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RESEARCH ARTICLE

Exploring heterogeneity in hospital length of stay of patients admitted for emergency abdominal surgery in Ireland: A quantile regression approach

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ABSTRACT

Background: Emergency abdominal surgery refers to a range of complex intra-abdominal surgical procedures associated with high mortality risk and long length of hospital stay. Length of stay is often used as a proxy measure for hospital resource utilisation in hospital capacity management and planning. Our objective was to explore the heterogeneity in length of stay among emergency abdominal surgery patients admitted at publicly funded hospitals in Ireland.

Methods*:* We analysed national hospital inpatient data (2014 – 2022) for adults discharged following emergency abdominal surgery. We used quantile regression methods to explore the heterogeneous effects along the length of stay distribution between 10th - 90th percentiles. We compared quantile regression with ordinary least squares estimates, and identified from which point in the length of stay distribution heterogeneous effects were different from ordinary least squares estimates.

Results: From the National Healthcare Quality Reporting System records for 15,408 emergency abdominal surgery adult inpatient episodes were obtained for analysis. We observed significant ($p < 0.001$) heterogeneous effects across most quantiles of the length of stay distribution. Length of stay was longer for patients with Charlson comorbidity indices of 4 or higher, American Society of Anaesthesiologists physical status scores of 2 and higher, admissions to critical care units, hospital readmissions within 30-days, discharges to nursing home and other hospital, and for patients treated in Model 4 hospitals. Length of stay was shorter for patients with a cancer diagnosis and patients who died during admission. Across these factors, statistically significant heterogeneous effects above ordinary least squares estimates were observed at the 70th to the 90th quantile.

Conclusions: The quantile regression methods identified the presence of significant heterogeneity across the entire length of stay distribution. Relative to ordinary least squares mean estimates, quantile regression is a better method for identifying heterogeneous effects by exploring the entire length of stay distribution. Our results highlight the importance of using appropriate methods for estimating skewed outcomes. This is important to provide valid and relevant empirical analysis to inform policy.

Keywords: Quantile regression, Methodology, Hospital length of stay, Emergency admissions, Emergency surgery, Outcomes, Heterogeneity, Ireland.

Introduction

In healthcare outcomes research, length of stay (LOS) is often used as a proxy measure for resource utilisation, effectiveness and efficiency[1-9]. Length of stay is an important indicator for assessing the efficiency of hospital management, capacity planning and patient quality of care[9]. Ireland has one of the highest hospital occupancy rates, and the lowest available hospital bed capacity across OECD countries[10-12]. Additionally, with the continued growth of the Irish older population, the demand for hospital beds is projected to increase between 26% and 41% by 2030[10]. Identifying the key factors contributing to prolonged hospital LOS is crucial for future planning and management of the increasing demand of hospital resources.

The distribution of hospital LOS (often skewed to the right) can pose some challenges for evaluating the relationship of factors leading to longer LOS. Generally, this skewness is a result of lower complexity patients requiring shorter hospital stays and more complex patients requiring longer stays and more intensive treatment. Challenges arise, if standard estimation techniques such as Ordinary Least Squares (OLS) regression are applied to report variation in LOS in heterogeneous samples of patients. Approaches like OLS, which estimate the mean effects of an outcome, are recognised for significant sensitivity to outlier values, which can lead to misleading results[13]. Thus, from a policy perspective, evaluating the relationship of factors across the full range of LOS rather than the mean, can provide more appropriate evidence for planning the management of patients with heterogeneous measures of LOS.

More appropriate approaches with less sensitivity to outliers and extreme values are required. Quantile Regression (QR) is one such approach, which enables analysts to model the quantiles over the full distribution of an outcome rather than just the estimated mean[8,14,15]. Quantile regression estimates the impact of an independent variable (e.g. Charlson comorbidity index) on the dependent variable at any percentile of the LOS distribution[14-16]. Quantile regression methods were introduced as an expansion to the standard OLS regression methods to allow for consideration of estimation outside the mean values of the sample distribution[14].

Quantile regression approaches have been demonstrated in health services and outcome research and recent studies have focused on applications to LOS measures. Quantile regression analyses have been used to analyse LOS differences between private and public hospitals and have identified that significantly greater LOS differences appear at the higher quantiles, compared to LOS differences at lower quantiles[7]. Similarly, LOS among severely obese patients have been found to be significantly longer from the 50th to the 95th quantiles[6]. Additionally, analysis of the impact of social care services along the entire LOS distribution showed that the provision of additional social care led to shorter LOS, indicating that these resources are more beneficial to patients within higher LOS quantiles[17]. Similarly, the QR approach was used to test for heterogeneity among palliative care patients with significant effects identified at the 75th [18] and 90th[19] quantiles. Within a hospital Emergency Department (ED) setting, significant LOS variation for patients with varied clinical needs along the 90th quantiles was identified[20]. More recently, the QR approach was used to identify risk factors associated with LOS among hospital admitted COVID-19 patients[21,22]. The QR method has been recognised to provide a better interpretation of results along the entire LOS distribution[8,20,23].

However, limited research evidence has focused on examining the factors influencing LOS after emergency abdominal surgery (EAS). The aim of this study was to identify the key factors affecting LOS among patients admitted for EAS in Ireland. Emergency abdominal surgery includes a range of complex intra-abdominal surgical procedures associated with high morbidity, high mortality risk, prolonged LOS and high demand of hospital resources[24-27]. We use the QR method to investigate the heterogeneity in LOS, and compare these with estimates from OLS regression. In addition, we contribute to the limited empirical evidence on the heterogeneous effects for LOS after emergency surgery within the Irish context.

Methods

QUANTILE REGRESSION

The Quantile Regression (QR) method is particularly useful when focus is on the extreme values of the dependent variable, rather than the mean, and if considering full non-transformed or untrimmed data[15]. The QR approach has several useful features including: *1)* The models can characterise the entire distribution of a dependent variable for given independent variables[6,15-17,28] *2)* The models have a linear programming representation, making estimation easy[14,15,28] *3)* The QR function is a weighted sum of absolute deviations, giving a robust measure of location, making estimated coefficients less sensitive and more robust to extreme values of the dependent variable[14,15,28] *4)* If the error term is non-normal, QR estimators can be more efficient than OLS estimators[28,29] *5)* Solutions at specified quantiles are interpreted as differences in the response of the dependent variable, to changes in the independent variables at various points of the dependent variable distribution[14,28] *6)* Generally, based on a linear combination of quantile estimators, the linear estimators are more efficient than least squares estimators[16,28]. The QR method is an extension and complement to OLS regressions when certain assumptions are violated, such as the presence of outliers and long tails in the data distribution[29]. Furthermore, QR is a useful approach for detecting heterogeneous effects of covariates and differences in longitudinal changes, at different percentiles of the outcome measure[29].

The QR approach assumes that the independent variables (x) and the dependent outcome (y) can be related as follows (adapted from Koenker and Bassett (1978)):

$$y_i = x_i\beta_\tau + \varepsilon_{i\tau}$$

Where y is the outcome, x represents the independent variables. Subscript τ, $0 < \tau < 1$, denotes a quantile of y and ε is the error term. QR seeks to model the regression function for quantile τ of outcome y conditional on independent variables x which can be summarised as follows:

$$Quant_\tau(y_i|x_i) = x_i\beta_\tau$$

DATA AND ANALYSIS

We used national Hospital In-Patient Enquiry (HIPE) episode data for 2014-2022 for patients who underwent an Emergency Abdominal Surgery (EAS). HIPE is a national dataset of hospital activity, where each discharge record holds demographic, clinical and administrative data for completed inpatient episodes in Irish public hospitals[30]. Procedures and diagnoses are coded according to the Australian Classification of Health Interventions and the International Classification of Diseases, 10th edition, updated for Ireland[31]. Only EAS recorded as the principal procedure were included in our analysis. The exact specification of included procedure codes are reported elsewhere[25].

Given the non-normal skewed distribution of the hospital LOS, we estimated LOS using a standard linear OLS regression, and compared these mean estimates against the QR estimates at different quantiles: 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th and 90th of the LOS distribution. We reported differences between the two estimation approaches and interpreted our results based on whether the QR estimates fell below, within or above the mean OLS regression estimates. We also identified from which point along the LOS distribution statistically significant heterogeneous effects were evident. We adjusted the estimations by including the following patient case-mix characteristics and hospital outcomes in our analysis: patient sex (male, female), age, age-squared (to account for the non-linear relationship of age), Charlson Comorbidity Index score (clinical measure of patient's comorbidity level or burden of disease based on the number and severity of selected comorbid conditions, where a higher score indicates a higher burden[32]), American Society of Anaesthesiologists (ASA) physical status classification score (a classification system of the health status of a patient prior surgery, where a lower score indicates a completely healthy fit patient, and a higher score represents more complex patients[33]), diagnosis of cancer, occurrence of Intensive Care Unit (ICU) admission, hospital readmission within 30-days, discharge destination after surgery (home, transfer to another hospital, in-hospital death), and hospital model (a proxy for the level of hospital specialisation[34-36]). We also included hospital fixed effects in our estimation to capture some of the geographic and demographic variations that may impact the delivery of EAS. To account for differences over time, we also included yearly fixed effects in our analyses. Observations with missing ASA score and patients admitted from a nursing home (representing an alternative patient trajectory to the majority of patients) were excluded from our analysis.

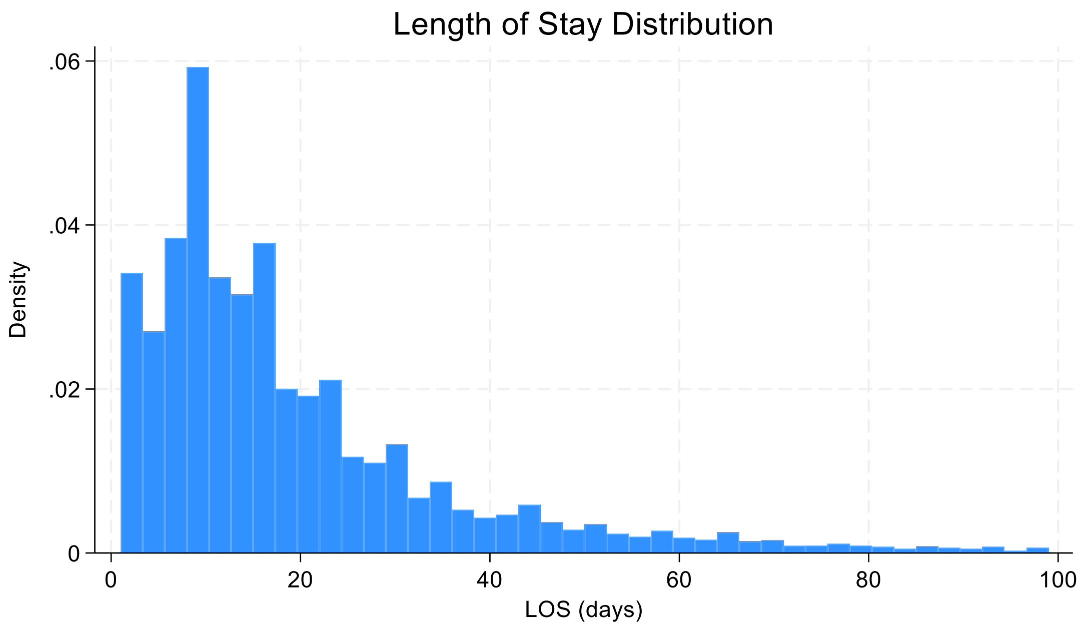
Prior to the quantile analysis, we explored maximum likelihood specifications as alternatives to the OLS regressions including the Generalised Linear Model (GLM) with a log-link function and a Poisson distribution (Appendix I). However, these approaches did not improve the model fit and produced similar estimates to those from the OLS regressions.

Results

DESCRIPTIVE STATISTICS

Figure 1 illustrates the distribution of the hospital LOS for all EAS patients. It is evident that LOS in our data is skewed to the right, suggesting the presence of long hospital stays among EAS patients.

Figure 1. Length of Stay distribution



Note: Length of stay was trimmed at 100 days

Table 1 summarises the descriptive statistics for the data used in the analysis. 15,408 adults with EAS were admitted over the period 2014-2022. The average LOS across the entire period was 22.5 days. The share of female patients was 52.3%, and the majority of patients (22.6%) were aged 70-79 years. 15.9% of all patients had a cancer diagnosis. As expected, the majority (92.4%) of all patients were admitted from home, and a relevant proportion (23.2%) had a Charlson comorbidity score of +10 (multiple severe comorbidities). A high proportion (40.4%) of patients were admitted to the ICU, and 10.8% of all patients were discharged to a nursing home.

Table A2, Appendix I presents data of the total LOS variation along with the mean, standard deviation and number of patient cases, for each explanatory variable, at different percentiles of the data distribution. Clear LOS variation can be observed at the higher quantiles across most variables, from the 50th – 90th quantiles.

Table 1. Descriptive statistics

Variables	Summary
n (%)	15408 (100.0)
Age, mean (SD)	61.3 (17.9)
Sex, n (%)	
Male	7356 (47.7)
Female	8052 (52.3)
Charlson Comorbidity Score, n (%)	
0	9701 (63.0)
1-3	700 (4.5)
4-6	705 (4.6)
7-9	836 (5.4)
10+	3466 (22.5)
ASA score, n (%)	
1	1489 (9.7)
2	5933 (38.5)
3-5	7986 (51.8)
Cancer Diagnosis, n (%)	
No	12886 (83.6)
Yes	2522 (16.4)
ICU admission, n (%)	
No	9201 (59.7)
Yes	6207 (40.3)
Discharge Destination, n (%)	
Home	11715 (76.0)
Nursing Home	1627 (10.6)
Transfer	880 (5.7)
Death	1186 (7.7)
Readmission within 30 days, n (%)	
No	13683 (88.8)
Yes	1725 (11.2)
Hospital Model, n (%)	
Model 3	6067 (39.4)
Model 4	9341 (60.6)

Note: *ICU* = Intensive Care Unit; *ASA score* = American Society of Anaesthesiologists Classification physical status classification score. Hospital model is based on the Irish classification of hospitals based on increasing levels of hospital specialisation.

ANALYTICAL RESULTS

Table 2 reports the estimated coefficients from OLS and QR analyses. Figure 1 illustrates the key variables where heterogeneity is mostly statistically significant, for QR estimation at the 10th, 20th, 30th, 40th,50th, 60th, 70th, 80th and 90th LOS quantiles, relative to mean OLS regression estimates (represented by the red reference line).

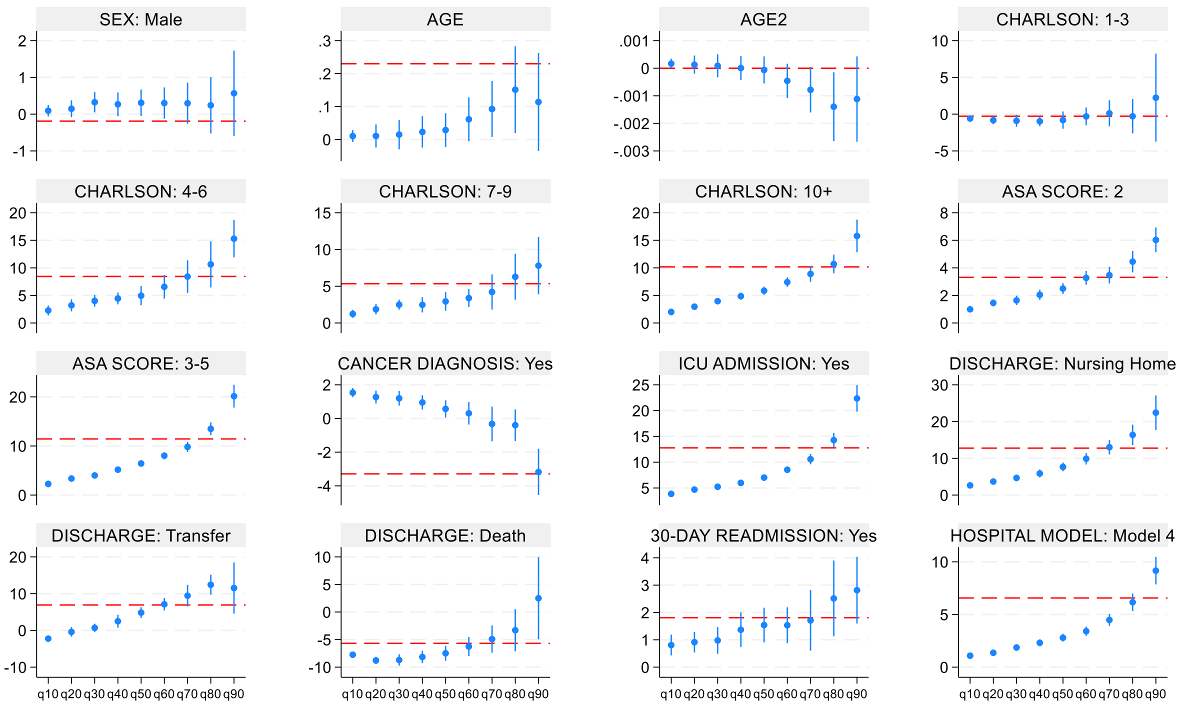
Table 2. Results of coefficients for all explanatory variables – OLS and QR estimates (n=15,408)

Variable	OLS	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
Sex										
Male	-0.19	0.09	0.15	0.33*	0.27	0.31	0.30	0.30	0.24	0.57
Age	0.23***	0.01	0.01	0.01	0.02	0.03	0.06	0.09*	0.15*	0.11
Age^2	-0.00***	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.00*	0.00
Charlson comorbidity score										
1-3	-0.28	-0.59***	-0.82**	-0.90*	-0.96**	-0.81	-0.3	0.12	-0.28	2.24
4-6	8.44***	2.27***	3.21***	4.02***	4.45***	4.96***	6.57***	8.42***	10.64***	15.30***
7-9	5.34***	1.24***	1.87***	2.49***	2.47***	2.93***	3.39***	4.22***	6.29***	7.80***
10+	10.18***	2.01***	2.96***	3.96***	4.86***	5.86***	7.41***	8.90***	10.71***	15.79***
ASA score										
2	3.31***	0.99***	1.46***	1.64***	2.05***	2.50***	3.27***	3.47***	4.45***	6.03***
3-5	11.43***	2.28***	3.37***	4.00***	5.19***	6.44***	8.02***	9.82***	13.49***	20.14***
Cancer diagnosis										
Yes	-3.29***	1.54***	1.28***	1.20***	0.96***	0.57*	0.31	-0.32	-0.40	-3.18***
ICU admission										
Yes	12.78***	3.86***	4.69***	5.24***	5.99***	7.02***	8.54***	10.60***	14.28***	22.36***
Discharge destination										
Nursing home	12.77***	2.64***	3.68***	4.68***	5.88***	7.66***	9.89***	13.03***	16.38***	22.43***
Transfer	6.92***	-2.24***	-0.41	0.70	2.49**	4.83***	7.12***	9.45***	12.43***	11.52**
Death	-5.68***	-7.74***	-8.78***	-8.70***	-8.15***	-7.48***	-6.25***	-4.91***	-3.30	2.50
30-day readmission										
Yes	1.81*	0.81***	0.91***	0.98***	1.37***	1.54***	1.53***	1.71**	2.51***	2.81***
Hospital model										
Model 4	6.57***	1.09***	1.37***	1.87***	2.32***	2.79***	3.41***	4.49***	6.16***	9.16***
Constant	-1.71	0.56**	1.40**	2.06***	2.56***	3.19***	3.26***	3.84***	3.73*	7.51***

Significance levels: *p<0.1; **p<0.05; ***p<0.01

The mean OLS estimates showed statistical significance with regards to LOS effects on patient age and age-squared. The estimated sex difference (after adjustment) was insignificant. In contrast, the QR estimates did not suggest that any of these patient factors were significantly heterogeneous across the LOS quantiles, which is also observed in Figure 1.

Figure 1. Coefficient estimates by independent variable



Note: OLS regression coefficients are represented by the red reference lines

The clinical variables including the Charlson comorbidity score, ASA score, Cancer diagnosis and Intensive Care Unit (ICU) admission were statistically significant ($p<0.01$) for the mean OLS estimates and largely significant across most QR quantiles. The number of comorbidities were positively associated with LOS. For patients with a Charlson comorbidity score of 4-6, the mean LOS was significantly longer by 8.4 days, relative to patients without comorbidities. Similarly, across all quantiles, LOS was significantly longer, ranging from an additional 2.3 days at the 10th quantile, to an additional 15.3 days at the 90th quantile. Additionally, ASA score 3-5 estimates suggested significantly longer mean LOS (by 11.4 days) and across all quantiles (ranging from 2.28 days (10th quantile) to 20.14 days (90th quantile)). As expected, LOS was significantly longer (mean and across quantiles) for patients admitted to the ICU. However, having a cancer diagnosis provided a less clear picture. OLS estimates suggested a significantly shorter average LOS (by 3.29 days), relative to QR estimates which suggested an increase in LOS at the 10th (by 1.54 days), 20th (by 1.28 days), 30th (by 1.20 days) and 40th (by 0.96 days) quantiles, with non-significant results observed at the higher quantiles. Overall, significant heterogeneous effects above the mean OLS estimates were evident for the QR estimates from the 70th (ASA score), 80th (Charlson comorbidity score and ICU admission) and 90th quantiles (Figure 1). These clinical factors significantly impacted the LOS of EAS patients, as evident by the increasing magnitude of the effect with increases in the quantile, while retaining the statistical significance across all measures.

For the remaining variables, OLS identified a statistically significantly longer mean LOS for patient discharges to a nursing home by 12.8 days and by 6.9 days for transferred patients, relative to discharges to home. In comparison, the QR estimates suggest an increasing magnitude of effects across the LOS distribution. From the 10th to the 90th quantiles, patient LOS is 2.6 and 22.4 days longer. The QR estimates have additionally identified statistical significance for patient readmissions within 30-days post EAS, with the effects increasing at the highest quantiles of the LOS distribution (from 0.8 days at the 10th quantile to 2.8 days at the 90th quantile). Surprisingly, the mean estimates for patients who died during their hospital stay, suggested on average a shorter LOS by 5.7 days (p<0.001). However, these effects for QR estimates appeared to reduce across the LOS distribution from shorter LOS by 7.7 days (10th quantile) to 4.9 days (70th quantile), and non-significant effects observed at the 80th and 90th quantiles. Similarly, positively increasing effects were evident for patients who were transferred to other hospitals, with their LOS estimated to increase by 4.8 and 11.5 days, at the 50th and 90th quantiles, respectively (effect almost double to OLS). Finally, LOS for patients treated in Model 4 hospitals, was on average 6.6 days longer. However, the QR estimates, suggested an increasing effect across the LOS distribution, with LOS increasing by 1.1 days at the 10th quantile, to an additional 9.2 days at the 90th quantile. Statistically significant heterogeneous effects above OLS estimates were observed for all hospital outcomes at the 70th (Transfer and hospital mortality), 80th (nursing home discharges and 30-day readmission) and the 90th (Model 4 hospitals) quantiles (Figure 1). Relative to OLS estimates, the QR estimates provided additional explanatory power to identify significant heterogeneity along the LOS distribution for EAS patients.

Discussion

We explored and identified statistically significant heterogeneous effects across the LOS distribution of EAS patients in Ireland by comparing linear mean OLS estimates with those of QR. Both OLS and QR estimates identified statistically significant effects across the included descriptive variables. However, our results indicated that estimating mean effects on patient LOS does not provide a full picture of the heterogeneous effects of patient, clinical and hospital characteristics, across different parts of the LOS distribution. For example, we identified higher heterogeneous effects in the higher tail of the LOS distribution across most factors included in our analysis, i.e. from the 70th to the 90th quantiles. Thus, richer inferences can be drawn about inpatient LOS from QR estimates, which cannot be drawn from OLS estimates. The analysis confirms the previously highlighted advantage of the QR approach in LOS estimation, and the fact that the skewed nature and the extreme values across the entire distribution are considered[8,29].

Our results are similar to previous studies which also found patient sex to be an insignificant factor in explaining hospital LOS across its distribution [23]. Similarly, significantly longer LOS for ICU patient admissions have been reported[8]. Likewise, significantly longer LOS across the higher quantiles have been identified[17]. In addition, hospital type (i.e. specialisation) has been identified as a significant factor influencing hospital LOS[37]. Evidently, LOS varies across different patient groups, but it is difficult to compare our QR estimates directly with those from other studies due to differing patient case-mix across other jurisdictions. Nevertheless, it is important to highlight similarities resulting from QR estimates across different jurisdictions.

The key strength of this study is the analysis of a complete national dataset of EAS patients over an 8-year period. Other studies were often cross-sectional, or limited to a shorter period of analysis [7,18,19]. Therefore, the results from our analysis, covering a longer time perspective, are more robust in informing hospital policy and decision makers. For instance, policy choices regarding hospital resource allocation and utilization could target specific patient subgroups across the LOS distribution, as identified by the significant QR estimates. Such targeted interventions have the potential to be more impactful than more generic increases in funding. Furthermore, decisions based on OLS estimates alone may underestimate bed occupancy, with significant adverse implications on hospital resources. The substantial heterogeneity in LOS identified by the QR approach can help to inform where potential capacity may arise or where additional bed occupancy may be required, and thereby aid future hospital planning and patient flow improvement programmes.

One of the key limitations in our study was related to the data used in our analysis. Although we were able to capture a great variety of patient, clinical and hospital characteristics, our analysis would have benefited from additional information for example such as quality of life measures, hospital team competence information, organisation of care, staff information and additional patient and regional information [7]. Thus, future analyses should consider including additional information, which would improve the overall explanatory power of the QR approach in the identification of heterogeneous effects across patient hospital LOS. This would provide more in-depth evidence for hospital management, especially in the areas of workforce and capacity planning.

Conclusion

The quantile regression (QR) approach identified the presence of heterogeneity effects across the entire length of stay (LOS) distribution for emergency abdominal surgery patients in Ireland. This suggests that relative to mean ordinary least squares (OLS) estimates, QR is a better method for identifying heterogeneous effects, by considering the entire LOS distribution, and including higher extreme values in the estimation, which tends to bias OLS estimates. This draws attention to the importance of using the correct methodological approach when the outcome of interest does not follow a normal distribution, particularly when generating evidence to inform future healthcare and policy decisions.

Conflicts of Interest Statement:

None

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Appendix I

Table A1. Coefficients from GLM log-link & Poisson distribution regression vs. OLS

Variable	OLS	GLM
Sex		
Male	-0.19	-0.10
Age	0.23***	0.12***
Age^2	-0.00***	-0.00***
Charlson comorbidity score		
1-3	-0.28	-0.01
4-6	8.44***	7.30***
7-9	5.34***	4.23***
10+	10.18***	9.36***
ASA score		
2	3.31***	2.35***
3-5	11.43***	9.73***
Cancer diagnosis		
Yes	-3.29***	-2.10***
ICU admission		
Yes	12.78***	10.53***
Discharge destination		
Nursing home	12.77***	10.40***
Transfer	6.92***	5.23***
Death	-5.68***	-4.19***
30-day readmission		
Yes	1.81*	1.08**
Hospital model		
Model 4	6.57***	5.29***
Constant	-1.71	1.68**
Log-likelihood	-72868	-156211
AIC	9.5	20.3
BIC	11407	94387
N	**15408**	**15408**

Table A2. Summary of LOS variation for all independent variables used in estimation

	N	Mean	SD	p10	p25	p50	p75	p90
All	15408	22.8	29.9	4	8	14	26	47
Male	7356	23.2	29.2	5	8	15	26	47
Female	8052	22.5	30.6	4	8	14	26	47
Age	15408	13.3	15.0	2	4	10	15	29
Charlson 0	9701	17.7	22.8	4	7	12	21	35
Charlson 1-3	700	21.7	26.2	4	8	14	25	44.5
Charlson 4-6	705	34.1	39.3	8	13	22	40	70
Charlson 7-9	836	28.7	36.6	6	11	18	33	57
Charlson +10	3466	33.6	39.3	8	12	22	40	69
ASA score 1	1489	9.6	9.4	2	4	7	12	19
ASA score 2	5933	15.7	15.6	4	7	12	19	30
ASA score 3-5	7986	30.5	37.5	6	11	20	35	64
Cancer diagnosis No	12886	22.6	31.3	4	8	14	26	47
Cancer diagnosis Yes	2522	23.8	21.9	8	11	18	28	45
ICU admission No	9201	16.3	19.9	4	7	11	20	33
ICU admission Yes	6207	32.5	38.5	7	12	21	38	68
Discharge Home	11715	19.2	23.5	5	8	13	22	38
Discharge Nursing home	1627	38.8	43.0	10	15	26	45	79
Discharge Transfer	880	34.6	41.1	3	12	24	43	68
Discharge Death	1186	27.7	42.9	2	5	15	32	65
30-day readmission No	13683	22.5	29.9	4	8	14	26	46
30-day readmission Yes	1725	25.6	30.4	6	10	16	29	54
Hospital Model 3	6067	19.4	22.8	4	8	13	23	41
Hospital Model 4	9341	25.0	33.6	5	9	15	28	52