PRELIMINARY WORK - PLEASE DO NOT CITE

The price sensitivity of acute stroke care

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8th December 2011

Abstract

To contain costs at the macro level, activity based hospital reimbursement schemes may include a decrease in the marginal tariff for production above a prospectively set production target. When quality is unspecified and demand is inelastic with respect to quality, hospitals may respond to a reduction in marginal tariffs by reducing quality. We apply a regression discontinuity design to test the effect of a short term price decrease on the quality of acute stroke care in Danish hospitals. We use a rich dataset describing the quality of care by 9 process indicators and include tests for gaming behaviour in hospitals. We find only week indications of reductions in quality, and our results are sensitive to choice of bandwidth and scaling of the running variable.

1 Introduction

Activity based funding (ABF) has become a common way of funding hospitals since the prospective payment system was introduced in the US Medicare/Medicaid in the early 1980s (Forgione et al., 2004; Kimberly et al., 2008). By linking hospital reimbursement to activity through a fixed tariff per discharge, the scheme was introduced in the US to incentivise efficiency increases and cost containment at a micro level (Chilingerian, 2008). However, as ABF also incentivises increased activity, at a macro level this hospital funding scheme may lead to uncontrollable costs if the system is open-ended (Jegers et al., 2002; Street et al., 2007).

In order to contain costs at the macro level, activity based hospital reimbursement schemes may reduce the marginal tariff when total hospital production is above a prospectively set

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activity target expressed in the monetary value of production and known as the hospital baseline.

The aim of this paper is to test whether hospitals respond to such a short term decrease in marginal tariffs by decreasing the level of quality provided. This may be the case when quality is unspecified in the reimbursement scheme and patient demand does not reflect quality (Chalkley and Malcomson, 1998). We use the discontinuity in the hospital reimbursement scheme when the hospital crosses the baseline for identifying the casual effect of a decrease in marginal prices on the quality of care.

We test our hypothesis on acute stroke care. Acute stroke is the second most common cause of death in the world, causing 9 percent of all deaths - in western countries 10-12 percent of all deaths. It is the sixth most common cause of reduced disability-adjusted life years, and the costs of acute stroke to society has been estimated for the for the U.S. to be US$ 100 per capita per year (Donnan et al., 2008). We find this area suitable for testing our hypothesis due to the acute nature of stroke which makes is plausible that patients do not choose hospital on the basis of information about quality.

Hospitals may be assumed to care about quality for different reasons. The level of quality provided may enter the hospitals utility function directly (as in Newhouse, 1970), or indirectly as a part of a profit maximising objective if demand is assumed to be elastic with respect to quality (as in Pope, 1989; Allen and Gertler, 1991; Hodgkin and McGuire, 1994; Rogerson, 1994; Ma, 1994). In the latter case, hospitals have an incentive not to cut quality on areas where demand is quality elastic. However, as pointed out by Chalkley and Malcomson (1998) when quality is unspecified in the reimbursement scheme hospitals may lower quality on areas of care where patient demand does not reflect quality.

A few empirical studies have previously assessed the effect of price decrease on health care quality. Lindrooth et al. (2007) found that price cuts in Medicare payments introduced by the Balanced Budget Act in 1997 led not-for-profit hospitals to decrease treatment intensity for profitable treatments in 50th 75th and 95th quantiles of treatment intensity. They found no statistically significant effect of the price cut in public and for-profit hospitals. Wu and Shen (2011) studied the impact of the same reform focusing on the long term effects on structure, process and outcome quality. They found no effects on in-hospital acute myocardial infarction (AMI) mortality but explain this by shorter length of stay in hostpials that experienced large price reductions. Outcomes were found not to be affected in the early years after the reform, but the study identified an increase in 7- 30- and 90-day and 1 year AMI mortality rates from 2001-2005 in hospitals that experienced large and medium price cuts. The effect can be explained by reductions in staffing levels and operating costs.

Our study adds to the existing literature in 3 ways. Firstly, we assess the impact of a *short term* price decreases which may be a part of a macro level cost containment policy. It has previously been suggested that hospitals facing payment decreases may respond by attempting to increase efficiency in areas not related to quality (Wu and Shen, 2011). However, the response may be different in the context of short term decreases in price. In that case it may be more plausible for hospitals to focus on costs that are variable

in the short run. Thus, processes of care that are associated with variable costs may be especially prone to be cut when prices are decreased. Secondly, the previous studies that take point of departure in Medicare price changes are challenged by the fact that Medicare is not the only payer for health care services at US hospitals. Thus, a provider may shift-costs—that is, charge higher prices from private customers, when Medicare payments are cut (Ginsburg, 2003; Wu, 2010). Thus, these studies may underestimate the effect of a price decrease on the quality of care. In comparison, the hospitals included in our study are paid by one payer only and we can be confident that cost-shifting does not affect our results. Finally, the data set we use for assessing the quality of care contains a much richer description of the processes of care than what have previously been used and participation in the scheme is mandatory for all public hospitals treating acute stroke patients. This allow us to get a more detailed picture of how short term payment decreases affects the quality of care and examine whether changes which might be difficult to capture with cruder measures of quality such as readmission rates or mortality and there are no selection issues.

1.1 Institutional context

Danish hospitals are owned and funded by the 5 regions, which are in turn funded jointly by the central government and the local governments within the region's geographical boundaries. Each region is free to design its' own hospital funding scheme. The only requirement is, that at least 50% of the hospital funding is distributed on the basis of activity using the Danish version of the DRG system.

In such a payment scheme, the hospital revenue function can be described as

$$R = Z + Q(p - \theta \times I(Q > \bar{Q})) \tag{1}$$

where Z is a block grant that covers non-activity related costs, Q is the level of production, $\bar{Q}$ is the production target (baseline), and I is an indicator denoting whether the hospital has crossed the baseline. The baseline is an activity budget or production target for a given hospital in a given year expressed in monetary DRG production value. It is usually set on the basis of last years production or last years baseline plus a productivity requirement of 2-6 percent. p is the national tariff and θ is the reduction in the national tariff that occurs when the hospital produces above the baseline.

If hospitals do not meet the baseline the hospital must pay back the region some share of the value of the unmet production. This share may be the same as the marginal tariff for production above the baseline. We call such scheme S(ymmetric) schemes because the tariff the hospital is paid for production above the baseline is the same as the tariff the hospital must pay for unmet production below the baseline. Most schemes are (A)symmetric, meaning that the tariff the hospital is paid for production above the baseline is lower than the tariff the hospital must pay for unmet production.

The regional reimbursement schemes and the share of the national tariff paid to the hospital for production above the baseline is summarised in table 1.

Table 1: Regional reimbursement schemes

Region	Year	$1-\theta$	Type
Northern Jutland	2007	.20	A
Northern Jutland	2008	.20	A
Northern Jutland	2009	.20	A
Northern Jutland	2010	.20	A
Central Denmark	2007	0	A
Central Denmark	2008	0	A
Central Denmark	2009	0	A
Central Denmark	2010	0	A
Southern Denmark	2007	14	A
Southern Denmark	2008	14	A
Southern Denmark	2009	0	A
Southern Denmark	2010	0	A
Zealand	2007	55	A
Zealand	2008	55/10	A
Zealand	2009	55/10	A
Zealand	2010	55/10/0	A
Capital	2007	50	S
Capital	2008	50	S
Capital	2009	50	S
Capital	2010	50	S

2 Data and Methods

2.1 A Regression Discontinuity Design

To identify the casual effect of a price decrease on the quality of acute stroke care, we apply a sharp[1] regression discontinuity design (RDD). RDD is a method for identifying treatment effects and was introduced by Thistlethwaite and Campbell (1960). The method has increasingly found application in economics during the past 10–15 years (Lee and Lemieux, 2010). Jones and Rice (2009) noted that only a few applications exist in health economics, but that has rapidly changed since then (e.g. Hullegie and Klein, 2010; Almond et al., 2010; Andalón, 2011; Almond and Doyle, 2011). The method has it's name from the discontinuity with which the probability of receiving treatment changes when a forcing (or running) variable X observed for the subjects under study crosses a known threshold or cutoff point.

In our application the running variable is accumulated hospital production and the cut-off value is the production threshold that determines by which proportion of the national tariff activity is reimbursed. Thus for subject i treatment is assigned if the running variable exceeds the cutoff value:

$$D_i = \begin{cases} 1 & \text{if } X > x_0 \\ 0 & \text{if } X \leq x_0. \end{cases} \tag{2}$$

[1]Fuzzy RDD is another possible design. In the fuzzy RDD the probability of receiving treatment changes when the threshold is crossed, while in the sharp RDD, treatment status is assumed to change deterministically as a function of X. At this point we apply a sharp RDD.

where x_0 is the cutoff value. Hahn et al. (2001) showed that the estimation of treatment effects from RDD requires only that the continuity of potential outcomes assumption is fulfilled—that is that treatment status is not directly manipulatable for the subjects under study. This assumption can be tested by comparing baseline characteristics for subjects above and below the threshold. Lee (2008) showed that under a few week additional assumptions in a neighborhood around $X = x_0$, the variation in treatment status is if randomised.

2.2 Running variable: accumulated hospital production

Our running variable is accumulated production measured in DRG-value by hospital by day from January 1st to December 31st. As a new baseline is set for each hospital each year, on the 1st of January, the variable is reset to zero. To construct this variable we obtained data from administrative datasets on all somatic inpatients and outpatients treated at all Danish public hospitals that treated acute stroke patients from January 20007 to December 2010. In total this corresponds to more than 40 million records from patients treated at 33 hospitals. For each patient we obtained information on DRG-price, discharge date for inpatients, and date of visit for outpatients. We then accumulated the DRG-value of each patient by hospital by day. This allowed us to trace production over time and determine on which date the hospital crossed the baseline. In addition this approach allowed us to link the running variable to our patient level quality data which also contains a date variable. In that way we knew on which side of the baseline a given patient had been treated, and thus whether he had been exposed to treatment or not. For all but one region we can compare our calculation of the running variable with the regions' own calculation as expressed in the annual account. We drop observations for which there is a $> 2\%$ difference between the region's value and our own. For the remaining observations the mean deviance is 1%.

2.3 Cut-off value: the hospital baseline

The central requirement for using the hospital baseline for identifying the effect of a short term price decrease is whether the hospitals incentives for delivering all dimensions of quality is different on each side of the baseline.

As noted by Wu and Shen (2011) whether a price decrease induce reductions in treatment quality depends on several factors; the size of the decrease, the previous level of reimbursement, the hospitals production efficiency, competition from other providers and the elasticity of demand with respect to quality may all determine the hospitals response to a price decrease. As mentioned above we can distinguish between type A and S reimbursement schemes. In both type A and type S systems, the degree of cost sharing between the region and the hospital changes when the hospital crosses the baseline. In both systems the share of costs covered by the hospital increases. For that reason, the regions in both reimbursement schemes are included in the analysis.

In addition, using the baseline for identifying the effect of price decrease presupposes that the hospital management information systems can identify the point in time when the hospital crosses the baseline. Hospitals can follow their production throughout the year, and should know in due time when they expect to cross the baseline and take measures accordingly. It is not a prerequisite that payment incentives are directly carried on to the department level. As long as the hospital management is aware that the hospital is crossing the baseline, it may communicate cost containment orders through information and fiat.

The baseline may be adjusted during the year. Adjustments may occur if the departments are moved between hospitals, or large unexpected changes in production occur. In macro economics, the impact of data revisions have been discussed under the heading of real-time data analysis Croushore (2011). When analysing data available at present correct inference about past time behaviour may be incorrect, because the data available today is different from the data available at the when the decision was made. In our context, the relevant baseline would be the baseline available to the hospital decision makers when the baseline is crossed. Information about the updated baseline will be available to the hospital during the year as they are calculated by the region. It was not possible to obtain information on adjustments of hospital baselines over time. Instead we use the final baseline that is used in the annual accounts. As the baseline is usually crossed at the end of the year, we believe this to be a fair approximation<.

2.4 Dependent variables: measuring the quality of acute stroke care

In order to measure the quality of the acute stroke treatment we obtained patient level data from the Danish National Indicator Project (DNIP) which operational acute stroke care quality on 9 process.

The provision of one of the process indicators depends on whether the patient has atrial fibrillation or not. Thus maximally 8 processes can be provided and measured by DNIP. The process indicators may be thought of as dimensions of quality that the hospital can choose to provide to a given patient. The data set that could be linked to hospitals for which the marginal tariff decreased after crossing the baseline consists of quality indicators for 25,028 acute stroke patients who were treated at Danish hospitals between 1 January 2007 and 31 December 2010.

The quality indicators are selected by a council of medical doctors on the basis of clinical evidence (See Mainz et al., 2004, for a decription of the process). The evidence that form the basis of the indicators is ranked by the DNIP from evidence type A (Meta studies and randomised controlled trials) to D(expert judgments, survey articles and editorials). The indicators are described in Table 2 which also indicates the strength of the evidence on which the indicator is build.

For each indicator, hospitals may report the indicator as having been fulfilled or not, or that the indicator is not clinically relevant for the specific patient. In addition a date variable specifies which date the indicator was achieved. The latter variable is used for

assessing whether performance is within pre-specified targets defined in the indicator guidelines from DNIP. Summary statistics for each of the 9 indicators can be found in Table 3.

Hospital level performance on the indicators are made publicly available as ratios of patients receiving a given indicator at hospital level on the internet, but performance information is not linked to hospital reimbursement.

For hospital k on day d the official measure of quality dimension i may be expressed as a ratio which we, inspired by Gravelle et al. (2010) describe as

$$q^{O}_{ikd} = N_{ikd}/D_{ikd} = N_{ikd}/(T_{kd} - I_{ikd} - M_{ikd}) \tag{3}$$

N_{ikd} is the number of patient for whom the quality indicator is delivered within the specified time (see Table 1). The denominator $D_{ikd} = (T_{kd} - I_{ikd} - M_{ikd})$ is the number of patients for whom the indicator is deemed clinically relevant and non missing. T_{kd} is the total number of patients admitted for acute stroke on a given date. I_{ikd} is the number of patients for which the indicator has been deemed clinically irrelevant by the hospital and M_{ikd} is the number of patients for whom information on fulfilment was missing or for which the date variable for provision of the indicator was missing. According to the official guidelines missing and clinically irrelevant (as judged by the hospital) should be excluded form the calculation of the official indicator.

It follows, that hospitals can game this indicator by increasing the number of patients for which the quality indicator is deemed clinically irrelevant, I_{ikd} or by increasing the number of patients for whom achievement status of a given indicator or the date of achievement is not reported M_{ikd} . For that reason, we also calculate an unadjusted quality indicator q^U which is equal to

$$q^{U}_{ikd} = N_{ikd}/T_{kd}. \tag{4}$$

To investigate whether reducing the tariff induces gaming and what type of gaming, we further define the proportion of patients for whom a given indicator was reported to be clinically irrelevant:

$$q^{I}_{ikd} = I_{ikd}/T_{kd} \tag{5}$$

and the proportion of patients for whom achievement status or date was not reported

$$q^{M}_{ikd} = M_{ikd}/T_{kd}. \tag{6}$$

Table 2: The DNIP indicators

Indicator	Indicator domain	Description	Target	Evidence strength
1	Treatment, care and rehabilitation in a stroke unit	Admission to a stroke unit no later than the 2nd day of hospitalisation	>= 90%	A
2	Secondary prophylactic medical treatment	Treatment with antiplatelet inhibitor initiated no later than the 2nd day of hospitalization for acute ischemic stroke patients without atrial fibrilation	>= 95%	A
3	Secondary prophylactic medical treatment	Treatment with oral anticoagulants initiated no later than the 14th day of hospitalisation for acute ischemic stroke patients with atrial fibrillation	>= 95%	A
4	Diagnostics with CT/MR scan	Examiniation/diagnostics with CT/MR scan on the first day of hospitalisation	>= 80%	D
5	Assessment by physiotherapist	Assessment by a physiotherapist no later than the 2nd of hospitalisation in order to clarify the extent and type of rehabilitation needed and time for initiation of physiotherapy	>= 90%	D
6	Assessment by occupational therapist	Assessment by a occupational therapist no later than the 2nd day of hospitalisation in order to clarify the extent and type of rehabilitation needed and time for initiation of occupational therapy	>= 90%	D
7	Assessment of nutritional risk	Assessment of nutritional risk no later than the 2nd day of hospitalisation	>= 90%	D
8	Dysphagia screening	Assessment by bedside screening in order to determine the extent of aspiration and the severity of swallow dysfunction no later than the 1st day of hospitalisation	>= 90%	D
9	Ultrasound/CT angiography	Ultrasound/CTangiography of the carotid ateries no later than the 4th day of hospitalisation	>= 90%	N/A

Table 3: Summary statistics for the indicators

Valid %		I1	I2	I3	I4	I5	I6	I7	I8	I9
	Yes	74.79	4.74	7.72	98.27	79.83	81.10	74.56	79.80	34.68
	No	24.79	15.28	5.00	0.27	1.70	1.85	5.90	5.79	10.39
	No (contraindicated)	.	58.01	35.36	.	.	.	.	.	.
	Not clinically relevant	.	.	0.50	0.50	15.68	14.18	11.43	14.41	29.04
Missing %		0.42	21.96	51.92	0.97	2.79	2.87	8.12	24.81	25.89
Total %		100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

2.5 Estimation

We take a non-parametric approach to estimating the treatment effect. Following Lee & Lemieoux (2010), in the case of a rectangular kernel, this equals estimating a standard regression within a window of width k on both sides of the cutoff value. In other words we basically compare the average level of quality on both sides of the threshold.

Although our data is essentially longitudinal, we follow the average cluster approach as does Lemieux and Milligan (2008); Battistin et al. (2009); Dong (2011) To be able to pool hospitals with different baselines in the same analysis and over time, we translated the running variable from the monetary value to days from threshold. Thus, we define the bandwidth by the number of days on each side of the threshold for which observations are used.

To the left of the threshold, the regression model is

$$q = \alpha_l + \beta_l(X - x_0) + \epsilon \text{ for } x_0 - k \leq X < x_0 \tag{7}$$

where q is the outcome variable of interest, X is the running variable, in our case accumulated production value, x_0 is the cutoff value (baseline) and k is the bandwidth.

On the right side of the threshold, the model is

$$q = \alpha_r + \beta_r(X - x_0) + \epsilon \text{ for } x_0 \leq X \leq x_0 + k \tag{8}$$

The treatment effect, τ is then equal to the difference in the constant terms, i,e, $\tau = a_r - \alpha_l$.

We estimate τ by running a pooled regression on both sides of the cutoff value:

$$Y = \alpha + \tau D + \beta(X - x_0) + \epsilon \text{ for } x_0 - k \leq X \leq x_0 + k \tag{9}$$

3 Results

Table 4 - 12 presents the results from our model specifying different bandwidths and scales of the dependent variable. Each table presents the results from one of the 9 process indicators.

Table 4: Indicator 1: Admission to a stroke unit no later than the 2nd day of hospitalization

	xscale=1				xscale=3				xscale=5				xscale=7			
	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M
Treatment effect (k=3)	0.0646	0.0665	0	0.00406	0.0781	0.0724	0	-0.00568	0	0	0	0	0	0	0	0
Treatment effect (k=5)	-0.0309	-0.0332	0	0.00921	0.0454	0.0411	0	-0.00914	0.136	0.140	0	-0.00779	0	0	0	0
Treatment effect (k=7)	-0.0759	-0.0789	0	0.00963	-0.0455	-0.0498	0	-0.00541	0.0390	0.0439	0	-0.00985	0.148	0.147	0	0.00361
Treatment effect (k=10)	-0.0861	-0.0891	0	0.00840*	-0.0333	-0.0367	0	-0.00446	0.0851	0.0892	0	-0.00810*	0.119	0.118	0	0.00263

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All dependent variables are ratios, expressing the ratio of patients that received or did not receive the specific process of care at a given hospital at a given day. The coefficients are the estimate of the local average treatment effect—that is the effect of reducing the tariff the hospital is paid for treatment. We pool all observations across hospitals and years.

As a sensitivity check, in each table the four versions of the dependent variable are presented in four blocks (columns). Each block represents a scaling of the running variable in 1, 3, 5, or 7 days. Grouping the observations in blocks of days may increase the efficiency of the estimates.

In each block there are four variations of the dependent variable, one per column. The first column of each block represents official quality, q^O as defined by a given indicator and using the official definition of the indicator which is adjusted for missing values and instances where a quality indicator was deemed not clinically relevant. The second column represents the unadjusted quality indicator, q^U which is goal attainment when missing values and relevance of the indicator is not taken into account. The dependent variable of the third column represents the ratio of instances where the indicator was found clinically irrelevant, q^I and in the fourth column the dependent variable is the ratio of missing values, q^M. The latter two are included to assess whether hospitals attempt to game the quality indicator by changing their level of missing values and exception reportings in response to crossing the threshold. In doing so, hospitals may provide fewer dimensions of quality but still perform well on the official quality indicators.

In addition for each indicator we present 4 rows of results with bandwidths 3, 5, 7, and 10 days. A bandwidth of 3 means that observations from 3 days above and 3 days below the threshold were included in the regression. We cannot estimate the treatment effect for a bandwidth of three days with a scale of 5 and 7 days or for a bandwidth of 5 days for a scaling of 7 days.

Our analysis suggest no statistically significant effect of temporarily decreasing the marginal price on the proportion of patients being treated at a stroke unit, although the coefficient on the official indicator q^O is in most cases negative. As the costs of running a stroke unit are fixed in the short run this finding is in line with out expectations. Neither do we find consistent evidence of an effect of the proportion of patients that receive treatment with antiplatelet inhibitor. For patients with atrial fibrillation, we find some evidence of an increase in q^O for treatment with oral anticoagulants possibly caused by

Table 5: Indicator 2: Treatment with antiplatelet inhibitor is initiated no later the an the 2nd day of hospitalization (patients without atrial fibrillation only)

	xscale=1				xscale=3				xscale=5				xscale=7			
	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M
Treatment effect (k=3)	0.401	0.0140	0	0.00321	0.402	0.0342	0	0.00132	0	0	0	0	0	0	0	0
Treatment effect (k=5)	0.330	0.00364	0	0.0234	0.324	0.0355	0	0.00359	0.127	0.0483	0	-0.0452	0	0	0	0
Treatment effect (k=7)	0.345	-0.00700	0	0.0380	0.149	0.0190	0	0.00782	0.124	0.00748	0	-0.00837	0.0538	0.0261	0	-0.0309
Treatment effect (k=10)	0.161	0.00965	0	0.0108	0.0698	0.0352	0	-0.0143	0.0684	0.0801**	0	-0.0741**	0.0285	0.0318	0	-0.0251

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Indicator 3: Treatment with oral anticoagulants is initiated no later than the 14th day of hospitalization (patients with atrial fibrillation only)

	xscale=1				xscale=3				xscale=5				xscale=7			
	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M
Treatment effect (k=3)	0.745*	0.0545	0	-0.0137	0.395	0.0475	0	-0.0285	0	0	0	0	0	0	0	0
Treatment effect (k=5)	0.645**	0.0562	0	-0.0179	0.353	0.0256	0	-0.0190	0.857	0.0461	0	-0.0612*	0	0	0	0
Treatment effect (k=7)	0.378*	0.0735**	0	-0.0470	0.246	0.0350	0	-0.0252	0.0751	0.0541	0	-0.0651	0.107	0.0762**	0	-0.0950**
Treatment effect (k=10)	0.201	0.0598*	0	-0.0512	0.109	0.0245	0	-0.0230	0.0442	0.0169	0	-0.0229	0.0444	0.000200	0	-0.0159

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Indicator 4: CT/MR scan on the first day of hospitalization

	xscale=1				xscale=3				xscale=5				xscale=7			
	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M
Treatment effect (k=3)	0.199*	0.141	0.0107	0.0414	0.00600	0.00235	-0.00518	0.0252	0	0	0	0	0	0	0	0
Treatment effect (k=5)	0.139	0.113	0.00508	0.00902	-0.0490	-0.0549	-0.00710	0.0334	-0.118	-0.150	0.0172	0.0809***	0	0	0	0
Treatment effect (k=7)	0.0557	0.0298	0.0103	0.0226	0.0182	0.00930	-0.00385	0.0333	-0.0242	-0.0401	-0.000658	0.0398**	0.0587	0.0322	0.000551	0.0473**
Treatment effect (k=10)	0.0366	0.0107	0.0104	0.0263	-0.0534	-0.0631	-0.00355	0.0298*	-0.0337	-0.0516	-0.00104	0.0319*	-0.0183	-0.0348	-0.00403	0.0271*

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Indicator 5: Assessment by a physiotherapist no later than t he 2nd day of hospitalization

	xscale=1				xscale=3				xscale=5				xscale=7			
	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M
Treatment effect (k=3)	0.00467	0.0723	-0.139*	-0.0770	-0.0754	0.0341	-0.127	-0.136	0	0	0	0	0	0	0	0
Treatment effect (k=5)	-0.0952	-0.0467	-0.0784	-0.0184	-0.109	-0.0242	-0.108	-0.117	-0.0375	0.111	-0.197**	-0.210**	0	0	0	0
Treatment effect (k=7)	-0.0688	-0.0306	-0.0570	-0.0220	0.0185	0.0467	-0.0580	-0.0693	-0.0270	0.108	-0.148**	-0.177**	0.0753	0.115	-0.0573	-0.0560
Treatment effect (k=10)	-0.0505	-0.0278	-0.0373	-0.0202	0.00390	0.0145	-0.0356	-0.0514	-0.0984	0.0197	-0.115*	-0.125**	0.130	0.141	-0.0366	-0.0394

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Indicator 6: Assessment by an occupational therapist no later than the 2nd day of hospitalization

	xscale=1				xscale=3				xscale=5				xscale=7			
	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M
Treatment effect (k=3)	-0.0472	0.0281	-0.0649	-0.0733	0.00849	0.0487	-0.0650	-0.0526	0	0	0	0	0	0	0	0
Treatment effect (k=5)	-0.144	-0.114	-0.00468	0.00482	-0.0422	-0.0204	-0.0708	-0.0356	0.00825	0.0706	-0.128*	-0.106	0	0	0	0
Treatment effect (k=7)	-0.0920	-0.0685	0.00444	0.000474	0.0662	0.0606	-0.0223	0.00448	0.0420	0.0571	-0.0534	-0.0424	0.0921	0.0789	-0.00848	0.0178
Treatment effect (k=10)	-0.0394	-0.0184	-0.000425	-0.0137	0.0700	0.0619	-0.00774	0.00476	-0.0321	-0.0114	-0.0388	-0.0236	0.127	0.0927	0.00699	0.0289

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Indicator 7: Assessment of nutritional risk no later than the 2nd day of hospitalization

	xscale=1				xscale=3				xscale=5				xscale=7			
	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M
Treatment effect (k=3)	0.0645	0.0675	-0.0792	-0.0272	-0.267**	-0.0329	-0.0642	-0.148	0	0	0	0	0	0	0	0
Treatment effect (k=5)	0.0211	-0.0120	-0.00803	0.0402	-0.217*	-0.0527	-0.0507	-0.117	-0.0705	-0.00257	-0.0351	-0.0772	0	0	0	0
Treatment effect (k=7)	0.0125	-0.0254	-0.0357	0.0445	-0.156*	-0.0575	-0.0765	-0.0627	-0.140	-0.0926	-0.0287	0.00601	0.0551	0.0698	-0.0388	-0.0487
Treatment effect (k=10)	-0.0433	-0.0494	-0.0635	0.0180	-0.178**	-0.120	-0.0568	-0.0122	-0.132	-0.113	0.00115	0.0201	0.0225	-0.0181	0.00781	0.0157

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Indicator 8: Assessment by bedside screening in order to determine the extent of aspiration and the severity of swallow dysfunction no later than the first day o f hospitalization

	xscale=1				xscale=3				xscale=5				xscale=7			
	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M
Treatment effect (k=3)	0.292**	0.299**	-0.111	-0.114	0.0298	0.142	-0.145*	-0.150	0	0	0	0	0	0	0	
Treatment effect (k=5)	0.112	0.113	-0.0344	-0.0525	0.0711	0.106	-0.108	-0.0902	-0.0395	-0.0396	-0.136	-0.00554	0	0	0	0
Treatment effect (k=7)	0.0623	0.0453	-0.0624	-0.00691	0.0381	0.0846	-0.150**	-0.0944	-0.0650	-0.0382	-0.120*	-0.0110	0.105	0.121	-0.107	-0.0463
Treatment effect (k=10)	0.0336	0.0243	-0.0658	0.0111	-0.00247	0.0304	-0.134**	-0.0538	-0.0601	-0.0137	-0.0958*	-0.0317	-0.0113	0.0340	-0.0602	-0.0253

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Indicator 9: Proportion of patients who undergo an ultrasound/CT-angiography of the carotid arteries no later than the 4th day of hospitalization

	xscale=1				xscale=3				xscale=5				xscale=7			
	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M
Treatment effect (k=3)	-0.148	-0.166	0.125	0.160	0.209	-0.00618	0.0636	0.190	0	0	0	0	0	0	0	0
Treatment effect (k=5)	-0.369***	-0.295***	0.182*	0.192*	0.0429	-0.112	0.0456	0.208*	-0.0347	-0.125	0.0662	0.154	0	0	0	0
Treatment effect (k=7)	-0.262**	-0.214***	0.124	0.166*	0.0514	-0.0229	-0.0240	0.114	-0.122	-0.0860	-0.0502	0.0646	0.192	0.164*	-0.191**	-0.121
Treatment effect (k=10)	-0.118	-0.120*	0.0689	0.103	0.101	0.0129	-0.0433	0.0795	-0.0403	-0.000864	-0.105	-0.00538	0.112	0.0650	-0.111	-0.0519

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

a decrease in the proportion of missing values q^M when the marginal price decreases. This finding is surprising, but the statistical significance of these findings is weak. We find similar results for q^O for receiving a CT/MR scan, but this time coinciding with an increase in q^M. However, again the results are relatively statistically insignificant although there is a tendency towards more statistical significance as the scaling of the running variable increases.

There is some evidence of a decrease in q^M for assessment by a physiotherapists when the marginal price is decreased. In many cases this corresponds with a decrease in q^I, the proportion of patients for whom the indicator is deemed clinically irrelevant, but this effect is inconsistent. Assessment by an occupational therapist does not appear to be affected by a short term decrease in marginal prices. For assessment of nutritional risk we find some evidence of a decrease in q^M but the statistical significance of this finding is highly dependent of the choice of bandwidth and scaling of the running variable. With respect to dysphagia screening, we find some signs of a decrease in q^I. The effect is strongest for a scaling of 3 of the running variables, and is consistent, though not as statistically significant for other scalings of the running variable. The effect on q^O is inconsistent. Finally, there is some evidence that the proportion of patients who undergo an ultrasound/CT-angiography of the carotid ateries decreases when the marginal price is temporarily reduced driven by an increase in q^I and q^M. However, this finding is dependent on the scaling of the running variable.

3.1 Sensitivity analysis

To test the assumption that the covariates are continuously distributed across the threshold, we perform the same analysis again, this time using the baseline covariates as dependent variables instead of the quality indicators. Insignificant treatment effects is a an indication that we are right in assuming local randomisation of the treatment indicator. The covariates we examine in table 13–23 are whether the patient is a daily smoker, an occasional smoker or previously has been a smoker; whether the patient previously had a stroke or an acute myocardial infarct (AMI); whether the patient lives alone, with others or in an assisted living facility; the gender and age distribution of the patients; and whether the patient consumes more alcohol than recommended by the national guidelines.

For all variables we find no or extremely week evidence that a change in the patient as measured on these variables across the threshold. This indicates that the assumption of continuity of potential outcomes is appropriate.

As a test of impact on short term marginal price changes, we test whether we can observe the effect on quality of crossing the 1st of January instead of crossing the baseline. At the beginning of the year, the reimbursement scheme is reset and the marginal tariff increases again. By using new year as the threshold instead of the baseline, we expect to find the opposite effect of what we previously expected—that is, we expect the provision of quality to increase again if it decreased when the hospital crossed the baseline.

Table 13: Proportion of occasional smokers

	(1) xscale=1	(2) xscale=3	(3) xscale=5	(4) xscale=7
Treatment effect (k=3)	0.00983	-0.00568	0	0
Treatment effect (k=5)	0.00953	-0.00821	0.0169	0
Treatment effect (k=7)	0.00197	-0.00770	0.0137	-0.00623
Treatment effect (k=10)	0.00672	-0.00323	0.00972	-0.00545

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Proportion of daily smokers

	(1) xscale=1	(2) xscale=3	(3) xscale=5	(4) xscale=7
Treatment effect (k=3)	-0.0574	0.0368	0	0
Treatment effect (k=5)	-0.0711	0.0344	-0.119	0
Treatment effect (k=7)	-0.177**	-0.115	-0.0901	-0.0329
Treatment effect (k=10)	-0.102	-0.0744	-0.0135	-0.0301

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Proportion of non-smokers

	(1) xscale=1	(2) xscale=3	(3) xscale=5	(4) xscale=7
Treatment effect (k=3)	0.109	0.00312	0	0
Treatment effect (k=5)	0.0407	0.0146	0.143	0
Treatment effect (k=7)	0.0431	0.0480	0.0863	0.0816
Treatment effect (k=10)	0.0869	0.0756	0.0478	0.0427

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Proportion of ex-smokers

	(1) xscale=1	(2) xscale=3	(3) xscale=5	(4) xscale=7
Treatment effect (k=3)	-0.0176	-0.0494	0	0
Treatment effect (k=5)	-0.0346	-0.0117	0.129	
o.Treatment effect (k=5)				0
Treatment effect (k=7)	0.0703	0.0670	0.0359	0.0362
Treatment effect (k=10)	-0.0463	-0.0159	-0.0483	0.0482

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Proportion living in own home

	(1) xscale=1	(2) xscale=3	(3) xscale=5	(4) xscale=7
Treatment effect (k=3)	0.0587	-0.0735	0	0
Treatment effect (k=5)	0.0637	-0.0535	-0.0193	
o.Treatment effect (k=5)				0
Treatment effect (k=7)	-0.0305	-0.109*	-0.0481	-0.0212
Treatment effect (k=10)	-0.0128	-0.0617	-0.00548	0.0484

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Proportion living with others

	(1) xscale=1	(2) xscale=3	(3) xscale=5	(4) xscale=7
Treatment effect (k=3)	-0.0827	-0.0409	0	0
Treatment effect (k=5)	-0.131	-0.0225	-0.0649	
o.Treatment effect (k=5)				0
Treatment effect (k=7)	-0.186**	-0.127	-0.0890	-0.0470
Treatment effect (k=10)	-0.0880	-0.0258	-0.0189	0.0680

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Proportion of males

	(1) xscale=1	(2) xscale=3	(3) xscale=5	(4) xscale=7
Treatment effect (k=3)	-0.0687	0.186	0	0
Treatment effect (k=5)	-0.107	0.0153	-0.178	
o.Treatment effect (k=5)				0
Treatment effect (k=7)	-0.0914	0.0588	-0.132	-0.0956
Treatment effect (k=10)	-0.0246	0.0945	-0.00242	0.0182

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20: Age

	(1) xscale=1	(2) xscale=3	(3) xscale=5	(4) xscale=7
Treatment effect (k=3)	3.705	-1.195	0	0
Treatment effect (k=5)	2.856	0.863	0.358	0
Treatment effect (k=7)	4.533**	1.910	-0.646	-1.608
Treatment effect (k=10)	2.504	0.800	-3.293*	-1.498

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Proportion that previously had a stroke

	(1) xscale=1	(2) xscale=3	(3) xscale=5	(4) xscale=7
Treatment effect (k=3)	0.0422	0.146	0	0
Treatment effect (k=5)	0.0724	0.0535	0.0131	0
Treatment effect (k=7)	0.0580	0.0499	0.00424	-0.00676
Treatment effect (k=10)	0.0549	0.0579	0.0287	-0.0616

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 22: Proportion that previously had AMI

	(1) xscale=1	(2) xscale=3	(3) xscale=5	(4) xscale=7
Treatment effect (k=3)	0.0268	0.116	0	0
Treatment effect (k=5)	0.0331	0.109	0.0364	0
Treatment effect (k=7)	0.0547	0.0773	-0.0169	-0.0388
Treatment effect (k=10)	0.0367	0.0502	-0.0181	-0.00574

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23: Proportion living in an assisted living facility

	(1) xscale=1	(2) xscale=3	(3) xscale=5	(4) xscale=7
Treatment effect (k=3)	0.00512	0.0152	0	0
Treatment effect (k=5)	0.0302	0.0360	-0.0348	0
Treatment effect (k=7)	0.0351	0.0613	-0.0410	-0.00822
Treatment effect (k=10)	0.0189	0.0271	-0.0518	-0.0770**

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 25: Indicator 1: Admission to a stroke unit no later than the 2nd day of hospitalization

	xscale=1				xscale=3				xscale=5				xscale=7			
	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M
Treatment effect (k=3)	-0.137	-0.147	0	0.0164	0.000471	-0.00248	0	-0.00975	0	0	0	0	0	0	0	0
Treatment effect (k=5)	-0.0480	-0.0483	0 0	0.00617 0	-0.0568 0	-0.0469 0	0	-0.0228	0.0818	0.0998	0	-0.0197				
Treatment effect (k=7)	-0.0549	-0.0537	0	0.00373	-0.0392	-0.0234	0	-0.0253**	0.0594	0.0864	0	-0.0294*	0.0825	0.0870	0	-0.00827
Treatment effect (k=10)	-0.0469	-0.0449	0	0.00116	-0.0450	-0.0295	0	-0.0211**	0.0226	0.0456	0	-0.0235**	0.0687	0.0762	0	-0.0104

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 26: Indicator 2: Treatment with antiplatelet inhibitor is initiated no later than the 2nd day of hospitalization (patients without atrial fibrillation only)

	xscale=1				xscale=3				xscale=5				xscale=7			
	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M
Treatment effect (k=3)	0	0.0173	0	-0.0173	0	-0.0386	0	0.0386	0	0	0	0	0	0	0	0
Treatment effect (k=5)	0	0.0291	0	-0.0291	0	-0.0250	0	0.0250	0	0.0202	0	-0.0202	0	0	0	0
Treatment effect (k=7)	-0.0512	0.0149	0	-0.0209	0.00632	-0.0279	0	0.0278	0.00301	-0.00195	0	0.00146	-0.0816	-0.00875	0	0.00802
Treatment effect (k=10)	0.00357	-0.0225	0	0.0237	0.0255	-0.0444	0	0.0456	0.0269	-0.0194	0	0.0200	-0.0806	-0.0113	0	0.0109

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We find no indications of an effect of increasing the marginal tariff on treatment with antiplatelet inhibitor, assessment of nutritional risk and dysphagia screening. With respect to treatment at a stroke unit we still find no consistent effect, although a few coefficients suggest an increase in q^M. We find some week signs of an increase in q^O for oral anticoagulants, but this is the same sign as for crossing the baseline. We find a few indications of an increase in q^I for CT/MR scan at the beginning of a year, but the size of the effect is too small to be of any practical importance. For assessment by a physiotherapist and occupational therapist we quite consistently find the opposite signs on the coefficients compared to crossing the baseline. This means some signs of an increase in q^O but the statistically significance of this result is limited. Finally, for ultrasound/CT-angiography of the carotid arteries we find some evidence of an increase in q^O and q^U which is the opposite of the effect we observed when the marginal price decreased. There is week signs of a coinciding decrease in q^M and increase in q^I

Table 27: Indicator 3: Treatment with oral anticoagulants is initiated no later than the 14th day of hospitalization (patients with atrial fibrillation only)

	xscale=1				xscale=3				xscale=5				xscale=7			
	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M
Treatment effect (k=3)	-0.286	0.00885	0	-0.0321	0.132	0.0174	0	-0.0628	0	0	0	0	0	0	0	0
Treatment effect (k=5)	0.0117	-0.0126	0	0.0169	0.233	0.0110	0	-0.0127	0.353*	0.0833	0	-0.0672	0	0	0	0
Treatment effect (k=7)	0.111	0.0462	0	-0.0377	0.359**	0.0491	0	-0.0382	0.418**	0.0590	0	-0.0360	0.212	-0.0355	0	0.0458
Treatment effect (k=10)	0.126	0.0769**	0	-0.0703*	0.326**	0.0487	0	-0.0388	0.354***	0.0763*	0	-0.0576	0.287**	-0.0116	0	0.0270

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 28: Indicator 4: CT/MR scan on the first day of hospitalization

	xscale=1				xscale=3				xscale=5				xscale=7			
	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M
Treatment effect (k=3)	-0.000731	-0.00449	-0.00469	0.00518	0.0770	0.0668	0.0192*	0.0170	0	0	0	0	0	0	0	0
Treatment effect (k=5)	0.00453	-0.00371	0.00421	0.00981	0.127	0.121	0.0105	0.0124	0.0439	0.0505	-0.00604	-0.00785	0	0	0	0
Treatment effect (k=7)	0.0104	0.00468	0.00550	0.00864	0.0306	0.0188	0.00980**	0.0204	-0.0162	-0.0265	0.0126***	0.0146	0.0106	-0.0214	-0.00408	0.0423
Treatment effect (k=10)	-0.0227	-0.0213	0.00325	-0.00171	0.0153	0.00929	0.00610	0.00758	0.0141	0.00327	0.0179	0.0150	-0.0228	-0.0393	0.0125	0.0241

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 29: Indicator 5: Assessment by a physiotherapist no later than the 2nd day of hospitalization

	xscale=1				xscale=3				xscale=5				xscale=7			
	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M
Treatment effect (k=3)	-0.0227	-0.0449	0.0530	0.0237	0.0505	0.0960	-0.0604	-0.0829	0	0	0	0	0	0	0	0
Treatment effect (k=5)	0.0452	0.0334	0.0542	-0.0219	0.0649	0.0656	0.0180	-0.0460	0.0766	0.119	-0.00746	-0.0397	0	0	0	0
Treatment effect (k=7)	0.0896	0.119	-0.0122	-0.0848	0.109	0.0900	0.0331	-0.0231	0.177**	0.156*	0.0241	0.0106	-0.106	-0.173*	0.121*	0.153**
Treatment effect (k=10)	0.0561	0.0281	0.0303	-0.00588	0.0218	-0.0165	0.0482	0.0179	0.0358	-0.0164	0.0777	0.0662	-0.161*	-0.172**	0.0702	0.0861

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 30: Indicator 6: Assessment by an occupational therapist no later than the 2nd day of hospitalization

	xscale=1				xscale=3				xscale=5				xscale=7			
	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M
Treatment effect (k=3)	0.0880	0.0604	0.0423	0.0154	0.227	0.309**	-0.101	-0.202**	0	0	0	0	0	0	0	0
Treatment effect (k=5)	0.0993	0.103	0.0426	-0.0333	0.131	0.163	-0.0177	-0.119	0.107	0.125	-0.00896	-0.0482	0	0	0	0
Treatment effect (k=7)	0.0783	0.114	0.0105	-0.0711	0.0879	0.0872	0.0158	-0.0454	0.134	0.128	-0.0215	-0.0329	-0.149	-0.239**	0.127*	0.225***
Treatment effect (k=10)	0.0241	0.0324	0.0103	-0.0256	-0.0239	-0.0163	0.0280	-0.0213	-0.0126	-0.0316	0.0306	0.0202	-0.213**	-0.229***	0.0764	0.0956

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 31: Indicator 7: Assessment of nutritional risk no later than the 2nd day of hospitalization

	xscale=1				xscale=3				xscale=5				xscale=7			
	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M
Treatment effect (k=3)	-0.0711	-0.0604	0.115	0.0285	0.175	0.159	-0.124	-0.111	0	0	0	0	0	0	0	0
Treatment effect (k=5)	-0.0391	0.0170	0.0310	-0.0698	0.0910	0.0697	-0.110	-0.0103	0.0592	0.0870	-0.0584	-0.0528	0	0	0	0
Treatment effect (k=7)	0.0206	0.0437	0.00753	-0.0640	0.103	0.0476	-0.0521	0.00835	0.0873	0.0350	0.0249	-0.0147	-0.0794	-0.00363	-0.0285	-0.0779
Treatment effect (k=10)	-0.0463	-0.0172	-0.000285	-0.0532	0.0373	-0.00472	-0.0295	0.00948	0.0477	-0.0159	0.0342	-0.000340	-0.00982	-0.000603	0.00626	-0.0260

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 32: Indicator 8: Assessment by bedside screening in order to determine the extent of aspiration and the severity of swallow dysfunction no later than the first day of hospitalization

	xscale=1				xscale=3				xscale=5				xscale=7			
	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M
Treatment effect (k=3)	-0.0155	0.00992	0.0866	0.0472	0.0528	0.0576	-0.0593	-0.110	0	0	0	0	0	0	0	0
Treatment effect (k=5)	-0.0495	0.0246	0.0211	-0.0450	0.155	0.0814	-0.00862	-0.0602	0.168	0.170	-0.0150	-0.0467	0	0	0	0
Treatment effect (k=7)	-0.0318	0.0227	-0.00635	-0.0593	0.0844	0.0601	-0.0485	-0.0879	0.0109	0.0402	-0.0382	-0.0741	-0.000823	-0.00376	0.0349	0.0127
Treatment effect (k=10)	-0.0840	-0.0362	-0.00234	-0.0342	-0.00638	-0.0228	-0.00351	-0.0258	-0.0165	-0.0189	0.0518	-0.0161	-0.0790	-0.0341	0.0440	-0.00651

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 33: Indicator 9: Proportion of patients who undergo an ultrasound/CT-angiography of the carotid arteries no later than the 4th day of hospitalization

	xscale=1				xscale=3				xscale=5				xscale=7			
	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M	q^O	q^U	q^I	q^M
Treatment effect (k=3)	0.00716	0.0858	-0.100	-0.205*	0.289	0.225**	0.0801	-0.0922	0	0	0	0	0	0	0	0
Treatment effect (k=5)	0.229	0.223***	-0.105	-0.269***	0.339**	0.189**	0.0513	-0.0251	0.391***	0.176**	0.0681	-0.0529	0	0	0	0
Treatment effect (k=7)	0.186	0.140*	0.0394	-0.154*	0.293**	0.119	0.211**	0.0194	0.244*	0.112	0.0935	-0.0503	0.0289	-0.0279	0.138	0.0484
Treatment effect (k=10)	0.0614	0.0524	0.0500	-0.0905	0.105	0.0384	0.156**	0.0331	0.192*	0.0629	0.125*	0.000800	-0.0453	-0.0364	0.132	0.00753

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4 Conclusion

In this paper we used a regression discontinuity design to test the effect of short term decreases in the marginal tariff on the quality of acute stroke care. We used a rich data set describing the quality of acute stroke care by 9 process indicators.

Our results does not suggest a strong effect on quality from temporary decreases in marginal tariffs. There were week indications of a decrease in the proportion of patients being assessed by a physiotherapist and the proportion of patients who undergo an ultrasound/CT-angiography of the carotid arteries when then marginal tariff is decreased. Equally week evidence suggested that the reverse was true when the marginal price increased again at the beginning of a new year. We note that these are also the indicators for which there is the least clinical evidence. It should also be noted that some indicators suggested an increase in the proportion of patients that received a given dimension of treatment as the price decrease. This results is not in line with our expectations. All results are highly dependent on the choice of bandwidth and scaling of the dependent variable, and we are reluctant to drawing any hard conclusions on the basis of our analysis.

A possible explanation for the inconsistent results may be that the information about a price decrease does not reach the hospital or the departments soon enough for the hospital to react. In addition there may be some measurement error in our operationalisation of the running variable, although out verifications with annual budgets does not suggest that is the case. In the future, a fuzzy design approach may be attempted to allow for a change in the probability of treatment instead of the more restrictive assumption of perfect compliance which may have been too hard an assumption.

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