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THE IMPACT OF THERAPEUTIC PROCEDURE INNOVATION ON HOSPITAL PATIENT LONGEVITY: EVIDENCE FROM WESTERN AUSTRALIA, 2000-2007

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The Impact of Therapeutic Procedure Innovation on Hospital Patient Longevity: Evidence from Western Australia, 2000-2007

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ABSTRACT

We investigate the effect of therapeutic procedure innovation in general on the longevity of all hospital patients, i.e. patients with a variety of medical conditions. The analysis is based on data on over one million discharges from public and private hospitals in Western Australia (WA) during the period 2000-2007. We can measure survival for a period as long as 8 years after admission, and we know the date each procedure was added to the Medicare Benefits Schedule.

Estimates based on patient-level data indicate that therapeutic procedure innovation increased the life expectancy of WA hospital patients by almost 3 months between 2000 and 2007, controlling for the patient's age, sex, Diagnosis Related Group (DRG, over 600 categories), Aboriginal status, marital status, insurance coverage (whether or not the patient had private insurance), postcode (over 400 postcodes), year of hospital admission, and number of procedures performed.. Estimates based on longitudinal DRG-level data also indicate that therapeutic procedure innovation increased the life expectancy of WA hospital patients, but the implied increase may be smaller—about 2 months. In either case, therapeutic procedure innovation in WA hospitals appears to have been remarkably cost-effective, because it increased the cost of medical procedures by a negligible amount.

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A number of previous studies have examined the effects of specific medical innovations, or innovations for specific medical conditions, on longevity and other patient outcomes. For example, McGovern et al (1993) found that there were marked improvements in survival from 1970 to 1985 among hospitalized stroke patients in the Twin Cities; these improvements occurred almost exclusively in the acute hospitalization phase, and improved medical care probably contributed to gains in survival. Gockel et al (2008) argued that surgical therapy for esophageal carcinoma has undergone distinct changes over the past 20 years, and that these changes have led to a significantly more favorable long-term prognosis. Ravi (2007) found that recent advances in the study and treatment of esophageal disorders allow for more accurate diagnosis of known esophageal disorders and have introduced previously unexplored disorders. Noble (2003) argued that "developments in neonatal technology continue to improve infant outcomes." Dobson (2003) found that "advances in medical technology account for a third of the reduction in road traffic deaths," and Dobson (2002) found that "murder rates would be up to five times higher than they are but for medical developments over the past 40 years." However, Lameire et al (2009) found that, "overall, the major technological advances in dialysis have not yet been translated into longer patient survival."

In this study, we will investigate the effect of therapeutic procedure innovation *in general* on the longevity of *all* hospital patients, i.e. patients with a variety of medical conditions. The analysis will be based on data on over one million discharges from public and private hospitals in Western Australia (WA) during the period 2000-2007. The hospital discharge data, contained in WA's Hospital Morbidity Data Collection, are linked to WA Death Registration data up until March 1, 2008, so we can measure survival for a period as long as 8 years after admission.

Each hospital discharge record includes up to eleven procedure codes. Since 1 July 1999, procedures have been coded using the *International statistical classification of diseases and related health problems, 10th revision, Australian modification* (ICD-10-AM). An important feature of ICD-10-AM was the addition of a classification of procedures based on the

Commonwealth Medicare Benefits Schedule (MBS) of fees for health services.[1] The MBS is a listing of the Medicare services subsidized by the Australian government.[2] New procedures are added to the MBS each year. In order to be included in the MBS, new medical technologies and procedures must be assessed by the Medical Services Advisory Committee (MSAC, http://www.msac.gov.au/), an independent scientific committee comprising individuals with expertise in clinical medicine, health economics and consumer matters. The MSAC undertakes a rigorous and transparent assessment of new medical technologies in consultation with the applicant, and advises the Minister for Health and Ageing on whether new medical services should be publicly funded based on an assessment of their safety, effectiveness and cost effectiveness, using the best available evidence.

Each procedure in the MBS has a "start date," i.e. the date the procedure was added to the MBS. As of 1 November 2010, the MBS included 5756 items (procedures). As shown in Figure 1, 40% of the items included in the 1 November 2010 MBS were added by the end of 1992, 59% were added by the end of 1999, and 79% were added by the end of 2004. Henceforth I will refer to the year in which a procedure was introduced into the MBS as the *vintage* of the procedure.[3]

Innovation may be defined as "the introduction of a new idea, method or device."[4] Our measures of innovation will be based on the mean vintage of the procedures used to treat a patient or group of patients.

We will investigate the effect of therapeutic procedure innovation[5] on hospital patient

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[1] It was a deliberate decision of the Casemix Implementation Project Board in 1995 to create this Australian procedure classification based on the fee schedule so that the classification of procedures in the public and private sectors, as well as in ambulatory situations, would be more consistent. The Australian procedure classification, known as the Medicare Benefits Schedule, Extended (MBS-E), is more specific than MBS, and is organised logically according to body system and site and includes a detailed index. Codes have been added for procedures not currently eligible for benefits, such as cosmetic surgery, obstetrics and allied health procedures. See Roberts et al (1998).

[2] The Schedule is part of the wider Medicare Benefits Scheme managed by the Department of Health and Ageing and administered by Medicare Australia.

[3] According to the Merriam Webster dictionary, one definition of vintage is "a period of origin or manufacture (e.g. a piano of 1845 vintage)". http://www.merriam-webster.com/dictionary/vintage

[4] This is a synthesis of the two definitions of innovation provided by the Merriam Webster dictionary: "(1) the introduction of something new, and (2) a new idea, method, or device." http://www.merriam-webster.com/dictionary/innovation

[5] About 90% of the procedures (and procedure fees) included in WA's Hospital Morbidity Data Collection are accounted for by therapeutic (category 3) procedures. Most of the remaining procedures are diagnostic imaging (category 5) procedures.

longevity in two different ways. First, we will investigate the effect of therapeutic procedure vintage on patient survival using cross-sectional patient-level data. We will control, in a very unrestrictive manner, for the patient's age, sex, Diagnosis Related Group (DRG, over 600 categories), Aboriginal status, marital status, insurance coverage (whether or not the patient has private insurance), postcode (over 400 postcodes), year of hospital admission, and number of procedures performed.

These variables should control, to a very great extent, for the patient's underlying health status and mortality risk prior to treatment.[6] Nevertheless, there may be unobserved heterogeneity of patients with respect to mortality risk, which could bias our estimates of the effect of therapeutic procedure vintage on patient survival. However, both our own data and evidence from other studies suggest that the sickest patients tend to receive the newest treatments. A regression of mean procedure vintage on all of the variables listed above indicates that (1) mean vintage is positively correlated with the number of procedures performed; (2) procedures used on uninsured patients are newer than those used on insured patients; and (3) procedures used on men are newer than those used on women. Also, Hoover et al (2002) showed that mean annual medical expenditure on persons aged 65 and older were over five times as high during the last year of life as they were during nonterminal years. It is plausible that part of this expenditure differential is due to the use of newer, as well as more, procedures during the last year of life. If the sickest patients tend to receive the newest treatments, our estimates of the effect of therapeutic procedure vintage on patient survival are likely to be conservative if we don't adequately control for severity of illness.

We believe that heterogeneous treatment of patients, controlling for their diagnoses, demographic characteristics, insurance coverage, and other factors, is primarily due to physician practice variation. Wennberg (2004) argues that "unwarranted [treatment] variation—variation not explained by illness, patient preference, or the dictates of evidence-based medicine—is a ubiquitous feature of U.S. health care." This may also apply to Australia. A large number of studies have documented the importance of unexplained variation in medical care. Lee et al (2008) showed that "pediatric and adult transplant physicians differed significantly in their management strategies for chronic myeloid leukemia, acute and chronic graft-versus-host

[6] For example, old men from poor regions receiving large number of procedures face higher mortality risk than young women from wealthy regions receiving fewer procedures.

disease, and choice of graft source for patients with aplastic anemia. Among adult transplant physicians, there was little agreement on the patient factors favoring reduced intensity conditioning or myeloablative conditioning." DeSalvo et al (2000) reported "wide variation…in assignment of reappointment interval with mean return intervals…ranging from 2.2 to 20.5 weeks. Sex was a significant provider independent variable…Female providers assigned earlier reappointment intervals for their patients." Solomon et al (2003) found that "established risk factors for NSAID-associated gastrointestinal toxicity were poor predictors of who was prescribed a selective COX-2 inhibitor; in contrast, physician prescribing preference was an important determinant." De Las Cuevas et al (2002) showed that "there is a remarkable degree of variation in antidepressant prescribing by psychiatrists and general practitioners; this is due to economic and social factors as much as to morbidity differences." Rochon et al (2007) found that "residents in facilities with high antipsychotic prescribing rates were about 3 times more likely than those in facilities with low prescribing rates to be dispensed an antipsychotic agent, irrespective of their clinical indication."[7]

We will also investigate the effect of therapeutic procedure innovation on patient survival using longitudinal DRG-level data. This approach enables us to determine whether DRGs that exhibited more procedure innovation (larger increases in procedure vintage) had greater increases in patient survival, ceteris paribus. Estimates based on longitudinal DRG-level data are less subject to bias from unobserved patient heterogeneity than estimates based on cross-sectional patient-level data. Comparison of the two kinds of estimates can help us to assess the direction of bias, if any.

Section 2 describes the econometric models of patient survival we will estimate. Descriptive statistics are presented in Section 3. Empirical results are presented in Section 4. The cost-effectiveness of therapeutic procedure innovation is assessed in Section 5. Section 6 provides a summary.

[7] Using clinical and administrative data obtained from all facilities in a Department of Veterans Affairs integrated service network, Krein et al (2002) showed that there was variation in diabetes practice patterns at the primary care provider, provider group, and facility levels, and that the greatest amount of variance tended to be attributable to the facility level.

2, Econometric models of patient survival

A. Econometric models of patient survival based on cross-sectional patient-level data

Dependent variables. We will estimate two types of models of patient survival using cross-sectional patient-level data. In the first type, the dependent variable is a binary variable indicating whether or not the patient survived a specified length of time, i.e. whether the patient was discharged alive (which we refer to as "0 years"), and whether the patient was alive 1, 2, 3, 4, and 5 years after admission to the hospital.[8] These models will be of the form:

$$surv_{ni} = \beta\ vintage_i + \gamma\ Z_i + \varepsilon_i \qquad (1)$$

where

$surv_{ni}$ = 1 if patient i survived n years (n = 0, 1, …, 5)
= 0 otherwise
$vintage_i$ = the vintage of therapeutic procedures performed on patient i
Z_i = a vector of other attributes of patients i
ε_i = a disturbance

Since the dependent variable is a binary variable, we will estimate these models as probit models.

In the second type of model, the dependent variable is the number of years the patient lived after being admitted to the hospital. These models will be of the form:

$$years\_lived_i = \beta\ vintage_i + \gamma\ Z_i + \varepsilon_i \qquad (2)$$

where

$years\_lived_i$ = the number of years patient i lived after being admitted to the hospital

If the patient did not die by 1 March 2008 (the Death Registration cut-off date), this variable is right censored. I will account for this by using a statistical procedure (the SAS LIFEREG procedure) that fits parametric models to failure time data that can be uncensored,

[8] Because the coverage of the WA Death Registration data ends on March 1, 2008, 1-year survival can be measured for patients hospitalized during 2000-2006, but 5-year survival can be measured only for patients hospitalized during 2000-2002.

right censored, left censored, or interval censored. To reduce the degree of censoring, I will analyze people who were hospitalized during 2000-2004. I will assume that the number of years the patient lived after being admitted to the hospital (or the number of years till death) has the Weibull distribution, one of the most commonly used distributions in failure time analysis. The probability density function of a Weibull random variable *X* is:

$$f(x;\lambda,k) = \begin{cases} \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-(x/\lambda)^k} & x \geq 0, \\ 0 & x < 0, \end{cases}$$

where $k > 0$ is the *shape parameter* and $\lambda > 0$ is the *scale parameter* of the distribution.[9] The mean of a Weibull random variable can be expressed as $\lambda\,\Gamma(1+(1/k))$ where $\Gamma(z)$ is the Gamma function:[10]

$$\Gamma(z) = \int_0^\infty t^{z-1} e^{-t}\,dt\,.$$

We assume that the scale parameter λ depends on patient characteristics X as follows: $\lambda = \exp(\beta X)$. Hence $\ln \lambda = \beta X$, and $\ln(\text{mean survival time}) = \beta X + \ln(\Gamma(1+(1/k)))$. Therefore the estimated coefficient on a patient characteristic X_1 indicates the percentage change in mean survival time attributable to a unit increase in X_1.

Explanatory variables. The explanatory variable of primary interest is the mean vintage of procedures used to treat the patient. One potential measure of procedure vintage is the mean year in which the procedures performed on a patient commenced in the MBS:

$$\text{proc\_year}_i = \frac{\Sigma_p\, \text{item}_{pi}\, \text{item\_start\_year}_p}{\Sigma_p\, \text{item}_{pi}}$$

where

item_{pi} = 1 if patient i was treated with procedure p
= 0 if patient i was not treated with procedure p

[9] The shape parameter is what gives the Weibull distribution its flexibility. By changing the value of the shape parameter, the Weibull distribution can model a wide variety of data. If k = 1, the Weibull distribution is identical to the exponential distribution; if k = 2, the Weibull distribution is identical to the Rayleigh distribution; if k is between 3 and 4 the Weibull distribution approximates the normal distribution. The Weibull distribution approximates the lognormal distribution for several values of k.

[10] See http://en.wikipedia.org/wiki/Weibull_distribution and http://www.engineeredsoftware.com/nasa/weibull.htm.

$item\_start\_year_p$ = the year procedure p commenced in the MBS

However, as shown in Figure 1, item_start_year is, in effect, a "left-censored" variable: no items commenced before 1987, and a third of all items commenced in a single year (1991). Therefore, the following may be a better measure of vintage:

$$proc\_post1995\%_i = \frac{\Sigma_p\ item_{pi}\ item\_post1995_p}{\Sigma_p\ item_{pi}}$$

where

$item\_post1995_p$ = 1 if the year procedure p commenced in the MBS > 1995
= 0 if the year procedure p commenced in the MBS $\leq$ 1995

Hence $proc\_post1995\%_i$ is the fraction of procedures used to treat patient i that were "new" procedures, where a procedure is considered "new" if it commenced in the MBS after 1995 (approximately the median commencement year of items included in the MBS as of 1 November 2010).

In addition to procedure vintage, all of the models of patient survival we estimate using cross-sectional patient-level data will also include the following explanatory variables: dummy variables for the patient's (single year of) age, sex, Diagnosis Related Group (DRG, over 600 categories), Aboriginal status, marital status, insurance coverage (whether or not the patient has private insurance), postcode (over 400 postcodes), year of hospital admission, and number of procedures performed (1-11).

B. Econometric models of patient survival based on longitudinal DRG-level data

To determine whether DRGs that exhibited more procedure innovation (larger increases in procedure vintage) had greater increases in patient survival, ceteris paribus, we will use longitudinal DRG-level data to estimate models of the following form:

$$\ln(surv\%_{ndt}/(1- surv\%_{ndt})) = \beta\ proc\_post1995\%_{dt} + \gamma\ Z_{dt} + \alpha_d + \delta_t + \varepsilon_{dt} \qquad (3)$$

where

$surv\%_{0dt}$ = the fraction of patients discharged in year t in DRG d who were

discharged alive ("survived 0 years")

$surv\%_{ndt}$ = the fraction of patients discharged in year t in DRG d who survived n years (n = 1, 2,…,5)

$proc\_post1995\%_{dt}$ = the fraction of procedures performed in year t in DRG d that were "new" procedures

Z_{dt} = a vector of other attributes[11] of patients discharged in year t in DRG d

α_d = a fixed effect for DRG d

δ_t = a fixed effect for year t

ε_{dt} = a disturbance

Eq. (3) will be estimated via weighted least-squares, where the weight is the number of patients discharged in year t in DRG d (N_{dt}). We will allow for clustering of disturbances within DRGs.

3. Descriptive statistics

Descriptive statistics are shown in Table 1. The number of discharges ranged between 113 and 138 thousand per year. The mean age of patients was about 64 years. The average values of the 1-year, 3-year, and 5-year survival rates were 75.4%, 57.9%, and 48.7%, respectively. Not surprisingly, these are far below the corresponding survival rates of the general population of Western Australia. For example, according to the life table for Western Australia for the years 2001-2003, the 5-year survival rates of 64-year-old men and women in the general population were 93% and 96%, respectively. What is perhaps more surprising is that survival rates of WA hospital patients declined during this period.[12] For example, the 3-year survival rate declined from 59.8% in 2000 to 55.9% in 2004. This may be attributable to an increase in the average severity of illness of patients admitted to hospitals. Patients with low illness severity may have been increasingly treated in an outpatient setting.

The average number of therapeutic procedures per patient remained constant (at about 1.00) from 2000 to 2003, but declined 27% between 2003 and 2007. This is entirely due to the fact that, for unknown reasons, the fraction of patients who had no therapeutic procedures increased from one-fourth during 2000-2003 to one half in 2007.[13]

[11] The other attributes are mean age, mean number of procedures performed, and fraction of patients with private insurance.

[12] Survival rates of the WA general population increased during this period.

[13] Among patients who had any therapeutic procedures, the mean number of procedures increased from 1.31 in 2003 to 1.46 in 2007.

WA's Hospital Morbidity Data Collection does not contain any cost information, but we can compute the cost of each patient's therapeutic procedures (in 2010 dollars) by using the schedule fees contained in the 1 November 2010 MBS. Due to the decline in the average number of therapeutic procedures per patient, therapeutic procedure schedule fees per patient declined. But therapeutic procedure schedule fees per procedure increased from $268 in 2003 to $336 in 2007.

Both measures of procedure vintage increased during the sample period. The fraction of therapeutic procedures with an item start year greater than 1995 increased from 8.2% in 2000 to 14.6% in 2007.

4. Empirical results

First we will present estimates of eq. (1). To conserve space, we will provide complete estimates of just one model, and estimates of the key parameter of interest (β, the procedure vintage coefficient) from 12 models. Table 2 provides estimates of the model of the 2-year survival rate in which vintage is defined as proc_post1995% (the fraction of procedures that commenced in the MBS after 1995). The estimates in this table indicate that the probability of being alive two years after admission was significantly higher for women and for people with private insurance, and inversely related to age and to the number of procedures performed on the patient, controlling for the patient's DRG, postcode, year of admission, marital status, and aboriginal status. The estimates also indicate that patients receiving newer procedures were significantly more likely to be alive two years after admission to the hospital.

Table 3 presents estimates of β from 12 different models: 6 survival intervals (0-5 years), and two alternative measures of therapeutic procedure vintage (proc_year and proc_post1995%). In model 1, the dependent variable is a dummy variable equal to 1 if the patient was alive when discharged from the hospital, and the regressor is the mean year in which the procedures performed on the patient commenced in the MBS. The estimate of β is positive and significant, indicating that patients treated with newer procedures were more likely to be discharged alive. In models 2-6, the dependent variables are dummy variables indicating survival 1-5 years after admission to the hospital, and the same measure of procedure vintage is used. The estimates of β in all of these models are positive and significant. Models 7-12 are similar to models 1-6, but the

measure of procedure vintage is the fraction of procedures used to treat a patient that commenced in the MBS after 1995. The estimate of β is not significant in model 7, but it is positive and highly significant (p-value < 0.0001) in models 8-12.

As shown in Table 1, between 2000 and 2007, the fraction of therapeutic procedures that were "new" (commenced in the MBS after 1995) increased by .064, from 8.2% to 14.6%. We can use the estimates of β in models 7 to 12 to assess how much therapeutic procedure innovation increased survival rates. Let SURV_RATE denote the mean survival rate during the period, and $F^{-1}(\ )$ denotes the inverse of the standard normal cumulative distribution. Then $S_0 = F\,[F^{-1}(\text{SURV\_RATE}) - \beta\,(.064 / 2)]$ is the "predicted" survival rate if proc_post1995% had increased by .032 *less* than the actual increase; $S_1 = F\,[F^{-1}(\text{SURV\_RATE}) + \beta\,(.064 / 2)]$ is the "predicted" survival rate if proc_post1995% had increased by .032 *more* than the actual increase; and $S_1 - S_0$ is the change in the survival rate attributable to therapeutic procedure innovation. The results of these calculations are shown in the following table.

survival interval	S_0	S_1	$S_1 - S_0$
alive at time of discharge	97.8%	97.8%	0.0%
alive 1 year after admission	75.0%	75.8%	0.8%
alive 2 years after admission	64.2%	65.2%	1.0%
alive 3 years after admission	57.5%	58.4%	0.8%
alive 4 years after admission	52.5%	53.2%	0.7%
alive 5 years after admission	48.5%	49.0%	0.5%

Model 8 implies that, ceteris paribus, therapeutic procedure innovation during the period 2000-2007 increased the 1-year survival rate by .008, from 75.0% to 75.8%, and that it increased the 2-year survival rate by .010, from 64.2% to 65.2%. As noted above, survival rates of WA hospital patients declined during this period; our estimates indicate how much more they would have declined in the absence of therapeutic procedure innovation.

Now we will discuss estimates of eq. (2), in which the (right-censored) dependent variable is the number of years the patient lived after being admitted to the hospital. This equation was estimated using data on 448,829 hospital discharges during the period 2000-2004. About half of these observations were right-censored, i.e. the patient did not die before 1 March 2008. The estimate of the Weibull shape parameter was significantly less than one (0.882,

standard error = 0.0016), which indicates that the mortality rate decreases over time. This is not surprising, since the figures in Table 1 indicate that the probability of surviving 2 years, conditional on surviving one year (85.8% = 64.7% / 75.4%) is higher than the (unconditional) probability of surviving one year (75.4%).

When eq. (2) is estimated using proc_post1995% as the vintage measure, the coefficient on this variable is positive and highly significant:

Estimate	StdErr	ChiSq	ProbChiSq
0.383	0.019	399.5	0.0000

This indicates that the mean time till death of a patient treated with only old procedures was 32% (= exp(-0.383)) lower than the mean time till death of a patient treated with only new procedures, controlling for all of the covariates. The estimate also implies that the 2000-2007 increase in proc_post1995% increased the life expectancy of WA hospital patients by 2.4% (= 0.383 * .064). The *absolute* increase (in months) in life expectancy of WA hospital patients attributable to therapeutic procedure innovation is equal to the percentage increase (2.4%) times the mean life expectancy. We calculated mean life expectancy by estimating eq. (2) without any explanatory variables (only an intercept); in that model, mean life expectancy = $\lambda\,\Gamma(1+(1/k))$. This implied that the mean life expectancy of WA hospital patients (whose mean age was 64.4) was 9.61 years.[14] Hence we estimate that, between 2000 and 2007, therapeutic procedure innovation increased the life expectancy of WA hospital patients by almost 3 months (0.234 years = 2.4% * 9.61 years). Between 2002 and 2008, the life expectancy at age 64 of the overall WA population increased by 0.9 years.[15] The annual rate of increase in the life expectancy of WA hospital patients attributable to therapeutic procedure innovation is about 22% as large as the annual rate of increase of life expectancy at age 64 of the overall WA population.

Now we will present estimates of models of patient survival based on longitudinal DRG-level data. Estimates of the coefficient β in eq. (3) are shown in Table 4. Each estimate is from a different model. All models include mean age, mean number of procedures performed, the fraction of patients with private insurance, DRG fixed effects, and year fixed effects. Models

[14] Mean life expectancy at age 64 of the overall WA population was 18.6 years for men and 22.1 years for women during 2001-2003.

[15] Due to right censoring of the survival data, during this period the change in the life expectancy of WA hospital patients can't be reliably estimated.

were estimated via weighted least-squares, where the weight is the number of patients discharged in year t in DRG d (N_{dt}). Estimates allow for clustering of disturbances within DRGs. In models 13-18, the vintage measure is proc_year (the mean year in which the procedures performed commenced in the MBS). The estimate of β is positive and significant (p-value < .05) in models 13-16, indicating that DRGs with higher rates of therapeutic procedure innovation had larger increases in the odds of surviving until discharge and until 1, 2, and 3 years after admission.[16] In models 19-24, the other (we believe more reliable) vintage measure—proc_post1995% (the fraction of procedures that commenced in the MBS after 1995) —is used. The estimate of β is positive and significant (p-value < .05) in models 19-23, except in model 20 (1-year survival rate), where it is marginally significant (p-value = .0767).

Once again, we can use the estimates of β in models 19 to 23 to assess how much therapeutic procedure innovation increased survival rates. In this case, we define S_0 = 1/(1+(1/exp [ln(SURV/(1- SURV)) – β (.064 / 2)])) as the "predicted" survival rate if proc_post1995% had increased by .032 *less* than the actual increase; S_1 = 1/(1+(1/exp [ln(SURV/(1- SURV)) + β (.064 / 2)])) as the "predicted" survival rate if proc_post1995% had increased by .032 *more* than the actual increase; and $S_1 – S_0$ as the change in the survival rate attributable to therapeutic procedure innovation. These calculations, and a comparison of them with the corresponding calculations based on patient-level data, are shown below.

	patient level			DRG level		
survival interval	S_0	S_1	$S_1 - S_0$	S_0	S_1	$S_1 - S_0$
alive at time of discharge	97.8%	97.8%	0.0%	97.8%	97.9%	0.2%
alive 1 year after admission	75.0%	75.8%	0.8%	75.2%	75.6%	0.4%
alive 2 years after admission	64.2%	65.2%	1.0%	64.3%	65.0%	0.7%
alive 3 years after admission	57.5%	58.4%	0.8%	57.6%	58.3%	0.8%
alive 4 years after admission	52.5%	53.2%	0.7%	52.6%	53.0%	0.4%
alive 5 years after admission	48.5%	49.0%	0.5%			

In three cases, the estimate of the increase in the survival rate attributable to therapeutic procedure innovation based on longitudinal DRG-level data is smaller than the estimate based on patient-level data. In one case (the three-year survival rate), the two estimates are the same, and

[16] As shown in Table 1, the 4-year survival rate can only be measured during 2000-2003, and the 5-year survival rate can only be measured during 2000-2002.

in one case (survival until discharge), the estimate based on longitudinal DRG-level data is larger.

Estimates of the survival-time model (eq. (2)), which was based on patient-level data, indicated that, between 2000 and 2007, therapeutic procedure innovation increased the life expectancy of WA hospital patients by almost 3 months. The estimate of the increase in the 2-year survival rate attributable to therapeutic procedure innovation based on longitudinal DRG-level data is 30% smaller than the corresponding estimate based on patient-level data, so therapeutic procedure innovation may have increased the life expectancy of WA hospital patients by a smaller amount: about 2 months.

5. Cost-effectiveness of therapeutic procedure innovation

In addition to estimating the longevity benefit of therapeutic procedure innovation, it is worthwhile to estimate the cost of this innovation, and the ratio of the two: the incremental cost-effectiveness ratio (ICER).

$$\text{ICER} = \frac{\Delta \text{ PROC\_COST}}{\Delta \text{ LE}} = \frac{\Delta \text{ PROC\_COST} / \Delta \text{ PROC\_POST1995\%}}{\Delta \text{ LE} / \Delta \text{ PROC\_POST1995\%}}$$

where PROC_COST denotes the cost of therapeutic procedures and LE denotes life expectancy. We estimate the cost of each patient's therapeutic procedures (in 2010 dollars) by using the schedule fees contained in the 1 November 2010 MBS:

$$\text{PROC\_COST}_i = \Sigma_p \, \text{item}_{pi} \, \text{schedule\_fee}_p$$

where

item_{pi} = 1 if patient i was treated with procedure p
= 0 if patient i was not treated with procedure p

schedule_fee_p = the fee for procedure p in the 1 November 2010 MBS

To estimate the effect of therapeutic procedure innovation on cost, we can estimate an equation similar to eq. (1), in which the dependent variable is the (log of) the patient's procedure cost:

$$\ln(\text{PROC\_COST}_i) = \beta\ \text{PROC\_POST1995\%}_i + \gamma\ Z_i + \varepsilon_i \qquad (4)$$

The estimate of β in eq. (4) is 0.426 (t-value = 112.6). The cost of procedures performed on patients receiving new procedures is higher than the cost of procedures performed on patients receiving old procedures. However, the percentage increase in procedure cost attributable to the 2000-2007 increase in PROC_POST1995% is quite small: 2.7% (= 0.426 * 6.4%). Among people who had positive procedure cost, mean procedure cost per hospital discharge during 2000-2004 was $367. Therefore, therapeutic procedure innovation is estimated to have increased mean procedure cost by only $10 (= 2.7% * $367).

Therapeutic procedure innovation in WA hospitals during the period 2000-2007 appears to have been remarkably cost-effective: it increased the life expectancy of patients by 2-3 months, and increased medical expenditure by a negligible amount. This may be due in part to the fact that decisions about whether new medical services are publicly funded are based on an assessment of their safety, effectiveness and cost effectiveness, using the best available evidence.

6. Summary

A number of previous studies have examined the effects of specific medical innovations, or innovations for specific medical conditions, on longevity and other patient outcomes. In this study, we investigated the effect of therapeutic procedure innovation *in general* on the longevity of *all* hospital patients, i.e. patients with a variety of medical conditions. The analysis was based on data on over one million discharges from public and private hospitals in Western Australia (WA) during the period 2000-2007. The hospital discharge data, contained in WA's Hospital Morbidity Data Collection, are linked to WA Death Registration data up until March 1, 2008, so we could measure survival for a period as long as 8 years after admission. Measurement of procedure innovation was facilitated by the fact that hospital procedures are coded using the Commonwealth Medicare Benefits Schedule (MBS), and we know the date each procedure was added to the MBS.

We investigated the effect of therapeutic procedure innovation on hospital patient longevity in two different ways. First, we investigated the effect of therapeutic procedure innovation on patient survival using cross-sectional patient-level data. We controlled, in a very unrestrictive manner, for the patient's age, sex, Diagnosis Related Group (DRG, over 600

categories), Aboriginal status, marital status, insurance coverage (whether or not the patient had private insurance), postcode (over 400 postcodes), year of hospital admission, and number of procedures performed. We also investigated the effect of therapeutic procedure innovation on patient survival using longitudinal DRG-level data. This approach enabled us to determine whether DRGs that exhibited more procedure innovation had greater increases in patient survival, ceteris paribus.

Estimates based on patient-level data indicated that therapeutic procedure innovation increased the life expectancy of WA hospital patients (whose mean life expectancy was about 10 years) by almost 3 months between 2000 and 2007. (Between 2002 and 2008, the life expectancy of the overall WA population of the same mean age (64) increased by about 11 months.) Estimates based on longitudinal DRG-level data also indicated that therapeutic procedure innovation increased the life expectancy of WA hospital patients, but the implied increase may be smaller—about 2 months. In either case, therapeutic procedure innovation in WA hospitals appears to have been remarkably cost-effective, because it increased the cost of medical procedures by a negligible amount.

References

Australian Bureau of Statistics, Life Tables, Western Australia, 2007-2009, http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/3302.5.55.0012007-2009

De Las Cuevas C, Sanz EJ, De La Fuente JA (2002). Variations in antidepressant prescribing practice: clinical need or market influences? *Pharmacoepidemiol Drug Saf.* 2002 Sep;11(6): 515-22. http://www.ncbi.nlm.nih.gov/pubmed/12426937

DeSalvo, Karen, Bruce E. Bowdish, Alys S. Alper, David M. Grossman, William W. Merrill (2000), Physician Practice Variation in Assignment of Return Interval, *Arch Intern Med.* 160:205-208. http://archinte.ama-assn.org/cgi/content/abstract/160/2/205

Dobson R. (2002), "Medical advances mask epidemic of violence by cutting murder rate," *BMJ*. Sep 21;325(7365):615.

Dobson R. (2003), "Advances in medical technology account for a third of the reduction in road traffic deaths," *BMJ*, May 10;326(7397):1004.

Gockel I, Sultanov FS, Domeyer M, Trinh TT, Gönner U, Junginger T. (2008), [Surgical therapy for esophageal carcinoma: a prospective 20-year analysis]. [Article in German], *Zentralbl Chir*. 2008 Jun;133(3):260-6.

Hoover, Donald R, Stephen Crystal, Rizie Kumar, Usha Sambamoorthi, and Joel C Cantor (2002), "Medical Expenditures during the Last Year of Life: Findings from the 1992–1996 Medicare Current Beneficiary Survey," *Health Serv Res.* December; 37(6): 1625–1642.

Krein, Sarah L, Timothy P Hofer, Eve A Kerr, and Rodney A Hayward (2002), Whom Should We Profile? Examining Diabetes Care Practice Variation among Primary Care Providers, Provider Groups, and Health Care Facilities, *Health Serv Res.* 37(5), October: 1159–1180. http://www.ncbi.nlm.nih.gov/pmc/articles/PMC1464024/

Lameire N, Van Biesen W, Vanholder R. (2009), "Did 20 years of technological innovations in hemodialysis contribute to better patient outcomes?," *Clin J Am Soc Nephrol*. 2009 Dec;4 Suppl 1:S30-40.

Lee, Stephanie J., Steven Joffe, Andrew S. Artz, Richard E. Champlin, Stella M. Davies, Madan Jagasia, Nancy A. Kernan, Fausto R. Loberiza, Jr, Robert J. Soiffer, Mary Eapen (2008), Individual Physician Practice Variation in Hematopoietic Cell Transplantation *Journal of Clinical Oncology*, Vol 26, No 13 (May 1), 2008: pp. 2162-2170, http://jco.ascopubs.org/content/26/13/2162.full

McGovern PG, Pankow JS, Burke GL, Shahar E, Sprafka JM, Folsom AR, Blackburn H. (1993), "Trends in survival of hospitalized stroke patients between 1970 and 1985. The Minnesota Heart Survey," *Stroke*. 1993 Nov;24(11):1640-8.

Noble L. (2003), "Developments in neonatal technology continue to improve infant outcomes," *Pediatr Ann*., Sep;32(9):595-603.

Ravi K, Francis DL. (2007), "New technologies to evaluate esophageal function," *Expert Rev Med Devices*. Nov;4(6):829-37.

Roberts, Rosemary F., Kerry C. Innes, and Susan M. Walker (1998), "Introducing ICD-10-AM in Australian hospitals," *Medical Journal of Australia*; 169: S32-S35, http://www.mja.com.au/public/issues/oct19/casemix/roberts/roberts.html

Rochon PA, Stukel TA, Bronskill SE, Gomes T, Sykora K, Wodchis WP, Hillmer M, Kopp A, Gurwitz JH, Anderson GM (2007), Variation in nursing home antipsychotic prescribing rates. *Arch Intern Med.* 167(7):676-83, Apr 9. http://www.ncbi.nlm.nih.gov/pubmed/17420426

Solomon DH, Schneeweiss S, Glynn RJ, Levin R, Avorn J (2003). Determinants of selective cyclooxygenase-2 inhibitor prescribing: are patient or physician characteristics more important? *Am J Med.* 115(9):715-20, Dec 15. http://www.ncbi.nlm.nih.gov/pubmed/14693324

Wennberg, John (2004), "Practice Variations and Health Care Reform: Connecting the Dots," *Health Affairs*, October 7, http://www.pnhp.org/news/2004/october/practice_variations_.php

Woolf SH, Johnson RE, Phillips RL Jr, Philipsen M. (2007), “Giving everyone the health of the educated: an examination of whether social change would save more lives than medical advances,” *Am J Public Health*., Apr;97(4):679-83. Epub 2007 Feb 28.

Figure 1
Cumulative % of items included in the Medicare Benefits Schedule
as of 1 November 2010, by start year

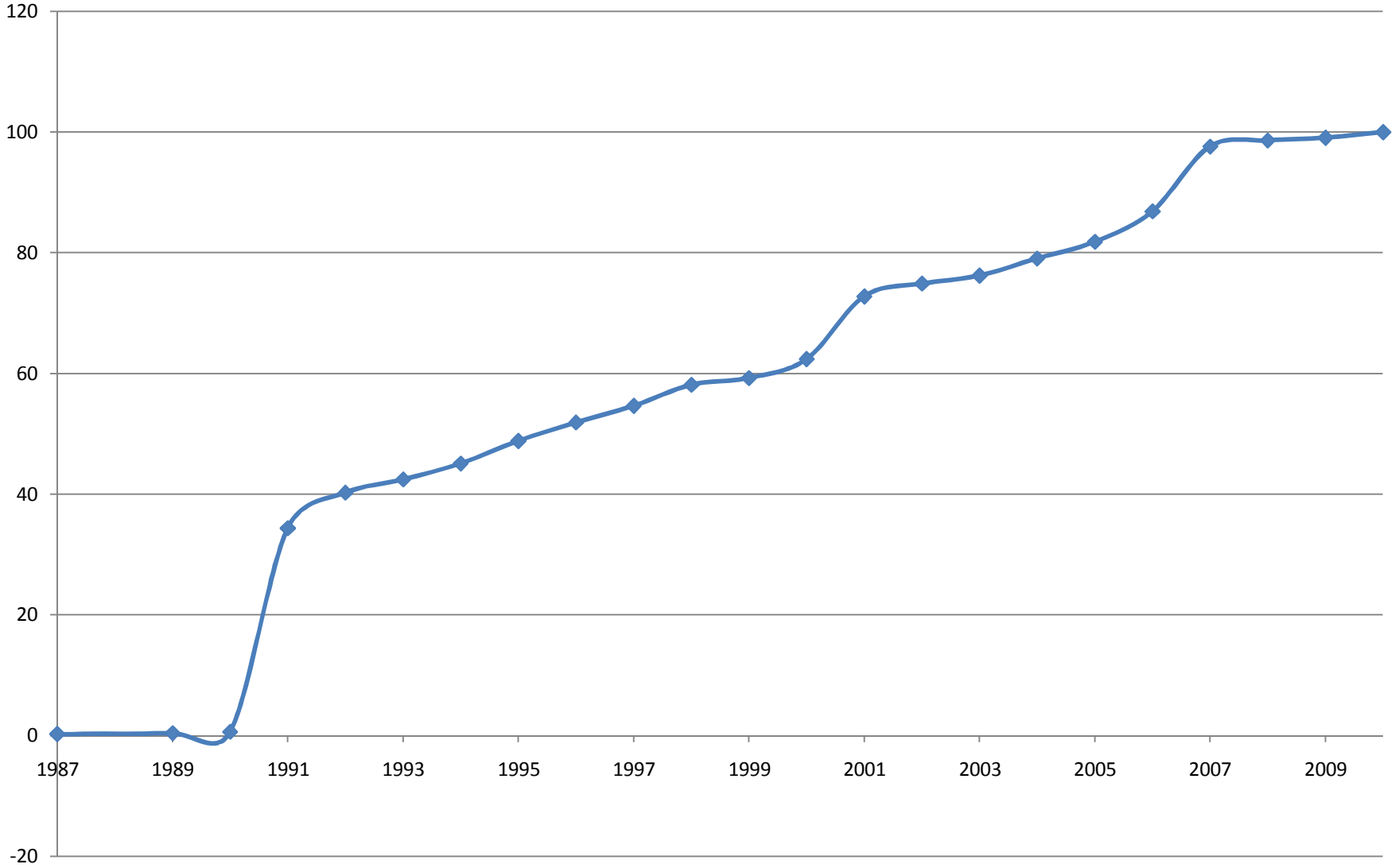

Table 1

Descriptive statistics

admission year	no. of discharges	surv0	surv1	surv2	surv3	surv4	surv5	AGE	male	private insur.	mean number of ther. procs	% with no ther. procs.	sum of fees for ther. procs.	total number of ther. procs.	mean ther. proc. start year	fraction of ther. procs. with item start year > 1995
2000	113,205	97.8%	76.9%	66.9%	59.8%	54.8%	50.4%	63.6	54%	34%	0.97	26%	$279	109,462	1992.17	8.2%
2001	119,216	97.8%	76.7%	66.1%	58.9%	53.8%	49.1%	63.9	54%	37%	0.97	25%	$270	115,169	1992.21	8.5%
2002	126,190	97.8%	75.8%	65.1%	58.4%	52.2%	46.9%	64.3	54%	39%	0.98	24%	$269	123,922	1992.29	9.5%
2003	128,123	97.9%	75.6%	65.2%	57.1%	50.9%		64.2	53%	40%	1.00	23%	$269	128,461	1992.39	10.4%
2004	131,472	97.9%	75.6%	63.6%	55.9%			64.5	54%	40%	0.90	34%	$262	117,670	1992.38	11.7%
2005	138,362	97.9%	73.8%	61.8%				64.8	54%	41%	0.78	45%	$248	108,399	1992.37	13.2%
2006	136,877	97.9%	73.6%					64.9	54%	42%	0.76	48%	$249	104,118	1992.43	14.3%
2007	121,403	97.8%						64.5	55%	41%	0.73	50%	$247	89,152	1992.40	14.6%
2000-2007	1,014,848	97.8%	75.4%	64.7%	57.9%	52.8%	48.7%	64.4	54%	39%	0.88	35%	$261	896,353	1992.33	11.1%

Table 2

Estimates of the 2-year survival rate model

Parameter	Level1	Estimate	StdErr	ChiSq	ProbChiSq		Parameter	Level1	Estimate	StdErr	ChiSq	ProbChiSq
proc_post1995%		0.405	0.015	729.76024	0.0000		Private insurance	No	-0.108	0.005	575.9	0.0000
SEX	Female	0.151	0.004	1190.445	0.0000		Private insurance	Yes	0.000			
SEX	Male	0.000					Admission year	2000	0.106	0.008	198.6	0.0000
AGE	00 - 04 AGE	1.714	0.032	2833.3333	0.0000		Admission year	2001	0.112	0.007	226.7	0.0000
AGE	05 - 17 AGE	1.535	0.023	4307.702	0.0000		Admission year	2002	0.083	0.007	131.6	0.0000
AGE	18 - 24 AGE	1.341	0.030	1960.589	0.0000		Admission year	2003	0.112	0.007	246.4	0.0000
AGE	25 - 44 AGE	1.154	0.013	8244.2697	0.0000		Admission year	2004	0.043	0.007	35.6	0.0000
AGE	45 - 54 AGE	0.949	0.011	6949.4544	0.0000		Admission year	2005	0.000			
AGE	55 - 64 AGE	0.797	0.011	5688.7773	0.0000		ABORIG	Aboriginal and Torres	-1.003	0.401	6.2	0.0125
AGE	65 - 74 AGE	0.571	0.010	3240.0956	0.0000		ABORIG	Aboriginal not Torres	-1.237	0.298	17.3	0.0000
AGE	75 - 84 AGE	0.384	0.010	1545.4463	0.0000		ABORIG	Other	-1.172	0.297	15.6	0.0001
AGE	85 - 99 AGE	0.000					ABORIG	Torres Strait Islander	0.000			
No. of procedures	1	0.229	0.133	2.9822589	0.0842		Marital status	Divorced	-0.024	0.010	5.3	0.0213
No. of procedures	2	0.163	0.133	1.510947	0.2190		Marital status	Married (including de	0.007	0.006	1.3	0.2491
No. of procedures	3	0.089	0.133	0.4510063	0.5019		Marital status	Never married	0.085	0.010	73.5	0.0000
No. of procedures	4	0.008	0.133	0.0033609	0.9538		Marital status	Not Stated	0.009	0.015	0.3	0.5720
No. of procedures	5	-0.039	0.134	0.0855174	0.7700		Marital status	Separated	-0.166	0.015	122.7	0.0000
No. of procedures	6	-0.105	0.135	0.6024252	0.4377		Marital status	Widowed	0.000			
No. of procedures	7	-0.162	0.136	1.4172313	0.2339							
No. of procedures	8	-0.159	0.138	1.3197098	0.2506							
No. of procedures	9	-0.159	0.146	1.1797289	0.2774							
No. of procedures	10	-0.140	0.163	0.7406225	0.3895							
No. of procedures	11	0.000										

The parameters are probit estimates of the model $surv_{2i} = \beta\ proc\_post1995\%_i + \gamma\ Z_i + \varepsilon_i$. The model also includes dummy variables for each of over 600 Diagnosis Related Groups and for each of over 400 postcodes.

Table 3

Estimates of models of patient survival based on cross-sectional patient-level data

Model	dependent variable	independent variable	Estimate	StdErr	ChiSq	ProbChiSq
1	alive at time of discharge	proc_year	0.014	0.005	7.21	0.0072
2	alive 1 year after admission	proc_year	0.066	0.002	798.46	0.0000
3	alive 2 years after admission	proc_year	0.068	0.002	833.40	0.0000
4	alive 3 years after admission	proc_year	0.054	0.002	473.13	0.0000
5	alive 4 years after admission	proc_year	0.046	0.003	273.10	0.0000
6	alive 5 years after admission	proc_year	0.033	0.003	100.68	0.0000
7	alive at time of discharge	proc_post1995%	-0.010	0.041	0.06	0.8074
8	alive 1 year after admission	proc_post1995%	0.392	0.016	628.25	0.0000
9	alive 2 years after admission	proc_post1995%	0.405	0.015	729.76	0.0000
10	alive 3 years after admission	proc_post1995%	0.324	0.015	438.52	0.0000
11	alive 4 years after admission	proc_post1995%	0.293	0.017	303.25	0.0000
12	alive 5 years after admission	proc_post1995%	0.202	0.020	106.73	0.0000

Note: The estimates reported are estimates of the coefficient β in eq. (1): $surv_{ni} = \beta\ vintage_i + \gamma\ Z_i + \varepsilon_i$. Each estimate is from a different probit model. All models include dummy variables for the patient's age, sex, Diagnosis Related Group (DRG, over 600 categories), Aboriginal status, marital status, insurance coverage (whether or not the patient has private insurance), postcode (over 400 postcodes), year of hospital admission, and number of procedures performed.

Table 4

Estimates of models of patient survival based on longitudinal DRG-level data

Model	dependent variable	independent variable	Estimate	Stderr	Z	ProbZ
13	alive at time of discharge	proc_year	0.207	0.040	5.216	0.0000
14	alive 1 year after admission	proc_year	0.052	0.026	1.986	0.0470
15	alive 2 years after admission	proc_year	0.075	0.027	2.786	0.0053
16	alive 3 years after admission	proc_year	0.076	0.029	2.588	0.0097
17	alive 4 years after admission	proc_year	0.026	0.015	1.710	0.0872
18	alive 5 years after admission	proc_year	0.017	0.017	0.957	0.3384
19	alive at time of discharge	proc_post1995%	1.240	0.443	2.799	0.0051
20	alive 1 year after admission	proc_post1995%	0.315	0.178	1.770	0.0767
21	alive 2 years after admission	proc_post1995%	0.475	0.160	2.959	0.0031
22	alive 3 years after admission	proc_post1995%	0.507	0.154	3.295	0.0010
23	alive 4 years after admission	proc_post1995%	0.252	0.109	2.317	0.0205
24	alive 5 years after admission	proc_post1995%	0.174	0.127	1.372	0.1699

Note: The estimates reported are estimates of the coefficient β in eq. (3): $\ln(surv\%_{ndt}/(1- surv\%_{ndt})) = \beta$ $proc\_post1995\%_{dt} + \gamma Z_{dt} + \alpha_d + \delta_t + \varepsilon_{dt}$. Each estimate is from a different model. All models include mean age, mean number of procedures performed, the fraction of patients with private insurance, DRG fixed effects, and year fixed effects. Models were estimated via weighted least-squares, where the weight is the number of patients discharged in year t in DRG d (N_{dt}). Estimates allow for clustering of disturbances within DRGs.