IDENTIFICATION OF BENCHMARK AND INVESTIGATION OF COST DRIVERS IN HOSPITAL INDUSTRY: HOW INEFFICIENT ARE U.S. HOSPITALS?

A Thesis

by

MARCELLA CRISPIM SARMENTO

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Chair of Committee,	Andrew L. Johnson
Committee Members,	Amarnath Banerjee
	Ursula U. Mueller
Head of Department,	César O. Malavé

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ABSTRACT

By how much can a hospital reduce cost level while maintaining the service provided? In our problem, we estimate an input oriented measure of inefficiency and a cost function to understand the relationship between cost and number of performed procedures in the U.S. hospital industry. In addition, our model accounts for contextual variables which provide insights regarding cost drivers. For estimation, we use the method called Multivariate Bayesian Convex Regression (MBCR).

Our data are composed from two databases. We use the American Hospital Association Annual Survey and the National Inpatient Sample provided by the Healthcare Cost and Utilization Program. Our cost measure is total expenditures and the output is number of procedures which is classified in four categories according to nature of service and type of operating room. The contextual variables (hospital size, region, teaching status and ownership) are selected using Bayesian Information Criterion (BIC).

Many factors can impact costs level. Our results show that larger hospitals and teaching hospitals located in the Northeast are more cost inefficient. In the same way, private hospitals are less cost inefficient compared to public hospitals. Average cost inefficiency levels for an ~10% sample of all U.S. hospitals are 27%, 18% and 23% for years 2004, 2007 and 2011, respectively. Further, we found evidence that production in the U.S. hospital industry might be better characterized by the Regular Ultra-Passum Law than by a convex cost function.

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To mainha and painho.

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NOMENCLATURE

AHA	American Hospital Association
AHAID	American Hospital Association Identification Number
BIC	Bayesian Information Criterion
CAH	Critical Access Hospital
DEA	Data Envelopment Analysis
DRG	Diagnosis Related Group
GDP	Gross Domestic Product
HCUP	Healthcare Cost and Utilization Project
ICD-9-CM	International Classification of Diseases, Ninth Revision, Clinical Modification
IOM	Institute of Medicine
MBCR	Multivariate Bayesian Convex Regression
MSE	Mean Squared Error
NIS	National Inpatient Sample
OECD	Organization for Economic Cooperation and Development
RJMCMC	Reversible Jump Markov Chain Monte Carlo
RSS	Residual Sum of Squares
SFA	Stochastic Frontier Analysis
ZMBCR-I	Multivariate Bayesian Convex Regression with Inefficiency and Z data

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1. INTRODUCTION

In order to improve health system and increase healthcare coverage, President Obama signed in 2010 the Patient Protection Affordable Care Act (ACA). The new policy promised a variety of benefits. However, it did not considered issues related to cost, sustainability and quality in its proposal and some believed the reform would turn the health system more bureaucratic and complex (Steinmetz, et al., 2013). Despite of the government investment in health, one cannot affirm that the system will be more efficient as more money is spent. Indeed, higher healthcare investment is not directly proportional to technical efficiency improvement (Varabyova and Schreyoegg, 2013).

For instance, in 2012 the United States' expenditures on health accounted for 16.9% of GDP, which is 7.5 percentage points above the OECD average for the same year (OECD, 2014). Thirty-one percent of U.S. healthcare expenditures are spent solely on hospital care or approximately 5% of GDP (The Henry J. Kaiser Family Foundation, 2012). Estimates of the excess cost in the system consistently exceed $750 billion and range as high as half of all healthcare expenditures (PricewaterhouseCoopers LLC, 2009). Because hospitals make-up such a large portion of healthcare expenditures, hospitals are a potential large source of cost savings. Motivated by these factors, our research investigates the cost efficiency of hospitals.

There are approximately 5,627 registered hospitals in the U.S. (American Hospital Association, 2016) with approximately 50% are Not-For-Profit Community Hospitals, approximately 20% are Investor-Owned Community Hospitals, approximately

20% are Local Government Community Hospitals, and the remainder are Federal, Psychiatric, or Nonfederal Long Term Care. Among these hospitals, 35% are Rural Community hospitals, which are more susceptible to close due to budget constraints and lack of demand. One attempt to minimize rural hospital closure is the Critical Access Hospital (CAH) program. Hospital that are critical access certified receive a cost-based reimbursement from Medicare instead of standard fixed rates in order to enhance economic performance. Nedelea and Fannin, (2013) argue under this payment scheme, hospitals tend to over supply services in an attempt to increase revenues as evidence by their estimates that cost inefficiency increases by 4.8% for each additional year a hospital is enrolled in the program. A similar study was performed at the state level at Missouri also found that hospitals engaged in the CAH program have higher cost inefficiency levels (Gautam, et al., 2013).

However, contrary evidence also exists indicating some laws and policies have a positive effects on cost efficiency. The Certificate of Need is a legal document required by many states to justify the necessity of healthcare facilities in order to control costs (National Conference of States Legislatures, 2007). Rosko and Mutter (2014) showed that hospitals located in states which follow the regulation were on average more cost efficient. In addition, these hospitals had higher mean occupancy rate. Nevertheless, this sort of regulation may impact availability of service and competition. As a consequence, hospitals have less impetus to achieve excellence. Thus, the law promotes efficiency in hospitals; however, it could potentially jeopardize quality. These results and need for cost improvements motivate us to gather and analyze data describing a set of U.S. hospitals to understand the drivers of cost and cost efficiency.

2. LITERATURE REVIEW

Cost-control and cost-efficiency analyses are familiar to the hospital industry, where concerns over rising costs have been present since the 1950's and 60's (Sheps, 1955; Dowling, 1976; Griffin et al., 1976). It has been nearly 25 years since accountability and assessment were hailed as the next revolution in medical care (Relman, 1988), and yet the best models for efficiency measurement in hospitals suffer serious limitations and are rarely applied in practice. Efficiency is one of the six specific aims for quality improvement proposed in 2001 by the Institute of Medicine (IOM). Cost functions have been used to measure inefficiency in hospitals (Wagstaff, 1989; Zuckerman, et al., 1994). This literature review is structure to review several cost drivers discussed in the literature. Specifically, we will discuss scale economies, ownership, regional variations, rural/urban differences, impact of teaching, and critical access designation effects on cost. Then at the end of the literature review we will discuss specific issues related to modeling a cost function.

We observe an improvement of cost efficiency due to economies of scale in a wide variety of industries (Baumol et al., 1982). However, many smaller hospitals face the challenge of distributing high fixed costs over a relatively small capacity and provide a wide array of procedures. Kristensen et al. (2012) investigates optimal hospital size in Danish public hospitals. The results shown that medium sized hospitals have a constant economies of scale and larger sized hospitals have a decreasing economies of scale. The authors find for medium size public hospital a range of 205 and 276 beds maximizes resources utilization.

Public hospitals are managed by governments and are often found in rural areas. In general, these hospitals provide health services for those who have lower income, are uninsured or are covered by Medicaid. Additionally, those hospitals also provide trauma care for their local populations. On the other hand, not for profit hospitals are approximately 50% of all community hospitals across the country and are controlled by foundations and religious institutions. Compared to public hospitals, they have similar behavior regarding services provided, length of stay and number of beds (Fraze, et al., 2010). Private hospitals are profit-seeking whereas public and not for profit are not. Additionally, they are located in strategic markets in order to maximize revenues. Based on these selection issues, we expect private hospital to be more cost efficient. In contrast, Tiemann, et al. (2012) study German hospitals and finds that private and not for profit hospitals are less efficient than public hospitals.

The Census Bureau (2015) divide U.S. in four major regions (Northeast, Midwest, South and West) and each region has peculiarities regarding demographic characteristics. These regional difference can effect cost efficiency of hospitals. For instance, Sharma, et al. (2013) analyze procedure costs controlling for teaching hospital status, region, size and ownership and find for certain types of brain surgery that larger, public and teaching hospitals located in Northeast had lower costs.

Teaching hospitals may have multiple missions beyond healthcare including medical education. They are important establishments because they prepare future healthcare professionals. Further, highly specialized services are concentrated in teaching hospitals, as they often perform medical research (American Hospital Association, 2009). Teaching hospitals have significant costs beyond patient care related to residents training (Babineau, et al., 2004). However, Rosko (2004) found cost efficiency improvements for teaching hospitals in 1990's data and more recently Kane, et al. (2005) shows minimal impacts of teaching hospitals on cost levels.

Rural and urban areas have different demographic characteristics. In rural areas, population is older and they have a lower income compared to urban areas. Additionally, they are more likely to be uninsured and to have chronic diseases (American Hospital Association, 2011). Hospitals located in rural areas usually are smaller, have a low volume of patients and struggle to allocate high fixed costs. Moreover, rural hospital perform less procedures than urban hospitals caused by a possible lack of resources, like equipment and specialty physicians (Hall and Owings, 2014). Approximately 60% of rural hospitals revenue come from public programs, mainly Medicare and Medicaid, and reimbursements from these programs do not cover total cost of care (American Hospital Association, 2011). For this reason, differences in cost efficiency between hospitals in rural and urban settings are expected.

Critical Access Hospitals (CAH) are created to avoid rural hospital closure by increasing the rate of reimbursement. A study investigated how ownership and size influenced cost and efficiency in public and not for profit hospitals in Washington State. From this study, Coyne, et al. (2009) find that small, not for profit hospitals have similar cost efficiency to largest hospitals because 70% of this subset are CAH. Despite helping hospitals to have a more steady financial condition, this program does not address all economic problems.

Stochastic frontier analysis (SFA) (Aigner et al., 1977) and data envelopment analysis (DEA) (Cooper et al., 2007) are the methods most frequently applied to assess the cost functions of hospital production. However, both of these methods have serious shortcomings in the context of hospital production. DEA assumes that all data are perfectly observed without random variation and the cost/output models are exhaustively specified. SFA requires the specification of the functional form for production. These assumptions are clearly untenable in the complex, multi-output realm of hospital production. In this work, we propose to use methods which blend the advantages of each method to more accurately estimate the true cost frontier. A standard axiom of the cost function is convexity in outputs (Chambers, 1988), which provides additional structure and improves functional estimates in finite samples. However, nonparametric methods for estimation are preferred because parametric misspecification can lead to bias and inconsistent estimates (Skinner, 1994). Nevertheless, to be able to estimate potential cost saving, we must develop a regression model of the hospitals production process.

3. METHODOLOGY

Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) are the most popular methods to assess performance in an organization. DEA is a nonparametric method that estimates a piece-wise frontier using linear programming. The frontier envelops the observed data points and is built upon monotonicity, concavity and constant (or variable) returns to scale axioms. However, all the deviations from the frontier are considered as inefficiency for this method. SFA is a probabilistic method that involves parametric regression techniques using predefined functional forms for the frontier and inefficiency distribution assumptions. The main advantage of SFA over DEA is the decomposition of the error term into inefficiency and noise, which allows the estimator to also account for random error of measurement. In contrast, SFA requires a functional form which are hard to justify a particular specification. In our research we will try to combine the benefits of SFA and DEA. Axiomatic properties such as monotonicity or convexity are motivated by economic theory (Varian, 1992). Thus, we impose these shape constraint and model noise and inefficiency when estimating the hospital cost function.

3.1 Model

The regression model we will estimate is defined in (1):

$$\mathbf{C_i}=f(\mathbf{Y_i})e^{\varepsilon_i}e^{\delta \mathbf{z_i}}, \qquad (1)$$

where $\mathbf{C_i}$ is a vector of observed costs, $\mathbf{Y_i}$ is a matrix of observed number of procedures and f(·) represents the best attainable cost level. Residual, $\boldsymbol{\varepsilon_i}$, are initially defined as symmetric random observation specific term, and i is the index of observations, in our application these will be hospitals. The matrix $\mathbf{z_i}$ denote the contextual variables and the parameter $\boldsymbol{\delta}$ estimate the marginal effects of the contextual variable on costs.

The firm specific estimation equation (2) is

$$\ln(\mathbf{C}_i) = \ln\left(f(\mathbf{Y_i})\right) + \varepsilon_i, \quad i=1,\ldots,n \quad (2)$$

The two axioms we would like to impose, monotonicity and convexity results in two sets of constraints. The convexity constraint can be imposed via the gradient of function f(·) with respect of outputs. Let $f_i=f(\mathbf{Y_i})$ for notation simplicity, we can define the convexity property by (3).

$$f(\mathbf{Y}_i) \geq f\left(\mathbf{Y}_j\right) + \nabla f(\mathbf{Y}_j)^T\left(\mathbf{Y}_i - \mathbf{Y}_j\right) \ \forall i,j. \quad (3)$$

Hence, given that convexity constraints hold , monotonicity can be imposed by adding $\nabla f(\mathbf{Y}_i) > \mathbf{0} \ \forall i$ to the model. However, a function described by the maximum of hyperplanes automatically meets the convexity criteria. The estimation procedure below takes advantage of this fact making the estimator more efficient than brute constrained optimization in large data sets.

3.2 Multivariate Nonparametric Bayesian Convex Regression

Hannah and Dunson (2013) propose Multivariate Bayesian Convex Regression (MBCR), a methodology based on Reversible Jump Markov Chain Monte Carlo (RJMCMC) techniques. The method takes a random collection of hyperplanes and approximates a general convex multivariate regression function. At each iteration, hyperplanes can be added, removed or changed to propose a new collection of hyperplanes. Furthermore, the hyperplane-specific regression coefficients are computed assuming a Gaussian Mixture likelihood and Normal-Inverse Gamma conjugate prior distributions on the regression coefficients and the hyperplane-specific variance parameters respectively. MBCR has clear advantages over DEA and SFA as it allows to nonparametrically estimation of the production function, while accounting for nonzero noise levels on the data. Although other methods, such as Convex Nonparametric Least Squares (Kuosmanen, 2008) and Constraint Weighted Bootstrapping (Du et al. 2013) share these strengths, MBCR has shown to be more computationally effective for datasets up to a few thousand observations (Preciado Arreola and Johnson, 2015).

Recent work extends MBCR to propose MBCR-I, a semi-nonparametric method which incorporates the SFA-customary assumptions of multiplicative residuals, a noise/inefficiency decomposition, and allows for the use on contextual variables (Preciado Arreola and Johnson, 2015).Further, MBCR-I models heteroscedastic inefficiency, imposes shape constraints, and has a one-stage framework. This set of features is unique with respect to other SFA estimators. We choose MBCR-I as our estimation method given its computational efficiency on datasets of the size our application requires, its nonparametric framework and its ability to incorporate contextual variables, which is critical to our investigation of cost drivers in hospitals. We proceed to describe both our regression model and the use of MBCR-I to estimate it.

The multivariate regression function to estimate the convex function $f(\boldsymbol{Y})$ is

$$\hat{f}(\mathbf{Y})=\max_{k\in\{1,\ldots,K\}} \alpha_k+\beta_k^T\mathbf{Y}. \qquad (4)$$

MBCR-I proposes adding, removing and relocating hyperplanes at each iteration t. At a given iteration, the data is divided into $K^{(t)}$ basis regions, each of which is dominated by a hyperplane. The coefficients of each hyperplane are computed using bound-constrained nonlinear least squares. We define the *kth* basis region as

$$C_k=\left\{i{:}k=\arg\min_{k\in\{1,\ldots,K\}} \alpha_k+\beta_k^T\mathbf{Y}_i\right\}. \quad (5)$$

Proposals of a hyperplane additions, removals or relocations are conditional on our prior assumption on K and a tunable parameter c. The probabilities to propose a hyperplane addition, removal or relocation are given by the expressions (6).

$$b_{K^{(t)}}=c\min\left\{1,\frac{p(K^{(t)}+1)}{p(K^{(t)})}\right\},\; d_{K^{(t)}}=c\min\left\{1,\frac{p(K^{(t)}-1)}{p(K^{(t)})}\right\},\; r_{K^{(t)}}=1-b_{K^{(t)}}-d_{K^{(t)}} \qquad (6)$$

If a hyperplane relocation is proposed, the basis regions undergo minimal refitting-induced changes. However, if a removal is chosen, the observations on the basis region of the hyperplane proposed to be removed will be reassigned to other basis regions after refitting the remaining existing hyperplanes. In the case of a hyperplane addition proposal we take each potential hyperplane to be substituted, split its basis region into two and fit separate hyperplanes on them.

At each iteration, we compute mean squared error denote $MSE(t)=\frac{1}{n}\sum_{i=1}^{n}(\widehat{\mathbf{C}}_{\mathbf{i}}-\mathbf{C}_{\mathbf{i}})^2$, where $\widehat{\mathbf{C}}_{\mathbf{i}}=\hat{\mathbf{f}}_{\mathbf{i}}e^{\mathbf{v}_{\mathbf{i}}}e^{\delta\mathbf{z}_{\mathbf{i}}}$, to evaluate quality of the estimator. The parameters of each hyperplane $(\alpha_k,\beta_k)_{k=1}^{K}$ are obtained by the mathematical program described in (7). The parameters are estimated by nonlinear least square with monotonicity assumption.

$$\min_{\alpha_k,\beta_k} \begin{array}{l} \sum_{i=1}^{n_k} ((\ln(C_i)) + u_i - \ln(\alpha_k + \beta_k^T \mathbf{Y}_i))^2 \\ \text{subject to } \beta_k > 0, \quad k=1,\dots,K \end{array} \qquad (7)$$

We simulate the remaining parameters of the model during an iteration of MBCR-I. To do this, we specify a Gaussian Mixture likelihood on the noise terms (8). The hyperplane-specific noise variance parameters $(\sigma_k^2)_{k=1}^K$ are modeled to follow Inverse Gamma distributions (9). The prior inefficiency distribution is $\Gamma\,(w_0)$ as shown in (11) and we assume $w_0 = -1/\ln(\tau^*)$ where τ^* is an estimate of inefficiency. Equation (10) describes posterior inefficiency distribution following an exponential distribution. Additionally, residuals are denoted by $\varepsilon_i = \ln(Y_i) - \ln(x_i'\beta)$.

$$v_i \sim N(\ln(Y_i) - \ln(\hat{f}_i) + u_i, \sigma_{[i]}^2) \qquad (8)$$

$$\sigma_k^2 \sim IG(a_k^*, b_k^*), \quad k=1,\dots,K, \text{ where}$$

$$a_k^* = \tilde{a} + \frac{n_k}{2} \quad , \quad b_k^* = \tilde{b} + \frac{1}{2}\left(\sum_{i=1}^{n_k} (\ln(Y_{i[k]}) + u_i - \ln(\alpha_k + \beta_k^T X_{i[k]}))^2\right) \qquad (9)$$

$$u_i|\ldots \propto \text{Exp}\,(-1/2\sigma_{u_i}^2 \cdot (\mu_{u_i} - u_i)), \quad u_i \geq 0, \; i=1,\dots,n \text{ where}$$

$$\mu_{u_i} = -(\varepsilon_i + \theta\sigma_{[i]}^2) \quad \sigma_{u_i}^2 = \sigma_{[i]}^2 \qquad (10)$$

$$\theta|\ldots \sim \Gamma(n+1, w_0 + \sum_{i=1}^{n} u_i) \qquad (11)$$

Parameter K has a Poisson prior assumption with expected value λ and is used to determine whether hyperplanes will be added, relocated or removed. After proposing parameter values for the given split, removal or relocation, MBCR-I evaluates them in a Metropolis-Hastings acceptance probability calculation to see if the proposed move is a valid draw of the joint posterior distribution of all parameters. MBCR-I usually reaches stationarity within 100 iterations. Nevertheless, we disregard its first 150 iterations to further insure all our values correspond to steady-state draws. Finally, MBCR-I considers a stopping criterion, which is met when the median MSE has not significantly changes and variability across iterations is constant for at least 200 iterations.

We use the smoothed version of MBCR-I proposed by Preciado Arreola and Johnson (2015) as it performs better in datasets larger than 300 observations, which matches the specifications of our dataset.

3.3. Bayesian Information Criterion

The Bayesian Information Criterion is a method for model selection. This method is helpful when the problem have a large number of predictors available and the optimal model is unknown. Based on the likelihood function, BIC selects a model that minimizes

$$\mathrm{BIC} = -2 \times \log \mathrm{L}\left(\hat{\theta}\right) + \mathrm{d} \times \log(\mathrm{n}), \qquad (12)$$

where θ is the parameters of the model, n is the number of observations and d is the number of free parameters. The likelihood function of θ is given by $\mathrm{L}(\theta) = \prod_{i=1}^{n} f(y_i \mid x_i, \theta)$, where x and y are observed data (Schwarz, 1978).

The BIC indirectly estimates a test error to account for bias due to overfitting by adjusting the training error for the model size. Also, the number of observations must be much larger than the number of predictors and it is not recommended in cases with very complex collections of models. For a linear model fit using a least square model with d predictors BIC is given by (13).

$$BIC = \frac{1}{n}\left(RSS + \log(n) \times d \times \hat{\sigma}^2\right), \qquad (13)$$

where RSS is the residual sum of squares and $\hat{\sigma}^2$ is the variance of residuals (James, G. et al., 2013).

An alternative to determine an optimal model is to perform a backward stepwise selection which can provide a best subset selection. This strategy begins with a model that contains all predictors and it removes iteratively one predictor at a time. At each iteration, a variable is deleted by evaluating the smallest residual of sum of squares value among a subset of predictors. Formally, the method is given by the algorithm in Table 1, (James, G. et al., 2013).

Table 1 Backward stepwise selection algorithm

1. Let M_p be the full model with all *p* predictors and $M = \{M_0, \ldots, M_p\}$.
2. For $k = p, p\text{-}1, \ldots, 1$.
a) Consider all *k* models that contain all but one of the predictors in M_k for a total of *k*-1 predictors.
b) Choose the best model, which is selected according to the smallest value of residual sum of squares, among these k models and call it M_{k-1}.
3. Select a single best model from among M using cross-validated prediction error BIC.

The result from a backward stepwise selection is not guarantee to find the best model, however, the result is the most likely one. Unlike the best subset selection, which proposes to fit a model using a least square criteria for each possible combination of predictors (2^p), the backward stepwise selection search considers $1+p(p+1)/2$ models. Therefore, we select backward stepwise because it is computationally less demanding.

3.4. Method of Moments

The method of moments is a standard technique in the SFA literature for estimating the parameters of the noise and inefficiency distribution using information from the residual of a conditional mean estimator (Aigner et al., 1979). The method requires additional distributional assumption. In our case, we assume inefficiency with a half normal distribution $u_i \sim N^+(0, \sigma_u^2)$ and noise with a normal distribution $v_i \sim N(0, \sigma_v^2)$ (Kuosmanen and Kortelainen, 2012). The mean of the inefficiency term is calculated as, $\mu = E(u_i)$.

We can estimate second and third central moments of the residual with equations (14) and (15).

$$\widehat{M_2} = \sum_{i=1}^{n} \varepsilon_i^2 / (n-1) \qquad (14)$$

$$\widehat{M_3} = \sum_{i=1}^{n} \varepsilon_i^3 / (n-1) \qquad (15)$$

The second moment is a sample variance of residuals and the third moment is a component of skewness measure. If our distribution assumptions on noise and inefficiency hold, we have second and third moment equal to equations (16) and (17) respectively.

$$M_2 = \left(\frac{\pi - 2}{\pi}\right) \sigma_u^2 + \sigma_v^2 \qquad (16)$$

$$M_3 = \left(\frac{\sqrt{2}}{\sqrt{\pi}}\right)\left(1 - \frac{4}{\pi}\right) \sigma_u^3 \qquad (17)$$

As we can observe, the third moment only depends on standard deviation inefficiency. For this reason, we can estimate standard deviation of inefficiency and consequently calculate the standard deviation of noise.

4. PROBLEM INPUT

Hospitals are complicated entities that incur costs to provide a variety of services which can broadly be divided into two categories: diagnosis or treatment nature. Thus, hospitals are an integrated set of subsystems aiming at delivery healthcare. Within the healthcare industry, hospitals are important entity both because of the critical role they play in providing services and the significant portion of the cost they incur. Hence, cost analysis of hospitals is necessary for the improvement of the healthcare system. We gather a large data set to estimate cost inefficiency and to assess impact of contextual variables in cost for an approximate 10 percent sample of all U.S. hospitals.

4.1. Databases

Our data set is a combination of multiple data sources. We used the Healthcare Cost Utilization Project (HCUP) National Inpatient Sample (NIS) and American Hospital Association Survey Database to build our data set. The HCUP collects extensive information about all patients for a sample of approximately 1,000 hospitals. This data has extensive output measures and contains several variables that are cost drivers, but does not have information about costs or the resources used by the hospital. The American Hospital Association (AHA) has data for all U.S. hospitals describing specifically the resources they use and the costs they incur along with information on potential non-resource cost drivers. Each dataset will be described in detail below.

4.1.1. Healthcare Cost Utilization Project

The HCUP is a source of hospital database, reports, tools and software. The NIS is one of the databases available and it describes clinical and non-clinical information about patient demographics, diagnoses, service provider, treatments, and predicted and realized outcomes (length of stay, charges, mortality). Every year of the database contains approximately 8 million records of hospital activities. Until 2011, these observations constitute every discharge regardless of payer from each of a 20% sample of U.S. community hospitals (approximately 1,000 hospitals per year), stratified for size and location. These include non-Federal, short-term, general, and other specialty hospitals, excluding hospitals of institutions. The National Inpatient Sample database ideal for measuring outputs because up to 15 diagnosis related group (DRG) and ICD-9-CM codes are recorded for each patient visit.

Following Pope and Johnson (2013), we use 4 outputs, minor diagnostic procedures, major diagnostic procedures, minor therapeutic procedures, and major therapeutic procedures, categorized by their International Classification of Diseases, Clinical Modification (ICD-9-CM) codes. The distinguishing characteristic between minor and major procedures of each type is the use of an operating room and nature of service. The database also records variables related to the context of hospital operations, such as ownership status, urban/rural setting, teaching status, and classification of the hospital as part of a larger provider system (e.g., independent, centralized, decentralized). The HCUP data is available for the years 2004-2011.

4.1.2. American Hospital Association

Since 1946, the American Hospital Association does an annual survey of American hospitals to collect a wide range of information. Recently the survey covers 6,500 hospital systems and includes up to 1,000 variables regarding organizational structure, facility and services lines, inpatient and outpatient utilization, expenses, physician arrangements, staffing, corporate and purchasing affiliations and geography indicators. The variable expenses will be used to describe input level for this work. According to the survey instrument, the expenses accounts for payroll, employee benefits, depreciation, interest and supply. Also, percentage of inpatient surgeries, number of emergency room visits, number of beds and ownership were extracted from the database to be part of the potential contextual variable scope.

The AHA Survey Database access is possible due to a collaborative work with Sam Walton Business School at University of Arkansas and Industrial and Systems Department at Texas A&M. The AHA Survey Databases are available from 2004 until 2011.

4.2. Variables

The AHA identification number (AHAID) is used to merge the two databased and create a single hospital dataset with 500 observations on average per year. The cost and output measures described above are augmented with the following contextual variables listed below:

a) Hospital Size: hospital classification as small, medium or large.

b) Ownership: classification of hospital control in private, not-for-profit and public.

c) Location: whether a hospital is rural or urban.

d) Region: classification of hospital according to its geographical location.

e) Teaching status: whether a hospital is a teaching hospital or not.

f) Percentage of inpatient surgeries over total of surgeries.

g) Critical Access Hospital participation status of a hospital.

These seven contextual variables are explored to determine the best model using backwards stepwise selection and BIC. The data used and its sources are presented in Table 2.

Table 2 Description of input, outputs and contextual variable.

Variable	Description	Source
$\mathbf{x}$	Cost	AHA
$\mathbf{y_1}$	Number of minor diagnostic procedures	HCUP
$\mathbf{y_2}$	Number of major diagnostic procedures	HCUP
$\mathbf{y_3}$	Number of minor therapeutic procedures	HCUP
$\mathbf{y_4}$	Number of major therapeutic procedures	HCUP
$\mathbf{z_1}$	Hospital Size	HCUP
$\mathbf{z_2}$	Region	HCUP
$\mathbf{z_3}$	Teaching status	HCUP
$\mathbf{z_4}$	Ownership	AHA

In our dataset, 21% of hospital are teaching institutions. Regarding size, hospitals are classified as small, medium or large according to number of beds. The definition take into consideration region, teaching status and urban-rural designation (see Appendix A for details). Thus, hospitals are 39% small, 28% medium and 34% large in our dataset. Further, 20% of the hospitals are located in Northeast, 25% in Midwest, 27% in West and 28% in South. Also, 20% are public hospitals, 69% are not for profit and 11% are private. For the purpose of our analysis, the contextual variables are reorganized in dummy variables which are described in table 3.

Table 3 Description of dummy variables

Dummy code	Contextual variable associated	Description
z11	z_1	Impact of large hospital compared to small hospitals
z12	z_1	Impact of medium hospitals compared to small hospitals
z21	z_2	Impact of hospitals located in West region compared to Northeast region
z22	z_2	Impact of hospitals located in South region compared to Northeast region
z23	z_2	Impact of hospitals located in Midwest compared to Northeast region
z3	z_3	Impact of Teaching hospital regarding non-teaching hospitals
z41	z_4	Impact of Private hospital in contrast with public
z42	z_4	Impact of Not for profit hospital in contrast with public

5. RESULTS

5.1. Model Selection

We preferred to estimate a common model for all years. The model was selected by analyzing the 2007 data reported in Table 4. To verify the robustness of the results we also analyzed the 2010 data and found similar results (see Appendix B for details). At each iteration, a subset of the contextual variables, with one fewer contextual variable, was selected based on the lowest residual sum of squares. This was repeated until the subset contained no more contextual variables. We then computed the BIC value for each model with different numbers of contextual variables. The BIC measures trade-off between goodness of fitting and adding one more variable in the model; therefore, the lowest value of BIC implies the best model.

Table 4 Model section results of each subset for 2007

Number of Contextual Variables	Best model from each subset	BIC (x10^{15})
7	Hospital Size, Region, Teaching Status, Ownership, Hospital Location, CAH status and Percentage of inpatient surgeries	6.36
6	Hospital Size, Region, Teaching Status, Ownership, Hospital Location and CAH status	6.06
5	Hospital Size, Region, Teaching Status, Ownership and Hospital Location	5.94
4	Hospital Size, Region, Teaching Status and Ownership	5.88
3	Hospital Size, Region, Teaching Status	5.91
2	Region and Teaching Status	5.93
1	Region	6.07
0	None	6.48

The outcome of BIC analysis shows that best mix of contextual variables contains four variables (Hospital Size, Region, Teaching Status and Ownership).

5.2. Cost Drivers

Many are the features that can impact costs level in a hospital. Variety and complexity of services, bargaining power in purchasing supplies and demand are some examples. Additionally, some hospitals play a special roles in the society, such as teaching hospitals, which are an important figure to prepare future health practitioners. Teaching hospitals, with inexperienced professionals, are potentially subject to overutilization of resources (Brownlee, et al., 2014). Subsidized hospitals face similar challenges meaning these hospitals receive cost-basis reimbursements and therefore, they are inclined towards using more resources as well (Nedelea and Fannin, 2013). For example, hospitals participants of the CAH program are gradually less cost efficient for each more year enrolled as a subsided hospital (Nedelea and Fannin, 2013).

We estimated the impact of Hospital Size, Region, Teaching Status and Ownership (our set of contextual variables) on cost while jointly estimating the cost function using ZMBCR (without an inefficiency term). Table 5 includes a row for each dummy variable that appears in the ZMBCR model. Similar results were found when estimating cost function using ZMBCR-I (see details in Appendix C).The base case cost function is estimated for a small hospital in the Northeast that is not a teaching hospital and is publically own. The values reported in the table are the coefficients on the dummy variables for a cost function estimated in logs. Therefore, the coefficient can be interpreted as percentages. For example the table entry of -0.26 for Region (West-Northeast) and 2004 can be interpreted as, if all other things are held equal, then the costs for a hospital in the west are 26 percent lower than the costs of an equivalent hospital in the Northeast in 2004. Tables entries of * indicate the coefficient was not significant at the 5% percent level. All values including credible intervals for each year is presented in the Appendix D.

Table 5 Impact of contextual variable for all years using ZMBCR

Contextual Variable	Delta Values							
	2004	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**
Hospital size (large - small)	*	0.13	1.46	*	0.18	*	*	0.12
Hospital size (medium - small)	*	0.12	0.75	*	0.09	*	*	0.09
Region (West - Northeast)	-0.26	-0.26	-0.25	-0.32	-0.21	-0.21	-0.12	-0.12
Region (South - Northeast)	-0.17	-0.26	-0.35	-0.31	-0.23	-0.28	-0.22	-0.22
Region (Midwest - Northeast)	-0.12	-0.21	-0.39	-0.22	-0.08	-0.10	-0.10	-0.02
Teaching status (0 - no / 1 - yes)	*	*	1.19	*	*	0.10	*	*
Ownership (Private - Public)	*	-0.20	0.33	-0.16	*	-0.19	-0.26	-0.23
Ownership (Not for profit - Public)	*	*	*	*	*	*	*	*

(*) not significant result

The variety of offered services is an important aspect to evaluate when assessing costs. Intuitively, increasing hospital size should improve productivity due to economies of scale until a most productive scale size. Then, any increase beyond that size could lead to reduced productivity due to managerial challenges related to span of control. Our finds are in 2005, 2006, 2008 and 2011 smaller hospitals are significantly more cost efficient than large hospitals. However, 2006 seems to have some anomalies because of simple fitting. We relaxed convexity assumption and we found that 2006 fits a linear function. For this reason veracity of delta values might be affected.

We observed that hospitals located in the Northeast are less cost efficient than other regions of the U.S. The coefficient is negative for all dummies variables in all years that indicate hospitals located in South, Midwest and West are less expensive than hospitals located in Northeast. The Northeast region present highest CPI (consumer price index) value which is an economic indicator associated with cost of living (Bureau of Labor Statistics, 2016). Therefore, we expect that price of goods are more expensive in this region of the country.

Teaching hospitals are important to train the future healthcare professionals' education. Although students work under supervision, they are not completely ready to perform accurate diagnosis and treatment. Hence overutilization is a likely problem which can influence cost level (Brownlee, 2014). Our findings indicate that teaching hospitals have statistically significantly higher costs in 2006 and 2009.

Our database classified hospitals in three major categories of ownership regarding profit orientation and government sponsorship. The categories are public, not-for-profit and private. We find that public hospitals are more cost inefficient than private in five of the eight years we analyze (2005, 2007, 2009, 2010, and 2011), with two of the years indicated cost differences are insignificantly (2004 and 2008) and in 2006 private hospitals are found to be less cost efficient then public hospitals. The cost differences between not-for-profit and public hospitals are insignificant. Nevertheless, we can affirm that these categories of hospitals have a similar behavior as they do not have profits as main motivation to operate.

5.3. Cost Inefficiency

If all hospitals are efficient, then difference in performance are just random variation and a cost function should be estimated as the conditional mean of the data, Figure 1(a). Cost inefficient firms exhibit higher costs to produce a given output level. As we add inefficient firms to the example in Figure 1(a), true cost frontier shifts downwards as observed in Figure 1(b).

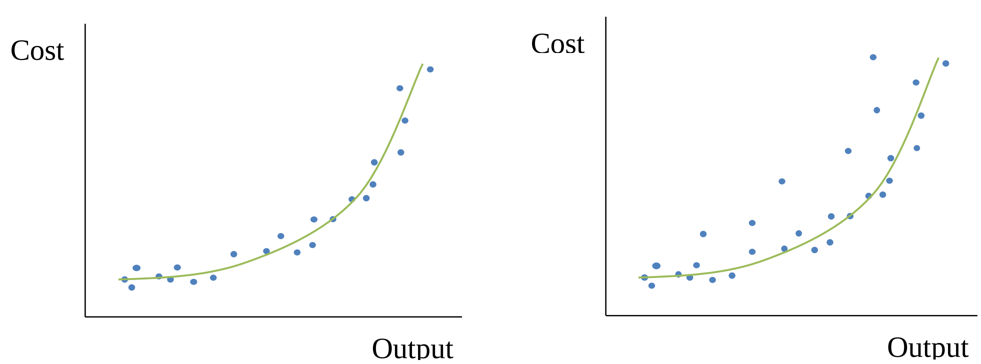

Figure 1 (a) Full efficient firms. (b) Not full efficient firms.

The method ZMCR-I incorporates the standard assumption from the SFA literature that the residual distribution should be a convolution of a symmetric error term and a skewed inefficiency term. The skewed inefficiency terms implies that the probability of observing an inefficient production unit is smaller than the probability of observed an efficient production unit. This assumption is intuitive in competitive markets where inefficient firms would be driven out of business under the efficient market hypothesis (Fama, 1965; Fama et al., 1993). However, the markets in which hospitals compete in unlikely to be efficient and therefore this classic assumption from SFA is less likely to hold. We find evidence for this as we are was unable to draw inefficiency in the Bayesian ZMCR-I in certain years (2006, 2008, 2009 and 2010). In an attempt to confirm our intuition that the problems related to inefficiency draws in ZMBCR-I is related to the skewness of the inefficiency term, we also estimated ZMBCR (without an inefficiency term) and then applied the standard method of moments to the residuals from ZMBCR. This method allows us to calculate the skewness of the residuals. In our model, we expect residuals to have a negative skew. Nonetheless, we found wrong skewness of residuals via ZMBCR followed by method of moments for 2005, 2006, 2008, 2009 and 2010. These results can be interpreted in at least two ways. First, perhaps the efficient market hypothesis is violated for this data set to the point where the probability of observing inefficient firms should be higher than the probability of observing efficient firms. Second, perhaps the systematic inefficient term for this set of hospitals is small relatively to the noise in the measurement of variables and in the model and therefore it is difficult to estimate the inefficiency distribution parameters.

Both interpretation are plausible and further research is needed to determine which effect is stronger.

Returning to the results of the ZMBCR-I model, table 6 reports the estimated average cost inefficiency for 2004, 2005, 2007 and 2011. We note that our 2005 inefficiency estimation is only possible due to the one-stage nature of ZMBCR-I. We reached this conclusion after attempting to obtain average cost inefficiency estimates using a two-stage framework, in which ZMBCR was used as a first stage and method of moments as a second stage. This two-stage approach resulted in wrongly-skewed residuals after the first stage. Table 6 also presents standard deviation of inefficiency.

The last column of table 6 reports the number of hyperplanes estimated by the ZMBCR-I procedure in each year. The estimation procedure fits approximately a linear cost function.

Table 6 Inefficiency attributes, mean square error of estimation and number of fitted hyperplanes

Year	Inefficiency (mean)	Inefficiency (standard deviation)	MSE	Number of fitted hyperplanes
2004	27%	0.46	0.23	1
2005	6%	0.02	0.09	1
2007	18%	0.24	0.14	1.008
2011	23%	0.30	0.11	1.005

On average, 89% of hospitals are at most 30% cost inefficient whereas 8% of hospitals have within 10% of the cost inefficiency, disregarding results from 2005. As each year of the database is a sample of all community hospitals, the graphs are not alike and we found discrepant outliers that boost average of the industry for most of the years. Figure 2 illustrates the distribution of cost efficiency in 2011. Typical cost efficiency estimates lie between 1 and 2, with 1 indicating efficient performance and 2 indicating 50% efficient. However, Figure 2 indicates there were four hospitals in 2011 outside of this range. These observations are likely to be data entry mistakes. In 2004 there are six observations of this type and in 2007 two observations of this type. The graphs showing the distribution of cost inefficiency for each year are reported in Appendix E.

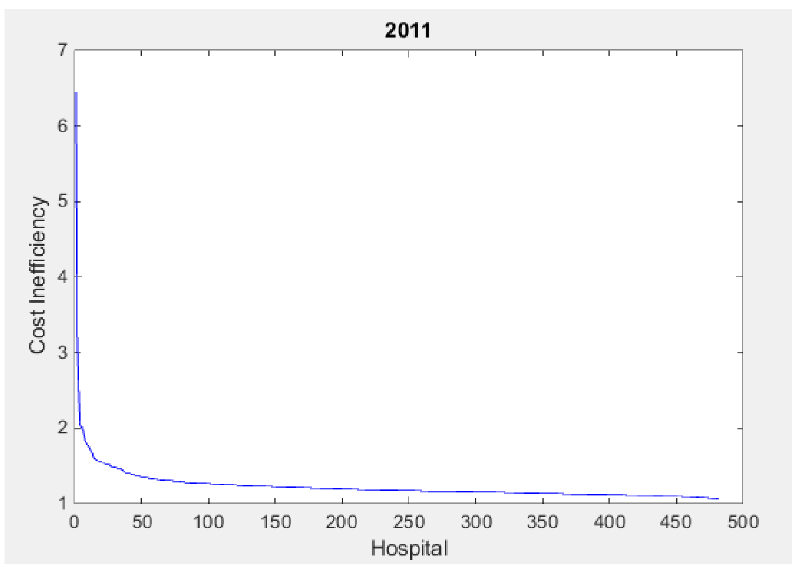

Figure 2 Cost inefficiency per hospital in 2011

If outliers are removed from the dataset (2004, 2007 and 2011), ZMBCR-I cannot draw the inefficiency parameter. Further, ZMBCR-I fit is slightly better when outliers are removed. However, number of hyperplanes remains approximately one, which indicates ZMBCR-I is fitting a linear function. We have a four dimensional output vector that makes visually our data somewhat challenging. For this reason, we plotted two-dimensional graphs with pairwise outputs. For most of the years, we observed the data clustered near the origin in a narrow cone. The narrowness of these cones are consistent with the use of a single hyperplane to fit this data. For illustration purposes, Figure 3 shows these graphs for 2011. These graphs for all year are in the Appendix F.

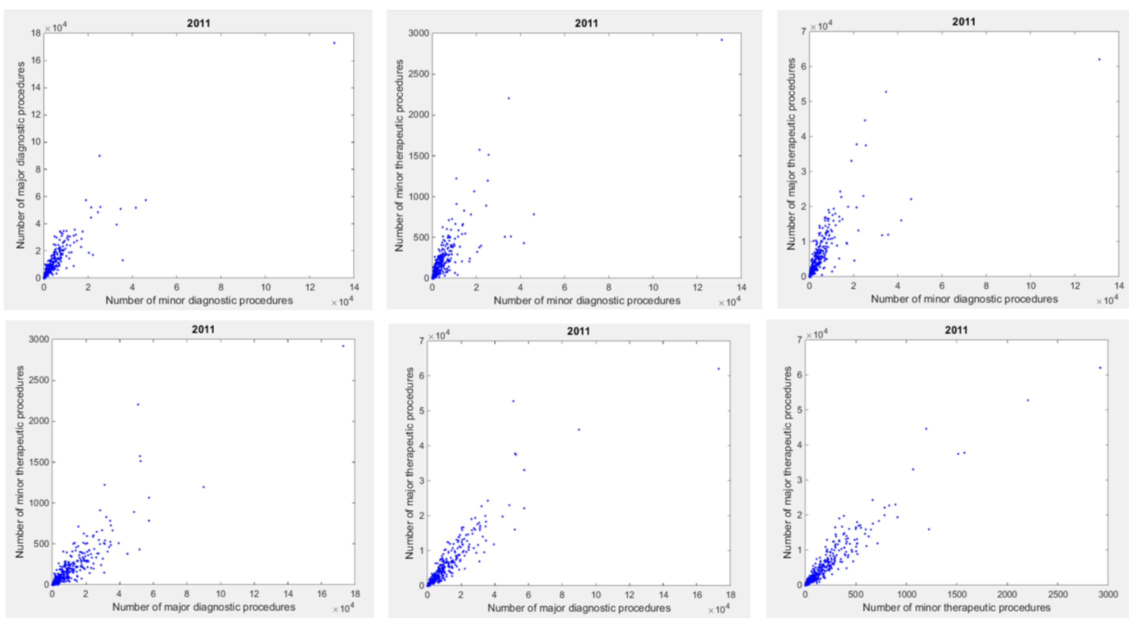

Figure 3 Pairwise outputs graphs

While cost functions are often assumed to be convex, our estimates indicated a linear fit is best. Thus, we also did some preliminary experiments to investigate alternative hypothesis. Specifically the Regular Ultra Passum Law proposed by Ranger

Frisch (1965), suggest that production and cost functions should have an increasing returns-to-scale region followed by an inflection point and a decreasing returns-to-scale region, see Figure 4. If a cost function satisfies the Regular Ultra Passum Law then beyond the inflection point the cost function is convex. We chose to split our data in half by selecting the hospitals with the largest costs to see if there was evidence that above a particularly cost level our cost data could be fit by a convex function more accurately. We found some evidence for this law. In Table 7, we report the number of hyperplanes used to fit only the largest half of hospitals in terms of cost. The average number of hyperplanes is slightly larger than almost all years (in 2005 the values are equal). In 2004 the number of hyperplanes is significantly larger, 2.1 compared to 1. While further research is needed to determine if this data would be well described by an estimator that imposed the Regular Ultra Passum Law, these results provide some support and motivation for future research in this direction.

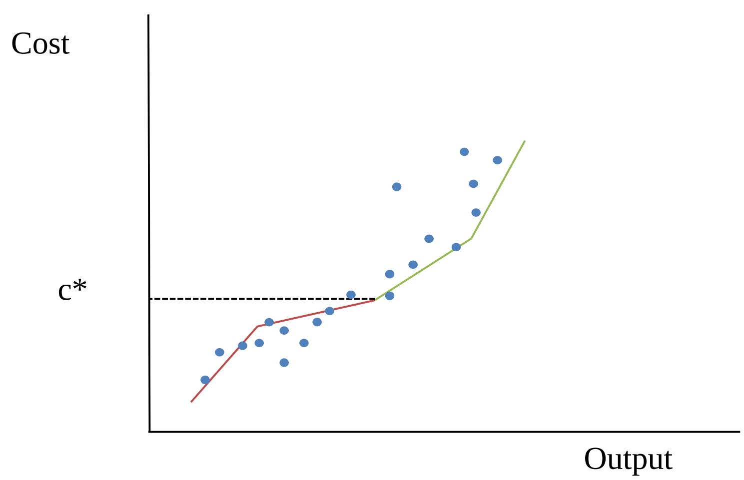

Figure 4 Illustration of S-shape cost function

Table 7 Number of hyperplanes per year for subset experiment

Year	2004	2005	2006	2007	2008	2009	2010	2011
Average number of fitted hyperplanes across iterations	2.10	1	1.04	1.35	1.02	1.01	1	1.02
Maximum number of fitted hyperplanes over all iterations	4	1	2	2	2	2	1	2

6. CONCLUSIONS

The healthcare industry is a large part of the U.S. economy and hospitals particularly make up 5% of GDP. Politicians have been working to restructuring the healthcare industry by making laws that will/are directly impacting hospitals' operations. Hospitals have a complex production process because of the wide array of services they provide and the critical timing in which they need to be provided. Thus, understanding the drivers of cost efficiency in hospitals is critical to help inform policy makers. In this work, we aimed to estimate cost benchmarks and cost efficiency for community hospitals. The efficiency analysis methods such as DEA and SFA that have been used to this point do not account for characteristics of hospitals' production systems. Therefore, we choose ZMBCR-I with the advantages it models noise and inefficiency and allows for the joint estimation of the effects of additional variables.

The main findings show that certain hospital profiles are less cost efficient than others, such as teaching hospitals, larger hospitals and hospitals located in the Northeast region. Regarding ownership, we find private hospitals are more cost efficient which is consistent with other research. Further, our findings indicate that our dataset has decreasing marginal product for high cost hospitals motivation further research to develop estimators that impose the regular Ultra Passum Law.

Our analysis is at the system or hospital level, thus our recommendations do not address specific operational practices within hospitals. Future research should look at integrating system level analysis with detailed operational analysis. While the scale economies of hospitals has received attention in the literature, the effects of scope has received less attention. Future research investigating the interaction between scale and scope decisions could provide considerable insights to the hospital industry.

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APPENDIX A

Hospital size classification

HOSPITAL CHARACTERISTICS	HOSPITAL SIZE		
	Small	**Medium**	**Large**
Northeast			
Rural	1-49	50-99	100+
Urban, non teaching	1-124	125-199	200+
Urban , teaching	1-249	250-424	425+
Midwest			
Rural	1-29	30-49	50+
Urban, non teaching	1-74	75-174	175+
Urban , teaching	1-249	250-374	375+
South			
Rural	1-39	40-74	75+
Urban, non teaching	1-99	100-199	200+
Urban , teaching	1-249	250-449	450+
West			
Rural	1-24	25-44	45+
Urban, non teaching	1-99	100-1	175+
Urban , teaching	1-199	200-324	325+

APPENDIX B

Full result model selection 2007

Number of Contextual Variables	Hospital Size	Location	Region	Teaching Status	Percentage of inpatient surgeries	CAH status	Ownership	RSS ($x10^{18}$)	BIC ($x10^{15}$)
	Model Subset								
7	x	x	x	x	x	x	x	2.91	6.36
6	x	x	x	x	x	x		2.99	-
	x		x	x	x	x	x	2.91	-
	x	x	x		x	x	x	3.00	-
	x	x	x	x		x	x	2.80	6.06
	x	x	x	x	x		x	2.92	-
	x	x		x	x	x	x	3.36	-
		x	x	x	x	x	x	2.98	-
5	x	x	x	x		x		2.86	-
	x	x	x	x			x	2.78	5.94
	x	x	x			x	x	2.87	-
	x	x		x		x	x	3.17	-
	x		x	x		x	x	2.78	-
		x	x	x		x	x	2.83	-
4	x	x	x	x				2.88	-
	x	x	x				x	2.86	-
	x	x		x			x	3.17	-
	x		x	x			x	2.78	5.88
		x	x	x			x	2.82	-
3	x		x	x				2.85	5.91
	x		x				x	2.86	-
	x			x			x	3.14	-
		x	x				x	2.93	-
2	x		x					2.95	-
	x			x				3.16	-
			x	x				2.97	5.93
1			x					3.03	6.07
				x				3.17	-
0								3.35	6.48

Full result model selection 2010

Number of Contextual Variables	Model Subset: Hospital Size	Location	Region	Teaching Status	Percentage of inpatient surgeries	CAH status	Ownership	RSS ($x10^{18}$)	BIC ($x10^{15}$)
7	x	x	x	x	x	x	x	2.60	6.03
6	x	x	x	x	x	x		2.69	-
	x		x	x	x	x	x	2.58	-
	x	x	x		x	x	x	2.60	-
	x	x	x	x		x	x	2.57	5.91
	x	x	x	x	x		x	2.60	-
	x	x		x	x	x	x	2.65	-
		x	x	x	x	x	x	2.65	-
5	x	x	x	x		x		2.63	-
	x	x	x	x			x	2.57	-
	x	x	x			x	x	2.56	-
	x	x		x		x	x	3.07	-
	x		x	x		x	x	2.54	5.75
		x	x	x		x	x	2.55	-
4	x		x	x		x		2.61	-
	x		x	x			x	2.57	-
	x		x			x	x	2.54	-
	x			x		x	x	3.05	-
			x	x		x	x	2.53	5.62
3			x	x		x		2.61	-
			x	x			x	2.58	-
			x			x	x	2.53	5.55
				x		x	x	3.04	-
2			x			x		2.65	-
			x				x	2.54	5.51
						x	x	3.44	-
1			x					2.64	5.60
							x	3.04	-
0								3.16	

APPENDIX C

Delta Values and Credible Interval using ZMBCR-I

Contextual Variables	**2004**			**2005**			**2007**			**2011**		
	Delta	Credible interval		Delta	Credible interval		Delta	Credible interval		Delta	Credible interval	
Hospital size (large - small)	0.02	-0.06	0.09	0.13	0.05	0.22	0.11	0.03	0.19	0.10	0.01	0.20
Hospital size (medium - small)	0.07	-0.01	0.15	0.12	0.03	0.20	0.06	-0.02	0.14	0.09	0.00	0.17
Region (West - Northeast)	-0.28	-0.38	-0.19	-0.25	-0.34	-0.16	-0.31	-0.39	-0.23	-0.12	-0.22	-0.03
Region (South - Northeast)	-0.20	-0.28	-0.11	-0.25	-0.36	-0.16	-0.31	-0.39	-0.23	-0.22	-0.30	-0.14
Region (Midwest - Northeast)	-0.12	-0.22	-0.04	-0.19	-0.31	-0.10	-0.20	-0.28	-0.11	0.00	-0.08	0.09
Teaching status (0 - no / 1 - yes)	-0.04	-0.13	0.05	0.00	0.00	0.00	0.04	-0.02	0.11	0.03	-0.05	0.11
Ownership (Private - Public)	-0.02	-0.09	0.07	-0.20	-0.32	-0.08	-0.16	-0.25	-0.05	-0.25	-0.38	-0.14
Ownership (Not for profit - Public)	-0.10	-0.23	0.01	-0.03	-0.12	0.05	-0.02	-0.09	0.05	-0.07	-0.15	0.00

APPENDIX D

Delta values and Credible Intervals using ZMBCR

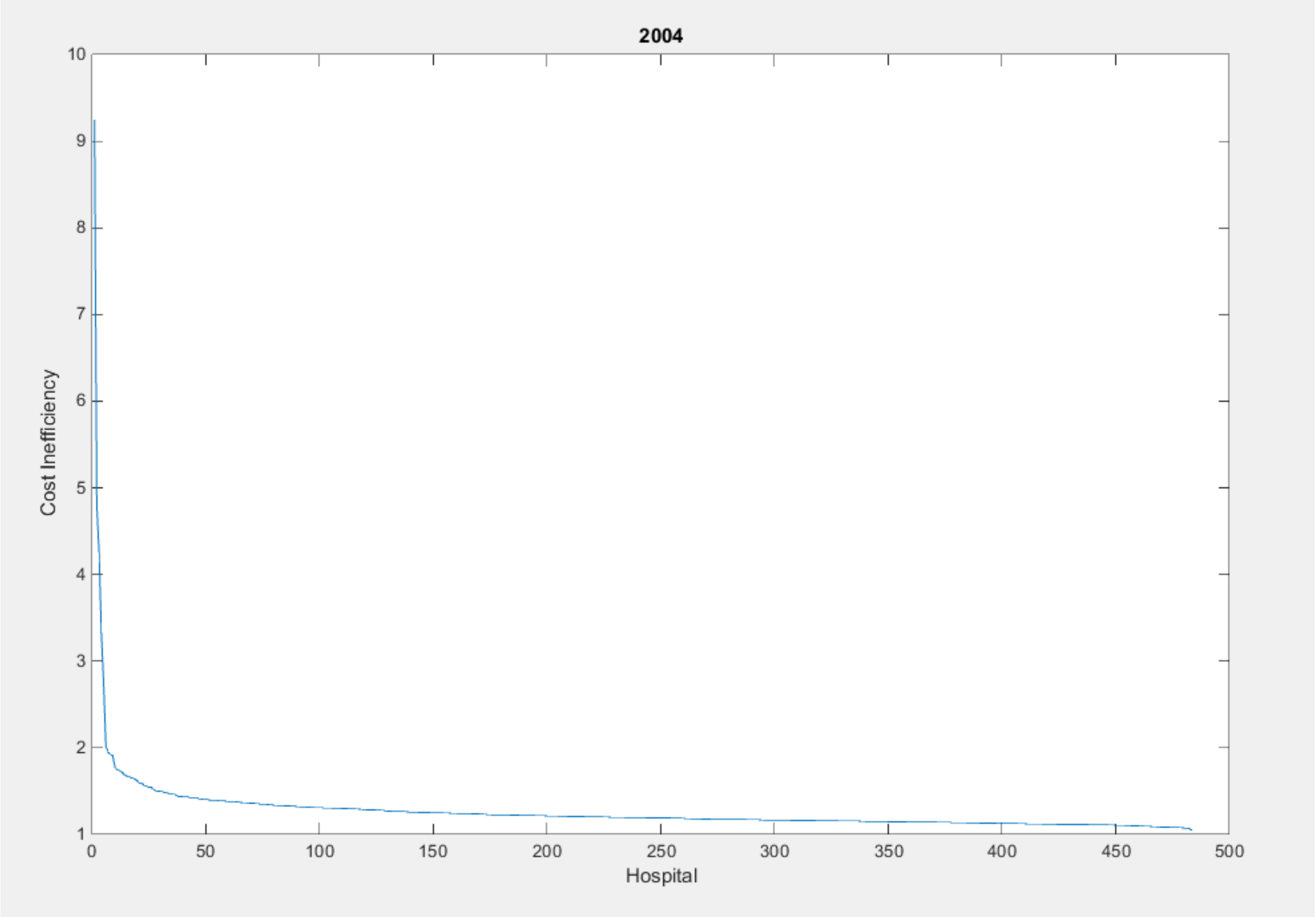
Contextual Variables	2004			2005			2006			2007		
	Delta	Credible interval		Delta	Credible interval		Delta	Credible interval		Delta	Credible interval	
Hospital size (large - small)	0.01	-0.09	0.10	0.13	0.05	0.20	1.46	1.31	1.60	0.09	0.00	0.17
Hospital size (medium - small)	0.06	-0.04	0.14	0.12	0.04	0.19	0.75	0.57	0.92	0.05	-0.03	0.14
Region (West - Northeast)	-0.26	-0.36	-0.17	-0.26	-0.34	-0.18	-0.25	-0.44	-0.08	-0.32	-0.40	-0.24
Region (South - Northeast)	-0.17	-0.26	-0.08	-0.26	-0.35	-0.17	-0.35	-0.53	-0.17	-0.31	-0.39	-0.23
Region (Midwest - Northeast)	-0.12	-0.22	-0.03	-0.21	-0.31	-0.11	-0.39	-0.55	-0.23	-0.22	-0.30	-0.13
Teaching status (0 - no / 1 - yes)	-0.02	-0.11	0.07	0.00	0.00	0.00	1.19	1.03	1.34	0.06	-0.02	0.14
Ownership (Private - Public)	-0.03	-0.11	0.05	-0.20	-0.31	-0.09	0.33	0.19	0.46	-0.16	-0.26	-0.06
Ownership (Not for profit - Public)	-0.10	-0.23	0.02	-0.03	-0.11	0.03	0.09	-0.14	0.32	-0.01	-0.09	0.05

Delta values and Credible Intervals using ZMBCR (cont.)

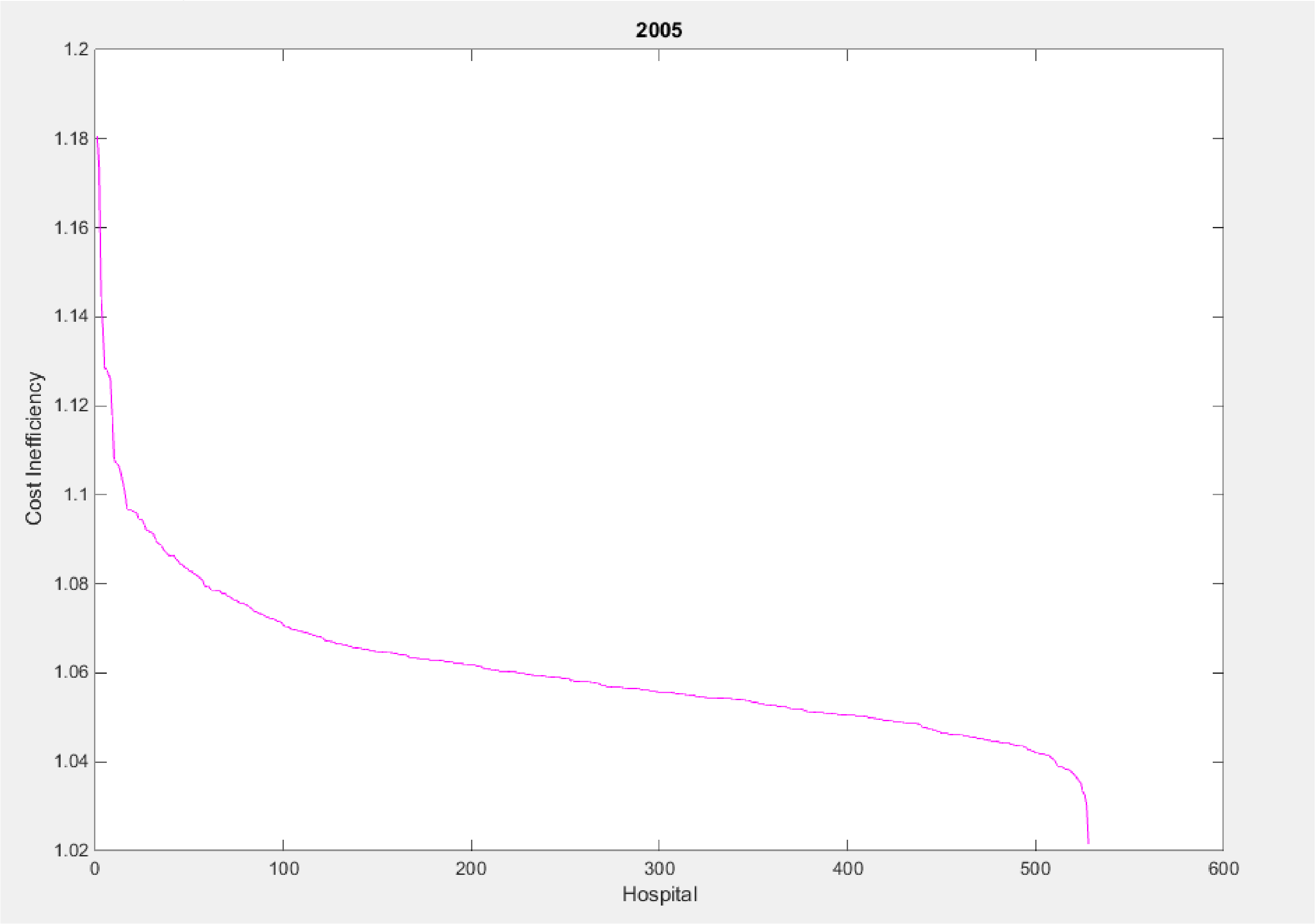
Contextual Variables	2008			2009			2010			2011		
	Delta	Credible interval		Delta	Credible interval		Delta	Credible interval		Delta	Credible interval	
Hospital size (large - small)	0.18	0.09	0.26	0.06	-0.02	0.15	0.02	-0.06	0.11	0.12	0.02	0.21
Hospital size (medium - small)	0.09	0.01	0.18	0.06	-0.03	0.15	0.04	-0.04	0.13	0.09	0.00	0.18
Region (West - Northeast)	-0.21	-0.29	-0.13	-0.21	-0.30	-0.12	-0.12	-0.21	-0.04	-0.12	-0.21	-0.04
Region (South - Northeast)	-0.23	-0.31	-0.15	-0.28	-0.37	-0.19	-0.22	-0.30	-0.15	-0.22	-0.30	-0.14
Region (Midwest - Northeast)	-0.08	-0.16	0.01	-0.10	-0.18	-0.01	-0.10	-0.19	-0.02	-0.02	-0.12	0.08
Teaching status (0 - no / 1 - yes)	0.07	-0.01	0.15	0.10	0.02	0.17	-0.01	-0.09	0.07	0.06	-0.03	0.14
Ownership (Private - Public)	-0.09	-0.21	0.02	-0.19	-0.31	-0.07	-0.26	-0.38	-0.15	-0.23	-0.35	-0.11
Ownership (Not for profit - Public)	0.02	-0.06	0.10	-0.01	-0.10	0.06	-0.04	-0.11	0.04	-0.07	-0.15	0.01

APPENDIX E

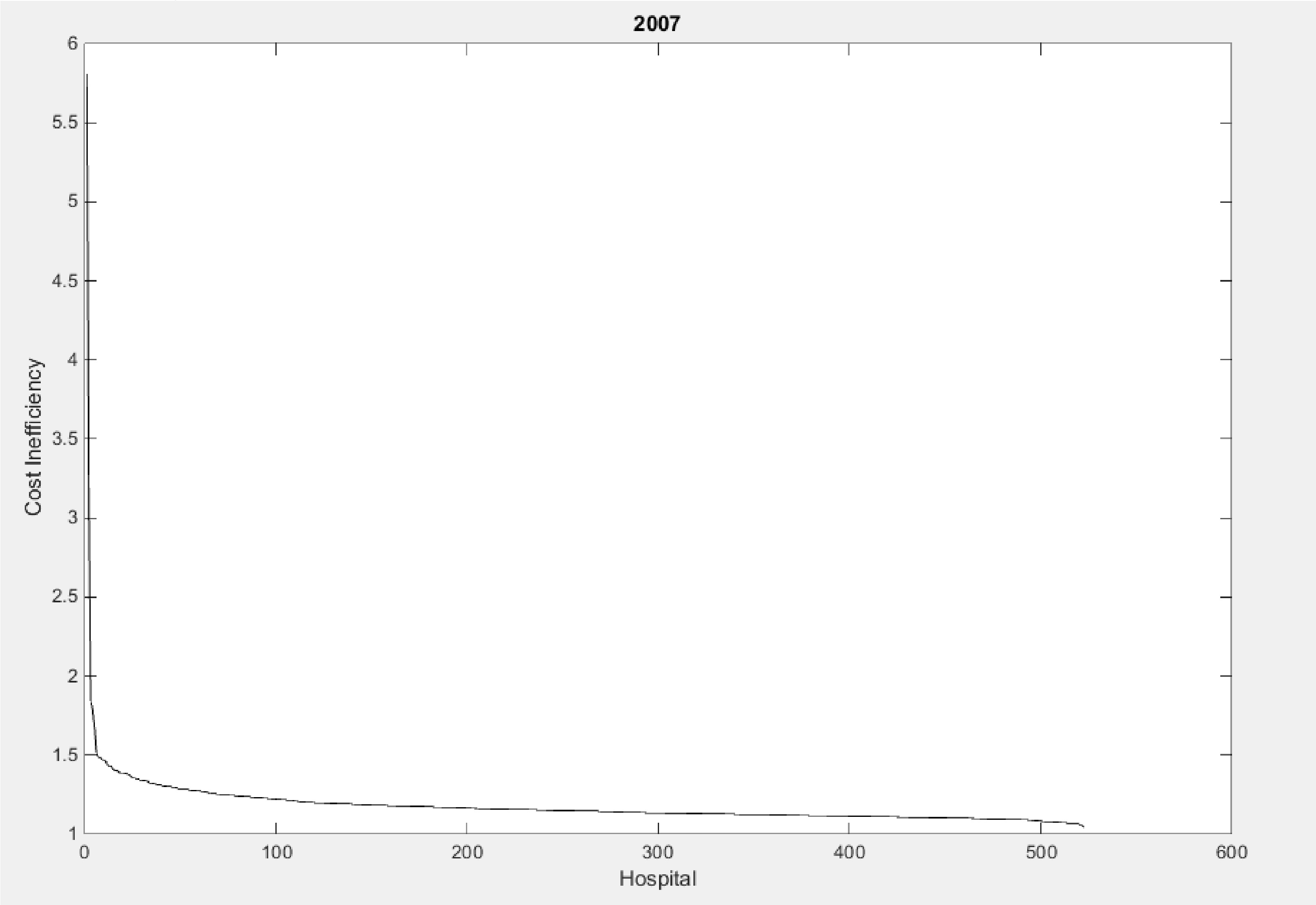
Cost Inefficiency per Hospital in 2004



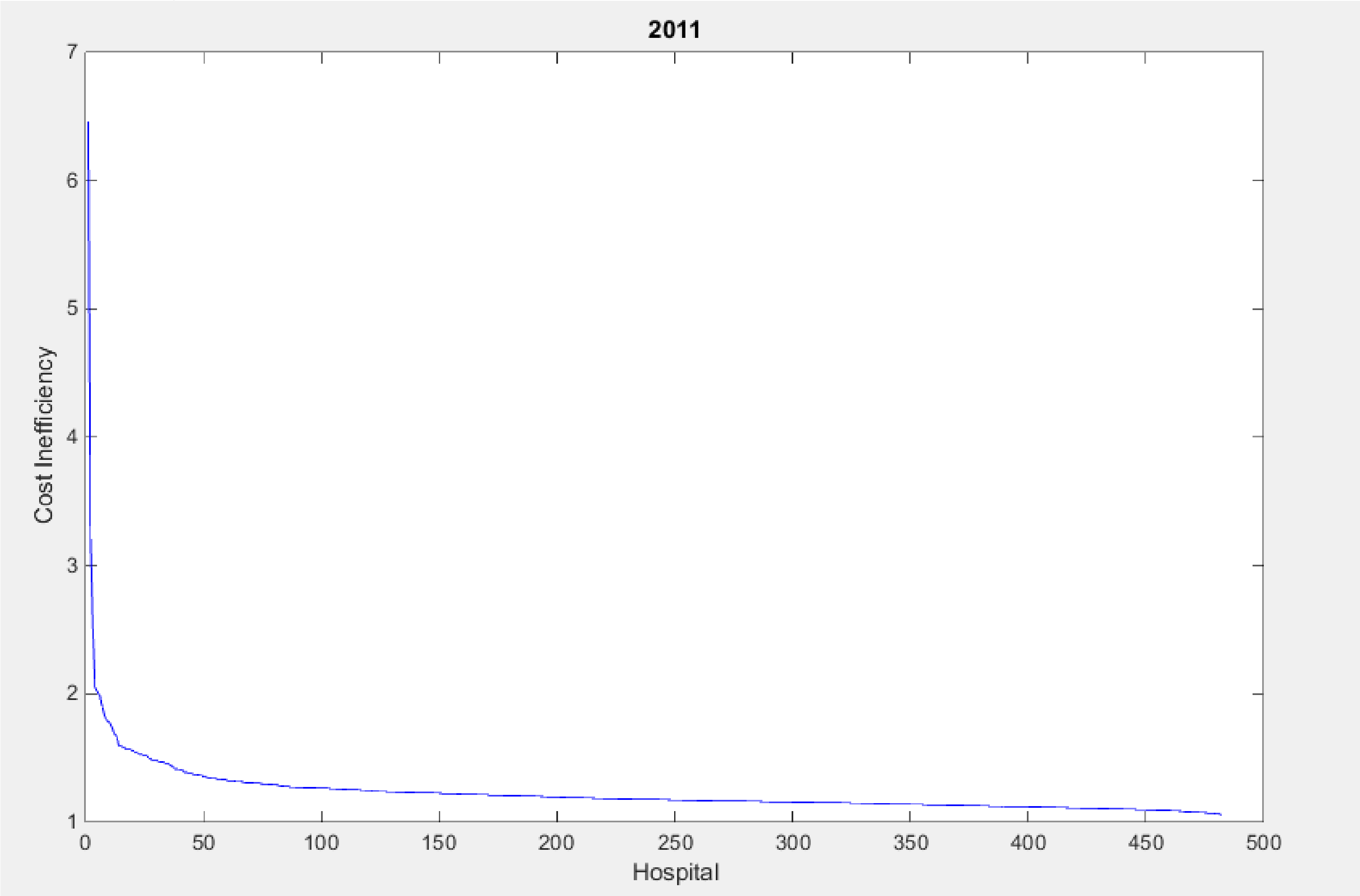
Cost Inefficiency per Hospital in 2005



Cost Inefficiency per Hospital in 2007

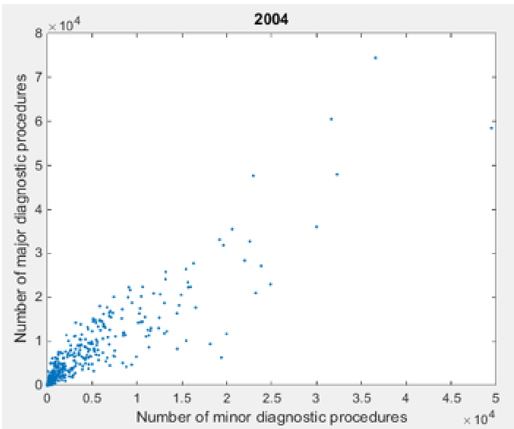


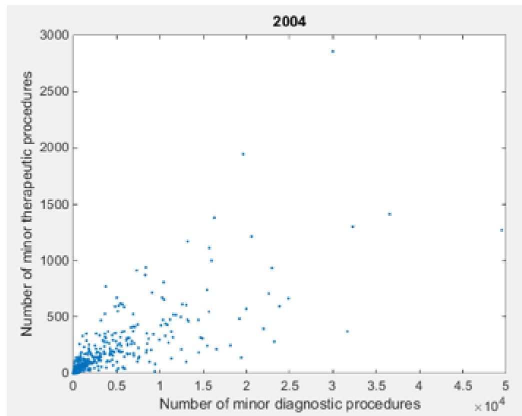
Cost Inefficiency per Hospital in 2011

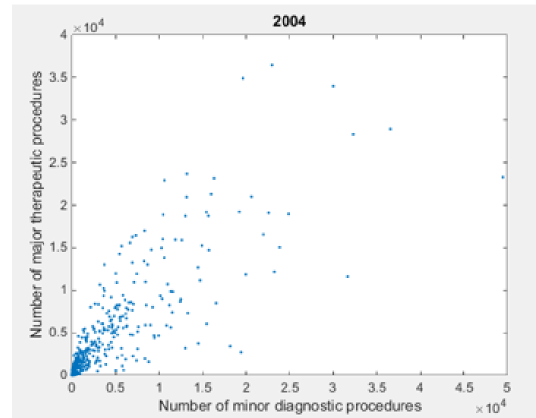


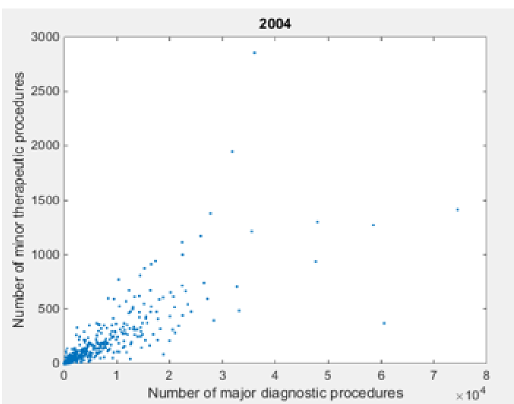
APPENDIX F

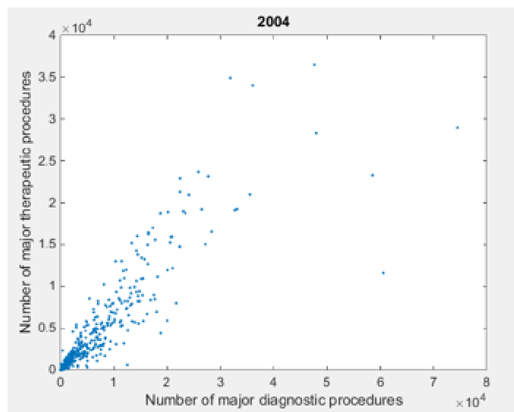
Pairwise output graphs for 2004

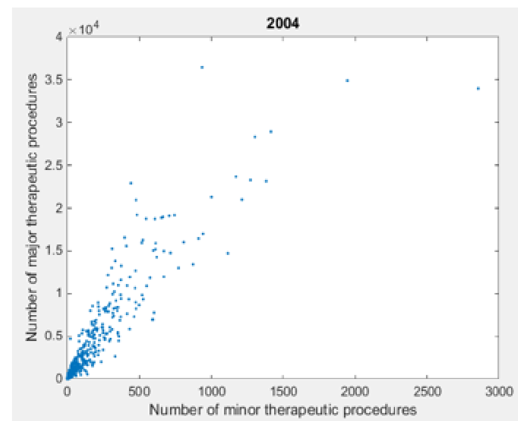




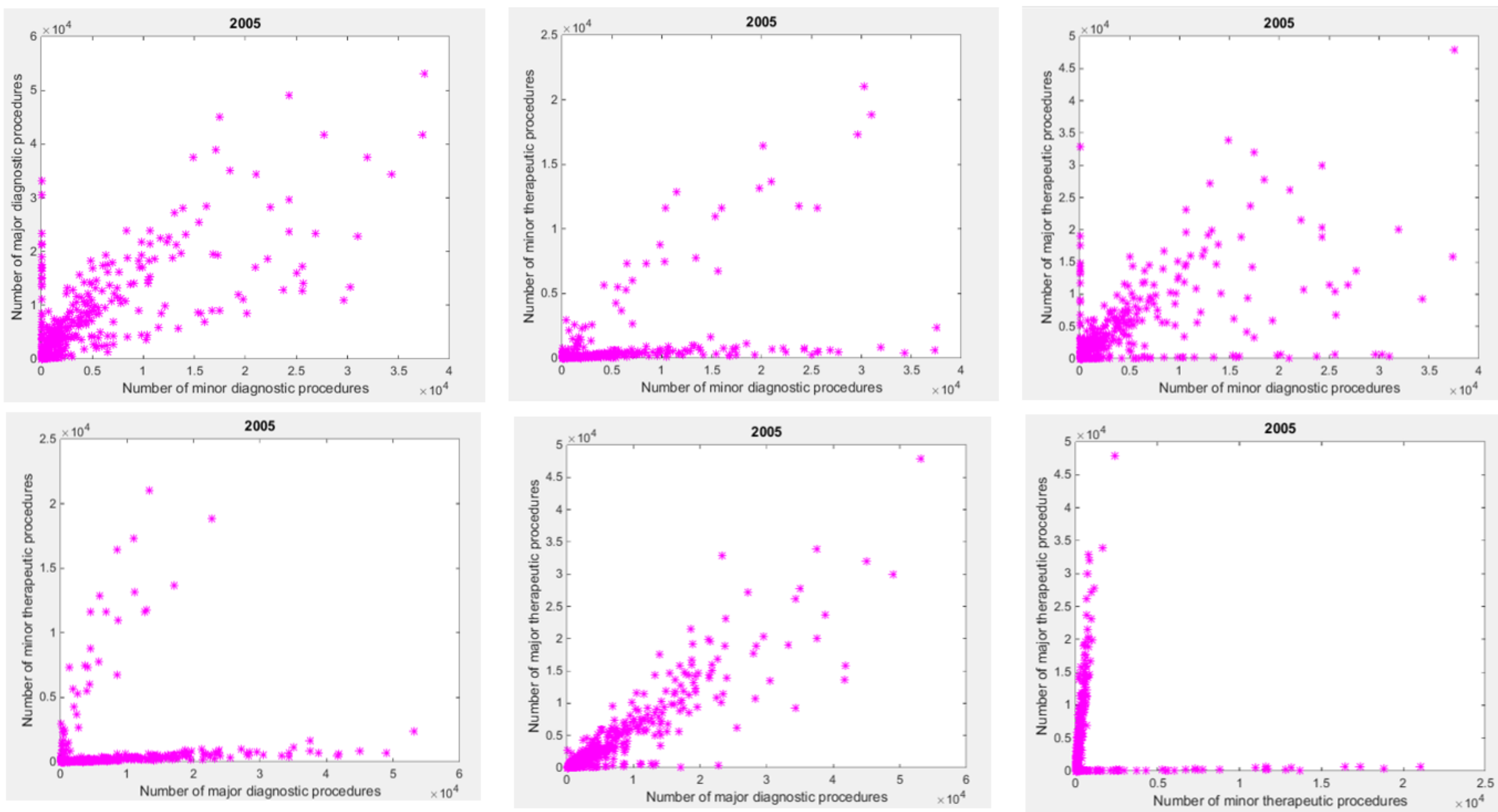




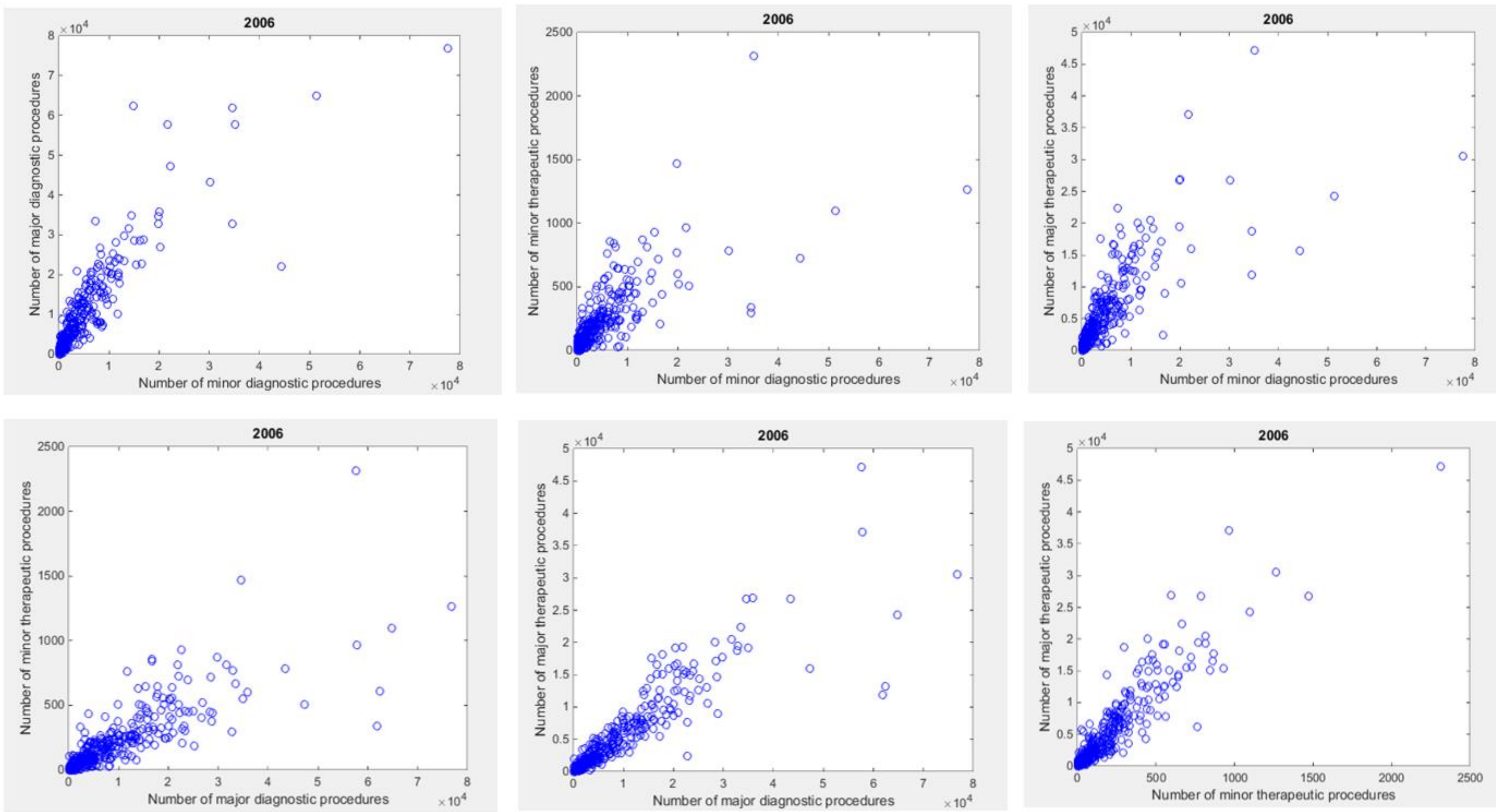




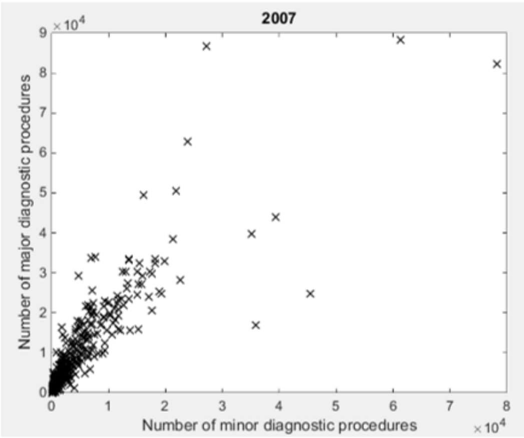
Pairwise output graphs for 2005

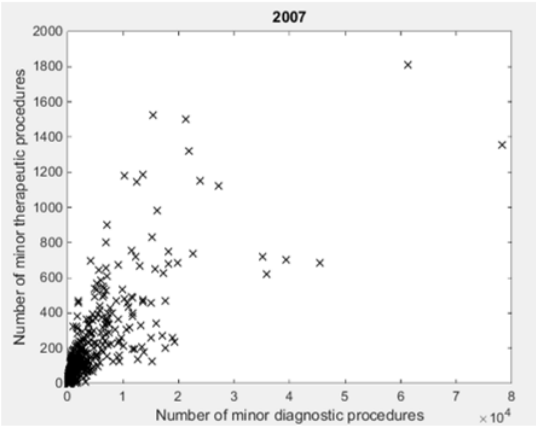


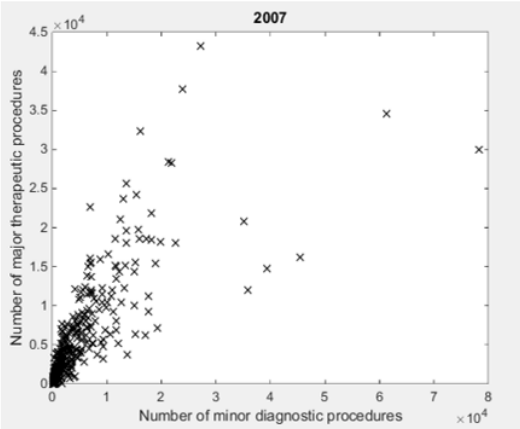
Pairwise output graphs for 2006

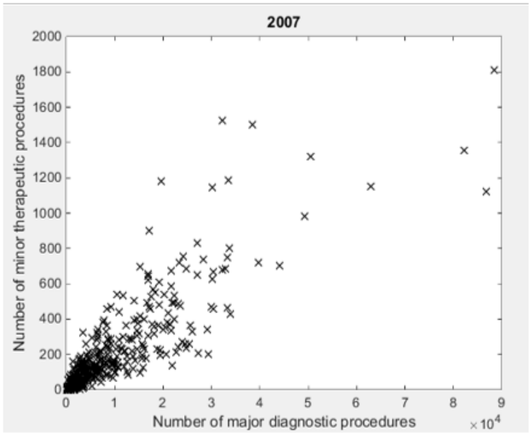


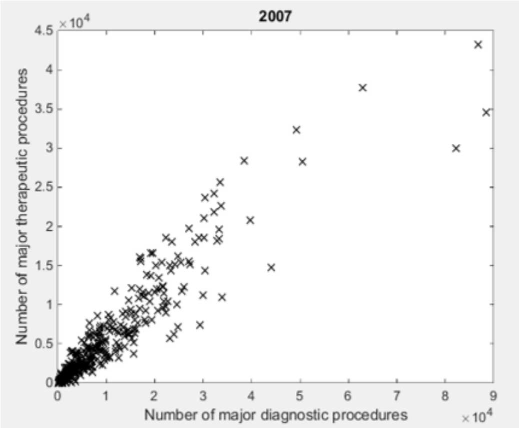
Pairwise output graphs for 2007

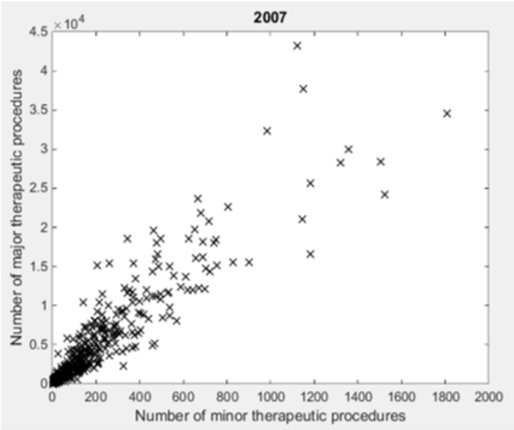




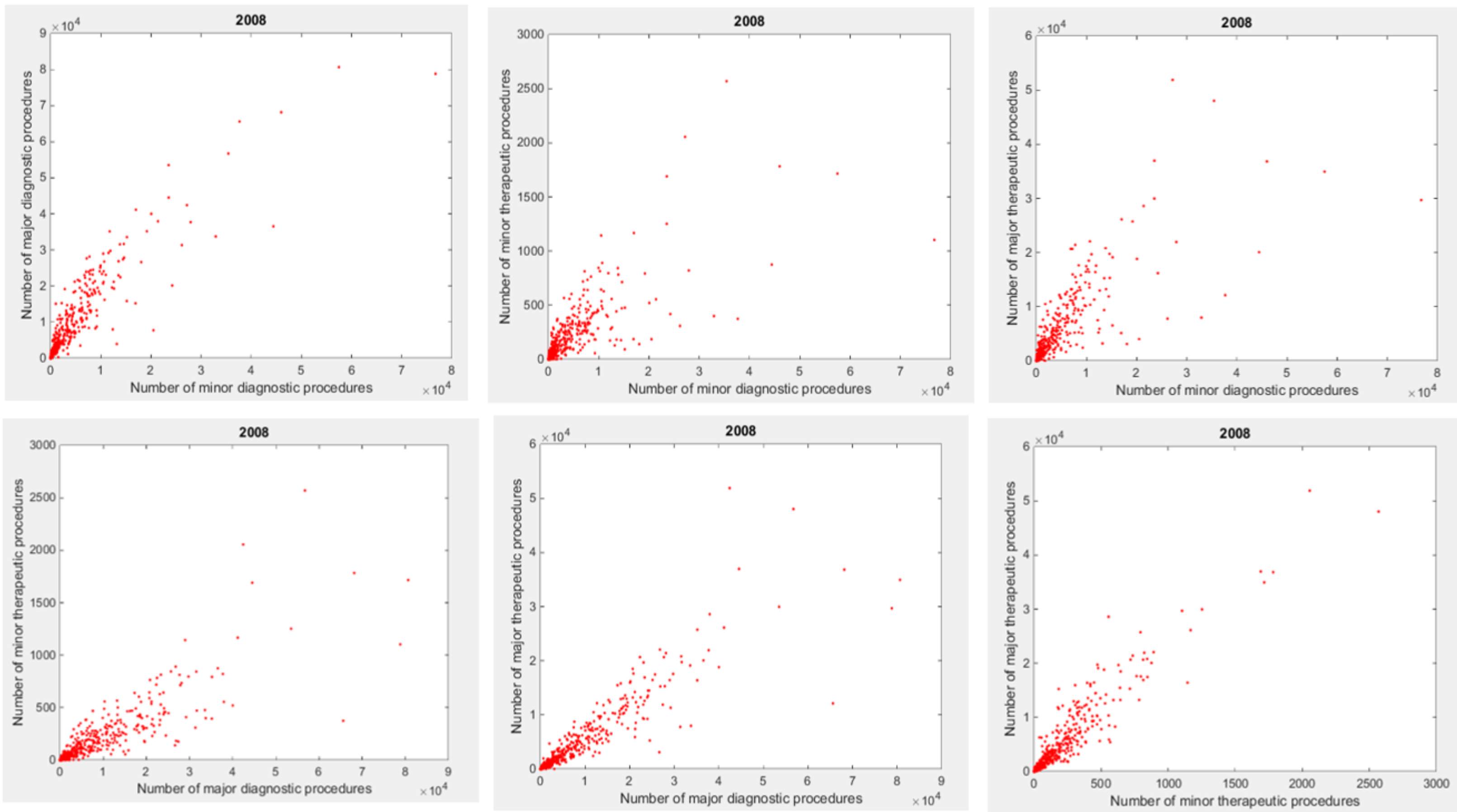




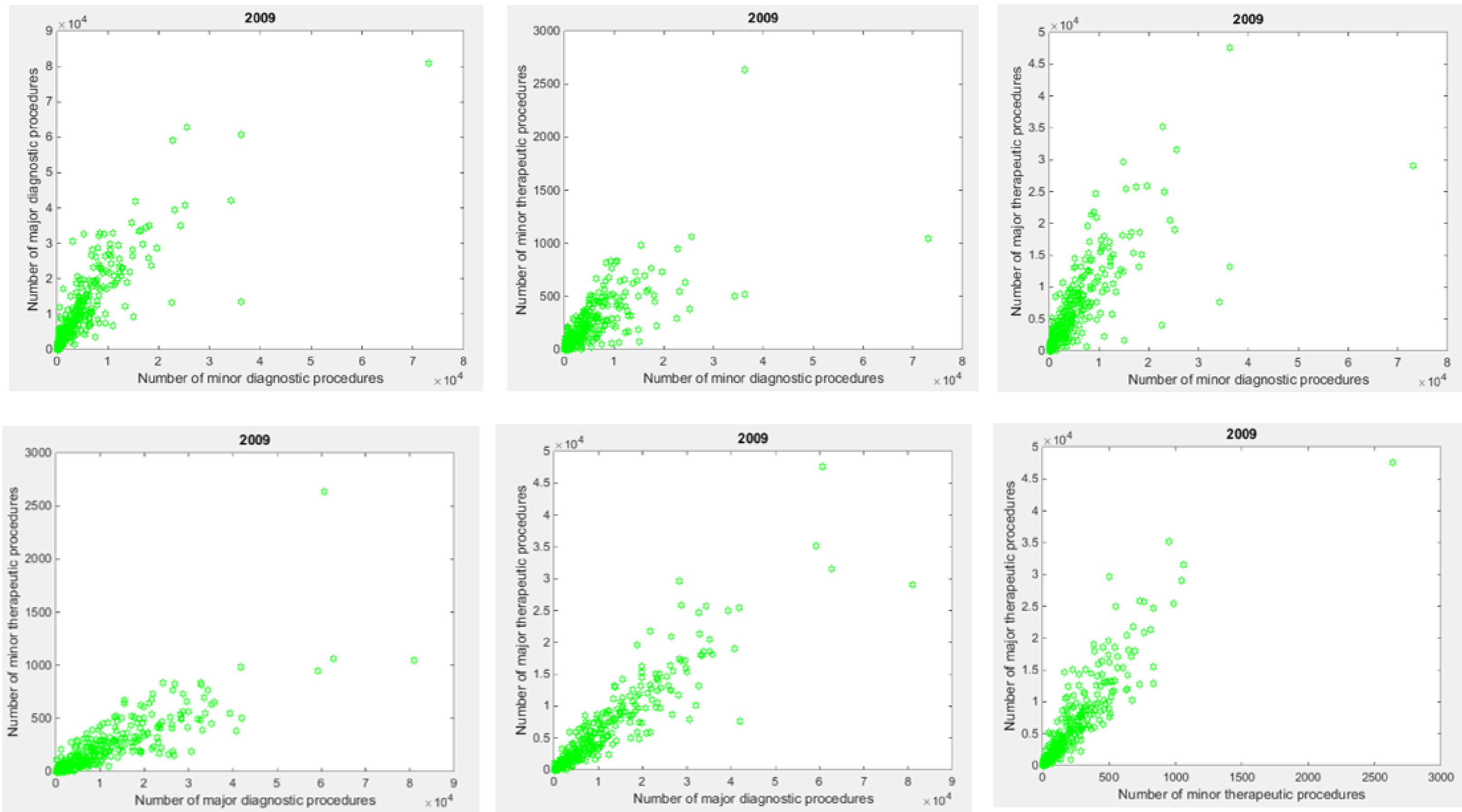




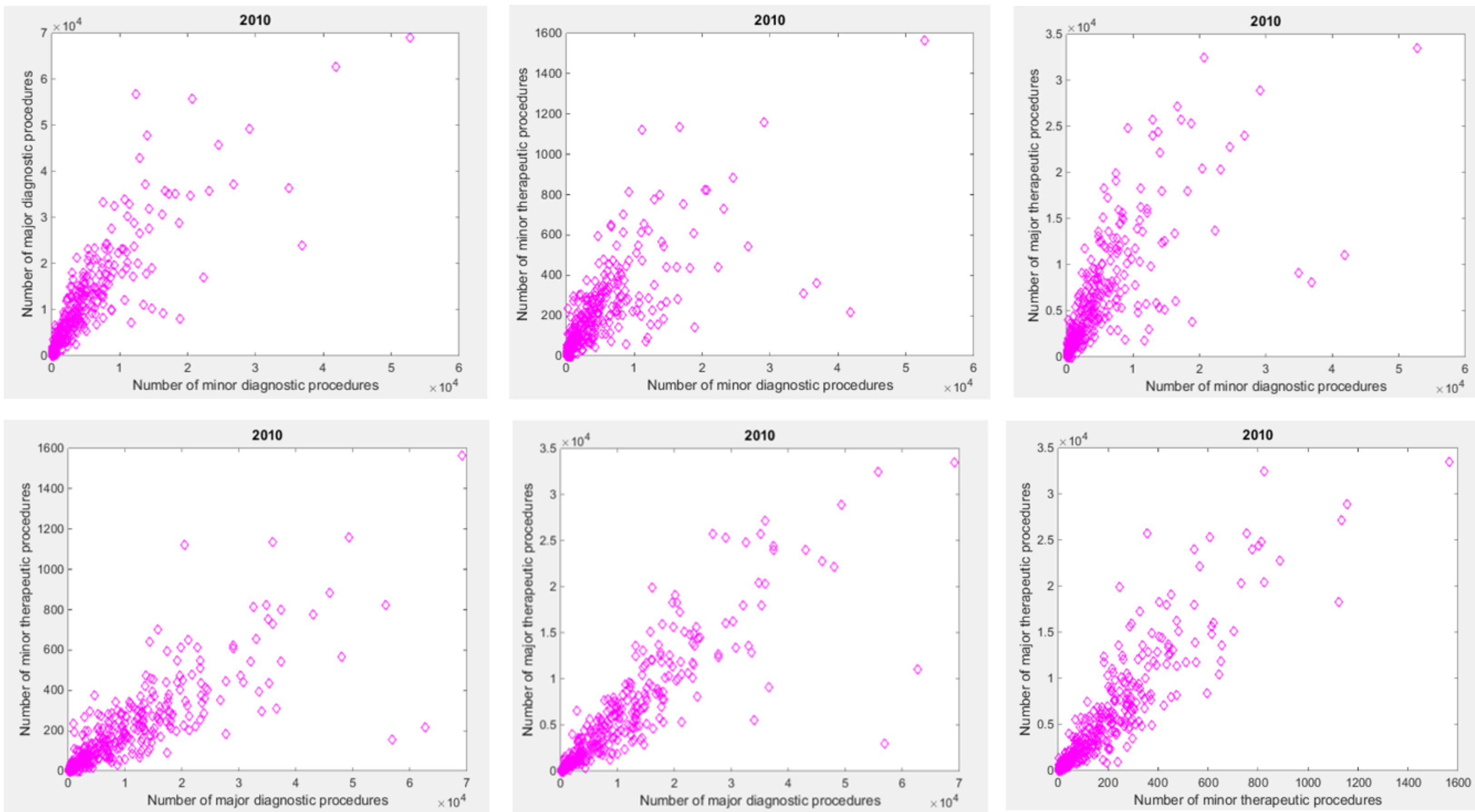
Pairwise output graphs for 2008



Pairwise output graphs for 2009



Pairwise output graphs for 2010



Pairwise output graphs for 2011