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SEMIPARAMETRIC STOCHASTIC FRONTIER ANALYSIS OF SPECIALIST SURGEON CLINICS

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ABSTRACT. A purposive sample of South African specialist surgeons was used to nonparametrically estimate production relations for single ouptut and multiple output production processes. The analysis was further extended to incorporate parametric assumptions associated with stochastic frontier analysis to provide estimates of technical efficiency within surgical practices. The results point to high levels of inefficiency, as well as consistency between single output and multiple output models.

1. INTRODUCTION

The supply-side of the South African health sector has not received much attention in the literature, and has tended to focus on the efficiency of the public sector in various provinces throughout the country. Kirigia, Lambo & Sambo (2000), as well as Kirigia, Sambo & Scheel (2001), have examined public hospitals and public clinics, respectively, in Kwa-zulu Natal. Zere, McIntyre & Addison (2001), on the other hand, focused on the public hospitals in the Eastern Cape, the Western Cape and the Northern Cape, while Kibambe & Koch (2007) have examined public hospitals in Gauteng. The private sector, which is the purview of this research, has, to the best of our knowledge, only been considered by Slabbert (2010), who has examined cost efficiency for specialists, and Koch & Slabbert (2010), who have examined cost and revenue structures for the same set of specialists.[1] The analysis reported here extends the previous papers by examining productive efficiency within the private sector, and by providing an application of semiparametric estimation.

The results of our research are also relevant to recent developments in national health policy. Specifically, the South African Department of Health has, once again, thrown its support behind a national health insurance plan. Although the details of such a plan have not been formally announced, one implication of national health insurance is that the private sector will be expected to provide care to a much larger number of patients than it does currently. However, it is not clear whether or not the private sector can accommodate more patients. An analysis of efficiency in the private sector, as is conducted here, can provide information on the ability of the private sector's potential (and unused) capacity.

Therefore, we examine productive efficiency in a subset of South Africa's health care sector, private specialist surgeons, using data collected through the support of a number of health professional bodies. We nonparametrically estimate conditional production relations, from which we extract efficiency. As there are a number of different measures of output, there are a number of comparable measures of

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[1]The examination of physicians, and, possibly, other healthcare delivery subsectors, is, as described by Thurston & Libby (2002) complicated by the pursuit of goals beyond profit maximization.

efficiency. Given small sample sizes, we further explore whether or not pooling the data could yield similar measures of efficiency, while also providing additional leverage to increase the precision of the estimates.

We find that efficiency in our sample of specialist surgeons is not exceptionally high, averaging about 65% for the measures of output available in the data. We further find that the responding surgeons are not generally either efficient or inefficient. In other words, some surgeons are better able to produce certain types of output than others. We also find that, in this sample, pooling yields comparable estimates of efficiency, and, therefore, precision can be improved through the estimation of a multiproduct production relation. However, the results must be treated carefully, since producer efficiency could be correlated with the probability of survey response, and we only have access to respondent data. Therefore, future research needs to focus on the collection of more and better data, from which more precise estimates of production and productive efficiency can be gleaned.

The paper continues in Section 2 with a review of some of the literature related to efficiency analysis in the health care sector. The semiparametric stochastic frontier analysis model is outlined in Section 3. Section 4 contains a description of the survey and resulting data used in the analysis. The empirical results and some sensitivity analyses are discussed in Section 5, while Section 6 contains a concluding discussion of the results and directions for future research.

2. Background

Healthcare delivery analysis has a rather lengthy history in the economics and the health care management science literature. Detailed reviews conducted by Hollingsworth (2003), Hollingsworth, Dawson & Maniadakis (1999) and Worthington (2004), for example, highlight the large amount of research available on the topic. Notably, a fair portion of the published research focuses upon hospitals located in developed countries.[2] The efficiency analyses reported in these reviews

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[2]Another interesting, but unrelated strand of the management care literature concerns itself with efficiency in operation room scheduling. See, for example, Overdyk, Harvey, Fishman & Shippey (1998), Dexter & Traub (2002) and Dexter, Epstein, Traub & Xiao (2004).

are primarily based on Data Envelopment Analysis (DEA), which is nonparametric, and Stochastic Frontier Anlaysis (SFA), which tends to be fully parametric.[3] Although hospitals, primarily in developed countries, receive the brunt of the attention, likely due to better data availability, physicians, clinics and specialists have not been ignored. Further, there has been a recent uptick in research focusing on healthcare delivery in developing countries.

2.1. **Physicians.** Reinhardt (1972) was one of the first to consider physician efficiency, showing that multi-physician single specialty practices were more efficient than multi-physician multiple specialty practices, due to better use of non-physician inputs. Reinhardt's (1972) study was extended by Rosenman & Friesner (2004) using both DEA and SFA models to consider inefficiencies in the scope of services delivered by single and multiple specialty groups in the United States (US). They find average efficiency (from DEA) in the range of 73.6% to 87.8% for primary care, but 56% to 66.5% for specialty care. However, SFA is only used for cost efficiency and correlates of efficiency. Their research highlights the distinction that has commonly been drawn in the literature: DEA for multiple output models and SFA for single output models.[4]

DEA has been used by Chilingerian & Sherman (1990) to examine cardiologists' success in treating low and high severity cardio shock, finding only three efficient cardiologists. Chilingerian (1993) and Chilingerian (1995) report DEA results based on data collected from 36 attending physicians at a teaching hospital in the US finding proportionally more efficient surgeons than efficient physicians. In addition to uncovering efficiency, the resulting efficiencies were regressed, via Tobit, against a number of items.[5] They find that the age of patients decreases overall efficiency, while HMO affiliation increases efficiency. On the other hand, Burns,

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[3]Marder & Zuckerman (1985), rather than estimating efficiency via DEA or SFA, consider survival analysis, wherein the most efficient firms are expected to survive for longer periods of time.

[4]However, the stochastic ray fronteir model, developed by Gerdtham, Löthgren, Tambour & Rehnberg (1999) is one exception to that rule. They find local councils adopting a new reimbursement scheme were 9.7% more efficient than those sticking with budget-based allocations.

[5]They base their follow-up regressions on research by Noren (1980), who finds that internists use more laboratory and X-ray tests than family GPs, while Eisenberg (1986) suggests that specialized, younger and less experienced physicians use more diagnostic tests and intensive care.

Chilingerian & Wholey (1994) use DEA to consider efficiency with respect to doctors in terms of child delivery services, and determine other correlates to efficiency. They find significant physician resource use heterogeneity, that specialist training is associated with lower levels of efficiency, managed care raises efficiency and that child delivery service efficiency rises if physicians work across a larger number of hospitals.[6] In addition to physicians, and their clinics, psychiatric clinics have also received attention from Halsteinli, Kittlesen & Magnussen (2001). They find similar technical efficiency results to the previously cited papers, with mean efficiencies slightly greater than 70%.

As noted earlier, DEA has often been used when analyzing health care delivery efficiency, due to its ability to handle multiple output production. However, SFA has also been used, although primarily when considering cost efficiency. For example, Gaynor & Pauly (1990) use SFA to consider the effect of compensation on productivity and efficiency, finding lower productivity in large groups, although no difference in efficiency. However, compensation and size, measured by the number of physicians, was affected. Gaynor & Gertler (1995) find similar results, while Defelice & Bradford (2004), using SFA, argue that both homogeneity and size affect efficiency. Schmacker & McKay (2008) find, in military hospitals, mean productive efficiency around 82.2%, which seemed to fall over the time period studied. They also extended the analysis to look into efficiency correlates, finding that a larger number of civilians - on staff - improves efficiency.

2.2. **Developing countries.** Although the majority of research on healthcare delivery has relied on data collected in developed countries, researchers in developing countries have, recently, been able to collect data and undertake efficiency analysis. Of particular relevance to the research reported here is efficiency analyses conducted in Zambia, Kenya, Namibia and Sierra Leone, four African countries ranked similarly to South Africa by Evans, Tandon, Murray & Lauer (n.d.). For

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[6]Additional research by Chilingerian & Sherman (1996), Wagner, Shimshak & Novak (2003), Ozcan (1998), Ozcan, Jiang & Pai (2000), Pai, Ozcan & Jiang (2000) also make use of DEA analysis. Notably, inefficient physicians were, on average, 30% less efficient in these papers.

comparison, efficiency in Angola, China, Ghana and Turkey, developing countries ranker higher than South Africa, is also briefly considered.

Masiye, Kirigia, Emrouznejad, Sambo, Mounkaila, Chimfwembe & Okello (2006) use DEA to examine 40 health centres in Zambia that were approximately equally split between public and private ownership. Average technical efficiency was 83%, while allocative efficiency averaged 88%; however, 29% of private facilities were allocatively efficient, compared to just 4% of public centres. In another Zambian study, Masiye (2007) finds 67% average technical efficiency. In Kenya, Kirigia, Emrouznejad & Sambo (2002) find 26% of hospitals to be technically inefficienct, but only about 16% inefficiency. Further, Kirigia, Emrouznejad, Sambo, Munguti & Liambila (2004), who also examine Kenya, find average efficiency levels around 65%. Although neither the Zambian nor the Kenyan studies are representative of their entire country's health sector, the estimated efficiency performance is generally better than it is in the South African analyses conducted by Kirigia et al. (2000), Kirigia et al. (2001), Zere et al. (2001) , Kibambe & Koch (2007).[7]

Additional analysis of healthcare delivery efficiency, primarily via DEA, has been conducted in Namibia and Sierra Leone. Zere, Mbeeli, Shangula, Mandlhate, Mutirua, Tjivambi & Kapenambili (2006) apply DEA to a Namibian sample; their techical efficiency estimate averages range between 62.7% and 74.3% from 1997 to 2001. Renner, Kirigia, Zere, Barry, Kirigia, Kamara & Muthuri (2005), who consider Sierra Leonen district hospitals, arrive at an average technical efficiency score of 63%.

Research from other countries in Sub-Saharan Africa, which are ranked higher than South Africa by Evans et al. (n.d.), such as Angola and Ghana show mixed results. Estimates of technical efficiency in Angola are rather similar to the other African studies, while estimated efficiencies in Ghana are quite a bit higher. Kirigia, Emrouznejad, Cassoma, Zere & Barry (2008) consider Angola finding technical

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[7]Kirigia et al. (2001) find that inputs could be reduced by approximately 30%, and still keep output constant, while Zere et al. (2001) find that efficiency ranges from 68-74% in their sample of public hospitals.

efficiency ranging between 65.8% and 67.5% from 2000 to 2002. Ghana is examined by Osei, d'Almeida, George, Kirigia, Mensah & Kainyu (2005) and Akazili, Adjuik, Jehu-Appiah & Zere (2008), who find that the average technical efficiency is much higher than in the other African countries considered. Osei et al.'s (2005) estimates average 81.4%, although 47% of the hospitals in their sample were technically inefficient, while Akazili et al.'s (2008) estimates average closer to 85%.

Surprisingly, the Chinese health sector, which is ranked more favourably than either Angola, Kenya, Namibia, South Africa or Zambia, appears to perform worse, at least on some comparisons that are available. Ng (2008) estimates that, overall, the Chinese health sector may be quite inefficient, averaging between 59.9% and 86.7% depending upon the year, location and output measure used in the anlayis. Turkey, also ranked higher by Evans et al. (n.d.), appears to perform more poorly than some of the results noted for Zambia and Kenya. Sahin & Ozcan (2000), for example, finds low levels of efficiency, averaging around 78.1%. In what follows, we provide further information on the efficiency of the South African healthcare sector, with special attention paid to the private sector, and compare our results to those already available in the literature.

3. Semiparametric Stochastic Frontier

The semiparametric stochastic frontier model is based on an extension of Aigner, Lovell & Schmidt's (1977) stochastic frontier model. Fan, Li & Weersink (1996) proposed the semiparametric extension, discussed below, which has recently been applied by Henningsen & Kumbhakar (2009).[8]

Consider the unspecified regression for observed production in (1), where each surgeon is denoted by $i \in \{1, \dots, n\}$ and each output measure is denoted by $j \in \{1, 2, 3\}$.[9]

$$(1) \qquad\qquad y_{ij} = g_j(x_{ij}) + \epsilon_{ij}$$

[8]Kumbhakar, Park, Simar & Tsionas (2007) examine a fully nonparametric model, but it is not considered here.

[9]Initially, the model is estimated separately for each j. However, a pooled model, pooled over j, is also considered.

Assume that x_{ij} is a $p \times 1$ vector of explanatory variables and is, for this data (described below), the same for all j. The conditional level of output j, denoted $g_j(x_{ij})$, is an unknown function of those explanatory variables. The error term, $\epsilon_{ij} = v_{ij} - u_{ij}$, is decomposed into two parts. Statistical noise, $v_{ij} \sim \mathcal{N}(0, \sigma_{vj}^2)$, and technical inefficiency. Technical inefficiency is embodied within $u_{ij} \sim |\mathcal{N}(\mu_j, \sigma_{uj}^2)|$; however, absolute value notation results in truncation at zero.

For identification purposes, u_{ij} and v_{ij} are assumed to be identically and independently distributed; thus, expected inefficiency can be estimated. The surgeon's production frontier in (2) results from the preceding assumptions and decomposition.

$$(2) \qquad\qquad y_{ij}^f = g_j(x_{ij}) + v_{ij}$$

For ease of interpretation, output is measured in its natural log, such that inefficiency, contained in u_{ij}, measures the percentage deviation between the observed output y_{ij} and the frontier y_{ij}^f.

Although the frontier production function is, of itself, interesting, the primary focus of the analysis is on the efficiency of these surgeon's practices. Therefore, we do not calculate or report $\hat{y}_{ij}^f$, although we do illustrate $\hat{g}(x_{ij})$, see Appendix A. Instead, the emphasis is placed on $\mu_j = E[u_{ij}|\epsilon_{ij}]$. [10]

Jondrow, Materov, Lovell & Schmidt (1982) provided an estimator for u_{ij}, given in (3), based on the preceding assumptions.

$$(3) \qquad\qquad E[u_{ij}|\epsilon_{ij}] = \frac{\sigma_j \lambda_j}{1 + \lambda_j^2}\Big[\frac{\phi(a_{ij})}{1 - \Phi(a_{ij})} - a_{ij}\Big]$$

The terms in (3) require additional elaboration.

$$(4) \qquad\qquad a_{ij} = \frac{\mu_{ij}}{\sigma_j \lambda_j} - \frac{\epsilon_{ij}\lambda_j}{\sigma_j}$$

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[10]Battese & Coelli (1995), which has been applied in numerous examples, assume that μ_{ij} is a linear function of a number of explanatory variables. We do not include that possibility in our model, although we do consider it in related research not yet completed.

In (3) and (4), $\sigma_j = \sqrt{\sigma_j^2} = \sqrt{\sigma_{uj}^2 + \sigma_{vj}^2}$, $\lambda_j = \sigma_{uj}/\sigma_{vj}$, $\phi(\cdot)$ is the normal density function and $\Phi(\cdot)$ is the normal distribution function. In our semiparametric analysis, we undertake a two step estimation procedure. In the first step, we nonparametrically estimate $\hat{g}(x_{ij})$, from which we calculate the composite error term ϵ_{ij}. In the second step, we decompose the error term to construct $E[u_{ij}|\epsilon_{ij}]$.

Semiparametric estimation of stochastic frontiers and productive inefficiency makes sense, given the possibility that production functions do not always fit the standard parametric cases, such as the Cobb-Douglas or Translog production functions. Furthermore, consistent semiparametric estimation has been available since at least 1996; however, semiparametric estimation has not been undertaken very often. Henningsen & Kumbhakar (2009) suggest that the lack of applications has been due to the underlying difficulties associated with implementation. They suggest, though, that the extension of computing power and feature-rich software has made possible the empirical implementation of such models. In particular, the "np" package, Hayfield & Racine (2008), combined with the "frontier" package, Coelli & Henningsen (2010), estimated in R, R Development Core Team (2009), provides one such implementation option, which we adopt.

In what follows, we consider a local linear estimation, or local weighted least squares regression, of $g_j(x_{ij})$, where the weights are given by a product kernel with an appropriate bandwidth.[11] Fan & Gijbels (1996) show that in local linear regression, the bias does not depend on the underlying density, and, therefore, has better bias properties than local constant regression.[12] In our formulation, the kernel bandwidths are chosen via least squares cross-validation. The underlying kernel employed for continuous data is the second order Gaussian kernel, while the kernel employed for discrete data was proposed by Aitchison & Aitken (1976); each of these kernels is naturally included within the "np" package. From the

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[11]See Li & Racine (2007) for a detailed exposition of the estimator and product kernels.

[12]Local regression implies that a regression function is performed for all of the data within a small window of the available data. However, the appropriate width of that window, the bandwidth, determines the smoothness of the overall regression function. In the limit, as the bandwidth increases, the local regression becomes a linear regression; however for very small bandwidths, the regression is performed on nearly every observation, resulting in noisy estimates.

nonparametric estimates, we compute residuals, which are then decomposed using the "frontier" package, allowing us to compute the underlying technical efficiency of the surgical pracitices.

4. Data

A purposive survey collected in 2007, and reported in Slabbert (2010) forms the basis for the empirical analysis and results reported below. The focus of the survey was specialist surgeons, and, therefore, the survey was sent to all Gauteng registered specialist surgeons. The survey, which was both voluntary and anonymous, queried surgeon and clinic characteristics, including experience, staff, patient amenities, patients, surgeries performed, and many other characteristics. Our analysis focuses only upon single surgeon practices and makes use of information related to the surgeon's experience, as well as other potential inputs and outputs. An analysis of practice income, costs and profits is undertaken elsewhere, see Koch & Slabbert (2010).

The South African Medical Association (SAMA), as well as the Foundation for Professional Development (FPD) sponsored the data collection efforts. The survey instrument supported by SAMA and FPD was broken into four major components. In the first component, the pratice and patient profile were attended to, and, thus, the questions were directed towards practice size, attention to patient comfort, the number of patients, consultation length, number of surgeries performed, and many other items. In the second component, practice expenditures over the past month were requested. The third component addressed the personal and professional profile of the survey respondent, while the fourth component focused on the most sensitive information, that related to practice revenues.

Initially, 260 specialist physicians were requested to complete the confidential survey. However, only 69 did respond. Despite a response rate of 26.5%, which is less than we would like, it is better than the response rate achieved by Brentnall (2007). She only received responses from 5% of her sample, although she did draw

from a much larger urn. The low response rate does raise concerns regarding the representativeness of the data, as well as our ability to generalize our results. Given that only eight respondents (11.5%) had been in private practice for five years or less, whereas 37 (53.6%) had been in private practice for fifteen years or more, it is likely that the resondents are not generally represented across the profession.[13] Further, only two female surgeons responded, while all but five respondents were white.

Possibly the greatest concern that might arise, when considering efficiency using voluntary responses, is that efficiency could very well be correlated with the likelihood of response. For example, it might be true that only the most efficient manage to respond, which would lead to underestimates of efficiency. On the other hand, it might also be true that only those with time on their hands, because they do less than they could, are likely to respond. If that is the case, then our estimates of efficiency could be overstated. Unfortunately, we do not have data that allows us to instrument for the likelihood of response, since we only have respondent data. Since data is respondent data, our reported results cannot be generalized to the population of specialist physicians practicing in Gauteng or beyond. Therefore, the reported results should be understood in that context.

The analysis of efficiency focused on information gleaned from the first and third survey components. In particular, we limited our data to single surgeon practicies, but also made use of information on the number of nurses, the number of administrative staff, the total number of patients, the number of new patients, the number of surgeries performed and the years of surgeon experience (years qualified). As previously noted, there were 69 respondents; however, due to missing data for various inputs or outputs, the analysis sample was trimmed to 57. Descriptive statistics of the data used in the analysis are reported in Table 1.

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[13]However, it would also be reasonable to believe that specialist migration could have been highest amongst the youngest practitioners, such that the responses are representative of the South African specialist surgeon population.

TABLE 1. Desrciptive Statistics

Output Measures			Input Measures		
	Mean	Std. Dev.		Mean	Std. Dev.
Total Patients	203.56	120.2	Years Qualified	25.61	12.2
New Patients	70.82	39.9	Nurse (=1 if positive)	0.33	0.5
Surgeries	37.84	26.5	Administrators	2.53	1.3
			Consultation Length	23.75	8.6

In addition to the means reported above, there were 36 Orthopedic surgeons in the data set, 12 vascular surgeons, and nine other surgeons in the remaining 57 observations. In the empirical analysis, below, we make use of the natural log of the continous input variables, such that the estimated gradients are related to output elasticities.

5. EMPIRICAL RESULTS

In this section, we present the primary results related to the error decomposition related to the semiparametric stochastic frontier model described in equations (3) and (4). For discussion of the nonparametric model described in equations (1) and (2), please see Appendix A.

5.1. **Technical Efficiency Measures.** The main focus of the analysis is the estimation of efficiency for each of the responding surgeons in our survey. The results from the efficiency analysis are presented in Table 2. As can be seen in the table, mean efficiency is approximately 65% for our surgeons, regardless of which measure of output is used. These efficiency measures are lower, but similar to those estimated by Zere et al. (2001). Similarly, our results are not all that different from Kirigia et al.'s (2001) estimates, although they present their estimates in a different fashion. If comparisons were drawn with other research conducted in Africa, our estimates are very similar to Zambian estimates, Masiye (2007), Kenyan estimates, Kirigia et al. (2004), Namibian estimates, Zere et al. (2006), and Sierra Leonen estimates, Renner et al. (2005).

In each of the analyses, the estimated mean from the truncated normal distribution, recall the assumption $u_{ij} \sim |\mathcal{N}(\mu_j, \sigma_{uj}^2)|$, hovers around -2.5 to -2.9, but is

TABLE 2. Error Decomposition and Efficiency Estimates

Variable	Total Patients Estimate (Std. Err.)	New Patients Estimate (Std. Err.)	Surgeries Estimate (Std. Err.)	Pooled Output Estimate (Std. Err.)
σ_j^2	1.892 (2.48)	1.942 (4.49)	2.288 (2.20)	2.188 (1.75)
λ_j	0.942^a (0.09)	0.948^a (0.11)	0.887^a (0.11)	0.926^a (0.06)
μ_j	-2.690 (5.17)	-2.548 (9.25)	-2.850 (4.37)	-2.847 (3.76)
$\overline{\overline{\text{Eff}}}_j$	0.66	0.65	0.65	0.65
n	57	57	57	171
$\ln \mathcal{L}$	-45.36	-45.71	-60.96	-157.65
[a] Significant < 0.001, $\overline{\overline{\text{Eff}}}_j$ - mean efficiency for output j.				

not significantly different from zero. Furthermore, the ratio of signal to noise, as defined by λ_j, is approximately 0.9, and is statistically significantly different from zero. Most worrying, within the decomposition analysis, however, is the estimate of the variance of the composite error term. The results suggest that this variance is not statistically different from zero, implying that the distributions of noise and inefficiency could be degenerate.[14]

5.2. **Efficiency Rankings.** Given the fact that a number of different stochastic frontier models were considered, we further examined the efficiency rankings across all of the different analyses to see if they were consistent. To do this, we first considered the correlation between estimated efficiency scores across each of the different output measures. The results are located in Table 3. Plots of the efficiency results are presented in Appendix B.

TABLE 3. Efficiency Correlations Across Output Measures

	Total Patients	New Patients
New Patients	0.79	
Surgeries	0.43	0.54

Although the estimated correlations are reasonably high, they are not indicative of strong similarities across the various measures of output. Therefore, we next

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[14]Future work will further examine this result.

considered correlations across the efficiency rankings. The ranking correlations are presented in Table 4, and an illustration of the ranks is available in Appendix B.

TABLE 4. Ranking Correlations Across Output Measures

	Total Patients	New Patients
New Patients	0.07	
Surgeries	0.04	0.05

The results in Tables 3 and 4 suggest that although there is a reasonable correlation between efficiency scores across the various measures of output, the actual efficiency rankings are not very similar. In other words, the respondents in our analysis are not generally efficient or generally inefficient. Some surgeons are better at retaining patients than others, while some surgeons are better at attracting new patients than others; further still, some surgeons are better at performing surgeries than others.

5.3. **Sensitivity Analysis.** Naturally, the lack of consistency across the analyses led us to wonder about the validity of pooling the data. For that reason, we also looked at the correlations between efficiency scores for the pooled data. Those results are available in Table 5.

TABLE 5. Efficiency Correlations Across Output Measures from Pooled Analysis

	Total Patients	New Patients
New Patients	0.80	
Surgeries	0.44	0.56

In comparing Tables 3 and 5, we see that the correlations are nearly identical, which provides some vindication for pooling the data.

In addition, we considered correlations between the efficiency scores calculated from the pooled analysis with the efficiency scores calculated in the separate analysis. Those results are available in Table 6. For example, we calculated the correlation between efficiency scores for the separate analysis of total patients and the efficiency scores for the total patient output in the pooled analysis. That is located

in the top left corner of Table 6. Similarly, we calculated the correlation between the efficiency scores of total patients from the separate analysis with the efficiency scores from new patient output in the pooled analysis, which is located in the first column of row two; that correlation can be compared with the correlation in the top left of Tables 3 and 5. The rest of the correlations are similarly defined.

TABLE 6. Efficiency Correlations Between Separate and Pooled Analysis

Separate	Pooled Analysis		
Analysis	Total Patients	New Patients	Surgeries
Total Patients	0.98		
New Patients	0.81	0.96	
Surgeries	0.44	0.54	0.96

The correlation results across the different analyses suggest that the correlations between the efficiency scores are very high, near unity, when comparing output-specific efficiency estimates. Furthermore, cross-analysis correlations are very similar to the within-analysis correlations. In other words, pooling the data does not affect the underlying efficiency scores. Therefore, pooling the data, which increases the total number of observations and, thus, improves precision in the underlying nonparametric regression, is a reasonable option in this limited sample.

6. DISCUSSION AND CONCLUSION

In the preceding analysis, we have used semiparametric stochastic frontier production functions to examine the technical efficiency of specialist surgeons practicing in Gauteng Province of South Africa. The responding surgeons are operating at 65% efficiency according to our analysis, suggesting that specialists are able to take on more patients and more surgeries than they are currently conducting with the same number of resources they are currently using.

The results are broadly similar to previous analyses of healthcare sector efficiency conducted in South Africa by, amongst others, Kirigia et al. (2000), Kirigia et al. (2001), Zere et al. (2001) and Kibambe & Koch (2007). All of these researchers have found that healthcare production in the South African public sector is rather

inefficient. The results presented above, suggest that the healthcare production in the South African private sector is also inefficient.

Although our results point to inefficiency in private healthcare delivery, it should be noted that there are a number of shortcomings in the preceding analysis. One major concern is the low response rate in our survey. Conservatively, it would be reasonable to assume that participation was more likely for those who were better organized or more efficient, in which case, our efficiency estimates would be understated. However, it would not be unreasonable to assume that participation was more likely amongst those not using their time to the fullest, in which case respondents might be more inefficient than the specialist surgeon population located in Gauteng.

Another concern, and one that arises in all examinations of health care production, is that our measure of output does not truly capture healthcare production. We would prefer to have a measure of health improvement, rather than a simple stock of patients or flow of patients and surgeries. However, data to that effect is not available to us, and, therefore, we can only report on efficiency based on stocks and flows of patients.

One other concern, which also often arises in examinations of health care production, is that we are not able to control for case-mix. We did include consultation length to control for the fact that more ill patients would likely need lengthier consultations, which would further impact on production. However, consultation length cannot control for the actual health of the patients seen by various surgeons in our survey. Given the nature of the specialties included in our survey, we would have expected orthopedic surgeons to see healthier patients than vascular surgeons, and, thus, we included specialty as a control in the analysis. However, specialty did not statistically affect any of our measures of output.

From a policy perspective, our results lend some support to the notion that the private sector is capable of serving additional customers, and that a national health insurance program could result in better resource allocations. However, given

the shortcomings in our data, we do not think it is appropriate to conclude that specialty surgeons in Gauteng are wasting resources, even though our results suggest that resources could be more appropriately allocated. Future research in this area needs to uncover more and better data in order to create a firmer picture of the delivery of healthcare within the private sector, providing much better information to those interested in further developing healthcare delivery policy.

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Appendix A. Nonparametric Estimates

In this Appendix, nonparametric stochastic frontier estimates are discussed. As already noted in the methodology section, a local linear regression of $E[y_{ij}|x_{ij}]$ is estimated, from which it is rather straightforward to examine efficiency. Bandwidths for the nonparametric regression are determined via least squares cross-validation. Local linear regressions are preferred to local constant regression, because they are less prone to bias, Fan & Gijbels (1996).[15] The kernel used in the estimates is second-order Gaussian for the continuous variables, while the kernel proposed by Aitchison & Aitken (1976) is used for the categorical variables.[16] Recall that all continuous variables, including the dependent variable, is logged. Therefore, gradients of continuous independent variables are related to output elasticities, while the gradients of discrete independent variables are related to percentage changes in output associated with a discrete change in the input.[17]

A.1. **Total Patients.** The first set of results are based on the nonparametric estimates of the specialist's production of (log) total patients. The gradients of the estimates, with bootstrapped standard errors are illustrated in Figure 1. The R^2 from the nonparametric regression is 0.44, while the estimated bandwidths are 0.5, 177341, 58929, 0.23 and 0.67 for nurses, the number of administrators, the years of experience, the average length of consultations, and the surgeon's specialty.

According to Figure 1, the nonparametrically estimated gradients are not generally statistically significantly different from zero. The only exception is for consultation length, when these become quite large. When the (log) consultation length

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[15]Additional cross-validation assumptions were considered, such as the Kullback-Leibler criterion discussed byHurvich, Simonoff & Tsai (1998). As expected, there were some differences in the estimated bandwidths between the two, but the results were not qualitatively different. Separate estimation results are available from the authors upon request.

[16]Other kernels were also considered; however, as with the choice of cross-validation, these other kernels did not result in qualitiative differences in the estimates, and are available from the authors upon request.

[17]The gradients are not the exact output elasiticities, since the non-parametric regression does not directly estimate the production function in the semiparametric stochastic frontier model, Fan et al. (1996).

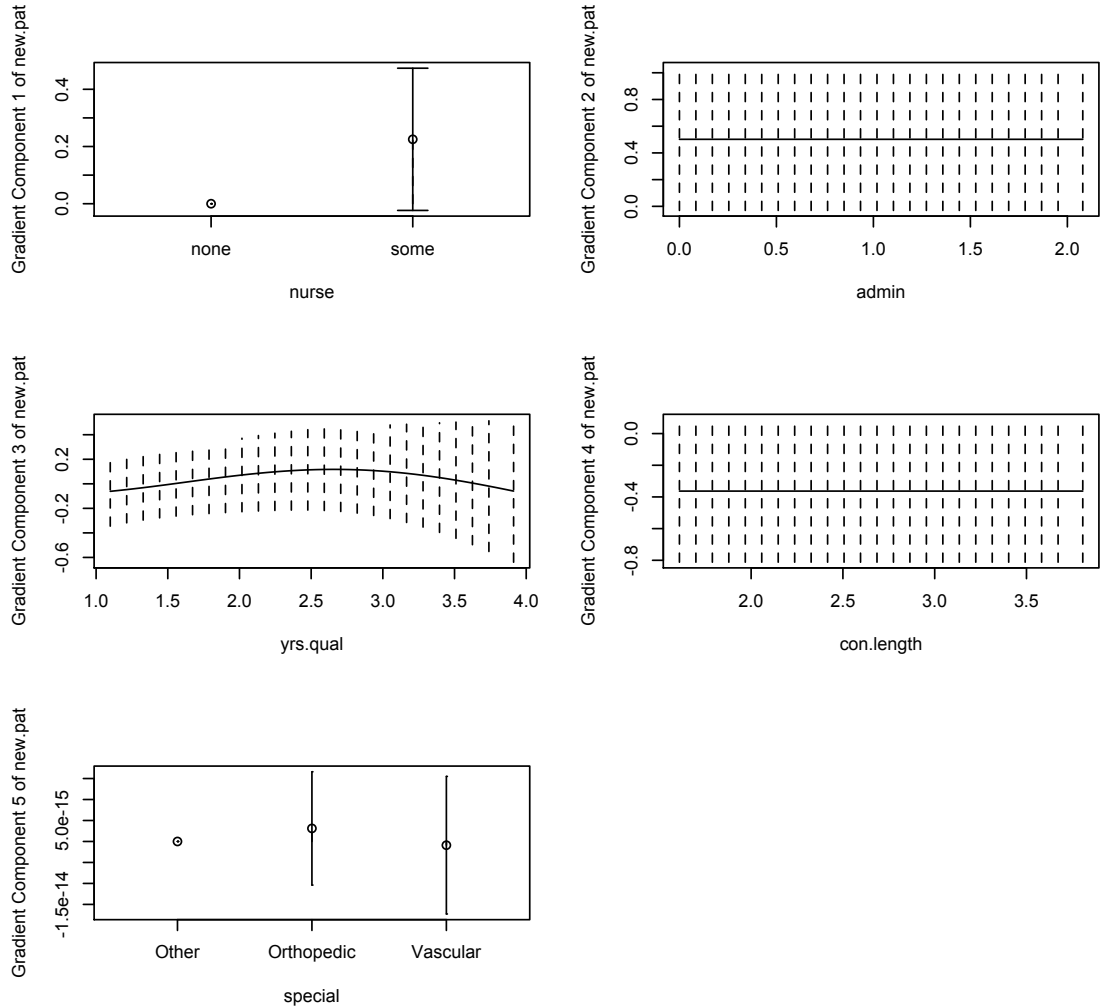FIGURE 1. Nonparametric Gradient Estimates of Total Patients
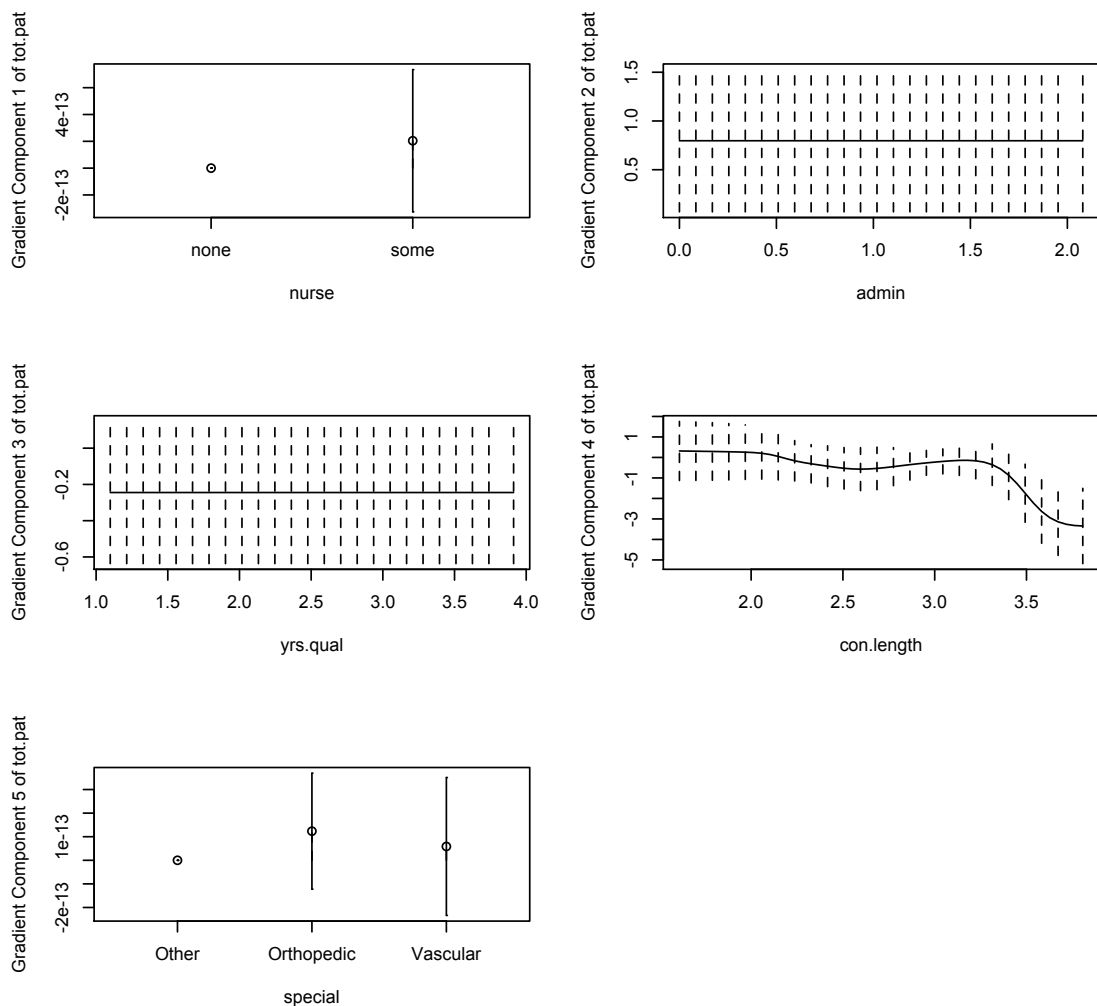
comes close to 3.5, so the actual consultation length nears 30 minutes, the gradient becomes significantly negative.

A.2. **New Patients.** In addition to considering the total number of patients, as a measure of output, we also considered the number of new patients. The nonparametric estimates of the gradient between new patients and clinic inputs is illustrated in Figure 2. The cross-validated bandwidths for the inputs are 0.14, 952689, 0.78, 2699705 and 0.67 for nurses, adminstrators, years of experience, consultation length

and surgeon specialty, respectively. Further, the nonparametric R^2 was calculated to be 0.27.

FIGURE 2. Nonparametric Gradient Estimates of New Patients

Similar to the nonparametric regression estimates for total patients, there is very little explanatory power in the variables. Unfortunately, there are no observed values of the independent variables for which the estimated gradient can be statistically distinguished from zero.

A.3. **Surgeries.** Figure 3 illustrates the nonparametric gradient estimates for the production of surgeries by the specialist surgeon, as a function of the various clinic inputs. The calculated R^2 from the nonparametric regression is 0.34. The estimated bandwidths for the regression illustrated in Figure 3 are 0.5 for nurses, 606613 for administrators, 0.64 for years of experience, 0.90 for length of consultation and 0.67 for surgeon specialty.

FIGURE 3. Nonparametric Gradient Estimates of Surgeries
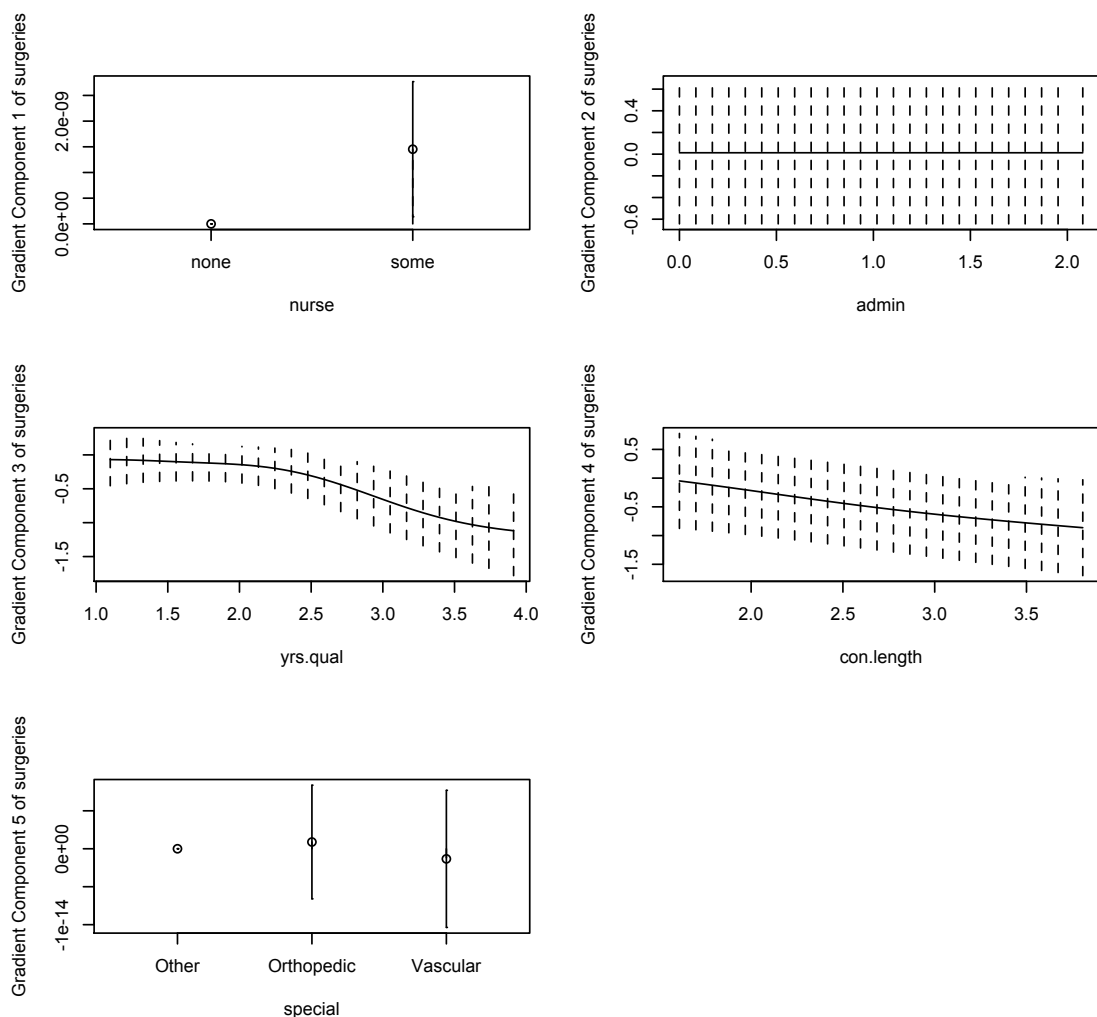
Unfortunately, as has been the case with both total patients and new patients, the estimated gradients are not generally statistically significant. However, years of experience is negatively related to surgery output, as we would expect, when the number of years of qualification becomes large enough. As can be seen in the figure, when (log) years of qualification exceeds 3.0, such that years of experience exceeds 20, the negative gradient becomes statistically less than zero.

A.4. **Multiproduct Production.** Given the similarities in the production functions, a final set of nonparametric estimates were determined based on a pooled regression, where all outputs were simultaneously regressed against all inputs.[18] This final regression included an additional categorical varaible indicating which, of the three measures of production, was associated with the observation. This last set of estimates is illustrated in Figure 4. The bandwidths for nurses, administrators, years of experience, consultation length, output measure and specialty were, respectively, 0.5, 878207, 3010395, 0.35, 0.006 and 0.67, while the nonparametric regression R^2 was calculated to be 0.64.

Pooling the data to undertake one regression appears to be reasonable, in the sense that the panels in Figure 4 do not look completely different from all of the panels in either Figures 1, 2, or 3.[19] Overall, the number of administrators have a small, apparently constant and statistically significant, impact on total output, while consultation length negatively impacts output, if consultation length becomes long enough. As expected, there are significant differences in base output across the output measures. Surgeons are able to retain more total patients than accept new patients; further, surgeons are able to accept and examine more new patients than require surgical interventions.

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[18]Although a Hausman test has not been constructed, there is one common feature across each of the regressions. That common feature is the general insignificance of the inputs across each of the regressions.

[19]There are a total of 20 comparable panels in the four figures. Assuming Figure 4 is correct, only a few panels in Figures 1, 2 and 3, would be significantly different from the panels in Figure 4.

FIGURE 4. Pooled Nonparametric Gradient Estimates of Output
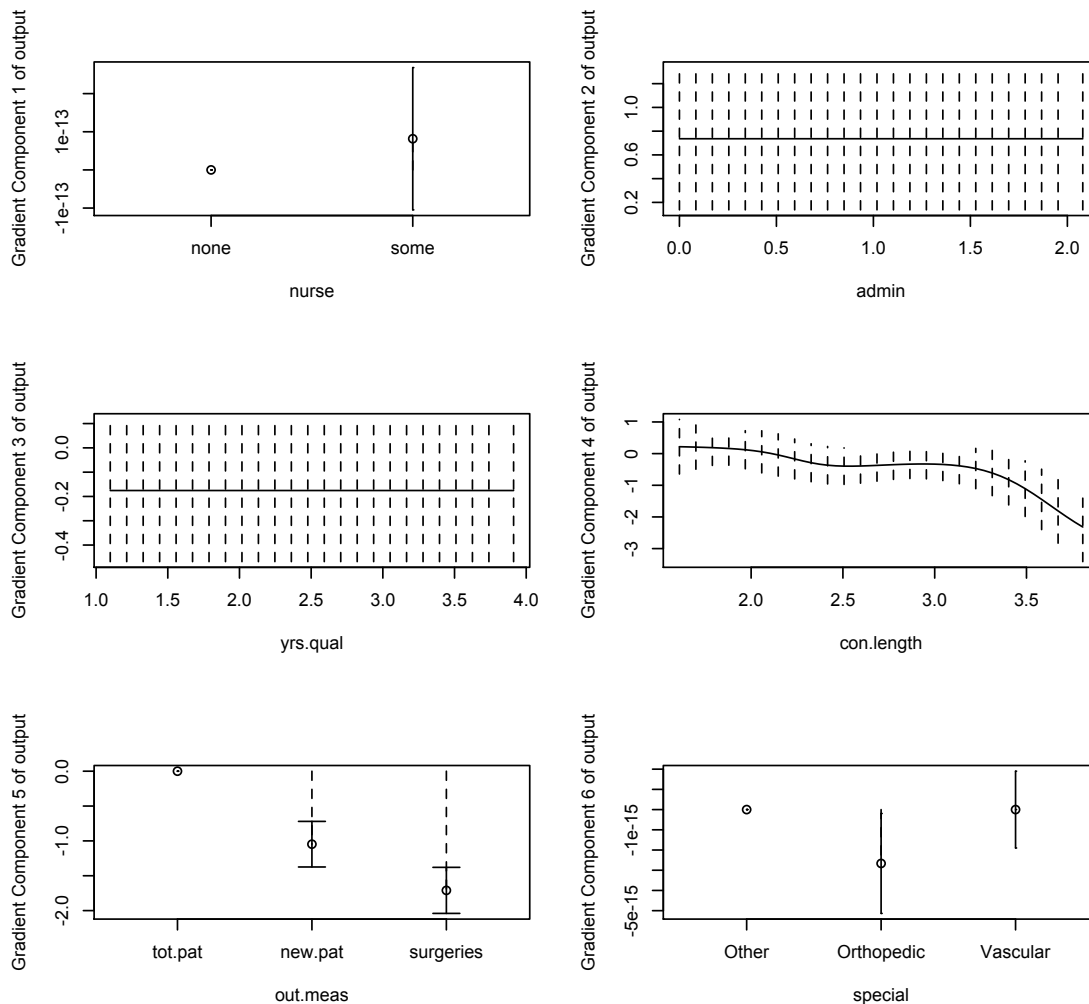

APPENDIX B. EFFICIENCY COMPARISONS ACROSS OUTPUT MEASURES

The correlations presented in Table 5.2 are calculated from the efficiency measures in the Stochastic Frontier Analysis. Plots of these are available in Figure 5. If the efficiency measures were nearly the same across each of the different output measures, the illustration would show a different points being either very close vertical neighbors or very close horizontal neighbors in each of the comparisons.

The figure further suggests that the efficiency measures, themselves, are not very identical.

FIGURE 5. Efficiency Comparisons Across Output Measures
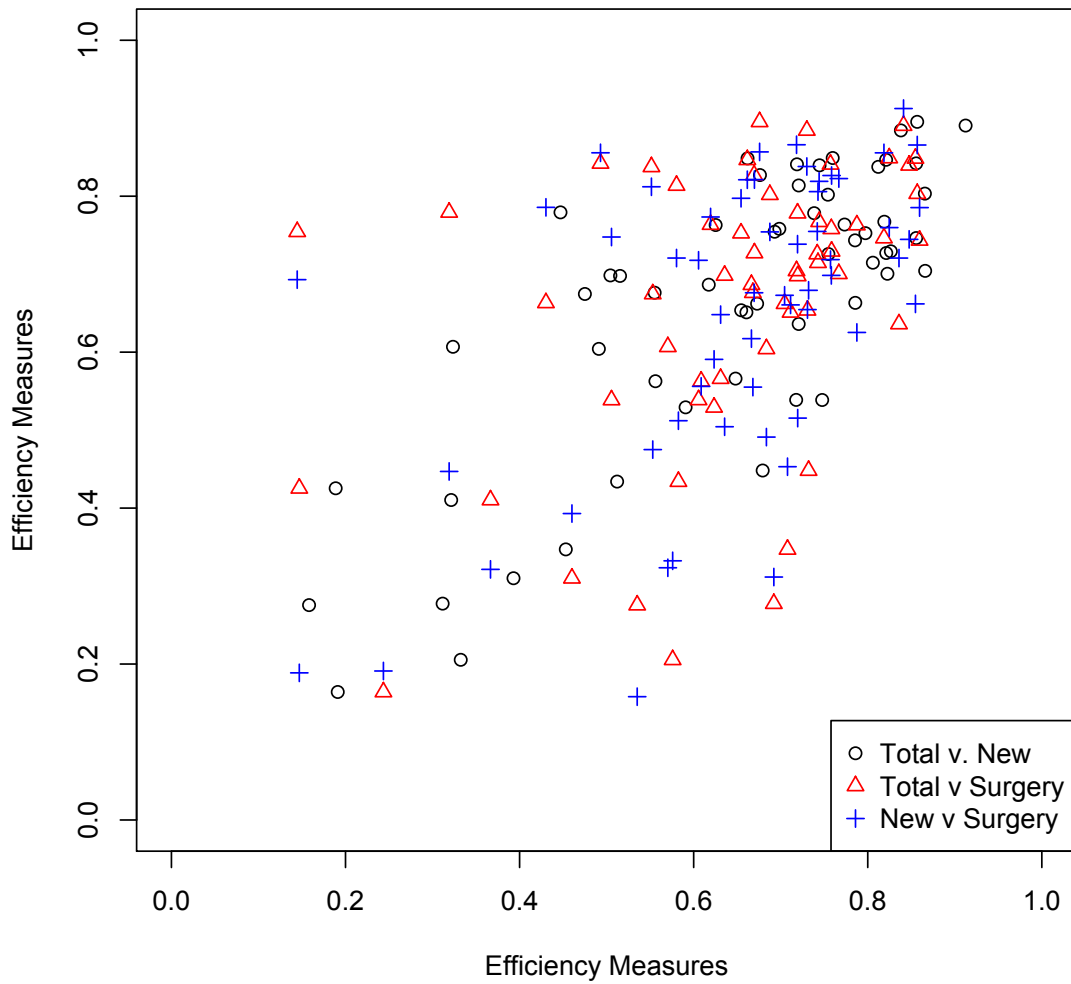
An illustration of the rankings is available in Figure 6. Again, if the rankings across the stochastic frontier analyses were similar, the illustration would show a number of points very close to each other horizontally and vertically. However, as

can be seen in the figure, the rankings are all over the place, as expected, given the results in Table 5.2.

FIGURE 6. Efficiency Comparisons Across Output Measures
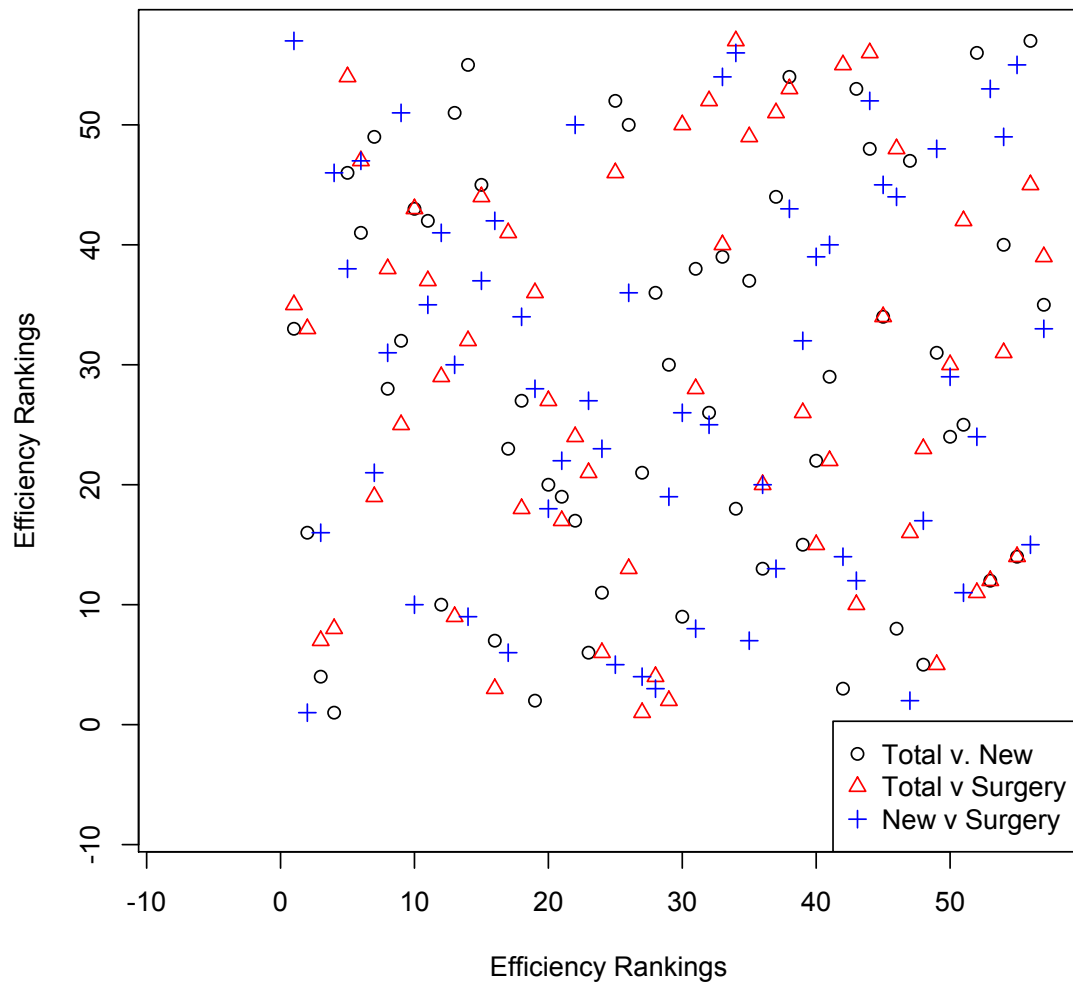
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