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Impact of Specialization on Health Outcomes - Evidence from U.S. Cancer Data

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Abstract

There have been many studies of the volume-outcome relationship. In all of these, the unit of analysis is the hospital or physician. However, this level of analysis is mostly limited to the use of in-hospital mortality rates and is particularly sensitive to selective referral. Moreover, the literature on agglomeration economies highlights the importance of information spillovers within regions (Glaeser, 2010). To overcome these problems, our study is the first that examines the volume-outcome relationship on a regional (county or cancer registry) level. Using data from the National Cancer Institute's Surveillance, Epidemiology and End Results program we find that regions with relatively more of the same cancer type exhibit relatively better health outcomes.

Keywords: Specialization, experience, cancer, survival

JEL classification: I12

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1 Introduction and motivation

The positive relationship between volume and outcome is confirmed for a wide variety of different procedures, time periods, and locations (Luft et al., 1979, Gillis and Hole, 1996, Begg et al., 1998, Birkmeyer et al., 2002, Birkmeyer et al., 2003, Allgood and Bachman, 2006, and Barocas et al., 2010; for a review see Halm et al., 2002) and has led to important health policy guidelines such as using minimum volume requirements as a quality indicator (Sfekas, 2009). In all these studies, the unit of analysis is the hospital or physician. However, this level of analysis is mostly limited to the use of in-hospital mortality rates and is particularly sensitive to selective referral. Moreover, the literature on agglomeration economies highlights the importance of information spillovers within regions (Glaeser, 2010).

Information spillovers are especially important in health care where physicians' learning about new techniques and procedures occur from direct contact with other physicians. Coleman et al. [1957] were among the first who find that doctors being integrated in the community of their collegues are the first to adopt new drugs. On the regional level Baicker and Chandra [2010] show that hospitals surrounded by higher quality hospitals improve in quality. Information spillovers become even more relevant for the treatment of complex diseases such as cancer, where several doctors from different institutions can be involved in the treatment process[1]. This makes it difficult to attribute improved outcomes to a specific institution (Chandra and Staiger, 2007). If information spillovers (e.g. between physicians and hospitals) are important, the physician or hospital is not the appropriate unit of analysis for studying the volume-outcome relationship - it is too narrow.

To overcome these problems our study examines the volume-outcome relationship on a regional (county or registry) level. While this level of analysis does not only capture information spillovers it is also less sensitive to selective referral. Using data from the National Cancer Institute's Surveillance, Epidemiology and End Results program (SEER), we analyze whether more cancer-specific knowledge in a given region leads to relatively higher survival rates compared to regions with less cancer-specific knowledge.

The paper is structured as follows. Section 2 presents a simple model of cancer survival. Section 3 is devoted to the econometric specification of the model and the data source. The estimation results are presented in Section 4. Section 5 concludes.

[1] E.g. it is common for patients to be diagnosed in one facility, receive surgery in a second one, have radiation and chemotherapy in yet another facility, and receive postoperative care in an outpatient setting (Hoelscher, 2001)

2 A simple model of cancer survival

The literature distinguishes three different types of survival rates (see e.g. Horner et al., 2008). The observed survival rate (S) is the probability of surviving all causes of death for a specified time after diagnosis of cancer. It considers deaths from all causes, cancer or otherwise. The expected survival rate (E) is the survival rate of a comparable set of people who do not have cancer. In turn, the relative survival rate (R) is defined as the ratio of the proportion of observed survivors (of all causes of death) in a cohort of cancer patients to the proportion of expected survivors in a comparable cohort of cancer-free individuals, S/E. For cancer survival, epidemiologists estimate the relative survival rate since it controls for survival gains from other diseases besides cancer.

The following model is based on Lichtenberg [2007b] and explains the survival rate as a function of different input factors. We assume that the relative survival rate in year 2002 depends on the treatment quality and the disease progression at time of diagnosis, ω:

$$R_{ir} = S_{ir}/E_{ir} = f_1(Q_{ir}, P_{ir\omega}) \tag{1}$$

or

$$S_{ir} = f_2(E_{ir}, Q_{ir}, P_{ir\omega}) \tag{2}$$

with,

- R_{ir}: The relative survival rate for cancer originating at site[2] i in region r in 2002
- S_{ir}: The observed survival rate for cancer at site i in region r in 2002
- E_r: The expected survival rate of the control group in region r in 2002
- Q_{ir}: Treatment quality for cancer at site i in region r
- $P_{ir\omega}$: Disease progression of cancer at site i in region r at time of diagnosis ω

The observed survival rate is hypothesized to be an increasing function of the quality of treatment ($\frac{\partial f_2(\cdot)}{\partial Q_{ir}} > 0$) and the expected survival rate ($\frac{\partial f_2(\cdot)}{\partial E_{ir}} > 0$) and a decreasing function of disease progression at time of diagnosis ($\frac{\partial f_2(\cdot)}{\partial P_{ir\omega}} < 0$).

Quality in health care is hard to define and quantify (see Donabedian, 1988). Lichtenberg [2007a] uses treatment vintage to measure treatment quality.[3] However, treatment quality is

[2] Site specifies the part of the body where the cancer originates, (e.g. breast colon, etc).
[3] The vintage of a treatment is the year in which a new treatment was first used.

also a function of knowledge and experience. According to Birkmeyer et al. [2002] low volume hospitals with less than 3 pancreatic resections per year report a 11 percent higher mortality rate than high volume hospitals with more than 16 cases.[4] In our study we consider two mechanisms in which it is thought that practice makes perfect. We distinguish between learning from recent experience (denoted with N_{irt-1} and N_{irt-2}) and learning from cumulative experience (denoted with $\sum_{t=1992}^{2002} N_{irt}$), where N_{irt} is the number of patients diagnosed with cancer at site i in region r in year t. Further, we include the current number of patients diagnosed with cancer at site i in region r, N_{irt}. This variable captures possible economies of scale and specialization effects. We assume that treatment quality for $t = 2002$ and cancer site i in region r is an increasing function of recent experience, cumulative experience, and current volume:

$$Q_{ir2002} = f_3(N_{ir2001}, N_{ir2000}, \sum_{t=1992}^{2002} N_{irt}, N_{irt}) \tag{3}$$

Substituting Eq. 3 into Eq. 2:

$$S_{ir} = f_2(E_{ir}, P_{ir\omega}, N_{ir2001}, N_{ir2000}, \sum_{t=1992}^{2002} N_{irt}, N_{irt}). \tag{4}$$

This leads to the fowllowing hypotheses to be tested empirically in Section 4:

H1: What is the impact of experience on cancer survival rates?

H2: What is the impact of current volume on cancer survival rates?

H3: What is the relative impact of experience and current volume on cancer survival rates?

H4: Are the results sensitive to the definition of the geographical area?

3 Econometric Model and Data

Based on Section 2 we estimate the following model:

$$\begin{aligned} f(S_{ir2002}) \quad = \quad & \beta_1 N_{ir2002} + \beta_2 N_{ir2001} + \beta_3 N_{ir2000} + \beta_4 \sum_{t=1992}^{2002} N_{irt} + \beta_5 E_{r2002} \\ & + \beta_6 LOC_{ir2002} + \beta_7 DIST_{ir2002} + \beta_8 SURG_{ir2002} + \beta_9 RAD_{ir2002} + a_i + d_r + \epsilon_{ir} \end{aligned} \tag{5}$$

where

[4] In a follow-up study similar results are found on the level of physicians Birkmeyer et al., 2003.

- i: Cancer site; r: Place of diagnosis (cancer registry or county).
- S_{ir2002}: Observed survival rate for cancer at site i in region r in 2002.
- N_{ir2002}: The number of people diagnosed with cancer at site i in region r in 2002. Since we include fixed site and region effects (see below) the variable measures whether cancers at site i are more abundant in regions r than on average. Economies of scale have been found to be the largest determinant of health outcomes assessed at the hospital level (Gaynor et al., 2005). Ho [2002] and Huesch and Sakakibara [2009] also find that higher volumes induce standardization of procedures leading to improved treatment processes. Thus, we believe that the higher the extent of the market, indicated by N_{irt}, the higher the scope for specialization and the higher the survival rate is likely to be.
- N_{irt-1} and N_{irt-2}: Following Gaynor et al. [2005] and Ho [2002] we use the number of people diagnosed with cancer at site i in region r in 2001 and 2002 as a proxy for recent experience. This mechanism assumes that a provider's own recent experience is more important in driving performance than more distant experience or cumulative experience. It is implicitly assumed that the stock of skills degrades quickly (Huckman and Pisano, 2006).
- $\sum_{t=1992}^{2002} N_{irt}$: The cumulative number of people diagnosed with cancer at site i in region r between 1992 and 2002. The more traditional 'learning-from-cumulative-experience' mechanism assumes instead that the stock of historically acquired experience continues to positively impact current health outcomes (Huesch and Sakakibara, 2009).
- E_{r2002}: Expected survival rate of the control group in region r in 2002. This variable controls for all factors that influence survival in general (e.g. gender, age, and race) but that are not related to cancer treatment. We should observe a positive impact.

The next four variables indicate by how much the cancer has spread and are used as a measure of mean progression of disease.

- LOC_{ir2002}: Share of cancer stage I or II for cancer at site i in region r in 2002. In stage I and II cancers are localized to one part of the body. The higher the share of cancers in stage I or II, the higher the survival rate is likely to be.
- $DIST_{ir2002}$: Share of cancer stage IV for cancer site at i in region r in 2002. In stage IV cancers have often metastasized, spread to other organs, or spread throughout the whole

body. The higher the share of cancers in stage IV, the lower the survival rate is likely to be.

- $SURG_{ir2002}$: Share of patients receiving surgery for cancer at site i in region r in 2002. When a surgery is performed as a primary treatment, chances are high for cure, especially if the cancer is localized and has not spread. However, a surgery can also be performed in order to remove as much as possible of the tumor in order to make chemotherapy or radiation more effective or to just improve the quality of life. Unfortunately we only know whether a surgery was carried out or not.

- RAD_{ir2002}: Share of patients receiving radiation for cancer at site i in region r. Radiotherapy may be used as therapeutic treatment where the therapy has survival benefit or as palliative treatment where cure is not possible anymore.

- a_i: Fixed effect for cancer site i

- d_r: Fixed effect for region r

- ϵ_{ir}: Error term

Data are obtained from the National Cancer Institute's Surveillance, Epidemiology, and End Results (SEER) program. It contains information from population-based cancer registries[5] covering approximately 26 percent of the US population. Since 1973, SEER program registries[6] have collected data on patient demographics, primary tumor site, tumor morphology and stage at diagnosis, first course of treatment, and follow-up for vital status. The variable of interest in our study is the survival rate. Survival rates may be calculated for different time intervals. To assess treatment effects for cancer the literature usually refers to 5-year survival rates. In addition we also estimate models for the 1-, 2-, 3-, and 4-year survival rate.

For the purpose of our analyis we group each individual-based cancer record according to region and aggregated cancer site. SEER provides two different geographical identifiers (unfortunately not the hospital). We will use both, the registry and the county identifier, for the estimation.

[5] Cancer registries are a systematic collection of data about cancer and tumor diseases. The geographic area of one SEER registry corresponds to approximately one U.S. state, except for the Californian registries, Seattle, rural Georgia, Atlanta, and Detroit.

[6] San Francisco-Oakland (since 1973), Connecticut (1973), Detroit (1973), Hawaii (1973), Iowa (1973), New Mexico (1973), Utah (1973), Seattle (1974), Atlanta (1975), Alaska (1992), San-Jose Monterey (1992), Los Angeles (1992), Rural Georgia (1992), remaining California (2000), Kentucky (2000), Louisiana (2000-2004), and New Jersey (2000).

Table 1: Summary statistics (registry and county level, aggregated sites) 2002

	registry				county			
Variable	Mean	sd	Min	Max	Mean	sd	Min	Max
1-year observed survival	0.78	0.18	0	1	0.78	0.26	0	1
2-year observed survival	0.70	0.21	0	1	0.69	0.30	0	1
3-year observed survival	0.65	0.22	0	1	0.65	0.31	0	1
4-year observed survival	0.61	0.22	0	1	0.61	0.32	0	1
5-year observed survival	0.58	0.23	0	1	0.58	0.32	0	1
1-year expected survival	0.98	0.01	0.95	1	0.97	0.02	0.79	1
2-yearexpected survival	0.95	0.02	0.91	1	0.94	0.04	0.61	1
3-year expected survival	0.93	0.03	0.85	1	0.92	0.06	0.46	1
4-year expected survival	0.91	0.04	0.80	1	0.89	0.07	0.34	1
5-year expected survival	0.88	0.05	0.75	0.99	0.86	0.09	0.24	1
N_{2002}	1,016	1,708	0	11,417	33	111	0	1904
N_{2001}	1,011	1,690	0	11,144	33	111	0	1,744
N_{2000}	990	1,658	0	10,919	32	109	0	1,821
LOC	0.53	0.38	0	1	0.51	0.41	0	1
DIST	0.24	0.32	0	1	0.24	0.34	0	1
SURG	0.60	0.31	0	1	0.60	0.36	0	1
RAD	0.30	0.20	0	1	0.28	0.28	0	1
max Observations	272							7,520

Note: The survival rates are weighted by N_{ir}.

Table 1 contains the summary statistics separately for the registry and county level according to aggregated sites.[7] In total we are left with 272 observations at the registry level, and 7,520 at the county level. Survival rates are weighted by the number of people diagnosed, N_{ir2000}. Chances of surviving cancer one year, three years, and five years after diagnosis are 78 percent, 65 percent, and 58 percent respectively. The differences between survival rates across registries are up to 23 percentage points and even higher across counties (32 percentage points).

Table 2 shows the number of people diagnosed according to SEER registry and aggregated cancer site. Ideally we would have information on the place where the diagnosed patient receives its treatment, however, this is not available in the SEER data.

There are two low volume registries, viz. Alaska and Rural Georgia with 260 and 509 cases respectively and three high volume registries with above 20,000 cases, viz. Los Angeles (29,232), New Jersey (38,172), and greater California (63,147). The cancers less common are at site eye and orbit (528) and bones and joint (659). In contrast, most common cancers are at site male genital system (51,864), digestive system (51,508), and breast (43,020).

[7] In this study we use the 16 aggregated (to broad sites, following the National Cancer Institute) sites based on the international classification of diseases for oncology, 3rd edition.

Table 2: Number of diagnoses according to registry and aggregated site, 2002

Registry	0	1	2	3	4	5	6	7	8
San Francisco	371	2,891	1,924	34	101	582	2,677	920	2,843
Conneticut	304	3,020	2,216	33	104	649	2,395	901	2,809
Metropolitan Detroit	390	3,081	2,632	33	107	674	2,415	1,018	3,723
Hawaii	136	1,088	582	11	33	190	779	293	677
Iowa	289	2,480	1,802	22	66	541	1,911	744	2,116
New Mexico	143	1,111	770	16	45	293	960	391	1,223
Seattle Puget-Sound	370	2,696	2,188	33	80	842	2,773	947	2,911
Utah	129	978	424	16	41	351	891	367	1,425
Metropolitan Atlanta	233	1,474	1,170	24	78	537	1520	515	1,778
San Jose Monterey	166	1,374	831	16	61	316	1,222	434	1,434
Los Angeles	653	5,864	3,393	83	201	1,150	4,804	2,019	5,432
Alaska	5	86	47	3	3	1	41	7	27
Rural Georgia	19	97	93	4	2	14	76	27	91
Greater California[1]	1,488	11,372	8,664	166	444	3,425	10,218	3,656	11,417
Kentucky	424	3,200	3,764	44	104	735	2,454	974	2,749
Louisiana	442	3,516	3,012	41	114	477	2,472	933	3,372
New Jersey	726	7,180	5,133	80	240	1,622	5,412	2,391	7,837
total	6,288	51,508	38,645	659	1,824	12,399	43,020	16,537	51,864
Registry	9	10	11	12	13	14	15		total
San Francisco	923	29	227	321	797	168	376		15,184
Conneticut	1,160	25	219	319	759	197	386		15,496
Metropolitan Detroit	1,201	29	250	329	794	238	452		17,366
Hawaii	250	1	47	129	194	45	101		4,556
Iowa	943	27	201	262	648	147	429		12,628
New Mexico	411	8	92	211	264	88	205		6,231
Seattle Puget-Sound	1,099	35	268	362	842	180	441		16,067
Utah	326	14	128	235	329	70	211		5,935
Metropolitan Atlanta	478	15	149	253	438	117	206		8,985
San Jose Monterey	442	19	114	163	415	89	211		7,307
Los Angeles	1,770	66	447	747	1,451	339	813		29,232
Alaska	11	0	4	7	6	4	8		260
Rural Georgia	36	1	3	8	21	9	8		509
Greater California[1]	4,246	131	1,053	1,277	3,081	721	1,788		63,147
Kentucky	1,235	41	248	284	837	217	414		17,724
Louisiana	1,243	23	219	335	757	261	457		17,674
New Jersey	2,782	64	506	936	1,806	472	985		38,172
total	18,556	528	4,175	6,178	13,439	3,362	7,491		27,6473

Note: 0: Oral cavity, 1: Digestive System, 2: Respiratory System, 3: Bones and Joints, 4: Soft tissue incl. heart, 5: Skin excl. basal and squamous, 6: Breast, 7: Female genital system, 8: Male genital system, 9: Urinary system, 10: Eye and orbit system, 11: Brain, 12: Endocrine System, 13: Lympoma, 14: Myeloma, 15: Leukemia. [1]: Excluding San Francisco, Los Angeles, and San Jose Monterey.

The aim of our analysis is to estimate the relationship between S_{ir}, the proportion survived, and the exogenous factors, X. As a first attempt, we will formulate the model as a linear logistic regression of S_{ir} on X, that is we will take the logit of S_{ir} and represent the response curve as a straight line:

$$ln(\frac{S_{ir}}{1 - Sir}) = \gamma_0 + \gamma_1 X \tag{6}$$

However, since we grouped the data (according to region and aggregated site) and these groups differ in terms of size it is not possible to use a standard logistic regression to fit the model. Thus, eq.5 is estimated using a GLM model with a logit link function and a binomial distribution function where the denominator is the number of diagnoses (see Stata, 2007). To control for disease and regional specific characteristics we include fixed effects for cancer site i and region r. A significant coefficient for the variable N_{ir2002} would then imply that the ratio of the odds of surviving from cancer at site B to the odds of surviving from cancer at site A is positively correlated, across regions, with the ratio of the number of patients diagnosed with cancer at site B to the number of patients diagnosed with cancer at site A (ceteris paribus, generalized to i cancer sites).

4 Estimation results

Table 3 contains the estimation results for the five different survival intervals. The standard errors are in parentheses and clustered according to each registry since observations within registries are possibly correlated (see Bertrand et al., 2002).

The coefficient for current volume is significant for all five survival intervals. Whereas recent experience is only weakly significant for the 1-year survival interval. Cumulative experience is not significant in all specifications. The value of the expected survival rate (remember this is the survival rate of a comparable set of people not having cancer) is only significant for the 4-, and 5-year survival rates, but has the expected positive sign in all specifications (except for the 1-year survival rate). The progression rate of cancer is especially important for survival when cancer belongs to the distant category. Metastasized cancer reduces survival chances considerably from the 2-year survival interval onwards. An important determinant for all survival intervals is the variable surgery whereas the variable radiation is only significant from the 3-year survival interval onwards.

Table 3: Estimation results (registry level), 2002

	Coefficients for (t)-year survival rates				
	(1)	(2)	(3)	(4)	(5)
$\ln N_{2002}$	0.400**	0.331**	0.381**	0.367**	0.435***
	(0.194)	(0.165)	(0.154)	(0.159)	(0.148)
$\ln N_{2001}$	-0.236*	-0.0846	-0.115	-0.198	-0.186
	(0.137)	(0.143)	(0.148)	(0.139)	(0.148)
$\ln N_{2000}$	-0.215	-0.231	-0.241	-0.183	-0.173
	(0.196)	(0.197)	(0.170)	(0.150)	(0.151)
$\sum_{t=1992}^{2002} N_t$	0.200	0.101	0.100	0.128	0.0162
	(0.231)	(0.284)	(0.272)	(0.214)	(0.222)
$\ln E_t$	-0.151	1.740	1.603*	1.937**	2.365***
	(3.657)	(1.383)	(0.967)	(0.825)	(0.628)
LOC	0.411	0.114	0.444	0.500	0.548
	(0.709)	(0.584)	(0.536)	(0.526)	(0.470)
DIST	-1.030	-1.464**	-1.588***	-1.793***	-1.730***
	(0.683)	(0.573)	(0.545)	(0.464)	(0.379)
SURG	1.010***	0.816***	0.732***	0.664***	0.587***
	(0.228)	(0.178)	(0.143)	(0.141)	(0.134)
RAD	0.219	0.333	0.431**	0.465***	0.373***
	(0.328)	(0.232)	(0.194)	(0.151)	(0.129)
AIC	6.89	7.31	7.47	7.49	7.50
BIC	-906.70	-890.63	-889.91	-900.46	-909.20
LogLikelihood	-906.69	-942.16	963.36	-966.83	-967.11
Observations	269	269	269	269	269

*** p<0.01, ** p<0.05, * p<0.1. *Note:* No complete observations for registry Alaska available. Fixed registry and cancer site effects are included, see Appendix; clustered standard errors are given in parentheses.

As an alternative to the broadly defined registries we also estimated Eq. 5 on the county level. The 17 registries are divided into 470 different counties leading to a maximum number of 7,520 observations. While this tests the robustness of our model it has the disadvantage that some of the site-county categories contain only a small number of diagnoses. Thus, in addition to the estimation results of the whole sample in Table 4 below we performed another estimation exluding the two least common cancer sites. The results are similar and relegated to the Appendix. The coefficient for current volume is again positively related to the survival rate and significant on the 1 or 5 percent level (except for the 1-year survival interval). However, this time the effects are smaller in terms of magnitude. Now, the highest effect is found for the 3-year survival rate instead of the 5-year as in the previous estimation. The smaller effects are likely due to the fact that the volume effect operates at a broader level than that of a given county, e.g. counties sometimes only have one hospital. Recent experience and cumulative experience is not significant for all five time intervals. Thus, with regard to the hypothesis H3

Table 4: Estimation results (county level), 2002

	Coefficients for (t)-year survival rates				
	(1)	(2)	(3)	(4)	(5)
$\ln N_{2002}$	0.0348	0.0803**	0.0934***	0.0801**	0.0921**
	(0.0426)	(0.0382)	(0.0362)	(0.0360)	(0.0360)
$\ln N_{2001}$	-0.0379	-0.00368	-0.0184	-0.0109	0.0184
	(0.0404)	(0.0342)	(0.0325)	(0.0324)	(0.0303)
$\sum_{t=1992}^{2002} N_t$	0.0722	0.0293	0.0596	0.0436	0.00420
	(0.0768)	(0.0659)	(0.0638)	(0.0624)	(0.0610)
$\ln E_t$	14.43***	7.023***	4.853***	3.914***	3.447***
	(0.903)	(0.429)	(0.268)	(0.204)	(0.162)
LOC	0.159	0.221	0.380***	0.317**	0.390***
	(0.168)	(0.159)	(0.142)	(0.136)	(0.132)
DIST	-1.849***	-1.992***	-1.892***	-1.908***	-1.872***
	(0.172)	(0.161)	(0.155)	(0.154)	(0.150)
SURG	1.061***	0.805***	0.740***	0.724***	0.671***
	(0.0905)	(0.0851)	(0.0822)	(0.0764)	(0.0728)
RAD	0.163*	-0.0502	-0.0151	0.0217	0.0161
	(0.0877)	(0.0792)	(0.0736)	(0.0699)	(0.0662)
AIC	3.01	3.30	3.41	3.47	3.50
BIC	-38,838	-38,501	-38,505	-38,437	-38,340
LogLikelihood	-7,866	-8,663	8,959	-9,109	-9,181
Observations	5,554	5,552	5,549	5,540	5,530

*** p<0.01, ** p<0.05, * p<0.1. *Note:* lnN_{2000} is dropped because of collinearity. Fixed county and cancer site effects are included; clustered standard errors are given in parentheses.

raised in Section 2 we can conclude that current volume (which is positively associated with specialization) has by far a higher impact on cancer survival rates than recent and cumulative experience for both levels of analysis. While the lack of influence of experience on outcomes is in contrast to many volume-outcome studies it is supported by Ho [2002], Sfekas [2009], Gaynor et al. [2005], and Huesch [2009] who cannot establish a positive relationsip between experience and outcomes for cardiac surgery on the hospital and surgeon level. As a possible explanation they argue that forgetting and high turnover rates for teams might be responisble for the absence of a relationship (a similar argument is put forward in Benkard [2000] who analyzed learning and forgetting in the context of aircraft production). Expected survival is now significant across all five survival intervals. Also the share of localized cancers becomes significant from the 3-year survival rate onwards. It is positively correlated with cancer survival whereas the share of distant cancers is significantly negatively correlated with surival rates of all five different survival rate intervals. Again the share of surgeries performed is positively related to survival while the share of performed radiation does not seem to be a significant determinant

of survival. To sum up, the results for the county level estimation confirm the results found on the registry level providing evidence on the robustness of the estimated model.

Limitations

Our study is subject to some limitations. First, the measures of current volume and experience are highly correlated. Therefore, eq.5 is reestimated on the county level including only the variable current volume. Thus, the estimated effect is hypothesized to reflect both volume and experience and represents an upper-bound estimate. The point estimates for N_{2002} become more precise with smaller clustered standard errors compared to the previous estimation. Except for the 1-year survival rate they are significant at the one percent significance level. The magnitude of the effect is almost the same as in Table 4, confirming that most of the improved survival chances are exclusively due to current volume.

Table 5: Estimation results without experience variables (county level), 2002

	Coefficients for (t)-year survival rates				
	(1)	(2)	(3)	(4)	(5)
$\ln Spec_{2002}$	0.0447	0.0758***	0.0975***	0.0803***	0.0872***
	(0.0290)	(0.0282)	(0.0268)	(0.0256)	(0.0249)
$\ln E_t$	13.97***	7.055***	4.897***	3.915***	3.451***
	(0.883)	(0.401)	(0.256)	(0.194)	(0.157)
LOC	0.149	0.178	0.345**	0.345***	0.419***
	(0.159)	(0.149)	(0.140)	(0.133)	(0.132)
DIST	-1.858***	-2.065***	-1.973***	-1.935***	-1.888***
	(0.167)	(0.152)	(0.149)	(0.146)	(0.144)
SURG	1.109***	0.835***	0.752***	0.733***	0.666***
	(0.0870)	(0.0817)	(0.0784)	(0.0726)	(0.0689)
RAD	0.196**	-0.0452	-0.0309	-0.00607	-0.00903
	(0.0845)	(0.0748)	(0.0699)	(0.0665)	(0.0630)
AIC	2.85	3.13	3.24	3.28	3.32
BIC	-43,385	-42,967	-42,902	-42,840	-42,703
LogLikelihood	-8,167	-9,009	9,339	-9,489	-9,557
Observations	6,078	6,075	6,071	6,062	6,047

*** p<0.01, ** p<0.05, * p<0.1. *Note:* Fixed county and cancer site effects are included; clustered standard errors are given in parentheses.

Second, as outlined in the beginning of this paper the positive effect of volume on outcomes may be due to endogeneity. Regions with higher survival rates may attract additional patients because of their reputation for better care. In principle, patients could migrate to receive their diagnosis and care at places other than their place of residence. We used data from the U.S. vital statistics which records every death in the U.S. according to cause of death to check where

patients indeed seek health care for particular cancer treatments. However, in 2002 only 13 percent of individuals died in a different county than their place of residence and only 8 percent died in a different state, speaking in favor of an exogenous N_{ir}. This finding also makes the use of the number of diagnoses as a proxy for treatment less restrictive and provides indirect support for the finding of Wennberg [1999] who states that admissions to the hospitals generally take place within a relatively short distance of where patients live or have been diagnosed with cancer.

Third, and related to the previous issue raised, improved survival rates may be only due to improved earlier detection of cancers - caused e.g. by new screening procedures. As the proportion of specific cancer types detected at screening increases in some regions, presumably as a result of increased screening efforts of local health authorities, the respective patient survival rates will increase, because they are based on survival time after diagnosis.[8] However, since we control for expected survival and cancer progression, we believe that our estimates are not subject to lead-time bias. Thus, the increased survival rates we find are mainly due to specialization gains.

Finally, the assignment of a given stage to a particular cancer may change over time due to advances in diagnostic technologies. Introduction of new technologies can give rise to a phenomenon known as stage migration. Stage migration occurs when diagnostic procedures change over time, resulting in an increase in the probability that a given cancer will be diagnosed in a more advanced stage.[9] The likely result would be to remove the worst survivors—those with previously undetected distant metastases - from the localized and regional categories and put them into the distant category. As a result, the stage-at-diagnosis distribution for a cancer may become less favorable over time, but the survival rates for each stage may improve (Feinstein et al., 1985). However, since we focused on a given time period the impact of the introduction of new technologies can be excluded.

[8] The interval between the time a cancer is diagnosed by a screening procedure and the time when the cancer would have been diagnosed in the absence of screening is called lead-time (Zelen, 1976).

[9] For example, certain distant metastases that would have been undetectable a few years ago can now be diagnosed by computer tomography (CT) scan or by magnetic resonance imaging (MRI). Therefore, some patients who would have been diagnosed previously as having cancer in a localized or regional stage are now diagnosed as having cancer in a distant stage.

5 Conclusion

From a simple model of cancer survival we derived the testable hypothesis whether regions with relatively more disease-specific knowledge exhibit higher survival rates. Using data from the National Cancer Institute's Surveillance, Epidemiology and End Results (SEER) our results support the notion that the physician or hospital level of analysis to examine the volume-outcome relationship may be too narrow since it does not account for possible information spillovers. We find that patients tend to survive longer in those areas where relativly more cancers of the same site occur. We further find that current volume has by far a higher impact on cancer survival rates than recent and cumulative experience at both the registry and the county level.

Thus, the effects of health care policies that aim to centralize health care provision into larger units may be overestimated since it is likely that the disease-specific knowledge of a local health care area influences treatment quality as well.

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Table 6: Complete estimation results (registry level), 2002

	Coefficients for (t)-year survival rates				
	(1)	(2)	(3)	(4)	(5)
$\ln Spec_{2002}$	0.400**	0.331**	0.381**	0.367**	0.435***
$\ln N_{2001}$	-0.236*	-0.0846	-0.115	-0.198	-0.186
$\ln N_{2000}$	-0.215	-0.231	-0.241	-0.183	-0.173
$\sum_{t=1992}^{2002} N_t$	0.200	0.101	0.100	0.128	0.0162
$\ln E_t$	-0.151	1.740	1.603*	1.937**	2.365***
LOC	0.411	0.114	0.444	0.500	0.548
DIST	-1.030	-1.464**	-1.588***	-1.793***	-1.730***
SURG	1.010***	0.816***	0.732***	0.664***	0.587***
RAD	0.219	0.333	0.431**	0.465***	0.373***
Conneticut	0.000552	0.0109	0.0221	0.0335**	0.0435***
Metropolitan Detroit	-0.178***	-0.135***	-0.106***	-0.104***	-0.0899***
Hawaii	0.160	0.0579	0.0578	0.0205	-0.0190
Iowa	-0.0644**	-0.0594*	-0.0436	-0.0165	-0.00682
New Mexico	0.0549	0.0206	0.0380	0.0246	-0.0214
Seattle Puget Sound	-0.0454**	-0.0128	0.0164	0.0518***	0.0523***
Utah	0.0471	0.0765	0.127	0.140	0.133
Metropolitan Atlanta	0.0594	0.0503	0.0549	0.0379	0.00381
San Jose Monterey	0.175*	0.156	0.177*	0.184**	0.192**
Los Angeles	-0.188**	-0.184**	-0.175*	-0.160*	-0.156*
Alaska	0.603	0.366	0.389	0.199	0.0809
Rural Georgia	0.341	0.0971	0.132	0.0935	0.110
Greater California	-0.0988	-0.180	-0.166	-0.0969	-0.207
Kentucky	0.0346	-0.116	-0.0916	-0.0555	-0.200
Louisiana	-0.00386	-0.145	-0.139	-0.0915	-0.229
New Jersey	0.0666	-0.0373	-0.0285	0.0305	-0.0775
Digestive system	-0.872***	-0.521*	-0.357	-0.212	-0.155
Respiratory system	-1.020***	-0.973***	-0.854***	-0.747***	-0.733***
Bones and joints	0.927***	0.820**	0.915***	0.880***	0.764**
Soft tissue incl. heart	0.370**	0.413**	0.486**	0.496***	0.452***
Skin[a]	1.120***	1.179***	1.154***	1.131***	1.065***
Breast	1.049***	1.098***	0.936***	0.861***	0.806***
Female genital system	0.297	0.485***	0.577***	0.633***	0.608***
Male genital system	2.136***	1.861***	1.970***	1.940***	1.925***
Urinary system	-0.143	0.214	0.301	0.375**	0.401***
Eye and Orbit system	2.273***	1.762***	1.461***	1.170***	1.067***
Brain	-0.854	-1.127**	-0.792	-0.725	-0.660
Endocrine system	1.305***	1.644***	1.686***	1.712***	1.653***
Lymphoma	0.360	0.353	0.721	0.797*	0.820**
Myeloma	1.563***	1.652***	1.917***	2.036***	1.843***
Leukemia	1.341***	1.679***	2.166***	2.446***	2.388***
Constant	-0.864	-0.639	-1.228	-1.356	-0.958
AIC	6.89	7.31	7.47	7.49	7.50
BIC	-906.70	-890.63	-889.91	-900.46	-909.20
LogLikelihood	-906.69	-942.16	963.36	-966.83	-967.11
Observations	269	269	269	269	269

*** p<0.01, ** p<0.05, * p<0.1. *Note:* The fixed site and registry effects have to be interpreted relative to the San Francisco and Oral cavity intercept. [a]Excluding basal and squamous. No complete observations for registry Alaska available.

Table 7: Estimation results (county level) excluding site bones/joints and eye/orbit, 2002

	Coefficients for (t)-year survival rates				
	(1)	(2)	(3)	(4)	(5)
$\ln N_{2002}$	0.0297	0.0736*	0.0880**	0.0792**	0.0865**
	(0.0433)	(0.0393)	(0.0368)	(0.0364)	(0.0365)
$\ln N_{2001}$	-0.0412	-0.00254	-0.0182	-0.0160	0.0141
	(0.0408)	(0.0347)	(0.0333)	(0.0331)	(0.0310)
$\sum_{t=1992}^{2002} N_t$	0.0753	0.0255	0.0591	0.0427	0.00821
	(0.0769)	(0.0669)	(0.0647)	(0.0633)	(0.0617)
$\ln E_{2002}$	14.12***	6.911***	4.866***	3.938***	3.474***
	(0.915)	(0.438)	(0.277)	(0.208)	(0.166)
LOC	0.138	0.223	0.365**	0.329**	0.409***
	(0.172)	(0.161)	(0.147)	(0.142)	(0.139)
DIST	-1.871***	-2.020***	-1.917***	-1.920***	-1.885***
	(0.177)	(0.163)	(0.161)	(0.157)	(0.154)
SURG	1.058***	0.797***	0.735***	0.741***	0.688***
	(0.0920)	(0.0868)	(0.0844)	(0.0787)	(0.0750)
RAD	0.187**	-0.0359	-0.00322	0.0214	0.0186
	(0.0886)	(0.0805)	(0.0747)	(0.0708)	(0.0667)
Observations	5343	5341	5338	5329	5320
AIC	3.09	3.37	3.47	3.52	3.55
BIC	-36,971	-38,501	-36,707	-36,670	-36,580
LogLikelihood	-7,759	-8,506	8,776	-8,897	-8,965
Observations	5343	5341	5338	5329	5320

*** p<0.01, ** p<0.05, * p<0.1. *Note:* lnN_{2000} is dropped because of collinearity. Fixed county and cancer site effects are included; clustered standard errors are given in parentheses.

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