Mortality and readmission differences associated with after-hours hospital admission: A population-based cohort study in Queensland Australia

Author

Bell, Anthony, Boyle, Justin, Rolls, David, Khanna, Sankalp, Good, Norm, Xie, Yang, Romeo, Michele

Published

2023

Journal Title

Health Science Reports

Version

Version of Record (VoR)

DOI

10.1002/hsr2.1150

Rights statement

Downloaded from

Griffith Research Online

Received: 2 January 2023 | Revised: 16 February 2023 | Accepted: 27 February 2023

DOI: 10.1002/hsr2.1150

ORIGINAL RESEARCH

Health Science Reports Open Access WILEY

Mortality and readmission differences associated with after-hours hospital admission: A population-based cohort study in Queensland Australia

Anthony Bell[1] | Justin Boyle[2] | David Rolls[3] | Sankalp Khanna[2] | Norm Good[2] | Yang Xie[4] | Michele Romeo[5]

[1]Queensland Department of Health, now at Rockingham General Hospital, Perth, Australia

[2]CSIRO, Brisbane, Australia

[3]CSIRO, now at Centre of Excellence for Biosecurity Risk Analysis, Melbourne, Australia

[4]CSIRO, now at McKinsey & Company, Sydney, Australia

[5]Queensland Department of Health, Brisbane, Australia

Correspondence

Justin Boyle, Surgical Treatment and Rehabilitation Service—STARS, Royal Brisbane and Women's Hospital, 296 Herston Rd, Herston, Qld 4029, Australia.

Email: Justin.Boyle@csiro.au

Funding information

Commonwealth Scientific and Industrial Research Organisation; Metro North Hospital and Health Service, Queensland Department of Health

Abstract

Background and Aims: Policy makers and health system managers are seeking evidence on the risks involved for patients associated with after-hours care. This study of approximately 1 million patients who were admitted to the 25 largest public hospitals in Queensland Australia sought to quantify mortality and readmission differences associated with after-hours hospital admission.

Methods: Logistic regression was used to assess whether there were any differences in mortality and readmissions based on the time inpatients were admitted to hospital (after-hours versus within hours). Patient and staffing data, including the variation in physician and nursing staff numbers and seniority were included as explicit predictors within patient outcome models.

Results: After adjusting for case-mix confounding, statistically significant higher mortality was observed for patients admitted on weekends via the hospital's emergency department compared to within hours. This finding of elevated mortality risk after-hours held true in sensitivity analyses which explored broader definitions of after-hours care: an "Extended" definition comprising a weekend extending into Friday night and early Monday morning; and a "Twilight" definition comprising weekends and weeknights.

There were no significant differences in 30-day readmissions for emergency or elective patients admitted after-hours. Increased mortality risks for elective patients was found to be an evening/weekend effect rather than a day-of-week effect. Workforce metrics that played a role in observed outcome differences within hours/after-hours were more a time of day rather than day of week effect, i.e. staffing impacts differ more between day and night than the weekday versus weekend.

Conclusion: Patients admitted after-hours have significantly higher mortality than patients admitted within hours. This study confirms an association between

Abbreviations: ANOVA, analysis of variance; CI, confidence interval; DRG, Diagnosis Related Group; ED, Emergency Department; HREC, Human Research Ethics Committee; OR, odds ratio; SEIFA, Socio-Economic Indexes for Areas.

mortality differences and the time patients were admitted to hospital, and identifies characteristics of patients and staffing that affect those outcomes.

KEYWORDS

after-hours care, healthcare disparities, night care, risk adjustment for clinical outcomes, time factors

1 | INTRODUCTION

There is a need to deliver healthcare in a manner that maximizes the outcome for patients. The challenge of delivering hospital care to achieve equitable outcomes irrespective of when patients arrive at hospital has been the focus of a growing body of research.[1–20] The issue has become politicized in some jurisdictions, and policy makers, health system managers and clinicians have been increasingly interested in the potential risks involved for patients admitted to hospital after-hours.[1]

The growing body of evidence suggesting outcome differences for patients admitted after-hours remains largely observational, has been described as low in quality,[9] and has matured to include improved risk adjustment methodology, and consideration of patient acuity measures to better understand the often contradictory findings.[10] One study in particular has generated considerable controversy,[5] evidenced by 69 published public responses ("Rapid Responses") accompanying the published work in the year following its publication. A review of these concerns highlights three gaps in knowledge relating to after-hours hospital admission: that observed mortality differences may be more associated with time-of-day rather than day-of-week; that staffing differences should be taken into account; and that it's imperative to account for patients that may be discharged from hospital to die in the community shortly after hospitalization. Our study attempts to improve the state of analysis by addressing these limitations.

The aim of this study was to investigate whether patients who were admitted to hospital outside of normal business hours compared to other times of the week have higher mortality or return visits to hospital. The main outcome measure of interest was mortality (within and outside of hospital) due to the wide acceptance of death being the ultimate outcome-based quality measure. A secondary outcome measure assessed in the study was 30-day readmission rates. Given the lack of consensus on the definition of after-hours, we undertook sensitivity analyses covering alternate definitions of after-hours to determine if any observed differences were associated with a twilight effect as opposed to a weekend effect.

Finally we sought to contribute evidence towards the role of staffing on any observed differences, as reduced availability of staff after-hours has been speculated as being attributable to observed differences in patient outcomes. This was assessed by including the variation in physician and nursing staff numbers and seniority as explicit predictors within patient outcome models reflecting the care team available at the time a patient arrived at hospital.

2 | METHODS

2.1 | Aim, design and setting

This multi-year study, aimed at quantifying mortality and readmission differences associated with after-hours hospital admissions, was based on patients admitted at the major public hospitals in Queensland Australia between April 2013 and December 2015. Queensland has a population of approximately 5 million and is serviced by both a public (60% of hospital episodes) and private (40%) health system.[21] The study focused only on inpatient episodes of public hospital care, as private hospitals in Australia are commercial enterprises and deliver more specialized care than public hospitals. Many private hospitals do not provide emergency department (ED) or other accident and emergency services which can affect the case-mix of admitted patients[22] and they account for only 8% of the total emergency admissions across Australia.[21] Only data from the largest hospital peer groups and sites with workforce information were included (25 hospitals). Results from a similar analysis of ED presentations has been published elsewhere.[17]

Episodes of care for patients admitted as an in patient via the hospital's ED were analyzed separately to elective episodes due to their different characteristics. This is consistent with other similar studies in the area that separate emergency and non-emergency admissions[4,11] or study emergency admissions only.[18] Our classification of patients into emergency or elective streams was on the basis of values in a data field representing admission status. Emergency/elective admission status is assigned on admission of the patient, where the distinguishing characteristic for an elective admission is that it could be delayed by at least 24 hours.[23] An example of when an elective patient might be admitted after-hours is if they are admitted via the outpatient clinic outside of the opening hours, or have arrived at the hospital after-hours due to travel, clinical or other logistical delays. Elective patients are not admitted through the hospital's ED.

Ethics approval for the study was obtained from the Royal Brisbane and Women's Hospital HREC (Ref HREC/15/QRBW/587) who waived the requirement for consent.

2.2 | Outcomes

Outcomes for the study were chosen on the basis that they could be linked to a single episode of patient care as opposed to monthly readmission performance for a particular hospital, for example. Characteristics of the outcome variables for the emergency and elective cohorts showing differences between normal hours and after hours are included within Table 1. The main outcome for this study was patient death (7-day, 30-day, and in-hospital mortality) and 30-day readmission was a secondary process outcome.

Patient episodes were linked to the Queensland death registry to identify out-of-hospital mortality for derivation of 7-day and 30-day mortality. The death registry is relied on as the single official source of deaths in the state. The mortality timeframes of 7 and 30 days are aligned with safety and quality literature and considered appropriate timeframes to link with the time of hospital care delivery.

While there may be skepticism around whether hospitals can practicably affect care for such a long period after discharge, the 30-day window for readmissions is aligned with financial incentives associated with the study sites and similar in magnitude to other readmission targets used by hospital administrators to improve system performance.[24,25] Readmissions could be for any reason (e.g., they weren't restricted to episodes having the same Diagnosis Related Group (DRG)[26] but excluded "routine" cases based on DRG. Further details regarding data preparation are presented in the Supporting Information Material.

2.3 | Processes and comparisons

The analysis assessed whether there were any differences in outcome based on the time inpatients were admitted to hospital (after-hours versus within hours).

We defined after-hours care to be the weekend (12am SATURDAY to 11.59pm SUNDAY) in alignment with other studies.[1–10,19] Sensitivity analyses explored an "Extended" definition covering the weekend plus Friday nights and Monday mornings (6pm FRIDAY to 6am MONDAY) as well as a "Twilight" definition comprising the weekend plus weekday nights (6pm to 6am).

2.4 | Statistical analyses

In keeping with the majority of the literature exploring outcomes associated with after-hours care delivery[3,11,20] we employed logistic regression models using predictor variables chosen to reduce the effects of confounding. Baseline predictors in our study were chosen to reflect differences in patient demographics for example, age, sex, socioeconomic index of disadvantage (SEIFA[27]), hospital peer group,[22] health condition (e.g., Charlson Comorbidity Index for chronic illness[28]) and patient-based differences in treatment (e.g. DRG diagnostic categories, DRG partitions [surgical/medical/ other][26]).

To consider the possibility of differences in baseline predictors ("case-mix") between within and after-hours admissions[11] our approach was to add to the baseline model, individually for each baseline predictor, an interaction term between the after-hour variable and the baseline predictor. In this way, we can isolate and study the role of case-mix for that variable. Analysis of variance (ANOVA) was used to test the significance of the included interaction term. With categorical baseline predictors, this tests the entire interaction, as opposed to testing coefficients from individual values of the categorical variable. A significant interaction was taken as a significant difference in the predictor between the within and after-hours periods.

Additional modeling and analysis was performed to consider the possible role of staffing in any difference in outcomes between within and after-hours admissions. A list of staffing metrics was identified from hospital payroll data (refer to Supporting Information Material), and staffing-enhanced models were created by adding each staffing metric, individually, to the baseline model. To allow for observed differences in staffing between hospital peer groups, these staffing-enhanced models introduced the staffing metric as a staffing-peer group interaction term. Staffing ratios were included using cubic splines to allow for a nonlinear effect on the outcome. See the Supporting Information for more information. As with the baseline models, an odds ratio with 95% confidence interval for the after-hours effect was obtained from these staffing-enhanced models. For a particular staffing ratio, non-overlapping confidence intervals between the baseline model and the staffing-enhanced model suggested that staffing metric might play an important role in determining any within hours/after-hours difference in the outcome variable of that baseline model. Differences in confidence intervals were assessed using "forest plots", which provide a concise visualization of the odds ratio and confidence interval for a baseline and staffing-enhanced models.

All analysis was performed in R.[29] Results for fitting binary logistic regression models used the glm function in the rms package.[30] ANOVA results were obtained using the anova function in the rms package.[30] Where splines were used, these were restricted cubic splines via the rcs function unless otherwise mentioned. B-splines used the ns function.

3 | RESULTS

3.1 | Study characteristics

Analysis was based on 988,883 episodes of care for patients admitted from emergency, 449,897 elective inpatient episodes, and clinical staff in attendance during the patient's hospital stay. Characteristics of the baseline predictors, staffing ratios and study outcomes are presented in Table 1. Results are separated into columns based on time of admission for each cohort. Due to smaller counts, several categories of DRG Hierarchy (Obstetric, Perinatal, Burns, Error, Alcohol and Drug, Female Reproductive Disorders, Eye

TABLE 1 Study cohort and outcome characteristics.

		Admissions from ED Time of admission		Elective admissions Time of admission	
		Normal hours	After hours	Normal hours	After hours
Number of patients (%)		725,806 (73.4%)	263,077 (26.6%)	441,873 (98.2%)	8024 (1.8%)
Predictors	**Category Level**				
Sex	Female	51.64	50.47	50.35	49
	Male	48.36	49.53	49.65	51
Age group	(25–45)	23.85	24.13	21.7	20.43
	(0–15)	9.16	10.01	4.61	6.63
	(15–25)	10.2	11.31	5.93	8.13
	(45–65)	24.5	23.27	33.34	25.71
	(65–85)	24.66	23.56	31.38	35.41
	(85, Inf)	7.63	7.72	3.04	3.7
SEIFA disadvantage decile group	(1–2)	12.23	12.09	11.8	10.99
	(2–5)	34.42	33.65	35.09	42.78
	(5–7)	24.3	24.45	24.18	22.03
	(7, Inf)	29.04	29.81	28.94	24.19
Hospital peer group	Public acute group A hospitals	47.12	46.76	40	39.68
	Principal referral hospitals	35.07	34.6	49.35	55.58
	Public acute group B hospitals	17.81	18.64	10.66	4.74
DRG hierarchy group	DRG_CircDis	17.05	15.23	6.01	14.83
	DRG_TransplantEtc	0.24	0.26	0.21	1.22
	DRG_NervousDis	7.79	8.36	5.03	2.92
	DRG_EarDis	4.58	4.87	6.86	5.88
	DRG_RespDis	9.96	9.98	2.53	4.61
	DRG_DigestDis	14.33	13.85	14.1	11.28
	DRG_HepaDis	2.54	2.36	2.91	2.24
	DRG_MuscleDis	8.64	10.2	12.89	12.03
	DRG_SkinDis	4.69	4.95	9.13	2.6
	DRG_EndoDis	1.88	1.63	1.85	1.5
	DRG_KidneyDis	5.67	5.63	7.27	4.27
	DRG_BloodDis	1.19	0.86	2.48	1.43
	DRG_Neoplastic	0.29	0.17	1.01	0.75
	DRG_InfectPara	2.48	2.55	0.32	0.6
	DRG_MentalDis	3.99	3.14	0.94	1
	DRG_InjExt	5.91	7.02	0.63	1.81
	DRG_UnSpec	1.02	0.84	5.48	2.82
	DRG_Other	7.76	8.09	20.33	28.22
DRG complexity	Inter	45.28	45.55	34.39	42.67
	Major	20.16	19.07	8.7	19.45
	Minor	11.63	12.9	15.44	9.28
	None	22.92	22.48	41.47	28.59

TABLE 1 (Continued)

Predictors	Category Level				
DRG partition	Medical	88.21	88.81	31.34	35.9
	Other	2.8	2.41	16.28	9.36
	Surgical	8.99	8.78	52.38	54.74
Charlson index sum group	(0–1)	81.77	83.39	81.27	80.25
	(1–2)	6.98	6.72	4.18	6.12
	(2–3)	6.65	5.99	11.19	9.68
	(3–4)	1.34	1.18	0.43	0.86
	(4–5)	1.09	0.97	0.53	0.77
	(5, Inf)	2.17	1.75	2.39	2.32
Number of distinct diagnoses group	(1–2)	23.55	25.05	30.66	21.64
	(2–3)	23.64	23.77	29.41	21.96
	(3–5)	26.29	26.12	26.1	26.33
	(5, Inf)	26.52	25.06	13.83	30.07
Day case	False	65.09	63.05	38.59	69.73
	True	34.91	36.95	61.41	30.27
Staffing level at admission hour: median (and interquartile range)	All.DocNurse.Pat.Ratio	0.52 (0.95)	0.357 (0.214)	1.095 (0.869)	0.432 (0.183)
	All.Doctors.Pat.Ratio	0.08 (0.36)	0.046 (0.05)	0.321 (0.414)	0.062 (0.048)
	All.Nurses.Pat.Ratio	0.42 (0.59)	0.303 (0.171)	0.76 (0.484)	0.368 (0.159)
	Junior.Doctors.Pat.Ratio	0.03 (0.09)	0.012 (0.019)	0.078 (0.097)	0.017 (0.021)
	Junior.Doctors.Ratio	0.26 (0.16)	0.29 (0.188)	0.25 (0.092)	0.289 (0.146)
	Junior.Nurses.Pat.Ratio	0.08 (0.08)	0.057 (0.043)	0.106 (0.066)	0.066 (0.042)
	Junior.Nurses.Ratio	0.17 (0.06)	0.184 (0.069)	0.149 (0.05)	0.187 (0.065)
	Senior.Doctors.Pat.Ratio	0.02 (0.15)	0.004 (0.011)	0.12 (0.158)	0.007 (0.011)
	Senior.Doctors.Ratio	0.29 (0.39)	0.088 (0.174)	0.346 (0.119)	0.12 (0.13)
	Senior.Nurses.Pat.Ratio	0.01 (0.14)	0.005 (0.005)	0.142 (0.144)	0.006 (0.004)
	Senior.Nurses.Ratio	0.05 (0.15)	0.016 (0.015)	0.178 (0.091)	0.015 (0.009)
Study outcomes	**Category level**				
Died in hospital: % (and count) (linked to time of Admission)	False	98.96 (718,258)	98.94 (260,288)	99.93 (441,564)	99.73 (8002)
	True	1.04 (7548)	1.06 (2789)	0.07 (309)	0.27 (22)
Died within 7 days since admission: % (and count) (anywhere ie. in or out of hospital)	False	99.06 (718,983)	99.01 (260,473)	99.95 (441,652)	99.9 (8016)
	True	0.94 (6823)	0.99 (2604)	0.05 (221)	0.1 (8)
Died within 30 days since admission; (anywhere ie. in or out of hospital)	False	97.88 (710,419)	97.86 (257,447)	99.74 (440,724)	99.56 (7989)
	True	2.12 (15,387)	2.14 (5630)	0.26 (1149)	0.44 (35)
Readmission within 30 days of Admission % (and count)	False	79.17 (574,621)	79.7 (209,672)	81.74 (361,187)	81.42 (6533)
	True	19.13 (138,847)	18.58 (48,880)	18.12 (80,067)	18.11 (1453)
	Na	1.69 (12,338)	1.72 (4525)	0.15 (619)	0.47 (38)

Abbreviations: DRG, Diagnosis Related Group; SEIFA, Socio-Economic Indexes for Areas.

Disorders and Male Reproductive Disorders) were collapsed into one "Other" category.

For patients admitted from the ED, 27% of episodes were admitted after-hours, whilst for elective patients, only 2% were admitted after-hours. We additionally observe other interesting differences between normal hours and working hours, particularly those relating to staffing ratios, for example, the proportion of junior doctors and nurses is higher after-hours than normal hours. The Supporting Information Methods section includes plots showing the dynamic workforce changes across a week within and after hours which reveal variation according to time of day, variation between staff hierarchical levels, and variation between hospital peer groups.

Modeling results are summarized in Tables 2 and 3 which show main effects, patient case-mix effects, and staffing effects. Odds ratios and their confidence intervals have been included for main effect models for each research outcome and are plotted in Figure 1.

When assessing the effect of staffing, there are several table entries indicating workforce metrics that play an important role in determining any within hours/after-hours difference in the outcome variable of that baseline model. These are indicated when confidence intervals for the staffing ratio interaction do not overlap the confidence intervals for the baseline model. Further explanation of this is presented in the Supporting Information Material. For elective admissions, much of the outcome data was too sparse to allow case-mix or staffing investigation and analysis was limited to main effect models, due to small number of elective surgeries performed after-hours.

3.2 | Mortality

The results (Table 2 and Figure 1) indicate significantly higher mortality for patients admitted on the weekend via the hospital's ED (7-day mortality OR = 1.12, 95% CI 1.07–1.18, 30-day mortality OR = 1.09, 95% CI 1.06–1.13, in-hospital mortality OR = 1.09, 95% CI 1.04–1.14). Table 1 includes counts of deaths in hospital (2789 after-hours vs. 7548 in normal hours), deaths within 7-days (2604 after-hours vs. 6823 in normal hours) and deaths within 30-days of admission (5630 after-hours vs. 15,387 in normal hours).

3.3 | Readmissions

There were no significant differences in 30-day readmissions for emergency patients admitted after-hours.

3.4 | Patient case-mix

No significant patient case-mix interactions were observed for mortality outcomes associated time of hospital admission. However numerous case-mix interactions were observed when assessing 30-day readmissions (patient comorbidities, age, DRG hierarchy, hospital peer group, and number of distinct diagnoses).

3.5 | Staffing effects

Workforce metrics that played a role in observed outcome differences within hours/after-hours were more a time-of-day rather than day-of-week effect. At these times, doctor-patient ratios and nurse-patient ratios appear to be strongly associated with observed within/after-hours outcome differences.

3.6 | Elective patients

For the tiny proportion of elective patients that were admitted after-hours, mortality differences were attributable to a time-of-day effect rather than day-of-week effect. There were no strong associations with staffing for mortality outcome differences in elective patients but there were for readmissions.

3.7 | Sensitivity analyses

The results of the sensitivity analyses exploring alternate definitions of after-hours are also presented in Tables 2 and 3. The finding relating to significant mortality differences for emergency patients admitted after-hours also applies to other definitions assessed. There were also additional patient case-mix and staffing effects observed when considering a broader definition of the after-hours period.

4 | DISCUSSION

4.1 | Emergency inpatients

This study has shown that for emergency patients, being admitted after-hours is associated with a statistically significantly higher risk of death either in-hospital or within 7 or 30 days from admission. These findings are generally consistent with many other retrospective studies such as Freemantle et al.[5] and references therein. As there is no universally accepted definition of after-hours, the present study additionally quantifies how alternate definitions affect the results, finding that the effect is stronger during the weekend compared to an after-hours period comprising weekends and weekday nights (i.e., "Twilight"). Compared to other times of the week, patients admitted on weekends via the hospital's ED were found to have 9% higher odds of dying while they were in-hospital or within 30-days, and 12% higher odds of dying within 7 days.

At a national level, approximately 2.9 million patients are admitted to public hospitals every year from ED.[21] Adopting the same proportion of patients admitted after-hours as our study (26.6%), roughly 770,000 patients every year are admitted to public

TABLE 2 Results — Admissions from ED.

Outcome	Time of admission = "Weekend"			Sensitivity analysis: time of admission = "Extended" (weekend plus Friday nights and Monday mornings)			Sensitivity analysis: time of admission = "Twilight" (weekend plus weekday nights)		
	Main effects	Patient case-mix effects	Staffing effects	Main effects	Patient case-mix effects	Staffing effects	Main effects	Patient case-mix effects	Staffing effects
7-day mortality	OR = 1.124 (1.073–1.178)	None observed	No strong associations-CIs overlap baseline CI	**OR = 1.118 (1.070–1.168)**	DRG complexity	No strong associations-CIs overlap baseline CI	**OR = 1.080 (1.035–1.127)**	SEIFA	Senior Doctor −Patient ratio, Senior Nurse −Patient ratio
30-day mortality	**OR = 1.092 (1.056–1.128)**	None observed	No strong associations-CIs overlap baseline CI	OR = 1.082 (1.049–1.116)	None observed	No strong associations-CIs overlap baseline CI	OR = 1.065 (1.034–1.097)	SEIFA DRG complexity	No strong associations-CIs overlap baseline CI
In-hospital mortality	**OR = 1.091 (1.042–1.142)**	None observed	No strong associations-CIs overlap baseline CI	**OR = 1.097 (1.051–1.145)**	DRG complexity	No strong associations-CIs overlap baseline CI	OR = 1.061 (1.018–1.106)	SEIFA DRG complexity	No strong associations-CIs overlap baseline CI
30-day readmiss-ion	OR = 0.996 (0.984–1.008)	Comorbidity Index, Age, DRG hierarchy, Hospital peergroup, Number of distinct diagnoses	No strong associations-CIs overlap baseline CI	OR = 1.001 (0.990–1.012)	Comorbidity Index, Age, DRG hierarchy, Hospital peer group, SEIFA, DRG complexity	No strong associations-CIs overlap baseline CI	OR = 1.004 (0.994–1.015)	Comorbidity index age DRG hierarchy hospital peer group SEIFA DRG complexity	Doctor−Patient ratio, Junior Doctor −Patient ratio

Note: Main effects show odds ratios (OR) and confidence intervals for baseline logistic regression models. Values above one indicate an increased likelihood of the outcome associated with after-hours versus within hours and are in bold if significant. Patient Case-mix effects show significant two-way interactions between baseline case-mix variables and the after-hour term. Case-mix models for elective patients could not be attempted due to data sparsity. Staffing effects show significant workforce metrics that play an important role in determining any within hours/after-hours difference in the outcome variable of that baseline model. These are indicated when confidence intervals for a staffing ratio interaction don't overlap the confidence interval for the baseline model.

Abbreviations: DRG, Diagnosis Related Group; SEIFA, socioeconomic indexes for areas.

TABLE 3 Results— Elective admissions.

	Time of admission = "Weekend"			Sensitivity analysis: time of admission = "Extended" (weekend plus Friday nights and Monday mornings)			Sensitivity analysis: time of admission = 'Twilight' (weekend plus weekday nights)		
Outcome	Main effects	Patient case-mix effects	Staffing effects	Main effects	Patient case-mix effects	Staffing effects	Main effects	Patient case-mix effects	Staffing effects
7-day mortality	OR = 0.939 (0.459–1.923)	Unable to comment—sparse counts	No strong associations- CIs overlap baseline CI	OR = 1.295 (0.715–2.345)	Unable to comment—sparse counts	No strong associations- CIs overlap baseline CI	**OR = 1.636 (1.039–2.575)**	Unable to comment—sparse counts	No strong associations- CIs overlap baseline CI
30-day mortality	OR = 1.025 (0.724–1.451)		No strong associations- CIs overlap baseline CI	OR = 1.168 (0.854–1.597)		No strong associations- CIs overlap baseline CI	**OR = 1.362 (1.070–1.734)**		No strong associations- CIs overlap baseline CI
In-hospital mortality	OR = 1.319 (0.842–2.064)		No strong associations- CIs overlap baseline CI	OR = 1.491 (0.991–2.245)		No strong associations- CIs overlap baseline CI	**OR = 1.582 (1.126–2.222)**		No strong associations- CIs overlap baseline CI
30-day readmission	OR = 1.020 (0.959–1.084)		Senior Nurse ratio, Senior Nurse-Patient ratio	OR = 1.015 (0.958–1.076)		Senior Nurse ratio, Senior Nurse-Patient ratio	OR = 1.016 (0.969–1.066)		Senior Doctor ratio, Senior nurse ratio, Doctor-Patient ratio, Junior Doc-Patient ratio, Senior Doc-Patient ratio, Senior Nurse-Patient ratio

Note: Main effects show odds ratios (OR) and confidence intervals for baseline logistic regression models. Values above one indicate an increased likelihood of the outcome associated with after-hours versus within hours and are in bold if significant. Patient Case-mix effects show significant two-way interactions between baseline case-mix variables and the after-hour term. Case-mix models for elective patients could not be attempted due to data sparsity. Staffing effects show significant workforce metrics that play an important role in determining any within hours/after-hours difference in the outcome variable of that baseline model. These are indicated when confidence intervals for a staffing ratio interaction do not overlap the confidence interval for the baseline model.

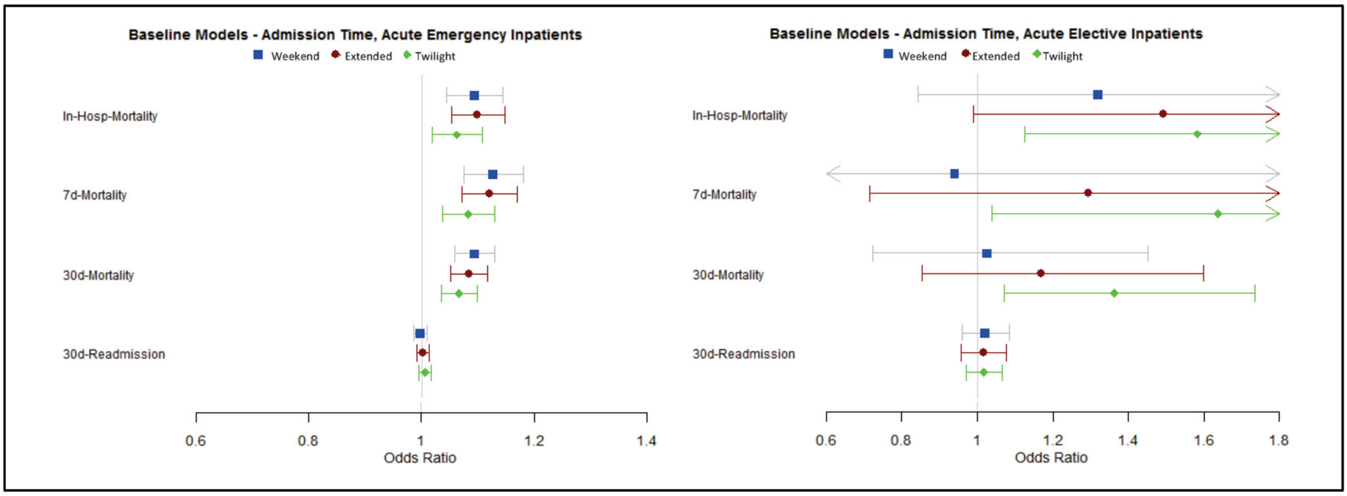

FIGURE 1 Baseline After-hours Odds Ratios for Inpatient Emergency Admissions (Left) and Inpatient Elective Admissions (Right) based on Time of Hospital Admission; Values above one indicate increased likelihood of the outcome associated with after-hours care versus within hours admission.

hospitals from ED on the weekends. In our study, the absolute difference between those who died within 7 days after being admitted within normal hours compared to a weekend was 0.05% (0.99%–0.94%). Applying this figure to the number of patients admitted after-hours nationally gives an estimate of the absolute increase in 7-day mortality for a weekend admission at a public hospital: 385 deaths/year, or an unadjusted increase of approximately a death per day. Although this figure is not adjusted for confounders, to put this in perspective, the leading cause of death in Australia was coronary heart disease where 16,587 people died in 2020.[31]

Very few studies have explored potential interactions between main effects and the after-hours effect, so it seemed sensible to explore the potential differences in outcomes that may be due to confounding between main effects and the after-hours period. Whilst Walker et al.[18] found an interaction between some test results and the after-hours period, no significant interactions were found with standard adjustment factors such as age and sex for example. They also did not test for the range of factors we have explored in our study. Our findings showed no significant patient case-mix interactions for mortality outcomes under the weekend definition of admitted after-hours, however there were for the alternative “Extended” and “Twilight” definitions of after-hours. DRG complexity appeared in the “Extended” model for in-hospital and 7-day mortality, suggesting that it influences short term outcomes only. However it was also significant in the 30-day mortality “Twilight” model along with SEIFA (a socioeconomic indicator based on a patient's geographical residence, where lower values indicate more disadvantage) with SEIFA being more associated with evening admissions.

Concerns regarding the level of staffing over the weekend have been raised in numerous studies. Hypotheses of poor outcomes suggested by these studies not only include the availability of adequate staff but also staff mix.[1] Nueraz et al.[32] found risk of mortality within hospital Intensive Care Units was highest when patient-to-caregiver ratios were highest-generally during night shifts for doctors and weekends for nurses. Ricciardi et al.[33] found that in-hospital mortality was higher for patients in hospitals with fewer nurses and physicians and weekend mortality was higher for hospitals with resident trainees compared to hospitals with no resident trainees. Aldridge et al.[3] surveyed hospital consultants across two days (a Sunday and Wednesday within the same week) and found no association between weekend staffing of hospital specialists and mortality risk for emergency admissions. Aiken et al.[34] used survey data to identify that that more professional nurses (with bachelor's qualifications) among nursing personnel was associated with lower mortality. Bion et al.[35] also used survey data to assess hospital quality of care (hours of consultant time per 10 emergency admissions), but focused on error rates and adverse events as opposed to mortality. They report hospitals with a larger weekend versus weekday difference in specialist staffing had no significant difference in care quality. We expanded beyond these approaches by including the variation in physician and nursing staff numbers and seniority as explicit predictors within patient outcome models reflecting the care team available at the time a patient arrived or left hospital. Our study evaluated a range of different staffing related variables in addition to baseline main effects models. For the emergency inpatient admission cohort, the addition of the senior doctor to patient and senior nurse to patient ratio interactions with peer group to the baseline model led to a strong shift in the after-hours odds ratio for the “Twilight” 7-day mortality model. Interpretation of these factors is difficult as there is also a significant interaction between after-hours and socioeconomic disadvantage as well. There is potential for confounding between these factors which needs to be considered in further analysis.

We also explored differences associated patient readmissions to hospital as a secondary process outcome. Unlike Rosenberg et al.[36]

who found that 30-day readmissions were significantly greater for patients undergoing a specific elective surgery procedure admitted at the weekend, we observed no clear after-hours effect for our 30-day readmission models. However, there were a number of significant case-mix interactions, and socioeconomic disadvantage and DRG complexity are persistent interactions in the "Extended" and "Twilight" models. Other factors such as Charlson Comorbidity Index, age group, DRG hierarchy and hospital peer group are also present for all after-hour definitions. Additionally, all doctor and junior doctor to patient ratios are present in the "Twilight" model. Staffing interactions seem to be confined to the "Twilight" definition only suggesting staffing impacts differ more between day and night than the weekday versus weekend.

4.2 | Elective inpatients

The choice of time and day for admission for an elective patient is largely a clinical/administrative decision. Therefore, any interpretation of results needs to be mindful of these underlying factors. Another issue associated with the elective cohort is the sparsity in mortality measures in after-hour periods.

There were staffing interactions for all 30-day elective readmission models. Interestingly the common staffing ratios were the senior nurse ratio and senior nurse to patient ratio interactions. Overall nursing ratios during after-hour periods were very low in these groups compared to other staff ratios.

5 | LIMITATIONS

To our knowledge, this is the first large-scale study to consider the effect of staffing based on administrative and payroll data across surgical and non-surgical emergency admissions and elective admissions. Considerable heterogeneity in staffing ratios was evident across peer groups and hospitals which posed challenges in modeling. While this study focused on system wide differences, further modeling could be done to explore particular peer groups or hospitals. Such a focused approach would avoid the system-wide variation.

The analysis treated each episode of care as an independent observation which ignores two sources of dependence: different patients in the same hospital, and different episodes for the same patient. The expectation is that while it does not affect the point estimates, properly accounting for this dependence might make the confidence intervals larger and reduce the number of significant results. By ignoring this we have followed the approach of others in this area but acknowledge that more computationally complex multilevel models could take this multi-level structure into account.

The methodology employed here studied the effect of individual staffing ratios. In reality, the hospitals in this study do not operate with a single category of doctor or nurse. The results illustrate there are complex relationships between different staff ratios and hospital categories. A future study could investigate the role of these interactions on outcomes of interest.

Staffing data was grouped by cost center to focus on clinical staff in attendance at the time a patient was admitted to hospital i.e. the available care team, whose presence was deemed to make a difference in care and reflecting the area where the staff member was costed to. It is acknowledged that this approach does not guarantee staff were on the floor caring for a specific patient. However it was impossible to audit and confirm exact locations of all staff working across the state for every hour of the study period and the approach adopted is considered a reasonable approximation of staffing level.

Using the methods in this study, we were able to identify some staffing ratios that appear to be strongly associated with after-hours/within hours differences in mortality outcomes for some after-hours definitions. The nature of this kind of study is that strong associations can be observed, but these do no imply that the staffing ratio is the cause of any after-hours/within hours differences. These strong associations highlight areas where further studies could be considered. Such studies would be designed to control for confounding and to strengthen the argument of a causal connection between the staffing ratio and the after-hours/within hours difference.

The focus of this study has been to explore after-hours/within hours differences in case-mix and a possible role of staffing. We relied on the adequacy of the coded data fields which may not have sufficiently adjusted for case-mix. Other factors in patient care like the number of critical care beds and operating theatres in the hospital, MRI (magnetic resonance imaging) and CT (computed tomography) usage[20] were outside the scope of this study. They could be explored in future modeling.

Also, while this study considered the interaction between disease groups and after-hours, it did not involve building separate models to identify after-hour effects in disease-specific groups. Meacock et al.[37] estimated the health gains and costs associated with providing 7-day service for emergency hospital admissions and recommend that policy makers and service providers identify specific service extensions as it may not be cost-effective to provide universal 7-day service. Therefore, future research can focus on specific disease groups and services.

Finally the hospital peer grouping did not include private hospitals. Although they cannot be directly compared with public hospitals, they are acknowledged to be a key component of hospital care.[21]

6 | CONCLUSION

The study found an association between patient mortality and after-hours hospital admission in Queensland, Australia. The study also resulted in an improved understanding of after-hours admission, identifying that some observed differences in outcomes and their associated patient case-mix and staffing effects are based on time-of-day as opposed to day-of-week. These results can inform policy around after-hours hospital services.

The methods of reshaping, aggregation and visualization of workforce data[38] and its linking with patient outcomes could be used in future analytical studies to assess the impact of workforce changes, visualize workforce productivity or assess additional outcome measures such as hospital acquired complications and adverse events.

AUTHOR CONTRIBUTIONS

Anthony Bell: Conceptualization; funding acquisition; investigation; methodology; writing—original draft; writing—review and editing. **Justin Boyle**: Data curation; formal analysis; investigation; methodology; project administration; resources; software; supervision; validation; visualization; writing—original draft; writing—review and editing. **David Rolls**: Data curation; formal analysis; investigation; methodology; resources; software; validation; visualization; writing—original draft; writing—review and editing. **Sankalp Khanna**: Data curation; formal analysis; investigation; methodology; resources; software; validation; visualization; writing—original draft; writing—review and editing. **Norm Good**: Formal analysis; investigation; methodology; resources; software; visualization; writing—original draft; writing—review and editing. **Yang Xie**: Data curation; formal analysis; investigation; methodology; resources; software; validation; visualization. **Michele Romeo**: Investigation; project administration.

ACKNOWLEDGMENTS

The authors acknowledge the custodians of the project data sets, and the services of data linkage teams and the Safety and Quality Unit of Queensland Department of Health. The study was funded by Metro North Hospital and Health Service, Queensland, and Commonwealth Scientific and Industrial Research Organisation. Funders had no role in study design; collection, analysis, and interpretation of data; writing of the report; and the decision to submit the manuscript for publication.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data sets generated and analyzed during the current study are not publicly available due to privacy and legislative restrictions.

TRANSPARENCY STATEMENT

The lead author Anthony Bell affirms that this manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned (and, if relevant, registered) have been explained.

ORCID

Anthony Bell http://orcid.org/0000-0002-6389-7869
Justin Boyle http://orcid.org/0000-0001-9025-1441

REFERENCES

1. Black N. Is hospital mortality higher at weekends? If so, why? *Lancet*. 2016;Jul 9 388(10040):108-111.
2. Bray BD, Cloud GC, James MA, et al. Weekly variation in health-care quality by day and time of admission: a nationwide, registry-based, prospective cohort study of acute stroke care. *Lancet*. 2016;388(10040):170-177.
3. Aldridge C, Bion J, Boyal A, et al. Weekend specialist intensity and admission mortality in acute hospital trusts in England: a cross-sectional study. *Lancet*. 2016;388(10040):178-186.
4. Freemantle N, Richardson M, Wood J, et al. Weekend hospitalization and additional risk of death: an analysis of inpatient data. *J R Soc Med*. 2012;105(2):74-84.
5. Freemantle N, Ray D, McNulty D, et al. Increased mortality associated with weekend hospital admission: a case for expanded seven day services? *BMJ*. 2015;351:h4596.
6. Ruiz M, Bottle A, Aylin PP. The global comparators project: international comparison of 30-day in-hospital mortality by day of the week. *BMJ Quali Saf*. 2015;24:492-504.
7. Aylin P, Yunus A, Bottle A, Majeed A, Bell D. Weekend mortality for emergency admissions. A large, multicentre study. *QSHC*. 2010;19:213-217.
8. Meacock R, Anselmi L, Kristensen SR, Doran T, Sutton M. Higher mortality rates amongst emergency patients admitted to hospital at weekends reflect a lower probability of admission. *J Health Serv Res Policy*. 2017;22(1):12-19.
9. Chen YF, Armoiry X, Higenbottam C, et al. Magnitude and modifiers of the weekend effect in hospital admissions: a systematic review and meta-analysis. *BMJ Open*. 2019;9(6):e025764.
10. Anselmi L, Meacock R, Kristensen SR, Doran T, Sutton M. Arrival by ambulance explains variation in mortality by time of admission: retrospective study of admissions to hospital following emergency department attendance in England. *BMJ Quali Safe*. 2017;26(8):613-621.
11. Good N, Khanna S, Boyle J. In-hospital mortality and the "weekend effect": can we find the underlying causes? *2016 IEEE-EMBS International Conference on Biomedical and Health Informatics (BHI)*. Las Vegas, NV, USA, 2016, pp. 336-339. doi:10.1109/BHI.2016.7455903
12. Singer Y, Gabbe BJ, Cleland H, Holden D, Schnekenburger M, Tracy LM. The association between out of hours burn centre admission and in-hospital outcomes in patients with severe burns. *Burns*. 2022;00202-9:S0305-4179.
13. Yu YY, Zhao BW, Ma L, Dai XC. Association between out-of-hour admission and short- and long-term mortality in acute myocardial infarction: a systematic review and meta-analysis. *Front Cardiovasc Med*. 2021;8:752675.
14. Leatherby RJ, Shan MR, Antoniou GA. Editor's choice—systematic review and meta-analysis of the effect of weekend admission on outcomes for ruptured abdominal aortic aneurysms: a call for an equitable seven day vascular service. *Eur J Vasc Endovasc Surg*. 2021;61(5):767-778.
15. Bray BD, Steventon A. What have we learnt after 15 years of research into the 'weekend effect'? *BMJ Quali Safe*. 2017;26(8):607-610.
16. Concha OP, Gallego B, Hillman K, Delaney GP, Coiera E. Do variations in hospital mortality patterns after weekend admission reflect reduced quality of care or different patient cohorts? A population-based study. *BMJ Quali Safe*. 2014;23(3):215-222.
17. Rolls DA, Khanna S, Boyle J, et al. After-hours emergency department care: does time or day of arrival affect survival? *Emerg Med Australasia*. 2021;33(2):232-241.
18. Walker AS, Mason A, Quan TP, et al. Mortality risks associated with emergency admissions during weekends and public holidays: an

analysis of electronic health records. *Lancet*. 2017;390(10089): 62-72.
19. Bhonagiri D, Pilcher DV, Bailey MJ. Increased mortality associated with after-hours and weekend admission to the intensive care unit: a retrospective analysis. *Med J Aust*. 2011;194(6):287-292.
20. Ozdemir BA, Sinha S, Karthikesalingam A, et al. Mortality of emergency general surgical patients and associations with hospital structures and processes. *Br J Anaesth*. 2016;116(1):54-62.
21. Australian Institute of Health and Welfare. Admitted patient care 2020–21. Accessed February, 2023. https://www.aihw.gov.au/reports-data/myhospitals/sectors/admitted-patients
22. Australian Institute of Health and Welfare. *Australian hospital peer groups. Health services series no. 66. Cat. no. HSE 170*. AIHW; 2015.
23. Queensland Health Statistical Services Branch Information Sheet. Episode of admitted patient care—emergency/elective admission status. Accessed February, 2023. https://www.health.qld.gov.au/__data/assets/pdf_file/0038/737975/info-sheet-admit-urgency-nov2018.pdf
24. Martin S, Street A, Han L, Hutton J. Have hospital readmissions increased in the face of reductions in length of stay? Evidence from England. *Health Policy*. 2016;120(1):89-99.
25. Yale New Haven Health Services Corporation/Center for Outcomes Research and Evaluation. Hospital-wide all-cause unplanned readmission measure final technical report. Accessed February, 2023. https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/HospitalQualityInits/Measure-Methodology
26. Independent Hospital Pricing Authority. Australian refined diagnosis related groups (AR-DRG) Version 10.0. Accessed February, 2023. https://www.ihacpa.gov.au/resources/ar-drg-version-100
27. Australian Bureau of Statistics. Socio-economic indexes for areas (SEIFA)—technical paper. 2011.
28. Charlson ME, Pompei P, Ales KL, MacKenzie CR. A new method of classifying prognostic comorbidity in longitudinal studies: development and validation. *J Chronic Dis*. 1987;40(5):373-383.
29. R Core Team. R: A language and environment for statistical computing. R Foundation for Statistical Computing; 2022. https://www.R-project.org/
30. Frank Jr., E. Harrell (2017). rms: Regression Modeling Strategies. R package version 5.1-1.
31. Australian Institute of Health and Welfare. Data tables: deaths in Australia (data from the National Mortality Database). Accessed February, 2023. https://www.aihw.gov.au/reports/life-expectancy-death/deaths-in-australia/data
32. Neuraz A, Guérin C, Payet C, et al. Patient mortality is associated with staff resources and workload in the ICU: a multicenter observational study. *Crit Care Med*. 2015;43(8):1587-1594.
33. Ricciardi R, Nelson J, Roberts PL, Marcello PW, Read TE, Schoetz DJ. Is the presence of medical trainees associated with increased mortality with weekend admission? *BMC Med Educ*. 2014;14:4.
34. Aiken LH, Sloane D, Griffiths P, et al. Nursing skill mix in European hospitals: cross-sectional study of the association with mortality, patient ratings, and quality of care. *BMJ Quali Safe*. 2017;26(7):559-568.
35. Bion J, Aldridge C, Girling AJ, et al. Changes in weekend and weekday care quality of emergency medical admissions to 20 hospitals in England during implementation of the 7-day services national health policy. *BMJ Quali Safe*. 2021;30(7):536-546.
36. Rosenberg A, Dominy C, Bueno BT, et al. Weekend admission increases risk of readmissions following elective thoracolumbar spinal fusion. *Global Spine J*. 2022. doi:10.1177/21925682221120788
37. Meacock R, Doran T, Sutton M. What are the costs and benefits of providing comprehensive seven-day services for emergency hospital admissions? *Health Econ*. 2015;24(8):907-912.
38. Xie Y, Khanna S, Good N, Boyle J. Weekly hospital workforce data: A data visualisation exercise. *Stud Health Technol Inform*. 2017;239: 153-159.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Bell A, Boyle J, Rolls D, et al. Mortality and readmission differences associated with after-hours hospital admission: a population-based cohort study in Queensland Australia. *Health Sci Rep*. 2023;6:e1150. doi:10.1002/hsr2.1150