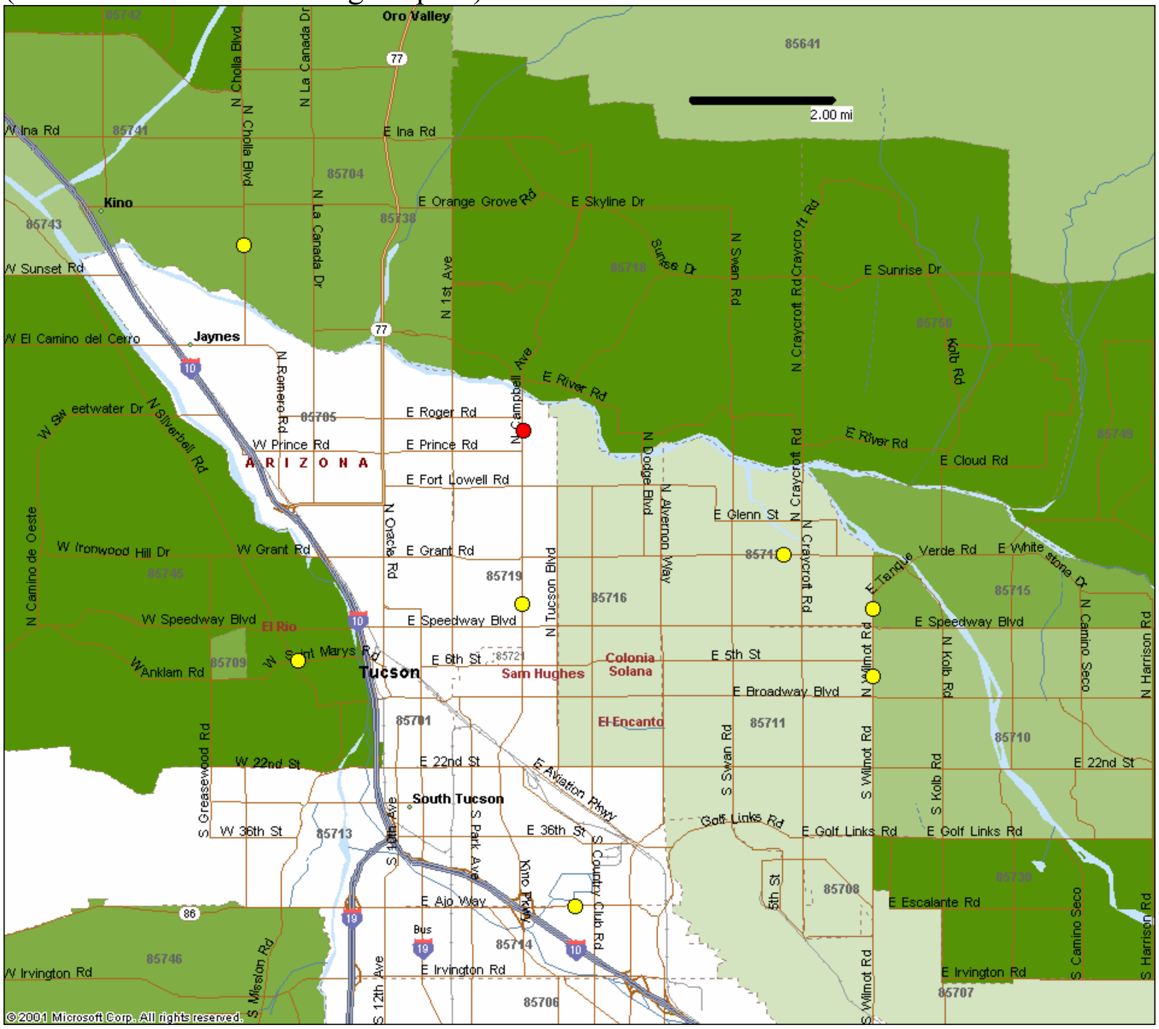
**Figure 2: Phoenix Closures**
(Red circles denote closing hospitals)




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.