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Do obese patients stay longer in hospital? Estimating the health care costs of obesity

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ABSTRACT

Objective

To determine if obese patients have longer average length of stay once they are admitted to hospital, across a range of specialties. This contributes to measuring the impact of obesity on health care resource use.

Data Sources/Study Setting

Administrative hospital data are used for the financial year 2005/06 covering all episodes of patient care (1.3 million) in 122 public hospitals in the state of Victoria, Australia. The data are collected as part of Diagnosis Related Group (DRG) case mix funding arrangements by the state government.

Study Design

Statistical analysis are undertaken using quantile regression analysis to determine differences in average length of stay within different specialties for two groups of patients, those classified as obese, and those not classified as obese. Quantile regression allows a comparison of differences between the length of stay of obese and non-obese patients across the whole distribution of length of stay of inpatients, in contrast to more commonly used statistical methods which use only the mean. We condition on a range of patient and hospital characteristics such as age, sex, socioeconomic status, medical complexity of patients, teaching status, size and location of hospitals.

Data Collection/Extraction Methods

Data on inpatient episodes with at least one overnight stay in hospital are used. We exclude episodes with missing information on one or more of the explanatory variables and we exclude specialties with less than 50 reported obese inpatients per financial year. The final sample consists of just over 460,000 observations.

Principal Findings

Large and significant differences in average length of stay are found between obese and non-obese patients for nearly all specialties. In some specialties, obese patients can stay up to 4 days longer. However, obesity does not necessarily lead to longer hospital stays. In a range of specialties, obese patients have shorter length of stay on average. In general, differences between obese and non-obese patients are more pronounced at greater levels of medical complexity. There is some evidence that differences may arise because obese patients are more likely to be treated medically rather than surgically, to be transferred to another hospital, thus shifting risks and costs, or to die from higher complication rates.

Conclusions

Our study sheds new light on the impact of obesity on health care costs. We demonstrate that an analysis across the whole spectrum of medical complexity provides much better estimates of resource use by obese patients than standard techniques. Future research should focus on differences in the way obese patients are managed in hospital. This will show where resource use is most intense, and help policy makers and hospital managers increase efficiency and quality of care for obese patients.

Key Words:

Obesity, Health Care Costs, Hospital Length of Stay, Hospital Specialties, Quantile Regression

Do obese patients stay longer in hospital? Estimating the health care costs of obesity

1. Introduction

Increasing obesity rates are a major public health concern in many countries, as the obese have significantly higher risks of developing serious illnesses such as type II diabetes, cardiovascular disease, osteoarthritis, and various cancers. Financial costs are high. In Europe and the USA costs of obesity have been estimated at over 6% of health care spending (Bolin and Cawley, 2007), which conservatively translates to US$120 billion annually in the USA alone. There are great variations in cost estimates, both within and between countries. For example, in the USA costs are estimated to lie between 4-8% of health spending (Allison et al, 1999, Colditz, 1999; Kortt et al, 1998), in Canada, costs have been estimated at up to 5% of health expenditure (CN$3.5-4 billion), (Birmingham et al, 1999; Katzmarzyk and Janssen, 2004). For France costs are estimated at 1.5-2.5% of health expenditure (Detournay, 2000; Levy et al 1995), and for New Zealand a figure of 2.5% has been estimated (Swinburn et al, 1997). A substantial portion of obesity costs are direct financial costs to the health care system. For example, of total costs estimated at A$3.7 billion in Australia, direct costs make up A$870 million, or almost one quarter (Access Economics, 2006).

Differences in estimates are partly due to differing prevalence rates across countries (Bleich, 2007), differing actual costs of treatment, and differing methodologies on which cost studies are based. Commonly, researchers identify a number of co-morbidities of obesity, and then estimate the extent to which each co-morbidity (and cost) is attributable to obesity. It is difficult to generate correct estimates of these 'population attributable fractions' (PAFs), because they depend on the accuracy of the measure of relative risk made use of. There are wide variations in estimates of relative risks of diseases, again, both within and between countries. This is a particular problem for obesity, in terms of interactions between risk factors (Mark, 2005). PAFs may systematically underestimate the economic cost of obesity because they neglect costs of treating illnesses not directly caused, but aggravated by obesity. Obesity may influence the progression or severity of many conditions, such as type II diabetes, hypertension, hypercholesterolemia, osteoarthritis, gallbladder disease, and some cancers (Muennig et al, 2006; Busija et al, 2007). This would imply that for a large variety of conditions, obese patients are more expensive to treat than non-obese patients. Overall, surprisingly little is known about the use of hospital resources by obese patients (Folmann et al, 2007; Shafer and Ferraro, 2007), especially when controlling for medical complexity.

In order to test the hypothesis that the obese use more resources, we estimate the differences in length of stay for public hospital admissions between obese and non-obese inpatients, conditional on explanatory factors, using Diagnosis Related Group (DRG) based utilization data, and controlling for medical complexity. We use data for inpatient episodes – covering 460,000 observations. The data contain rich information on patient and hospital characteristics, including whether a patient is classified as obese. We use quantile regression techniques to estimate the differences in length of stay (LOS) over the *whole* distribution for patients from various specialties, and for medical and surgical patients. LOS is a major determinant of hospital costs, and it gives a tractable measure of hospital resource use in management terms. Use of quantile regression techniques provides us with several estimates of differences in LOS over the whole range of patient medical complexity, and is therefore superior to standard techniques which generate only one estimate at the mean level of complexity. This provides hospital managers and policy makers with valuable extra information.

2. Data

We use the Victorian Admitted Episodes Data (VAED) for inpatients above 5 years of age in public hospitals in the state of Victoria, Australia, for 2005/06. The VAED are administrative hospital data for all public hospitals, and they are generally of high quality because hospitals have a strong financial incentive to generate detailed records of all their patients, as they receive the largest part of their budget via DRG based casemix funding. This type of funding was introduced in Victoria in 1993/94, so hospital administrators are experienced in collecting and processing patient level data.

Our sample consists of 461,563 inpatients in 17 specialties. We exclude specialties which predominantly treat day cases (patients with no overnight stay) and/or report only a small number of obese inpatients per financial year, because results from such a sample would not be robust. For the included specialties, the average number of reported obese patients is 357 (those excluded are *Ophthalmology, Dental Surgery, Oncology/Radiology, Psychiatry* and *Renal Dialysis)*. Within the remaining specialties, we exclude patients treated as day cases and with missing values on one or more of the explanatory variables. *Table 2* reports the frequencies and percentages of obese patients per specialty. Each data record contains one patient episode which starts with the patient's admission to a hospital department and ends with the patient's discharge from that department. *Table 1* shows all variables used in the estimation, with the dependent variable being a patient's length of stay (LOS) per episode, in days. A patient's total stay in hospital may be longer. If a patient is referred to another hospital, or even another department in the same hospital, this is recorded as a new episode. The way a patient is managed in hospital is likely to affect LOS, and therefore, we control for this as far as possible. We cannot link several episodes, but we try to take account of transfers by including information on the origin of patients at admission, and their destination at discharge. The variables *transadmi* and *transep* indicate whether a patient is admitted/discharged from/to another hospital, acute care centre, other department within the same hospital, or community based mental or aged care centre. We also distinguish whether a patient is discharged home or leaves against medical advice *(home),* or dies in hospital *(death).* We include a patient's type of admission, either as an emergency case *(nonelect),* from a waiting list *(elect),* or in another way *(othadmtype),* which covers mainly maternity or newborn patients.

We include four variables of medical complexity. *Numberdiag* and *numberop* are two discrete variables counting, respectively, the number of diagnoses and procedures undertaken on the patient, with the assumption that higher values of one or both variables characterize more complex patients. We also include a variable *comp* to indicate whether a patient experienced a medical complication. We define a medical complication based on *(a)* a set of specific international classification of disease (ICD) codes which - by definition - identify patients with a medical complication or adverse event before or during the episode and *(b)* a C-prefix to ICD diagnosis codes which identify patients who suffered a complication during the episode (we adopt the definition of medical complication as described in Jackson et al. 2006). This prefix is a unique feature of the VAED. As a fourth control for medical complexity, we use the cost weight of the patient episode *(w12wies)* which is derived from patient cost information and forms the basis for hospital reimbursement under the state casemix funding system.

We include several variables on patient characteristics to control for differences in medical need: *female* controls for gender differences, and a*ge* and *age*^{2} take account of potential nonlinear relationships between age and LOS. We use two (crude) measures of a patient's socioeconomic status. First, we include information on whether a patient paid privately for the admission *(private)* as a marker for income. In Australia, the majority of private payments are reimbursed by private health insurance funds. Around half of the population has private health insurance, and take-up is associated with income. Second, we link the VAED with an index of socio-demographic deprivation measured at postcode level. The socioeconomic index of relative advantage/disadvantage *(seifa)* is generated from 2001 census data information on residents' income, occupation, education, and other factors, and measures the relative socioeconomic advantage of geographical areas at postcode level. The index is centered around 1, and advantaged/disadvantaged areas are characterized by high/low values (ABS, 2003).

We also include several variables on hospital characteristics. *Major, city, ruralmed* and *ruralsmall* characterize size, teaching status and location of hospitals. We do not have information on the number of beds or staffing levels in the hospitals, but we can include information on the overall number of admissions in a year to account for the size of hospitals *(totsep).*

Obesity among patients: the 'false negatives' problem

The most important explanatory variable for the purpose of our analysis is whether a patient is obese. We define patients as obese if one of their diagnosis codes (beyond their first diagnosis) falls within the range of ICD codes E660 to E669 (conditions related to obesity). These are generic codes for obesity, meaning that patients are coded as obese independently of other diagnoses codes or the procedures or surgical activity undertaken on the patient.

In our sample, 6,086 (1.32%) of inpatients are classified as obese in this way. This implies that obese patients are underrepresented among the patient population - the prevalence of obesity in the general population of Victoria is markedly higher at 16% (VPHS, 2002). This indicates that there are a large proportion of false negatives - obese patients incorrectly reported as non-obese - in the patient population, which results in an underestimate of the extent of obesity among inpatients. This underreporting is a consequence of basing our classification of 'obese' on reported ICD codes, but lack of data forces us to adopt this definition. To get an understanding of the extent and possible causes of the 'false negatives' problem, we compare the prevalence of obesity in patients over different hospital specialties (see *table 2)*. Recorded obesity varies, with highest rates reported for *Endocrinology* (4.43%) and *Cardiology* (2.89%). These are specialties for which there may be a relatively big influence of a patient's weight on treatment choices and outcomes. It is plausible that medical staff are more vigilant in reporting obesity if it is thought to impact the patient's case. However, hospitals have no financial incentive for recording a patient as obese as this would make no difference to the final case-mix reimbursement. This may explain why *Obstetrics* (0.31%) and *Ear, Nose and Throat* (ENT) (0.47%) have the lowest rates of reported obesity. In these specialties, conditions that patients present with are similar and treatments are comparably standardized, such as in Obstetrics, and/or doctors may (rightly or wrongly) suspect that there is little influence of a patient's weight on final treatment outcomes, such as in ENT.

Random underreporting of obese patients would not create any serious problems in the statistical estimation, however, systematic underreporting may. It could imply that false negative (unreported) and true positive (reported) obese patients are managed in different ways. For example, reported obese patients could be more likely to be treated medically than non-reported obese patients because of a (perceived) greater risk associated with surgery. As a justification for the chosen treatment, these medically treated obese patients may be more likely to be reported as obese. On the other hand, obese patients who are treated surgically may be more likely to be reported as obese because administration of anesthetics requires the exact reporting of the patients' weight and may alert doctors. In econometric analysis terms, underreporting can be classified as an error-in-variables problem which can be alleviated with instrumental variables (IV) techniques (Green 2003). Instruments need to be correlated with the misreported variable, but not with the error term in the statistical model. As we have only limited information on patient characteristics, and these are most likely to influence both obesity and LOS (directly, or indirectly over medical complexity), there are no suitable instruments in our data and we cannot employ IV techniques. However, any possible bias arising from underreporting will most likely lead to insignificant results. The estimated differences in LOS between obese and non-obese will err towards zero, as the non-obese control group in our sample is 'contaminated' with unreported obese patients. This would imply that estimated differences are conservatively low estimates of the real differences. Given all of the above, any systematic underreporting, if it is present in our sample, is unlikely to cause misleading results.

Table 1 shows summary statistics of all variables, by obese and non-obese inpatients. The obese have a longer mean LOS, and they are more likely to be admitted as an emergency case. They are, on average, of greater medical complexity, as indicated by their higher average cost weight, have nearly double the co-morbidities, greater numbers of procedures undertaken, and higher rates of medical complications. On average, obese inpatients are older, more likely to be male, and have a slightly lower socioeconomic profile as indicated by the variables *private* and *seifa*. They are more likely to be admitted or discharged by transfer, but the difference is small, and they are more likely to be treated in one of the major teaching hospitals.

3. Methods

We estimate the following linear model:

los = f (obese, nonelect, othadmtype, transadmi, transep, death, w12wies, numberdiag, numberop, comp, age, age2, female, private, seifa, totsep, major, ruralmed, ruralsmall)

separately for 17 hospital specialties. We also estimate the model separately for patients treated medically and surgically, across all specialties. The estimated impact of obesity on LOS is provided by the coefficient on the dummy variable *obese*. A statistically significant positive (negative) coefficient shows the number of days that an obese patient stays longer (shorter) per episode than a non-obese patient, on average and conditional on other explanatory factors.

An analysis of the residuals from an ordinary least squares (OLS) regression on the whole sample shows a large proportion of outlying observations, both at the upper and lower ends of the distribution. We adopt a definition of outliers based on the interquartile range, so that an observation is defined as a lower outlier if res_{OLS} < Q(25) - 3*Inter Quartile Range, and an upper outlier if res_{OLS} > Q(75) + 3*Inter Quartile Range (Tukey 1977). According to this definition, 3.3% of patients have very long stays (upper outliers) and 1.3% very short stays (lower outliers), conditional on observable characteristics. Such a large proportion of outliers is incompatible with assumptions of normality imposed by OLS. A practical approach for dealing with outliers is to include a dummy variable among the regressors to indicate outlier status. However, this would effectively eliminate outlying patients from the analysis without providing a causal explanation for their outlier status. Outlying patients may convey valuable information on the relationship between obesity and LOS which should not be lost. Therefore, we adopt a quantile regression (QR) model which allows us to incorporate the information provided by outliers, but limits their detrimental effect on the estimation. The QR model relaxes the OLS assumption that the effect of *obese* is constant along the whole distribution of the dependent variable LOS (Koenker and Bassett 1978, Variyam et al. 2002). Quantiles of the conditional distribution of LOS are expressed as functions of observed covariates. The objective of QR is to estimate the median (rather than the mean) of the dependent variable conditional on the values of the independent variables. Thus, QR minimizes a sum of absolute residuals, as opposed to a sum of squared residuals. We use quantile regressions on 19 quantiles of LOS, ranging from 0.05 (very short LOS) to 0.95 (very long LOS), and including the median 0.5.

The residuals are weighted asymmetrically for all quantiles, except the median. This feature, together with estimation of the median, helps to alleviate the outlier problem. It guarantees that the influence of outliers is diminished on estimates generated from midranges and opposite ends of the distribution, as residuals at the extreme ends of the distribution are given a lower weight. In addition, QR generates different estimates of the impact of *obese* on LOS across the whole distribution of LOS. This gives us an insight into whether obesity has a larger or smaller effect among patients staying a long time in hospitals as opposed to patients staying a shorter time in hospital. Patients with long LOS are usually complex patients with comparably severe medical problems, so that, in fact, we are estimating whether the influence of obesity varies across the distribution of medical complexity. STATA 10 (STATA Corporation, 2007) is used for the estimations.

4. Results

Coefficient Estimates for the Whole Sample

Table 3 shows coefficient estimates for the model estimated by OLS regression on the whole sample. All coefficient estimates are statistically significant, which is partly explained by the large sample size. We are above all interested in the coefficient on *obese*, because it indicates differences in average length of stay (ALOS) between obese and non-obese patients. Perhaps surprisingly, the coefficient is negative, which implies that obese patients stay shorter than non-obese patients with comparable characteristics. The coefficient value of -0.4 means that obese patients stay on average about half a day shorter than non-obese patients. We discuss possible reasons for this result further down. With respect to the other explanatory variables, we find that there is a strong positive impact of the cost weight *w12wies* on LOS, indicating that patients of higher medical complexity and resource intensity stay longer in hospital. Increasing the cost weight by 1 point increases LOS by about 2.4 days, on average and conditional on other explanatory variables. Being admitted as an emergency or as an ‘other’ type of patient increases length of stay by over a day in comparison to being admitted as an elective patient, probably indicating greater medical complexity. Being admitted in a small rural hospital increases LOS by 1.8 days in comparison to being admitted to a big city hospital. If the episode ends with the death of the patient, we can observe that the episode is on average 1.2 days shorter than the one of a comparable patient which does not die. It may be that the stay of complex patients is cut short by their death. The rest of the variables influence ALOS by less than one day. We find that ALOS decreases with age, but the relation is nonlinear as indicated by the positive coefficient on *age*^{2}, and it decreases with the size of the hospital *(totsep)*. ALOS is shorter for patients paying privately for the hospital stay and living in a socially more advantaged area, indicating that patients of higher income and socioeconomic status have lower medical need. ALOS is slightly shorter in a major teaching hospital than in a normal city hospital, which is perhaps surprising because teaching hospital tend to treat more complex patients, on average. The shorter LOS may be due to greater efficiency in teaching hospitals. ALOS increases with the number of diagnosis and procedures undertaken on the patient, and it is higher for patients who suffer a complication or are transferred from or to another hospital, all indicating that more complex patients have longer ALOS. Females stay around 0.3 days longer than males.

Quantile regression (QR) results for the 10th quantile (short staying patient groups of low complexity), 50th quantile (patient groups with average lengths of stay) and the 90th quantile (patients with long lengths of stay) are presented in *tables 4, 5,* and *6*. The Median regression (50th quantile) is comparably to OLS, and by and large, the OLS estimates are confirmed by the QR results. The exception is the coefficient on *obese*. For the 10th and 50th quantile, the coefficient is not statistically significant. For the 90th quantile of long staying patients, the coefficient is positive and significant. It indicates that for medically very complex patients across the whole sample, obese patients stay about 0.2 days longer than non-obese patients, on average and conditional on other observable factors.

Estimates on the impact of obesity on specialty level

Results for the whole sample may be misleading, because it is likely that there are great differences between hospital specialties. Therefore, we estimate our model separately for 17 specialties. It is beyond the scope of this working paper to display results for every specialty, quantile and coefficient. We use figures and summary tables to compare the results in a manageable way, focusing on the coefficient for obese only. More detailed results are available from the authors on request.

When estimating the QR and OLS models separately by specialty, we find that being obese has a distinctly different influence on LOS according to the specialty treating the patient. Coefficient estimates for the variable *obese* are displayed in *Figures 1* to *19*. A positive (negative) coefficient implies that obese have a longer (shorter) average length of stay in hospital than non-obese. Plotted are the estimated coefficients and 95% confidence intervals, with increasing LOS towards the right side of the diagram. The OLS (mean) estimate, represented by the triangles is, by assumption, constant across the whole distribution of LOS. The QR coefficients, represented by the circles, can be seen to differ across the distribution.

For *General Medicine (figure 1),* the OLS coefficient has a statistically significant positive value, implying that obese patients experience, on average, around 1.7 days longer in hospital, conditional on other explanatory factors. QR results for *General Medicine* show that the coefficient estimates for obese increase over the distribution of LOS. This implies that there is no or only a small difference in ALOS between obese and non-obese patients for the lower end of the distribution, i.e. for shorter LOS or patients of lower medical complexity. However, obese patients start to have significantly longer stays in hospital from around the median LOS, with coefficient estimates increasing to nearly 4 days longer ALOS for the 95th quantile of very complex and long-staying patients.

We can observe similar results for eight other hospital specialties. At the lower end of the distribution (shorter LOS), differences between obese and non-obese patients are small or statistically insignificant, but at the upper end (longer LOS), obese patients stay significantly longer (see *figures 1* to *9). Table 7* provides a summary of the results shown in the figures. Reported are the maximum estimated difference in ALOS between obese and non-obese, and the percentile of the distribution of LOS at which this result is obtained. Only statistically significant coefficients are considered. Maximum average differences in LOS are nearly 2 days for *Plastic Surgery* (1.9 days at the 80th quantile), 1.4 days (95th quantile) for *Obstetrics,* 1.1 days for *ENT* (80th quantile), 1 day (90th quantile) for *Orthopedics,* 0.9 days (95th quantile) for *Gynecology,* 0.4 days (95th quantile) for *Neurology,* 0.4 days (75th quantile) for *Endocrinology,* and 0.2 days at the 75th quantile in *General Surgery*. A perfect trend of gradually increasing differences between obese and non-obese can only be observed for *General Medicine*. For *Obstetrics, Orthopedics* and *Gynecology,* differences in ALOS between obese and non-obese patients are negligible except for the highest quantiles, where there are comparably large differences in ALOS. This implies that the most complex obese patients in these three specialties stay longer than the most complex non-obese obstetrics patients, but there is no difference for patients at average and low levels of medical complexity. It is also noteworthy that differences in LOS for *Plastic Surgery*, *ENT* and *Endocrinology* peak around the 80th quantile (and not at the 95th quantile as one might expect) and become smaller again towards the highest quantile. This is most marked for *Endocrinology,* where differences for the four highest quantiles are insignificant. For *ENT* and *General Surgery* there are significant differences in LOS from low quantiles onwards - obese patients stay longer than non-obese patients across the whole range of complexity with no or only a slight increase. However, absolute differences in LOS are very small for *General* Surgery. For Neurology, differences are very small as well, with the only significant differences around the 60th quantile and the two highest quantiles. OLS coefficient estimates are significant only for *General Medicine* and *Orthopedics*. The OLS estimate for *Orthopedics* is negative, which may be due to the biasing influence of outliers affecting the OLS estimation. *Obstetrics* and *Endocrinology* also have negative OLS coefficients, but neither of them is statistically significant.

In summary, the ***positive pattern*** that obese patients stay -on average and at certain quantiles- more than one day longer in hospital than non-obese patients can be observed for the specialties *General Medicine, Plastic Surgery, Obstetrics* and *ENT*. Obese patients also stay longer in the specialties *Gynecology, Orthopedics, Neurology, General Surgery* and *Endocrinology,* but the maximum differences are less than one day. For nearly all of the above specialties, differences between the obese and non-obese samples tend to increase with LOS in hospital. The results for these specialties confirm our hypothesis that obese patients stay longer in hospital on average and are more expensive to treat than non-obese patients with the same observable characteristics, in particular similar levels of medical complexity. Differences tend to increase for the longer staying patient groups of greater medical complexity. This increase is not picked up by OLS, because it provides only an average estimate over the distribution of LOS. Moreover, we find that OLS, in comparison to QR, overestimates resource use for short-staying obese patients and underestimates it for long-staying obese patients. In turn estimates of the impact of obesity on health care resources by obese patients from the extreme ends of the distribution would be markedly different if they relied on the OLS results.

For eight specialties we find the surprising result that obese patients stay on average *shorter* than non-obese patients, especially patient groups at higher levels of complexity. *Figures 10 to 17* and *table 7* show results for these specialties with ***negative patterns***. We can see again that differences in ALOS tend to increase over the distribution of LOS up to the quantile of patients with high levels of medical complexity, but differences are in the opposite direction so that obese patients stay *shorter* on average than non-obese patients, conditional on observable explanatory factors. For all specialties with negative pattern, the QR results are confirmed by negative OLS coefficients, but they are only significant for *Vascular, Respiratory, Cardiology,* and *Nephrology*. For specialties with the negative pattern, OLS also tends to overestimate (underestimate) the difference between obese and non-obese patients for short (long) stays in comparison to QR, which would leads to different results on the resource use by obese patients.

According to the results from the Quantile Regressions, maximum differences in ALOS are -2.4 days (85th quantile) for *Vascular,* -1.7 days (95th quantile) for *Neurosurgery,* -1.5 days (95th quantile) for *Rheumatology,* -1.2 days (90th and 95th quantiles) for *Respiratory,* -1.1 (95th quantile) for *Cardiology,* -0.6 days (95th quantile) for *Hematology,* -0.5 days (95th quantile) for *Urology,* and -0.4 (70th and 75th quantile) for *Nephrology*. We observe a near perfect trend line with gradually increasing differences over the whole distribution of LOS for the specialties *Vascular* and *Cardiology*. We observe increasing differences from about the median quantile for the specialties *Rheumatology, Respiratory,* and *Hematology*. In these three specialties, for LOS below the median, coefficient estimates are mostly insignificant, indicating no difference in ALOS between obese and non-obese patients at lower levels of complexity. For *Respiratory* and *Rheumatology* they are even slightly positive, indicating that obese stay longer at low levels of complexity, but shorter at higher levels of complexity in these two specialties. For *Neurosurgery,* we observe significant differences for a few quantiles at the top of the distribution only, and no differences for the rest of the distribution. This means that only among the very long staying and complex *Neurosurgery* patients the obese stay shorter than the non-obese. The results for this specialty should be treated with caution, however, because it reported treating only 37 obese patients in the year and this small number may bias the results (see *table 2)*. For *Urology* and *Nephrology,* differences in ALOS are greatest for quantiles in the midranges of the distribution (between the 40th and 75th quantiles), i.e. obese patient stay only shorter than non-obese at those medium ranges of LOS and complexity. At higher quantiles, estimates for these two specialties are erratic and show no clear trend with one for the 90th quantile in Urology even being significantly positive, indicating a longer ALOS for the obese. In Nephrology, estimates for the 80th, 85th and 90th quantiles are not trustworthy because standard errors are incredibly small.

In summary, the ***negative pattern*** that obese patients stay -on average, conditional on explanatory factors, and at certain quantiles- at least one day less in hospital than non-obese patients can be observed for the specialties *Vascular, Neurosurgery, Rheumatology,, Respiratory,* and *Cardiology.* Obese patients also stay shorter in the specialties *Hematology, Urology,* and *Nephrology* but the maximum differences are less than one day. For nearly all of the above specialties, differences tend to be greater for patient groups with higher levels of medical complexity. The results for these eight specialties contradict our hypothesis that obese patients stay longer in hospital and use more resources than non-obese patients with the same observable characteristics. The implications of our results are that for these specialties, obese patients are less costly to treat than non-obese patients.

5. Discussion

Why do obese patients stay longer in some specialties, but shorter in others? One explanation could be that there are differences in the way obese and non-obese patients with the same condition are managed once they are in hospital. To explore this idea we estimate our model separately for medically and surgically managed patients, across all hospital specialties (for results see *figures 18* and *19,* and *table 7)*. The distinction between medical and surgical patients is derived from patient level ICD codes. We find that for the medically managed patient group, obese patients stay on average longer than non-obese patients at nearly all quantiles, with peaks around the midranges of the distribution and the high end of the distribution. Maximum difference at the 95th quantile is relatively small with 0.9 days. The OLS coefficient is significantly positive. Interestingly, surgically managed obese patients have a shorter stay than non-obese patients. Differences are only present for quantiles above the median, and are nonexistent for lower quantiles. The maximum difference is small, though, with only 0.4 days at the 90th quantile. The OLS coefficient estimate is negative but insignificant.

A discussion of the reasons for the observed positive and negative patterns is difficult without an in-depth analysis of potential differences in the way obese and non-obese patients are managed. Such an analysis is beyond the scope of this paper. Here, we can only speculate that obese patients may stay longer than non-obese when they are treated as a medical case because they are *more complex*. However, they may have a shorter stay when they are treated as a surgical case because they are *much more complex*. This may lead to them being transferred to another hospital, so that the hospital can shift the risk (and the cost) of treating complex obese surgical patients with a high likelihood of developing complications. Another reason may be that obese patients stay in hospital is cut short because they are more likely to die from complications due to surgery than non-obese patients with the same medical condition. Indeed we find that obese patients are transferred slightly more often and suffer more complications on average (see *table 1),* but they are less likely to die. However, conclusions derived from descriptive statistics such as this suffer from the fact that differences in medical complexity are not controlled for. Further analysis of differences in the way obese and non-obese patients are managed is warranted. It may be worthwhile to, for example, determine the probabilities of being treated as a medical case, being transferred or even to die, subject to whether being obese or not. Our data would not be suited for such an analysis, because on specialty level, sample sizes would be too small to obtain any reliable results, especially for deaths among obese patients.

6. Conclusions

The analysis undertaken here makes an important contribution to measuring the impact of obesity on health care resources. We show that obese patients stay longer in some specialties, but shorter in others. This means it cannot simply be assumed that it is more costly to treat obese patients on average. On the contrary, in some specialties they may be even less costly to treat. We demonstrate that looking at differences between obese and non-obese at average levels of medical complexity hides important information on differences in resource use among patient groups of varying medical complexity and length of stay and can lead to seriously misleading results. Using quantile regression analysis, we generate information on differences in resource use across the whole distribution of length of stay and medical complexity. Such information is crucial for policy makers and hospital managers to target resources across specialties.

Future research is warranted. It may focus on estimating the budgetary implications of results such as ours by, if possible (and beyond our data), attaching dollar values to the estimated differences in length of stay. Research may also focus on differences in the way obese patients are managed in hospital and detailed investigation into the different stages at which resource use is most intense for obese patients. This may help policy makers alleviate the financial impact of obesity and lead to efficiency gains for hospitals. It may also help improve the quality of care for obese patients.

Table 1: Variables definitions and summary statistics

Reported are means with standard deviations (in parentheses) for continuous variables, and percentages for binary variables.

		Total sample	Non-obese inpatients	Obese inpatients
		461,563	455,477 (98.68%)	6,086 (1.32%)
Dependent variable				
los	Length of stay in days	4.93 (8.97)	4.91 (8.97)	6.62 (9.46)
Explanatory variables				
Admission management				
nonelect	1 if patient is admitted as an emergency case, 0 if not	59.63 %	59.53 %	67.17 %
elect	1 if patient is admitted from a waiting list, 0 if not	28.97 %	28.95 %	29.90 %
othadmtype	1 if patient is neither an elective nor emergency patient, 0 otherwise	11.40 %	11.52 %	2.92 %
transadmi[1]	1 if patient is admitted from another department, hospital or care centre, 0 if admitted from home	6.09 %	6.07 %	7.71 %
Discharge management				
homesep	1 if patient is discharged home or left against medical advice, 0 otherwise	85.29 %	85.31 %	84.26 %
transep	1 if patient is discharged to another department, hospital or care centre, 0 otherwise	12.66 %	12.64 %	13.92 %
death	1 if patient dies in hospital, 0 otherwise	2.05 %	2.05 %	1.82 %
Medical complexity				
w12wies	Cost-weight (total weighted inlier equivalent separation including co-payments)	1.44 (2.34)	1.44 (2.34)	1.98 (2.85)
numberdiag	Total number of diagnoses and co-morbidities	4.52 (3.10)	4.48 (3.08)	7.72 (2.99)
numberop	Total number of procedures performed	2.45 (2.51)	2.45 (2.51)	3.01 (2.78)
comp	1 if patient experienced a medical complication before or during episode, 0 otherwise	16.49 %	16.44 %	20.46 %
Patient characteristics				
age	Age at admission in years	53.48	53.41	58.47

[1] Admission by transfer can be an elective, non-elective or another type of admission.

female	1 if patient is female, 0 if male, infant or intersex	56.33 %	56.37 %	53.86 %
private	1 if patient is admitted as a privately paying patient, 0 otherwise	8.29 %	8.32 %	6.41 %
seifa	Socioeconomic index of relative advantage/ disadvantage	988 (74.75)	988 (74.76)	976 (72.98)
Hospital characteristics				
totsep	Total separations of the hospital in the year	35,419 (24,555)	35,348 (24,527)	40,731 (26,035)
major	1 if major teaching hospital, 0 otherwise	71.74 %	71.72 %	73.61 %
city	1 if big city hospital, 0 otherwise	13.45 %	13.45 %	13.52 %
ruralmed	1 if medium sized hospital in regional centre, 0 otherwise	10.11 %	10.12 %	9.22 %
ruralsmall	1 if small rural hospital, 0 otherwise	4.70 %	4.71 %	3.65 %

Table 2: Obese patients by specialties

	Percent	Obese Patients Frequencies	All Patients Frequencies
Endocrinology	4.4	372	8,397
Cardiology	2.9	1,583	54,857
Respiratory	1.9	802	42,407
Nephrology	1.8	107	5,935
Vascular	1.7	86	5,052
Rheumatology	1.7	74	4,473
General Medicine	1.4	517	36,437
General Surgery	1.2	682	55,065
Neurology	1.1	252	22,712
Gynecology	1.1	131	11,908
Urology	1.1	202	18,961
Orthopaedics	1.0	397	39,178
Haematology	1.0	100	10,278
Gastroenterology	0.9	318	33,899
Neurosurgery	0.7	37	5,599
Plastics	0.6	67	11,513
ENT	0.5	82	17,347
Obstetrics	0.3	182	59,473

Table 3: OLS regression results on the whole sample

Source	SS	df	MS
Model	18507584.2	19	974083.381
Residual	18661842.9	461543	40.4335955
Total	37169427.2	461562	80.5296519

Number of obs	= 461563
F(19,461543)	=24090.94
Prob > F	= 0.0000
R-squared	= 0.4979
Adj R-squared	= 0.4979
Root MSE	= 6.3587

los	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
obese	-.4432528	.0830581	-5.34	0.000	-.606044	-.2804615
age	-.0328825	.0021111	-15.58	0.000	-.0370203	-.0287447
age2	.0005192	.0000199	26.03	0.000	.0004801	.0005583
female	.3179608	.0199817	15.91	0.000	.2787972	.3571244
nonelect	1.659798	.0227789	72.87	0.000	1.615152	1.704444
othadmtype	1.299771	.0368011	35.32	0.000	1.227642	1.3719
transadmi	.5190514	.0399814	12.98	0.000	.4406891	.5974137
private	-.1197908	.0342449	-3.50	0.000	-.1869097	-.0526719
seifa	-.0005178	.0001334	-3.88	0.000	-.0007793	-.0002564
w12wies	2.379662	.0048312	492.56	0.000	2.370193	2.389131
numberdiag	.2721024	.0039266	69.30	0.000	.2644064	.2797983
numberop	.1880404	.0049733	37.81	0.000	.1782929	.1977879
comp	.3004555	.0276291	10.87	0.000	.2463034	.3546076
transep	.6221396	.0306083	20.33	0.000	.5621483	.682131
death	-1.225421	.0687799	-17.82	0.000	-1.360227	-1.090614
totsep	-.0000177	5.07e-07	-34.96	0.000	-.0000187	-.0000167
major	-.0663907	.0310718	-2.14	0.033	-.1272904	-.005491
ruralmed	.1252748	.0397072	3.15	0.002	.04745	.2030997
ruralsmall	1.818782	.051869	35.06	0.000	1.717121	1.920444
_cons	-.5572582	.1402436	-3.97	0.000	-.8321313	-.282385

Table 4: Quantile regression results on the 10th quantile, whole sample

```
.1 Quantile regression                              Number of obs =    461563
  Raw sum of deviations   362965 (about 1)
  Min sum of deviations   340209                    Pseudo R2     =    0.0627
```

los	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
obese	.0000685	.0107496	0.01	0.995	-.0210004	.0211374
age	-.001803	.0002744	-6.57	0.000	-.0023408	-.0012651
age2	.0000362	2.60e-06	13.93	0.000	.0000311	.0000413
female	.0491488	.0025804	19.05	0.000	.0440913	.0542063
nonelect	.5178004	.0028796	179.82	0.000	.5121565	.5234442
othadmtype	.7019123	.0047048	149.19	0.000	.6926911	.7111335
transadmi	.0768514	.005219	14.73	0.000	.0666222	.0870806
private	.0141874	.0044278	3.20	0.001	.0055091	.0228658
seifa	-.0001594	.0000175	-9.09	0.000	-.0001938	-.000125
w12wies	.6706648	.0005491	1221.30	0.000	.6695885	.6717411
numberdiag	.0240526	.0005105	47.11	0.000	.023052	.0250533
numberop	.0868354	.000643	135.04	0.000	.0855751	.0880957
comp	.1146201	.0036959	31.01	0.000	.1073762	.1218641
transep	-.0750283	.004071	-18.43	0.000	-.0830073	-.0670494
death	-.3402695	.0088737	-38.35	0.000	-.3576617	-.3228773
totsep	-2.02e-06	6.46e-08	-31.32	0.000	-2.15e-06	-1.90e-06
major	.0149594	.004026	3.72	0.000	.0070685	.0228503
ruralmed	.0439188	.0051424	8.54	0.000	.0338398	.0539978
ruralsmall	.1518471	.006766	22.44	0.000	.138586	.1651082
_cons	.0626135	.0183434	3.41	0.001	.026661	.0985659

Table 5: Quantile regression results on the 50th quantile, whole sample

```
Median regression                                   Number of obs =    461563
  Raw sum of deviations  1639355 (about 3)
  Min sum of deviations  1191026                    Pseudo R2     =    0.2735
```

los	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
obese	-.0017679	.0230902	-0.08	0.939	-.047024	.0434882
age	-.0167716	.0005869	-28.57	0.000	-.0179219	-.0156212
age2	.000266	5.55e-06	47.96	0.000	.0002551	.0002768
female	.1479412	.0055553	26.63	0.000	.137053	.1588294
nonelect	1.286052	.006333	203.07	0.000	1.273639	1.298464
othadmtype	1.418474	.0102312	138.64	0.000	1.398421	1.438527
transadmi	.8020076	.0111156	72.15	0.000	.7802215	.8237937
private	.179319	.0095206	18.83	0.000	.1606589	.1979791
seifa	-.0004369	.0000371	-11.78	0.000	-.0005095	-.0003642
w12wies	1.351366	.0013431	1006.12	0.000	1.348734	1.353999
numberdiag	.1343683	.0010916	123.09	0.000	.1322287	.1365079
numberop	.3735434	.0013827	270.16	0.000	.3708334	.3762534
comp	.5970041	.0076814	77.72	0.000	.5819487	.6120595
transep	.1447832	.0085097	17.01	0.000	.1281045	.1614619
death	-.3849853	.0191215	-20.13	0.000	-.4224628	-.3475077
totsep	-3.71e-06	1.41e-07	-26.37	0.000	-3.99e-06	-3.44e-06
major	-.1568498	.0086385	-18.16	0.000	-.1737809	-.1399187
ruralmed	.1518687	.0110393	13.76	0.000	.1302319	.1735054
ruralsmall	1.04784	.0144204	72.66	0.000	1.019576	1.076103
_cons	-.3109414	.0389903	-7.97	0.000	-.3873613	-.2345215

Table 6: Quantile regression results on the 90th quantile, whole sample

```
.9 Quantile regression                               Number of obs =    461563
  Raw sum of deviations  1517523 (about 11)
  Min sum of deviations 828234.6                     Pseudo R2     =    0.4542

------------------------------------------------------------------------------
         los |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       obese |   .2018728   .0849429     2.38   0.017     .0353874    .3683581
         age |  -.0214345   .0021553    -9.94   0.000    -.0256589   -.0172101
        age2 |   .0004821   .0000204    23.62   0.000     .0004421    .0005221
      female |   .2001051   .0204387     9.79   0.000     .1600458    .2401643
    nonelect |   1.739039   .0248285    70.04   0.000     1.690376    1.787703
  othadmtype |   .5232556   .0382338    13.69   0.000     .4483185    .5981927
   transadmi |   1.935422   .0405322    47.75   0.000      1.85598    2.014864
     private |  -.0359601    .035034    -1.03   0.305    -.1046256    .0327055
       seifa |  -.0010283   .0001353    -7.60   0.000    -.0012934   -.0007632
     w12wies |   4.851081   .0060659   799.72   0.000     4.839192     4.86297
  numberdiag |    .288854   .0040367    71.56   0.000     .2809422    .2967657
    numberop |    .393806   .0057989    67.91   0.000     .3824403    .4051717
        comp |   1.096721   .0279632    39.22   0.000     1.041914    1.151528
     transep |   1.572372   .0297835    52.79   0.000     1.513998    1.630747
       death |    2.31425   .0700748    33.03   0.000     2.176905    2.451594
      totsep |  -9.65e-06   5.10e-07   -18.94   0.000    -.0000107   -8.66e-06
       major |  -.2791145   .0315785    -8.84   0.000    -.3410075   -.2172215
    ruralmed |   .1461406   .0403702     3.62   0.000     .0670164    .2252649
  ruralsmall |   2.459224    .052231    47.08   0.000     2.356853    2.561595
       _cons |    .066759   .1418455     0.47   0.638    -.2112539    .3447718
```

Table 7: Results on differences in ALOS between obese and non-obese inpatients, by specialty

	Specialty	Maximum difference between obese and non-obese patients, in days (SE in parenthesis)[1]	Percentile of the distribution of LOS at which maximum difference is observed
Positive Pattern (obese patients stay longer than non-obese patients)	General Medicine	3.8 (0.04)	95^{th}
	Plastic Surgery	1.9 (0.14)	80^{th}
	Obstetrics	1.4 (0.20)	95^{th}
	ENT	1.1 (0.05)	80^{th}
	Orthopedics	1.0 (0.13)	90^{th}
	Gynecology	0.9 (0.13)	95^{th}
	Neurology	0.4 (0.01)	95^{th}
	Endocrinology	0.4 (0.07)	75^{th}
	General Surgery	0.2 (0.03)	75^{th}
	Medically managed patients (across all specialties)	0.9 (0.00)	95^{th}
Negative Pattern (obese patients stay shorter than non-obese patients)	Vascular	-2.4 (0.33)	95^{th}
	Neurosurgery	-1.7 (0.37)	95^{th}
	Rheumatology	-1.5 (0.16)	95^{th}
	Respiratory	-1.2 (0.43)	95^{th}
	Cardiology	-1.1 (0.17)	95^{th}
	Hematology	-0.6 (0.00)	95^{th}
	Urology	-0.5 (0.01)	95^{th}
	Nephrology	-0.4 (0.04)	75^{th}
	Surgically managed patients (across all specialties)	-0.4 (0.03)	90^{th}

[1] only statistically significant coefficients are reported.

Figure 1: *General Medicine* – differences in LOS between obese and non-obese patients

(upper and lower bounds of the 95% confidence intervals are displayed for the OLS coefficient, but not the QR coefficients because interval bands are too small for all quantiles)

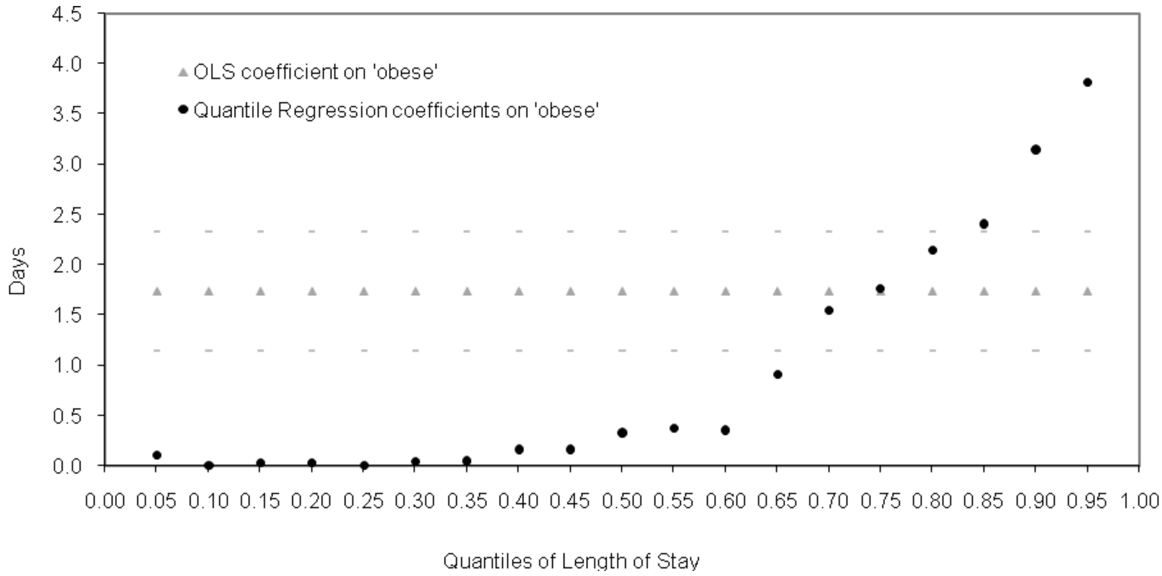


Figure 2: *Plastic Surgery* – differences in LOS between obese and non-obese patients

(for some quantiles, CI bands are so small that they are not displayed)

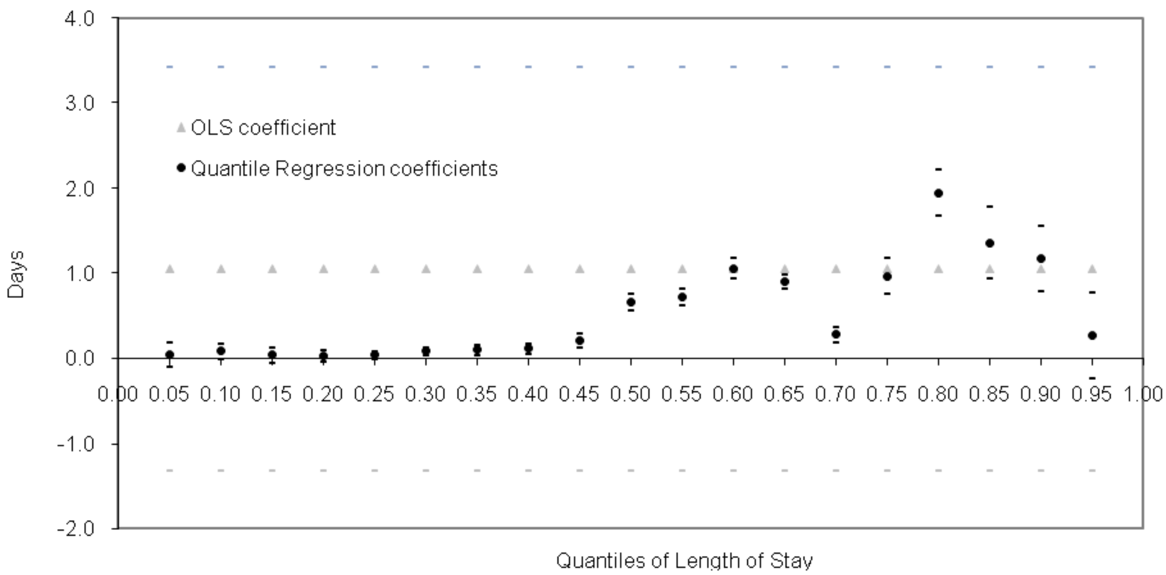


Figure 3: ***Obstetrics*** **– differences in LOS between obese and non-obese patients**

(for some quantiles, CI bands are so small that they are not displayed)

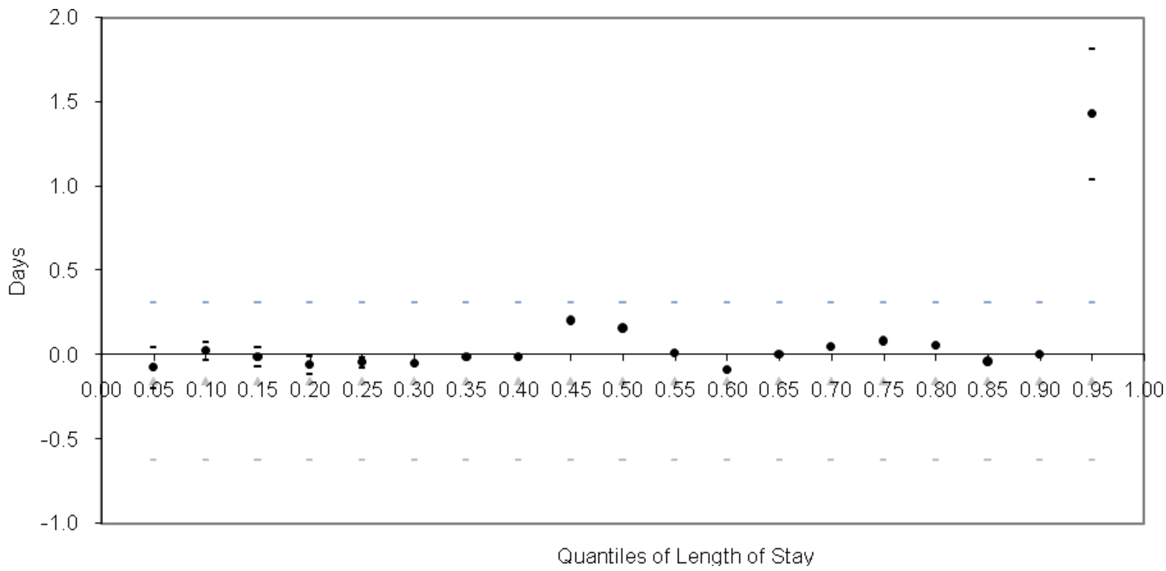


Figure 4: ***E NT*** **– differences in LOS between obese and non-obese patients**

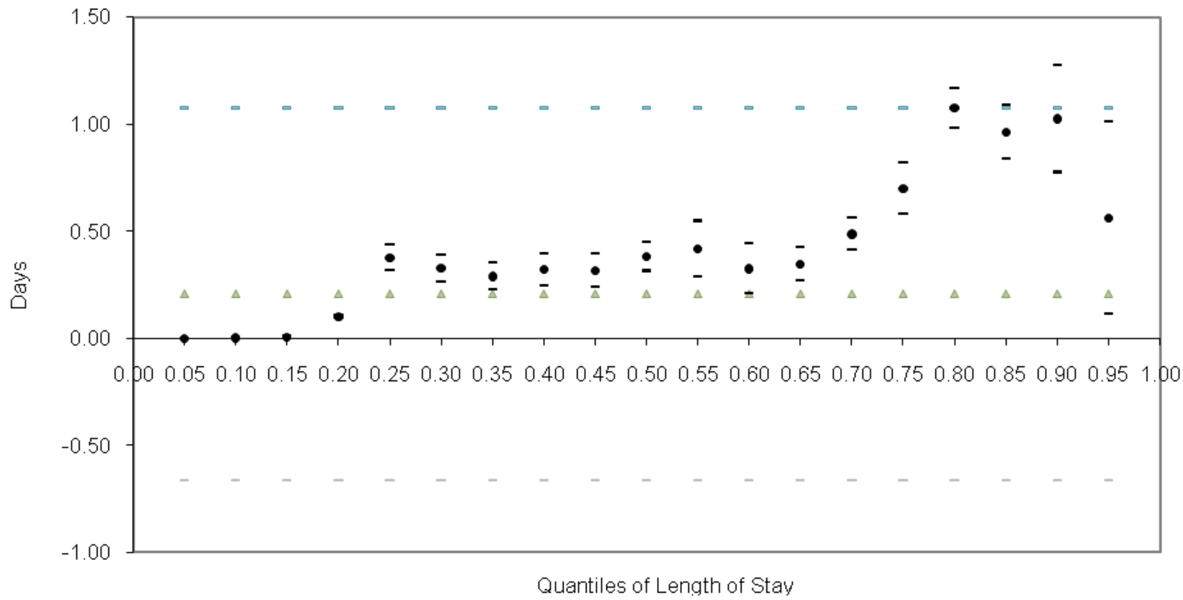


Figure 5: *Orthopedics* – differences in LOS between obese and non-obese patients

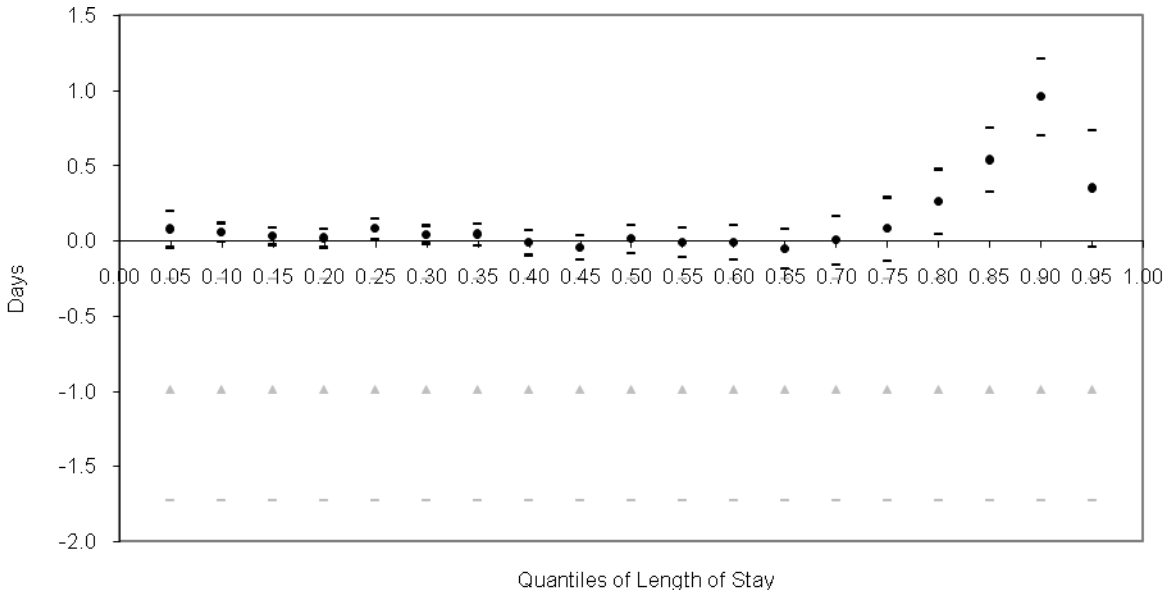


Figure 6: *Gynecology* – differences in LOS between obese and non-obese patients

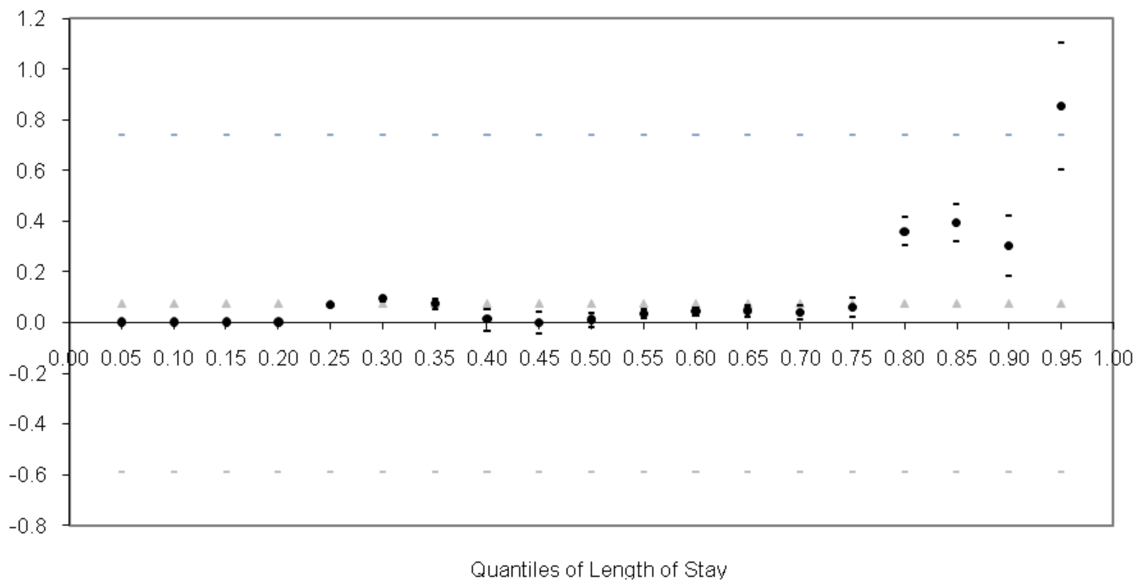


Figure 7: *Neurology* – differences in LOS between obese and non-obese patients

(for some quantiles, CI bands are so small that they are not displayed)

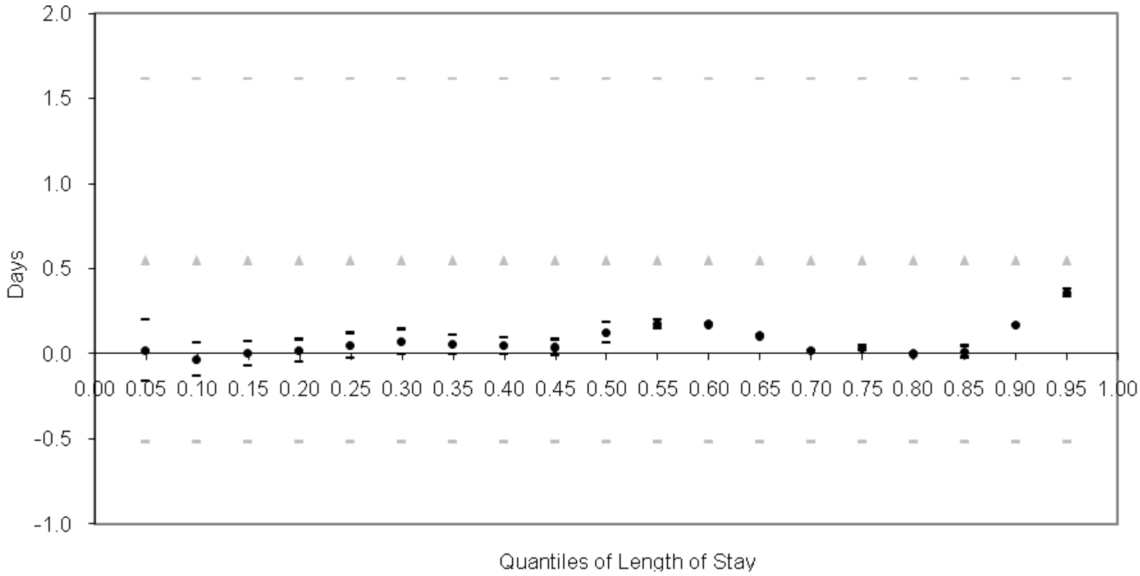


Figure 8: *Endocrinology* – differences in LOS between obese and non-obese patients

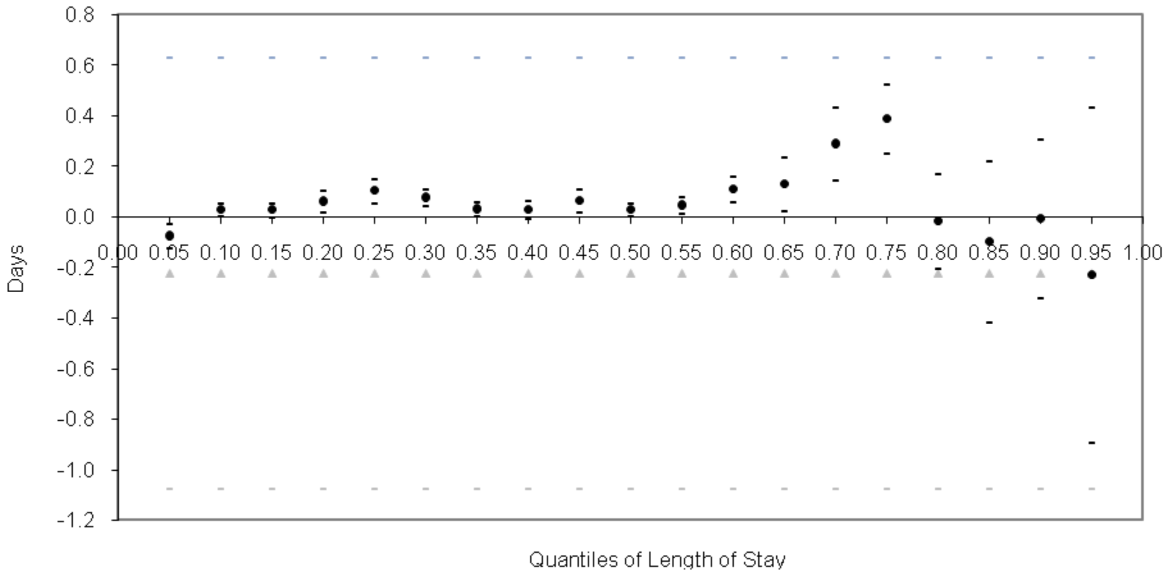


Figure 9: *General Surgery* – differences in LOS between obese and non-obese patients

(for some quantiles, CI bands are so small that they are not displayed)

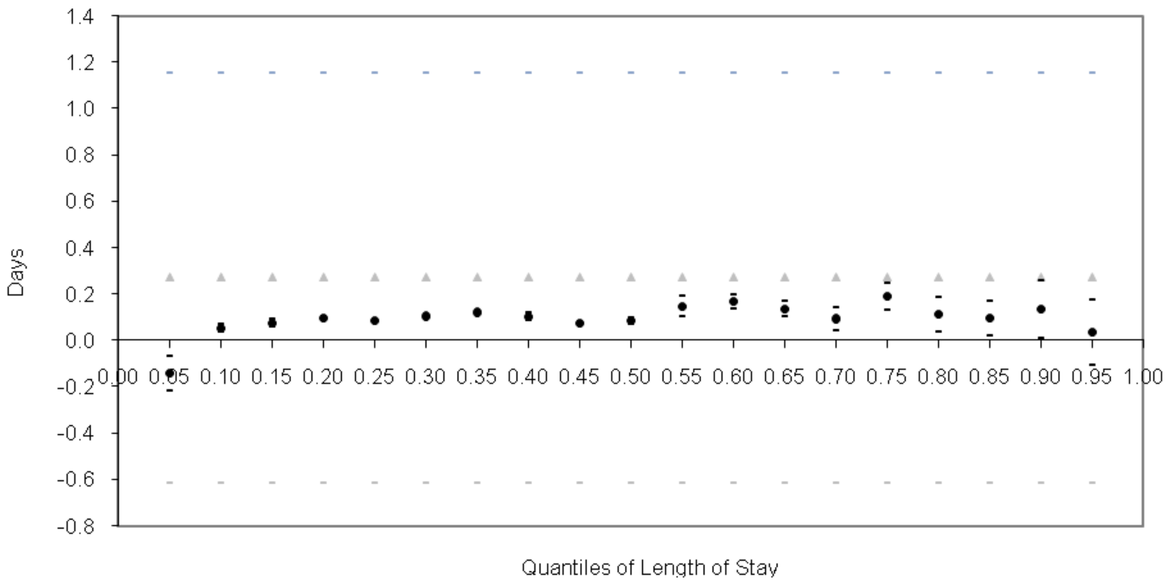


Figure 10: *Vascular* – differences in LOS between obese and non-obese patients

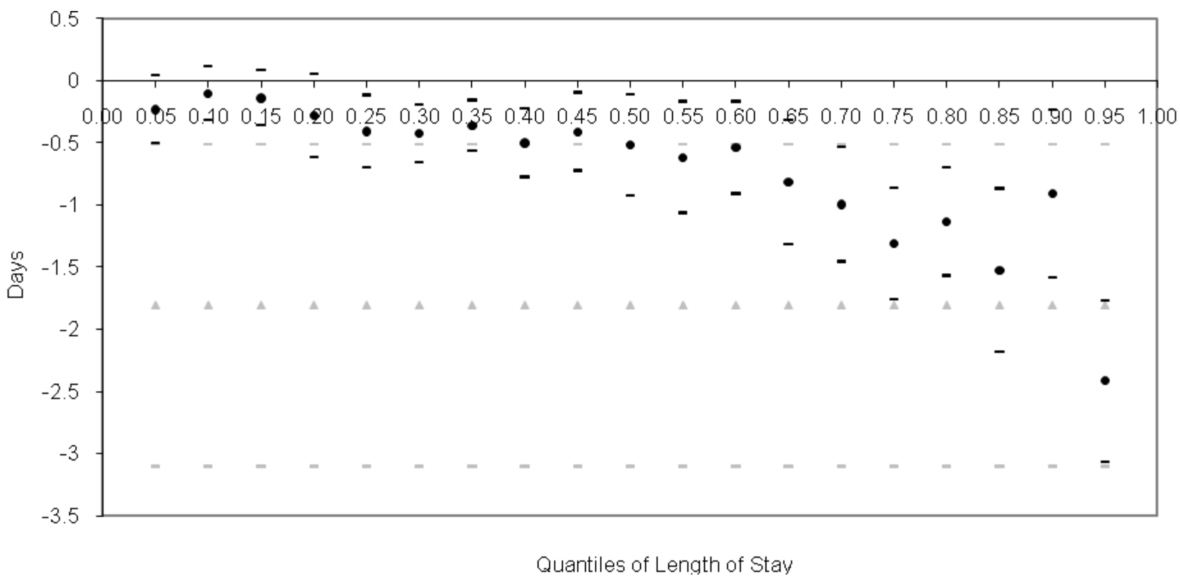


Figure 11: *Neurosurgery* – differences in LOS between obese and non-obese patients

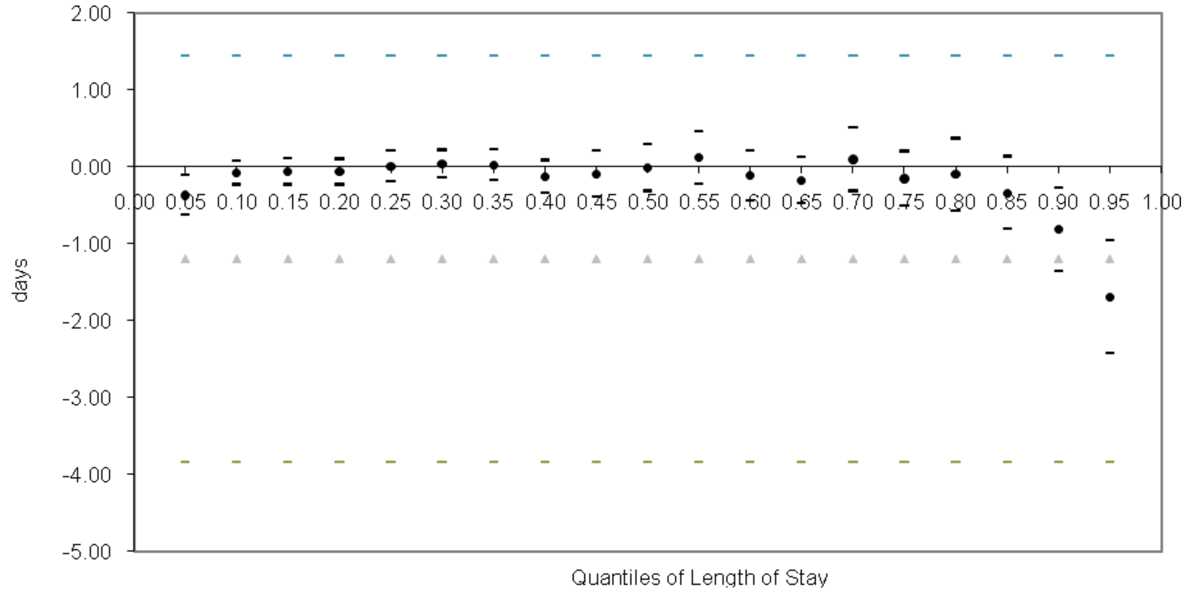


Figure 12: *Rheumatology* – differences in LOS between obese and non-obese patients

(for some quantiles, CI bands are so small that they are not displayed)

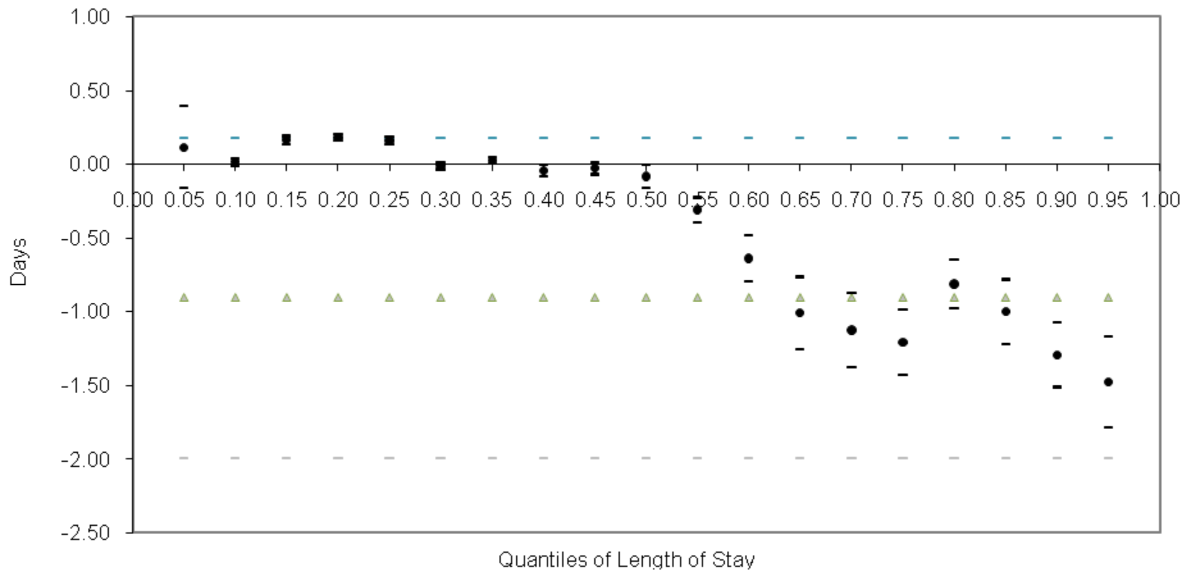


Figure 13: ***Respiratory*** **– differences in LOS between obese and non-obese patients**

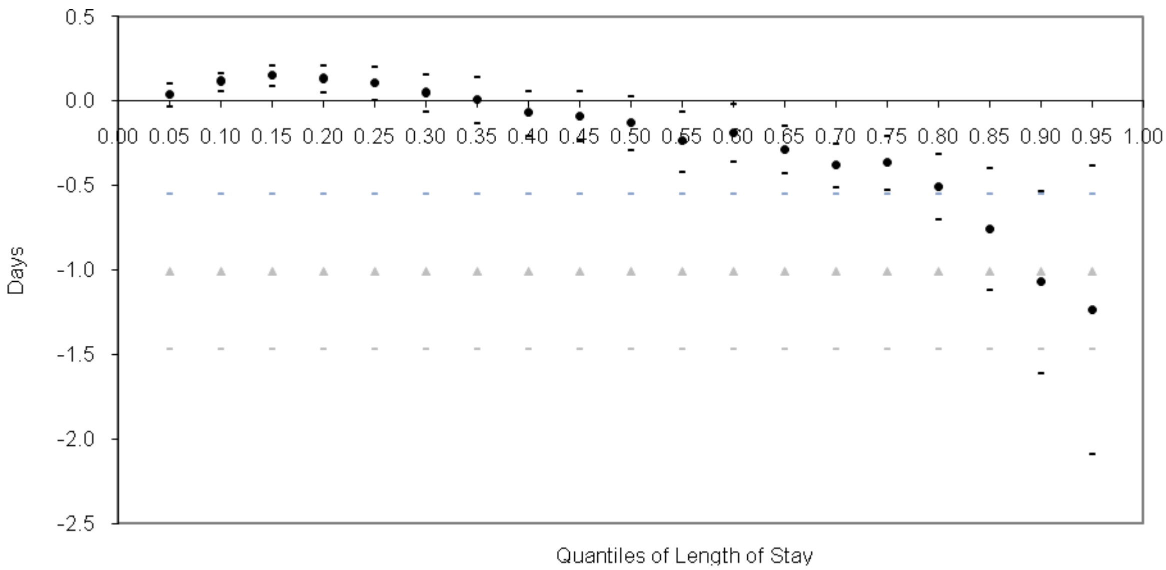


Figure 14: ***Cardiology*** **– differences in LOS between obese and non-obese patients**

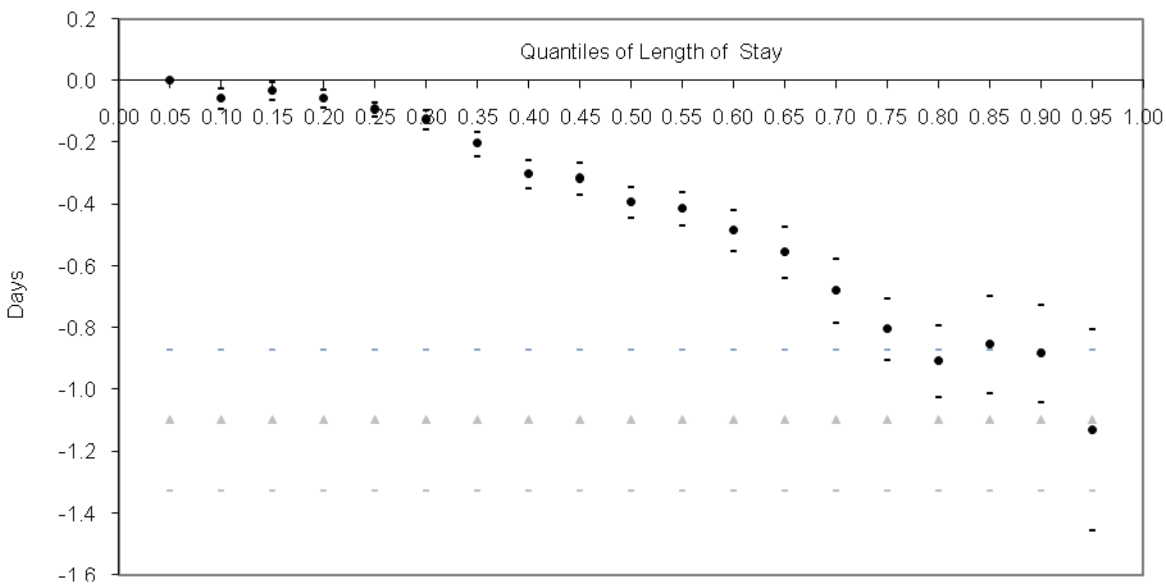


Figure 15: *Hematology* – differences in LOS between obese and non-obese patients

(for some quantiles, CI bands are so small that they are not displayed)

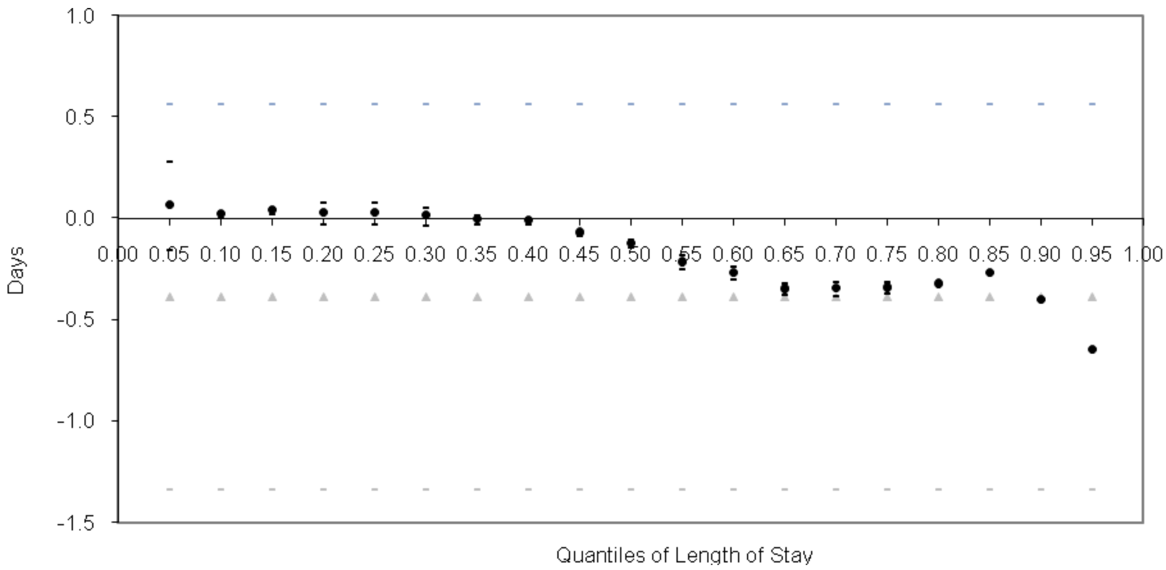


Figure 16: *Urology* – differences in LOS between obese and non-obese patients

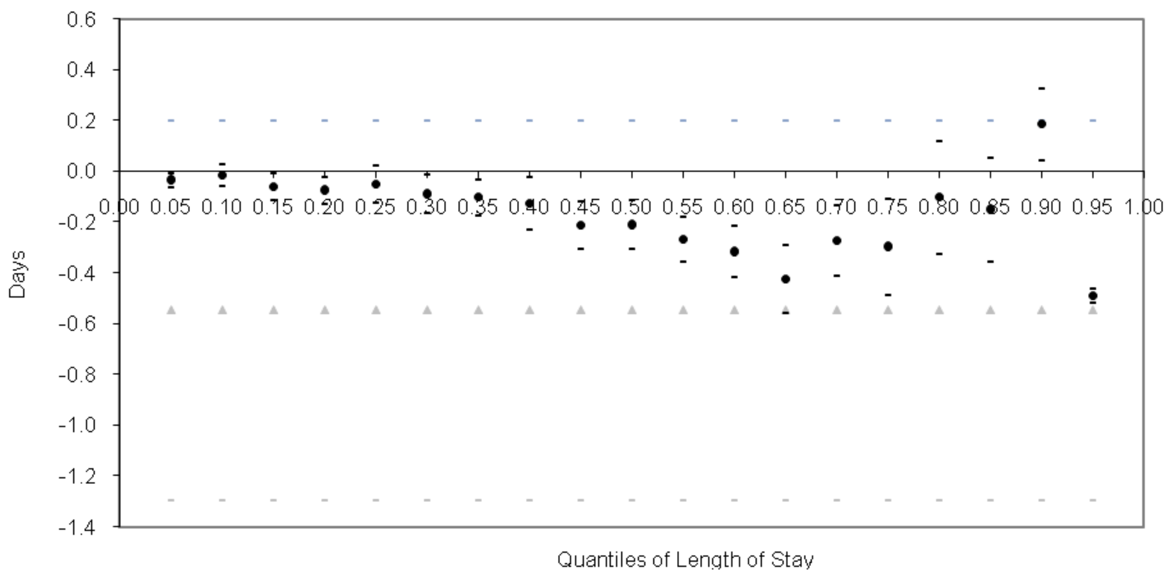


Figure 17: *Nephrology* – differences in LOS between obese and non-obese patients

(for some quantiles, CI bands are so small that they are not displayed)

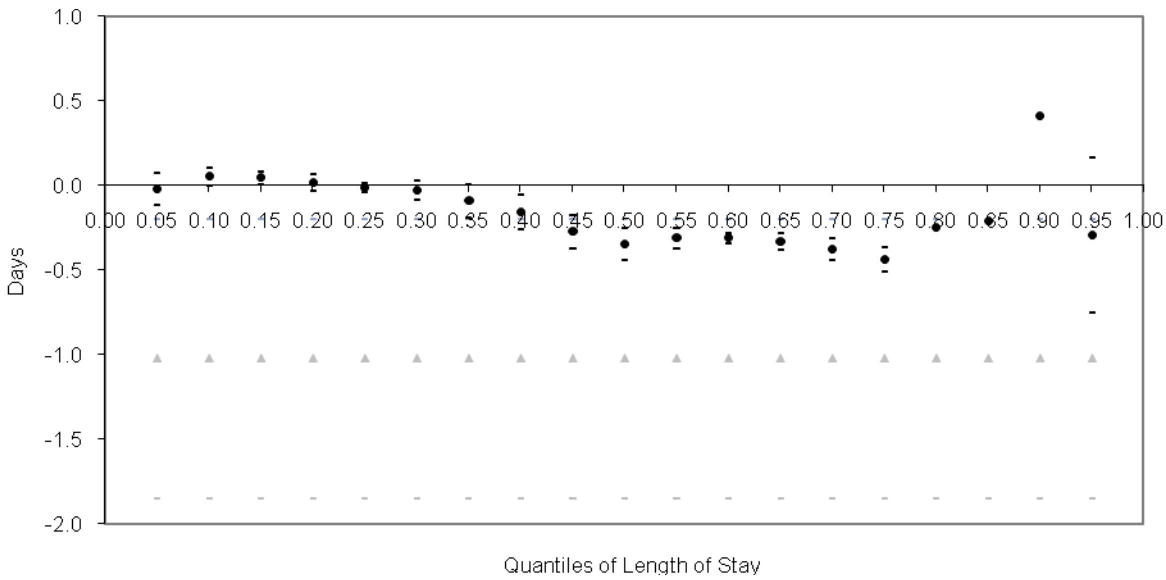


Figure 18: *Medically managed patients* (across all specialties) – differences in LOS between obese and non-obese patients

(for some quantiles, CI bands are so small that they are not displayed)

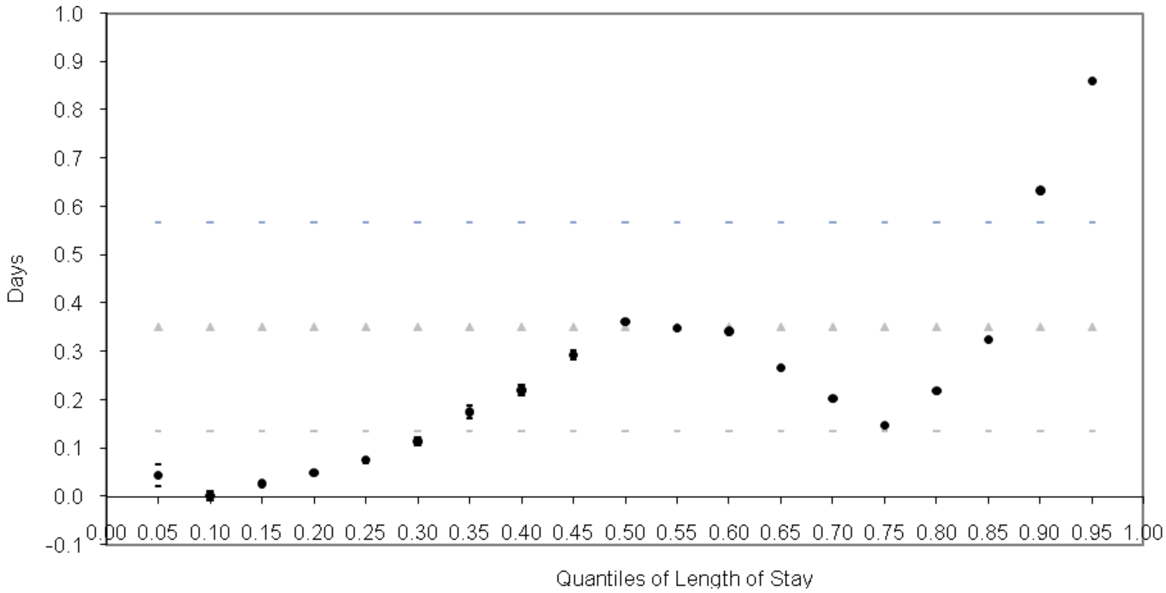
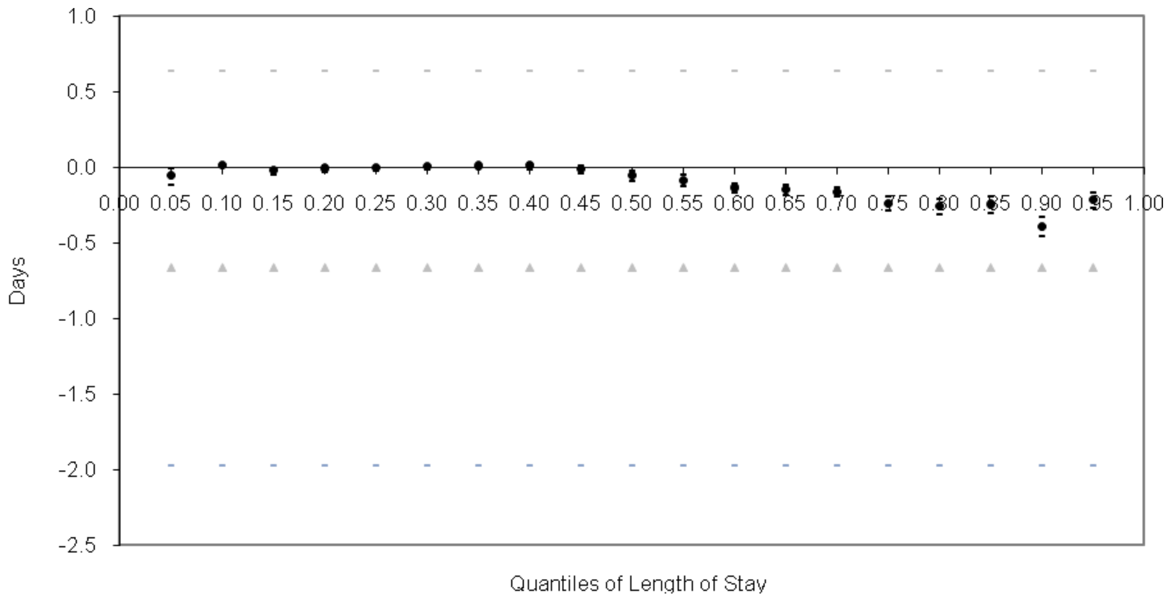


Figure 19: *Surgically managed patients* (across all specialties) – differences in LOS between obese and non-obese patients



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