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EVALUATING THE RELATIVE EFFICIENCY OF CANCER TREATMENTS IN NOVA SCOTIA USING THE PATIENT AS THE UNIT OF ANALYSIS

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Abstract.
This paper investigates the relative efficiency of cancer treatment in Nova Scotia using data envelopment analysis (DEA) and patients as the base decision-making unit. Using a unique data set, DEA treatment efficiency scores are included as a variable in a second stage (ordered) probit model measuring the likelihood of patient survival. The estimated efficiency scores generally have positive coefficients in the econometric models, suggesting that certain treatments increase the probability of survival. But more importantly, we find that inter-hospital or inter-regional differences in patient population (e.g. severity of illness, other health complications and living conditions) are also helpful in determining health care outcomes. We conclude that health care policy which ignores inherent differences in patient population is not acceptable as a basis for public decision-making.

Key Words: Cancer treatment, efficiency, probit estimation, health care policy.

JEL Codes: C14, D73, I12.

Résumé. Évaluation de l'efficacité de traitement du cancer en Nouvelle Écosse avec le patient comme unité d'analyse.
Dans cet article, on évalue l'efficacité de traitement du cancer en Nouvelle Écosse en utilisant *data envelopment analysis* (DEA) et les patients comme l'unité décisionnelle de base. Avec une base de données unique, les mesures de l'efficacité de traitement DEA sont inclues en tant que variable dans un modèle probit de deuxième ordre qui mesure la probabilité de survie du patient. Les mesures d'efficacité ont en général des coefficients positives dans les modèles économétriques, ce qui suggère que certains traitements augmentent la probabilité de survie. Mais, ce qui est plus important, nous avons trouvé que des différences entre hôpitaux ou interrégionales dans la population des patients (p. ex. la sévérité de la maladie, d'autres complications de maladie ou de conditions de vie, entre autres) sont aussi utiles dans la détermination des résultats de traitement de la santé. Nous arrivons à la conclusion que la politique de traitement de la santé qui ignore les différentes inhérentes au sein de la population des patients n'est pas acceptable en tant que base pour la prise de décision publique.

Mots clés : Traitement du cancer, efficience, estimation probit, politique de soins de santé.

Codes JEL: C14, D73, I12.

Introduction

With the goal of understanding and improving health care policy in this country, this study measures the effectiveness of cancer care as well as the use of pharmaceutical products for oncology treatment in a Canadian regional public health care system. Using detailed Nova Scotia public health data spanning the years 1997 to 2002, we find that an optimal allocation of resources to provincial oncology units on the basis of that data would not have been possible.[1] This conclusion does not rule out the possibility that an efficient outcome might have been reached, just that one cannot be determined from the current public health dataset. Given these findings, we argue more generally that the planning of health care allocations in this country would be well served by improved data collection. In particular, the collection of data on output or patient characteristics (e.g. severity of the patient condition) would help to direct spending of limited public funds to the highest and best possible uses of medical care.

The next sections review the empirical model of cancer treatment efficiency and patient mortality. A description of the data set is presented first, followed by illustration and discussion of the main empirical results. The final section concludes and identifies directions for further research.

Modeling Health Care Treatment Efficiency and Mortality

Measuring Health Care Treatment Efficiency – Data Envelopment Analysis

Data envelopment analysis or DEA is a frontier efficiency estimation technique that computes the technical efficiency (transformation of inputs into outputs) for each individual production unit relative to others in the sample. The technique is called "envelopment analysis" because the efficiency frontier generated by the method "envelops" the data geometrically. By definition, a producer is technically efficient if, for a given output level, no equiproportionate reduction of inputs could result in the same level of output. The method solves for an artificial frontier comprising a linear combination of the most technically efficient units in the sample. An efficiency score for a given producer or decision-making unit is calculated relative to this efficient frontier. The constraints in the DEA linear program dictate that the weights cannot yield a ratio of outputs to inputs greater than one, ensuring that a score of unity is the score of efficient units in the sample.

There are numerous studies examining the efficiency of health care provision using frontier methodologies, particularly for comparing performance at the hospital level. A large and growing literature includes research conducted across many countries (including

[1] Of course, this is neither the first nor the last call for reform to financial allocation and information gathering in health care in Canada. See Coyte and Landon (1990), or Barer (1993), as well as the Reports of the Romanow Commission (Romanow, 2002) and the Kirby Committee (Kirby and Lebreton (2002) and the large evaluative literature that followed in their wake.

Canada) and for a wide variety of types of hospital or treatment setting.[2] Some of this research relies upon non-parametric approaches to efficiency analysis, although depending on data availability, some researchers use parametric stochastic frontier estimation (see O'Neill et al, 2008). More recent developments in empirical techniques suggest that the application of a blend of parametric and non-parametric methods may yield results superior to the exclusive use of a single approach (e.g. Law and Nolan, 2002; Siciliani, 2006; Liu et al, 2008). The latter approach is the type that will be pursued here.

Econometric specification of mortality

Next, we need a model specification for mortality applicable to the cancer data. We consider two different strategies for this estimation. In the first, we estimate a binary probit model over five years of patient survival data. The dependent variable ($\boldsymbol{Y_{Alive}}$) is coded as 1 if a patient survived after five years and zero if he or she died. The problem with this strategy is that a poor treatment that leaves a patient dead in the first year is observationally equivalent under this estimation procedure to a "somewhat good" treatment that prolongs survival for four but not five years.[3]

The second, more detailed formulation uses an ordered probit model over the five years of cancer survival data. The dependent variable is defined as before but the sample is stratified or ordered by the year of death, if it occurs. Estimation of the ordered probit model helps us eliminate the particular problem raised with the binary model. Of course, we are aware that if the predictors are important in the first year then they might be important in years 2 through 5, but regrettably we have no applicable data for those years.

Probit models are widely used for data with a dichotomous response variable, while ordered probit models are estimated when the dependent variable consists of multi-valued responses that can be ordered or sorted (Verbeek, 2008). The use of ordered probit models has been commonly used in biometric applications (Aitchison and Silvey, 1957). The binary probit model is a special case of an ordered probit model in which the number of responses is limited to two. A complete discussion of the choice models estimated here, including their estimation, computing marginal effects, as well as the statistical relationship between them can be found in Wooldridge (2006) and Greene (2003).

In order to analyse the efficiency of cancer treatments in this sample, a set of comprehensive binary-choice regression models were estimated. Equation [1] presents the model in which the dependent variable ($\boldsymbol{Y_{Alive}}$) is specified as a function of a series of dummy and continuous socio-demographic, socio-economic and clinical variables. In this context, $\boldsymbol{Y_{Alive}}$ represents a successful outcome (i.e. the patient survived after five years) versus an unsuccessful outcome (i.e. the patient died), stratified by the year of death. Each

[2] There are numerous recent examples of this line of research. The following is a sampling; Austria: Sommersguter-Reichmann, 2000; Finland: Vitikainen et al, 2009; Germany: Herr, 2008; Japan: Fujii, 2001; Norway: Biorn et al, 2002; United States: O'Neill, 1998. Ancarani et al (2009) provide an example of another use of DEA scores used in subsequent second stage regression.

[3] The authors would like to thank Mel Cross for commenting on this problem at the 2004 Meetings of the Atlantic Canada Economics Association held at Mount Allison University, New Brunswick.

of the probit and ordered probit estimations described in the paper vary only slightly from the complete variable set structural equation shown in [1].

Finally, to avoid potential problems with multicollinearity in the estimates, we had to eliminate one category level from each of the group-dummy variables. In this context, patients with the following characteristics were considered to be the base group for the econometric estimates: male, located in the city of Halifax (LOC19), not diagnosed with a malignant cancer or mental condition or other unspecified complication, no more than one form of cancer, not admitted for palliative care, not treated with chemotherapy, radiation therapy, or major surgery.

$$\begin{aligned} Y_{Alive} = {} & \beta_0 + \beta_1\, age + \beta_2\, gen + \beta_3\, loc1 + \beta_4\, loc2 + \beta_5\, loc3 + \beta_6\, loc4 + \\ & \beta_7\, loc5 + \beta_8\, loc6 + \beta_9\, loc7 + \beta_{10}\, loc8 + \beta_{11}\, loc9 + \beta_{12}\, loc10 + \\ & \beta_{13}\, loc11 + \beta_{14}\, loc12 + \beta_{15}\, loc13 + \beta_{16}\, loc14 + \beta_{17}\, loc15 + \\ & \beta_{18}\, loc16 + \beta_{19}\, loc17 + \beta_{20}\, loc18 + \beta_{21}\, loc20 + \beta_{22}\, loc21 + \\ & \beta_{23}\, malig + \beta_{24}\, mentl + \beta_{25}\, signs + \beta_{26}\, othcanc + \beta_{27}\, othrcomp + \\ & \beta_{28}\, pallcare + \beta_{29}\, chmthrpy + \beta_{30}\, rdtnthrpy + \beta_{31}\, hospcanc + \beta_{32}\, mjrsrgry + \\ & \beta_{33}\, cdocvis + \beta_{34}\, criwday + \beta_{35}\, cdaysupp + \beta_{36}\, ncdocvis + \\ & \beta_{37}\, ncriwday + \beta_{38}\, ncdaysupp + \beta_{39}\, eff\,300 + \varepsilon, \end{aligned} \tag{1}$$

Data

The literature in health economics and policy yields a sizeable list of potential input measures, but essentially these can be divided into two categories. The first set may be termed “initial conditions”, including patient characteristics such as age, sex, willingness to comply with treatment, and health status before treatment (i.e. severity of illness to be treated, and other relevant or complicating health conditions). These are the “inputs” which the patient brings to the production of health.

The second set comprises health care system inputs, which are often mislabelled as outputs. Some examples of these inputs include physician visits, time in hospital, and pharmaceutical products. The fundamental output, however, is health – health status after treatment or change in health status. This output is usually measured by health indicators such as years of life or years of life adjusted by some kind of quality measure.

Table 1 shows basic descriptive statistics for the variables used in this study. The source of data is the Population Health Research Unit (PHRU) in Nova Scotia. It is important to note that the data are a sample containing only low-income, government-assisted patients. This sample selection was made in order to get drug information since it is for these patients that drugs would be funded by public bodies who can share that information provided patient anonymity is preserved. The data include treatment variables for one year (1997), vital statistics for five years (1997-2001), and underlying causes of death (if applicable) along with other conditions present at death (co-morbidity factors). The data is classified into three broad groups of continuous and dummy variables: socio-demographic characteristics, socio-economic factors, and clinical information.

TABLE 1 Summary Statistics for the Predictors [a]

Variable	Mean	Median	S.D	Min	Max	
***Age* (AGE)**	51.13	54.0	11.51	3.0	66.0	
***Gender* (GEN)**	0.586	1.0	0.493	0	1	(Female=1)
***Location* (LOC)**						
LOC1	0.025	0	0.157	0	1	Annapolis
LOC2	0.031	0	0.175	0	1	Antigonish
LOC3	0.145	0	0.352	0	1	Cape Breton
LOC4	0.056	0	0.231	0	1	Colchester
LOC5	0.063	0	0.243	0	1	Cumberland
LOC6	0.028	0	0.166	0	1	Digby
LOC7	0.028	0	0.166	0	1	Guysborough
LOC8	0.088	0	0.284	0	1	Halifax County
LOC9	0.037	0	0.191	0	1	Hants
LOC10	0.018	0	0.136	0	1	Inverness
LOC11	0.066	0	0.249	0	1	Kings
LOC12	0.069	0	0.254	0	1	Lunenburg
LOC13	0.041	0	0.198	0	1	Pictou
LOC14	0.025	0	0.157	0	1	Queens
LOC15	0.012	0	0.111	0	1	Richmond
LOC16	0.063	0	0.166	0	1	Shelburne
LOC17	0.034	0	0.111	0	1	Victoria
LOC18	0.063	0	0.243	0	1	Yarmouth
LOC20	0.034	0	0.183	0	1	Darmouth
LOC21	0.015	0	0.124	0	1	Sydney
***Malignant Cancer* (MALIG)**	0.914	0	0.279	0	1	
***Mental Condition* (MENTL)**	0.318	0	0.466	0	1	
***SIGNS* (SIGNS)**	0.692	0	0.460	0	1	
***Other Form of Cancer* (OTHCANC)**	0.422	0	0.494	0	1	
***Other Condition* (OTHRCOMP)**	0.974	0	0.157	0	1	
***Palliative Care* (PALLCARE)**	0.100	0	0.301	0	1	
***Chemotherapy* (CHMTHRPY)**	0.091	0	0.288	0	1	
***Radiation Therapy* (RDTNTHRPY)**	0.037	0	0.191	0	1	
***Admission to Hospital for Cancer Treatment* (HOSPCANC)**	0.526	1	0.500	0	1	
***Treatment with major Surgery* (MJRSRGRY)**	0.400	1	0.490	0	1	
***Household Average Annual Income* (AVGINC)**	17987.70	17019	2896.25	14214	22986	
***Household Education Level* (HSEDUCAT)**	0.678	0.663	0.075	0.466	0.788	

TABLE 1 contd.					
Household Unemployment Status **(UNEMPLY)**	0.126	0.104	0.054	0.072	0.342
Socio-Economic Status **Index (SES)**	0.930	0.853	0.295	0.431	1.428
Number of Doctor Visits for Cancer Related Reasons **(CDOCVIS)**	23.066	17.0	22.616	0	127.0
Number of Resource Intensity Weighted Days for Cancer Related Reasons **(CRIWDAY)**	37.991	2.981	100.717	0	831.514
Quantity of Cancer Related Drugs Received by Patient **(CDAYSUPP)**	70.571	0	132.246	0	760.0
Number of Doctor Visits for Non-Cancer Related Reasons **(NCDOCVIS)**	15.949	12.0	17.617	0	178.0
Number of Resource Intensity Weighted Days for Non-Cancer Related Reasons **(NCRIWDAY)**	8.851	0.002	31.474	0.004	374.08
Quantity of Non-Cancer Related Drugs Received by Patient **(NCDAYSUPP)**	240.230	120	307.687	0	1694.0
Estimated Efficiency Scores from DEA (EFF300)	0.226	0.09	0.295	0	1

[a] S.D. is standard deviation.

The socio-demographic set of variables is comprised of age (**AGE**), gender (**GEN**), and residential region where patient resides (**LOC**). The socio-economic factors include (for the residential region of each patient) household average annual income (**INC**), average level of education (**EDU**) and employment market condition (**EMP**). We combined the collected information related to the socio-economic factors and constructed a new predictor, an index of socio-economic status (**SES**), which was incorporated into the model.[4] The SES index is comprised of average county income, county secondary education completion rate, and one minus the county unemployment rate (the latter were collected from Statistics Canada). The SES index was built by normalizing each variable and then multiplying the normalized variables together for each observation.

The clinical information consists of 10 indicator or dummy variables and six continuous variables. The dummy variables include an indicator if the patient was diagnosed with a malignant cancer (**MALIG**); a mental condition (**MENTL**); a sign, symptom, or other unspecified condition (**SIGNS**); another form of cancer (**OTHCANC**); or any other remaining complicating factor (**OTHRCOMP**). Other clinical dummy variables indicate whether a patient was admitted for palliative care (**PALLCARE**), treated with chemotherapy (**CHMTHRPY**); or radiation therapy (**RDTNTHRPY**), admitted to hospital for cancer treatment (**HOSPCANC**), and treated with major surgery (**MJRSRGRY**). The continuous variables of the clinical information category-group used in the model include the number of doctor visits given to a patient for cancer-related reasons (**CDOCVIS**), the number of resource-intensity-weighted days spent in hospital by

[4] Health outcomes can be affected by socio-economic status in a variety of ways including its effect on access to health care. For a discussion of this impact in Canada, see Curtis and MacMinn (2008).

patient for cancer-related reasons (**CRIWDAY**), the quantity of cancer-related drugs received by patient (**CDAYSUPP**), the number of doctor visits given to a patient for non-cancer related reasons (**NCDOCVIS**), the number of resource-intensity-weighted days spent in hospital by patient for non-cancer related reasons (**NCRIWDAY**), and the quantity of non-cancer related drugs received by patient (**NCDAYSUPP**).

First, we perform data envelopment analysis to generate a technical efficiency score for patients, using "weeks of survival" as the output and the various health care system variables as inputs. The computed efficiency score is expressed in percentage terms relative to the most efficient overall patient treatment. The efficiency score (**EFF300**) is subsequently included in the econometric estimates as an additional independent variable. The variables and information used for the DEA computation are found in the Appendix.

Table 1 shows that the average quantity ("days prescribed") of cancer-related drugs received by a patient is 70.57, whereas the same figure for non-cancer-related drugs is 240.23. There is considerable variation in the strength and chemical composition of these drugs, so our summary measure is not especially informative insofar as it reveals a relatively high use, on average, of pharmaceutical products not specifically prescribed for cancer treatment.

Empirical Results

The goal of this analysis is to identify the determinants of the probability of cancer patient survival and to investigate the effect of *the level of treatment inputs* (e.g., physician visits, hospital procedures, drugs) and the influence of *how treatment inputs are combined* (through the treatment efficiency or EFF300 variable). We briefly discuss both probit and ordered probit specifications to compare the effects of other potentially important determinants of patient survival, such as geographic factors or socio-economic conditions. We also discuss the robustness of these results, particularly with respect to the effect of level and combination of treatment inputs on survival.

The base set of probit and ordered probit models that were estimated using STATA 7.0 and are shown in Tables 2 and 3. Along with the estimated parameters, the tables also include the computed marginal effect (ME) of each coefficient, which measures the impact of a unit change in each of the predictors on the probability of a success, i.e. the probability that a patient would survive after five years.

Binary Probit Estimates

Table 2 lists the parameter estimates of the base probit model in which the county effects and the division of variables into "cancer-related" and "non-cancer related" components are not taken into account. The likelihood ratio (LR) statistic test for this model was 129.49, rejecting the null hypothesis that all slope coefficients are zero at the 0.01 level of significance. The pseudo *R*-squared measure was 0.295, and is reasonable for models with cross sectional data. We see that AGE, MALIG, SIGNS, PALLCARE, HOSPCANC, and MJRSRGRY are statistically significant at the 99% level, while AGE and MALIG have the expected negative effects on patient survival. Since palliative care is associated with

lowered survival, this effect is likely due to some form of selection bias - patients judged to be in the terminal stages of their disease are entered into palliative treatment. Radiation treatment is also associated with reduced survival but whether this result arises because only those patients who are unlikely to survive for much longer receive this treatment or because this treatment is, ceteris paribus, harmful, cannot be determined from this data set. The variable related to the treatment with chemotherapy (CHMTHRPY) and the number of doctor's visits (DOCVIS), in general, are both statistically significant with 95% confidence.

TABLE 2 Base Probit model, Estimation Results [a]

Variable	Estimate (*p*-value)	Marginal Effects (*p*-value)
Constant	2.5743 (0.0000)	----
AGE ***	-0.0233 (0.0020)	-0.0091 (0.0020)
GEN	0.2101 (0.2300)	0.0824 (0.2260)
MALIG ***	-1.1076 (0.0040)	-0.4033 (0.0000)
OTHCANC *	0.3268 (0.0970)	0.1286 (0.0940)
MENTL	0.2522 (0.1650)	0.0997 (0.1650)
SIGNS ***	-0.4820 (0.0140)	-0.1900 (0.0130)
OTHRCOMP	0.3496 (0.5110)	0.1317 (0.4830)
PALLCARE ***	-2.3581 (0.0010)	-0.5207 (0.0000)
CHMTHRPY **	0.6105 (0.0460)	0.2388 (0.0350)
RDTNTHRPY *	-1.1091 (0.0800)	-0.3436 (0.0050)
HOSPCANC ***	-0.8823 (0.0000)	-0.3380 (0.0000)
MJRSRGRY ***	0.7558 (0.0010)	0.2935 (0.0000)
DOCVIS **	-0.0091 (0.0220)	-0.0036 (0.0220)
RIWDAY	-0.0014 (0.1620)	-0.0005 (0.1620)
DAYSUPP	-0.0001 (0.4410)	-0.00007 (0.4410)
Number of observations 317		
McFadden R-squared 0.2947		
Likelihood ratio statistic 129.49		
Degrees of freedom 15		
Prob [ChiSqd > value] 0.0000		

[a] Base probit model, without county effects and no division of variables into cancer-related and non cancer-related.

* Significant at 0.10, ** Significant at 0.05, *** Significant at 0.01.

We estimated a number of binary probit models, including or removing variables to uncover either locational, individual or treatment effects. Specially, we observed that county effects (relative to the city of Halifax) are generally positive or insignificantly different from zero. This suggests that the city of Halifax is either the least healthy location in the province or that patients with cancer tend to settle in the capital, possibly to be close to treatment centres. Otherwise, our results imply that cancer mortality rates do not differ widely across the province, especially since most of the treatments are performed in a single location, i.e., the city of Halifax. We infer that "how you live" seems to matter more than "where you live" and "how your cancer is treated" may matter still more.

Binary probit estimates also show that the incorporation of the EFF300 variable into the specification plays a significant role in determining the probability of survival. The marginal effect of this variable remains stable at around 0.01 (ranging from 0.011 to 0.013)

over several specification changes, lending some credibility to its overall importance. We also found consistently across these specifications that several other variables possessed coefficients significantly different from zero, suggesting there is more to cancer survival likelihood than just treatment.

Ordered probit estimates

Next we estimated a set of ordered probit models on patient survival. The base model is shown in Table 3. The estimated models included county effects, treatment efficiency scores from DEA, and a division of variables into cancer-related and non-cancer-related. A likelihood ratio (*LR*) test on the base model allowed us to test the overall significance of the independent variables chosen for the base estimation. This yielded the following test statistic:

$$LR = -2\left(LogL_R - LogL_{UR}\right) = -2\left[-444.98206 - \left(-302.12144\right)\right] = 285.72$$

with 39 degrees of freedom. The *LR* test statistic rejects the null hypothesis that all slope coefficients in the model are statistically equal to zero with 99 per cent confidence. In addition, the McFadden *R*-squared measure of fit in this instance (also known as Pesudo-R^2) is 0.32.

Overall, we found that the variables AGE, PALLCARE, HOSPCANC, MJRSRGRY, EFF300, and NCDAYSUPP are statistically significant at the 0.01 level. Other variables whose estimated parameters are statistically different from zero with 95% confidence are MALIG, MENTL, RDTNTHRPY, and CDOCVIS. In addition, estimated threshold parameters for the ordered probit indicate some dispersion of cancer treatments across the patients in our sample.

The ordered probit estimates indicate that as a patient gets older, *ceteris paribus*, their overall chances of survival increase up to the fourth year, and then decrease in the final sample year. As a patient moved toward the last three years of treatment, the likelihood of survival from cancer was increased for those patients who were not admitted for palliative care. In fact, a patient who was not admitted for palliative care had, on average, a better than 20% chance of being cancer-free, *ceteris paribus*, when compared to a patient who had been admitted for palliative care.

We found other interesting relationships. For example, patients who were co-diagnosed with mental illness on average had a 2 percent less chance of survival in the last year of treatment. This inverse relationship between the probability of survival and mental condition was observed throughout the entire period of the study. We also found that radiation therapy was a useful method of treatment for the last three years of the sample (marginal effects of RDTNTHRPY were all positive). We estimate that a patient who had been treated with radiation therapy, on average, had about a 9 percent greater chance of survival in the fifth year when compared to a patient who had not been treated in this way. Finally, we found that the marginal effects of MJRSRGRY were negative for each period of the study with the exception of the starting time for treatment. If a patient had major surgery during his/her cancer treatment, there was a reduced likelihood that they survived after five years.

TABLE 3 Base Ordered Probit Model, Estimation Results [a]

Variable	Estimate (*p*-value)	Variable	Estimate (*p*-value)
AGE ***	0.0225 (0.0020)	**MALIG** **	1.0681 (0.0170)
GEN	-0.2324 (0.1510)	**OTHCANC** *	-0.2947 (0.1010)
LOC1	0.1260 (0.8180)	**MENTL** **	-0.4034 (0.0250)
LOC2	-0.6392 (0.1880)	**SIGNS**	0.0816 (0.6740)
LOC3	-0.3918 (0.1870)	**OTHRCOMP**	-0.4050 (0.4920)
LOC4	-0.1370 (0.7210)	**PALLCARE** ***	1.3993 (0.0000)
LOC5	-0.0401 (0.9120)	**CHMTHRPY** *	-0.5247 (0.0710)
LOC6	-0.0452 (0.9210)	**RDTNTHRPY** **	0.7951 (0.0390)
LOC7	-0.3796 (0.5090)	**HOSPCANC** ***	0.5169 (0.0120)
LOC8	-0.2917 (0.3940)	**MJRSRGRY** ***	-0.8447 (0.0000)
LOC9	*0.6158 (0.1590)*	*CDOCVIS* **	*0.0098 (0.0480)*
LOC10	*-0.4844 (0.4240)*	*CRIWDAY*	*0.0009 (0.2200)*
LOC11	-0.0671 (0.8560)	**CDAYSUPP**	-0.0006 (0.3150)
LOC12	-0.4157 (0.2060)	**NCDOCVIS**	-0.0060 (0.2730)
LOC13	0.2057 (0.6380)	**NCRIWDAY**	0.0039 (0.1690)
LOC14	0.7408 (0.1280)	**NCDAYSUPP** ***	-0.0008 (0.0020)
LOC15	-0.5806 (0.4550)	**EFF300** ***	-0.0415 (0.0000)
LOC16	*-0.5554 (0.2660)*		
LOC17	-1.0307 (0.1590)		
LOC18	-0.3511 (0.3340)		
LOC20	-0.4723 (0.4690)		
LOC21	-0.6034 (0.3970)		
Ancillary parameters [b]**:**			
-cut1	0.37512 (0.8148)		
-cut2	0.54958 (0.8159)		
-cut3	0.76996 (0.8168)		
-cut4	1.15308 (0.8180)		
-cut5	2.33520 (0.8208)		

Iteration 0: log likelihood	-444.98206	Number of observations	317
Iteration 1: log likelihood	-318.51548	Log likelihood	-302.12144
Iteration 2: log likelihood	-303.85429	Likelihood ratio statistic	285.72
Iteration 3: log likelihood	-302.16124	Degrees of freedom	39
Iteration 4: log likelihood	-302.12146	McFadden R^2	0.3210
Iteration 5: log likelihood	-302.12144	Prob [ChiSqd > value]	0.0000

[a] Ordered probit model with county effects, division of variables into cancer-related and non cancer-related, and the estimated efficiency scores from DEA.
[b] Figures in parentheses are standard errors.
* Significant at 0.10, ** Significant at 0.05, *** Significant at 0.01.

Looking at the results from a broader policy perspective, we offer that this analysis demonstrates the value of additional detailed information about patient characteristics in the study of health care policy. Such information is essential in order to accurately inform comparative analysis of treatment efficiency in the public healthcare system. Given the significance of the various patient level factors found using this detailed dataset, we

conclude that the traditional method of computing treatment efficiencies over medical inputs used in the production of additional life years is flawed.

Our results are not an artefact of model specification either. If we interpret the similarities across both the probit and ordered probit formulations of our health care efficiency model in the context of policy, we can also conclude that it is not possible to distinguish between "bad treatment" and "acceptable treatment of severe conditions" on the basis of the type of information or data available to policy-makers in the Canadian health care system. In sum, our estimates indicate that since inter-hospital or inter-regional differences in patient population (severity of illness, other health complications, etc.) are important to the likelihood of survival, then prior analyses using the hospital as the decision-making unit while not accounting for inherent differences in the patient population have generated outcomes and interpretations detrimental to effective health policy formulation in Canada.

Discussion and Conclusions

As a sample, we have no reason to believe that our data set on cancer patients is biased in any way so it is very likely representative of many health care regions all across Canada. Using an econometric specification more appropriate to the analysis of patient survival and health care efficiency, we find that inter-hospital or inter-regional differences in patient population (e.g. severity of illness and other health complications …) are significantly related to cancer patient survival. Critically, this implies comparative health care studies that use the aggregate notion of the "hospital" as the health decision-making unit (while not accounting for inherent differences in patient population) will yield results and recommendations that are not suitable as a basis for health policy formulation.[5]

The most critical task for future research will be the development of more comprehensive databases that need to include, inter alia, improved measures of "severity" of health condition prior to the receipt of treatment.[6] We also find evidence that factors other than health care inputs are also very important to changes in individual health status. For comparative policy analysis, it would be worth collecting detailed information about those patient characteristics to help determine past, current, and future health status. From an economists' perspective, such information would best be captured in a variable measuring socio-economic status. If decision-makers cannot distinguish between "bad (or inefficient) care" and "acceptable care for severe health conditions", finding an optimized allocation of scarce health care resources is rendered more difficult.[7] Therefore it would be

[5] Note that the use of measures that partially reflect patient condition insofar as that is related to diagnosis — such as case-mix groups, diagnosis-related groups, and hospital resource-intensity-weights — goes only partway to resolving this problem. None of these groupings are *uniquely* dependent on the condition of a specific patient which we conclude is essential to the evaluation of the efficiency of the treatment provided to that patient.

[6] There have been many calls for improved health outcomes data. See, for example, Sharpe et al (2007).

[7] This conclusion parallels an observation from McKay and Deily (2008) who emphasize "the importance of distinguishing between 'good' costs that reflect the efficient use of resources and 'bad' costs that stem from waste and other forms of inefficiency" and assert that "hospital programs focused on reducing cost inefficiency are unlikely to be associated with worsened hospital-level mortality or complications rates,

worth the effort to identify certain output characteristics at the patient level (e.g. severity) to help manage public health care allocations.[8] Policy work using this type of data will hopefully bring an end to "fire-extinguisher" health care financing in Canada in which policy-makers, alerted by the news media to a "fire" or problem in the health care sector, disperse scarce health care funds towards the problem until the problem goes away or, at least, until the media lose interest in the story.

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while, on the other hand, across-the-board reductions in cost could well have adverse consequences on health outcomes by reducing efficient as well as inefficient costs." We wish to emphasize here that to make the distinction between efficient and inefficient costs a decision-maker requires sufficient information on health outcomes.

[8] In contrast, for some interesting examples of issues that may arise when attempting to use current (and possibly unsuitable) measures of health status and outcomes (proxied by DRGs or case-mix groupings) as the basis for funding allocation decisions, see Dismuke and Sena (1998), Brock et al (2007), and Sutherland and Walker (2008).

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Appendix

Data used for DEA

ID	Identification number of Decision-making-unit, an individual oncology patient
Output	Number of weeks survived by a patient, from 0 to 260
Docvis	Total number of doctor visits a DMU received
Riwday	Total resource intensity weighted (RIW) days spent in hospital by DMU
Daysupp	Total days supply of drugs received by DMU

Italicized variables can be separated as follows:

Ncdocvis	Number of doctor visits excluding those related to cancer
Ncriwday	Number of RIW hospital days excluding those related to cancer
ncdaysupp	Days supply of non-cancer related drugs received
cdocvis	Number of doctor visits pertaining only to cancer
criwday	Number of cancer-related RIW days spent in hospital
cdaysupp	Days supply of cancer drugs received

cdaysupp was further separated into:

canrx1	Group of cancer-treating drugs related to calcium levels and bone cancer
canrx2	Group of cancer-treating drugs that inhibit the production of one or more hormones
canrx3	Group of cancer-treating drugs referred to as Anti-metabolites
canrx4	Group of cancer-treating drugs referred to as Alkylating Agents
canrx5	Hormone drugs used to treat cancer

Note: the outcome from the DEA is the EFF300 variable (DEA efficiency score * 100)