Analysis of casemix data to inform risk adjustment and payment policies

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Analysis of casemix data to inform risk adjustment and payment policies

Part 1 - Analyzing sources of variation in hospital costs

Overview

- Explore factors that may explain variations in hospital costs:
  - Grouper and cost weights
  - Other patient characteristics
  - Other hospital characteristics
  - Stay characteristics
- Applications
  - Hospital efficiency benchmarking
  - Equitable pricing in payment system

Note: All analysis results in this presentation are based on mock data and do not represent Canadian data or data of any other jurisdiction

Casemix groupers and cost weights

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Casemix Group	Average Cost	Cost Weight
Hip Replacement	\$8,200	1.64
Asthma	\$2,400	0.48
Normal delivery	\$2,800	0.56
Normal newborn	\$700	0.14
All casemix groups, inliers only	\$5,000	1.0

$= \frac{8,200}{5,000}$

$= \frac{2,400}{5,000}$

$= \frac{2,800}{5,000}$

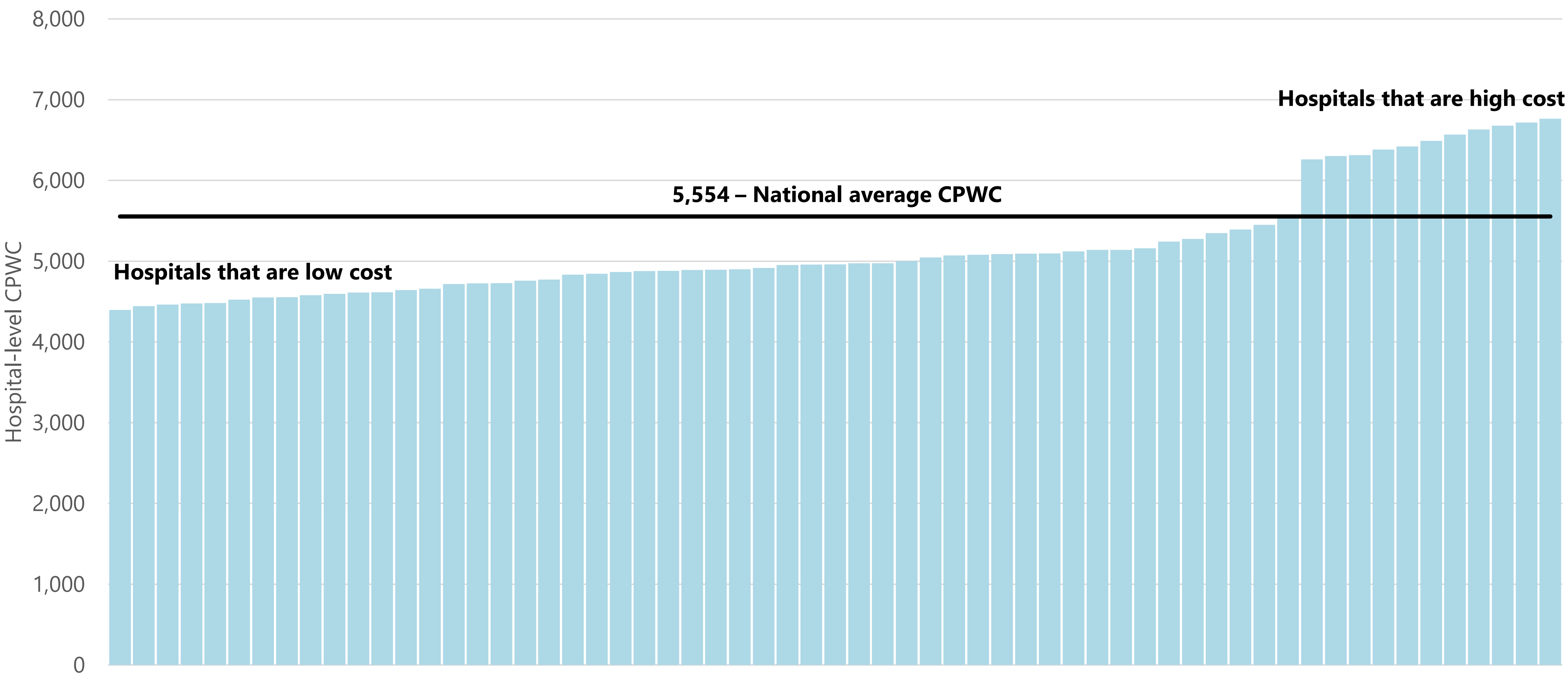
$= \frac{700}{5,000}$

Hospital	# of Cases	Total Inpatient Cost	Average Cost	Weighted Cases	CMI	CPWC
A	10,000	\$60M	\$6,000	15,000	1.5	\$4,000
B	10,000	\$60M	\$6,000	8,000	0.8	\$7,500
C	8,000	\$60M	\$7,500	16,000	2.0	\$3,750

$$\text{CMI} = \frac{\text{Weighted Cases}}{\text{Number of Cases}} = \frac{\text{Sum of cost weights}}{\text{Number of Cases}}$$

$$\text{CPWC} = \frac{\text{Sum of Costs}}{\text{Sum of Weighted Cases}} = \frac{\text{Average Cost}}{\text{CMI}}$$

CPWC Variation by Hospital



Vertical bars represent results for individual hospitals

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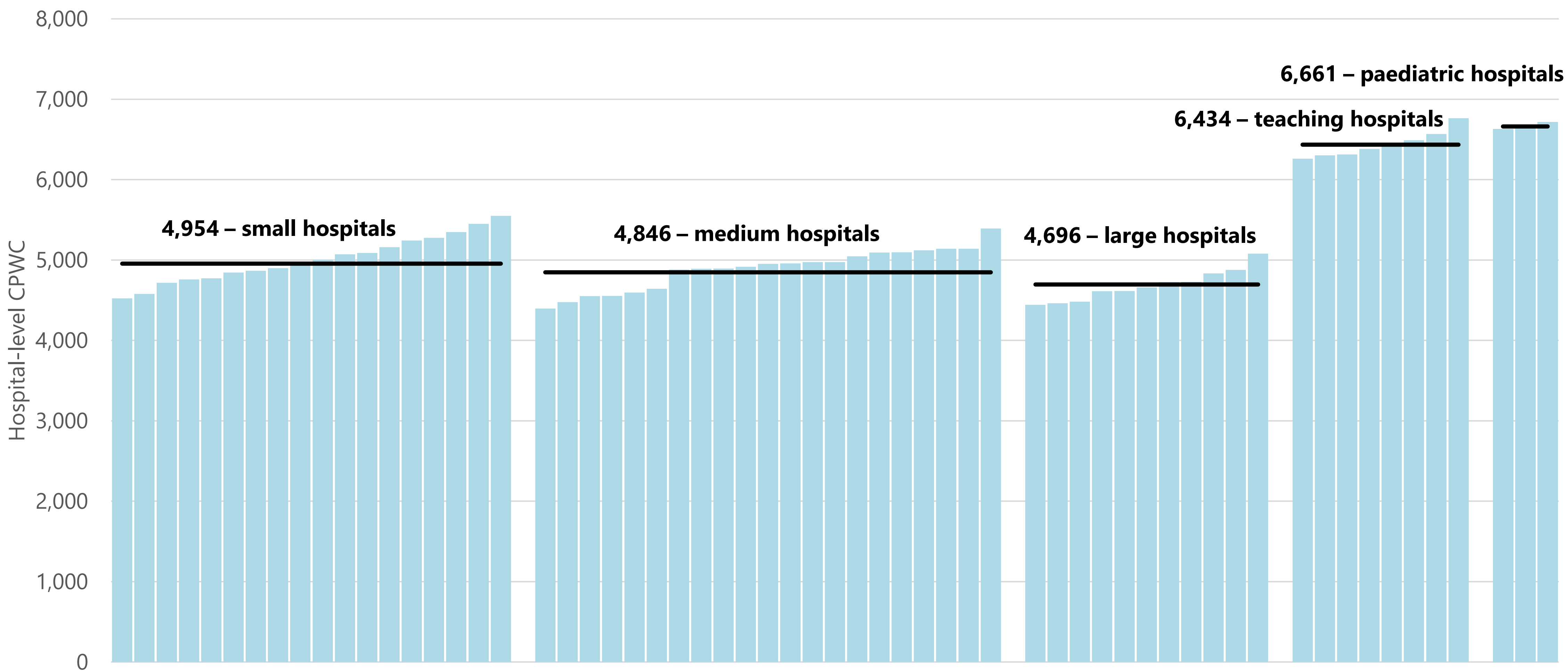
CPWC Variation by Hospital Type



Vertical bars represent results for individual hospitals

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Group discussion #1: Risk-adjustment factors

Assume you have been tasked to do an analysis of the variations in costs across the hospitals in your province/territory/state/region/country. You have casemix data on these hospitals…

1. Propose a short list of characteristics to evaluate as risk-adjusters in your analysis, additional to the casemix grouper and cost weights?
   – Patient characteristics?
   – Hospital characteristics?
   – Stay characteristics?
2. For each characteristic, what data would you use to measure it?

Characteristics that might explain/cause cost variations across providers*

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Hospital characteristics

- Size/volume
- Specialization/tertiary care
- Teaching – training medical students
- Mission – providing care to the uninsured/under-insured
- Remoteness/isolation – from other providers
- Urbanicity – higher wage rates in urban areas
- Practice patterns
- ???

Patient characteristics

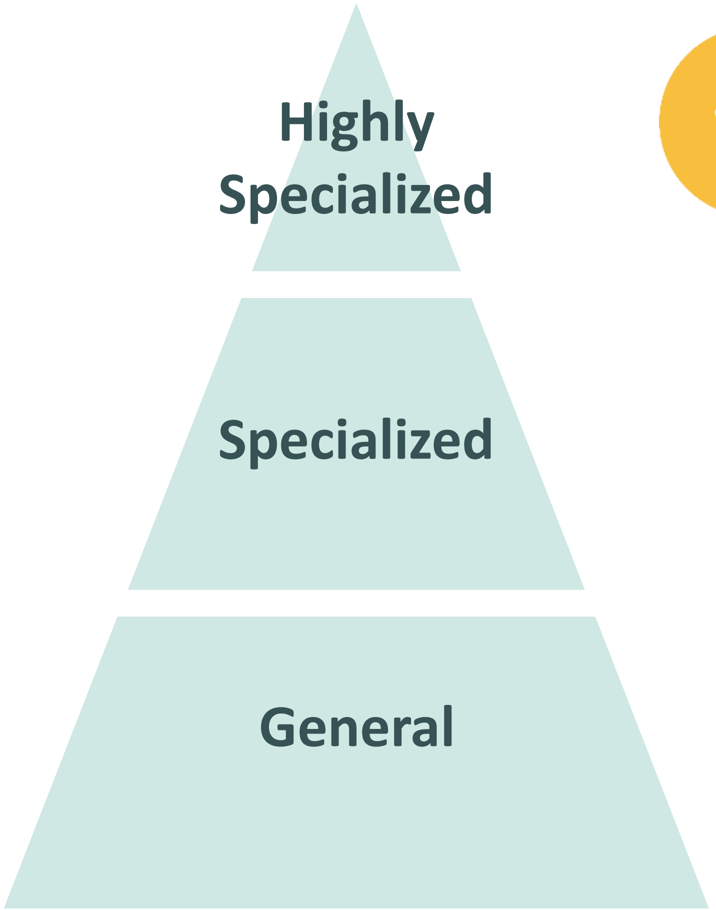
- Socio-demographics
- Readmission
- Hospital acquired conditions
- ???

Stay characteristics

- Readmissions
- Hospital acquired conditions (e.g., sepsic)
- Falls
- ???

* Additional to casemix

CMG* Care Level



Assigns each CMG to 1 of 3 broad categories

- **Highly specialized:** advanced care requiring complex medical and/or surgical interventions that focused in a few teaching hospitals per jurisdiction.
- **Specialized:** care that is often intervention-based and likely to be provided by a specialist. Is often rationalized to larger, more urban centers within each health region.
- **General:** care that is typically available at all hospitals, and with a generalist most responsible provider.

*CMG is the Canadian DRG grouper for inpatient care

What is CMG Care Level based on?

- Intervention (surgical) vs. diagnosis (medical) partition
  – All intervention cases are secondary or tertiary
- % specialist
  – The portion of the CMG that is considered a "specialist"*
- Out of region travel
  – Portion of patients that travelled into the health region to receive care; patient's home postal code is not within the same health region as the hospital
- Concentration of services - rationalization of services
  – The type of health care services within a hospital
  – The number of hospitals that provided that health care service

* Most responsible provider is not general pediatrics, family medicine, internal medicine or another non-physician

Concentration matrices – Herfindahl index

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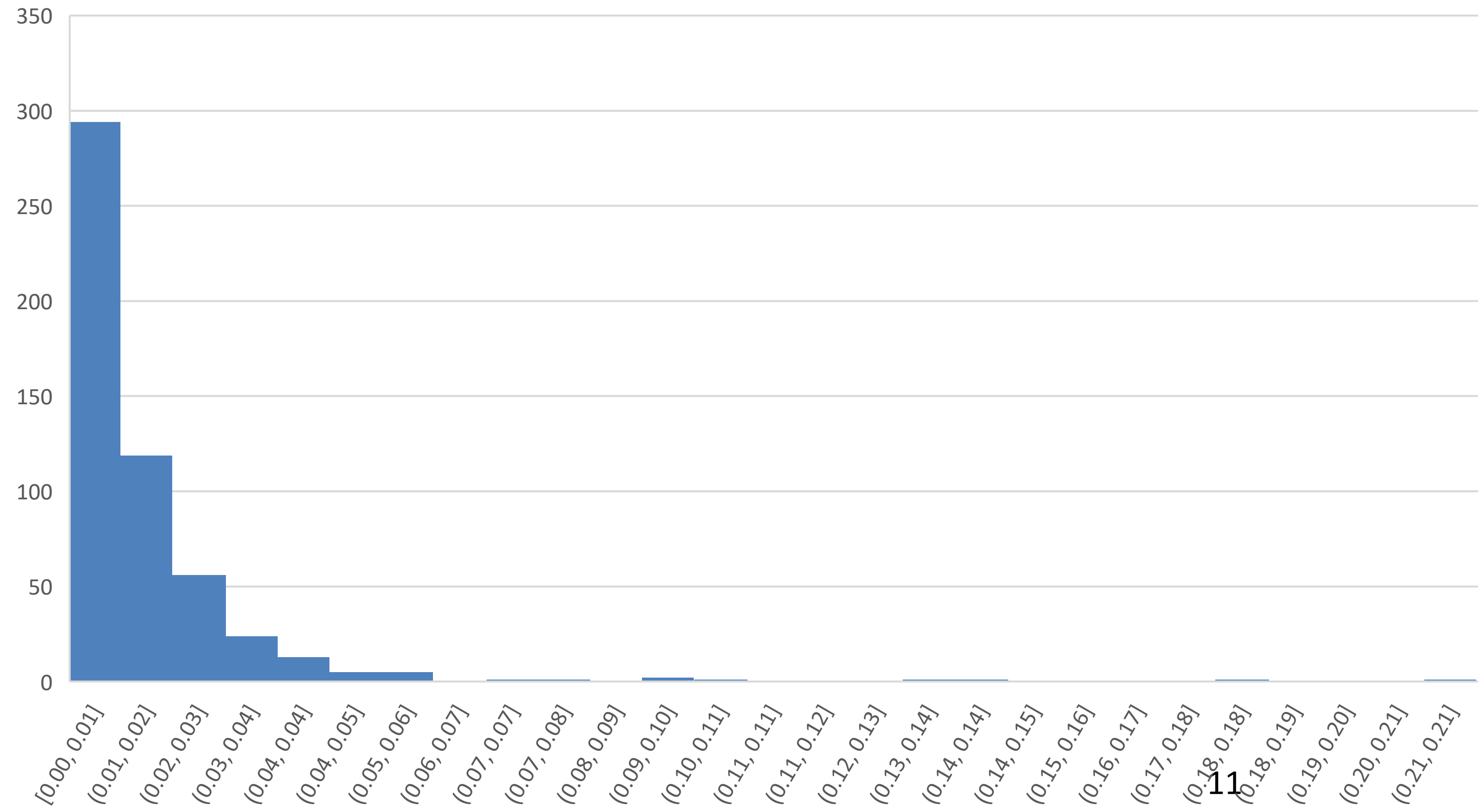
- Market share distribution for each CMG is summarized using Herfindahl index that is used to measure market concentration
- Scores normalized between 0-1
- Very few CMG having a score >.05



056 - Other Ophthalmic Intervention
725 - Organ Transplant with Trauma/Complication of Treatment
532 - Fetal Intervention
051 - Lens Extraction/Insertion
052 - Vitrectomy
054 - Sclera/Choroid/Retina Intervention without Vitrectomy
171 - Coronary Artery Bypass Graft without Coronary Angiogram with MI/Shock/Arrest without Pump
169 - Coronary Artery Bypass Graft with Coronary Angiogram without MI/Shock/Arrest without Pump
167 - Coronary Artery Bypass Graft with Coronary Angiogram with MI/Shock/Arrest without Pump

CMG care level by hospital peer group

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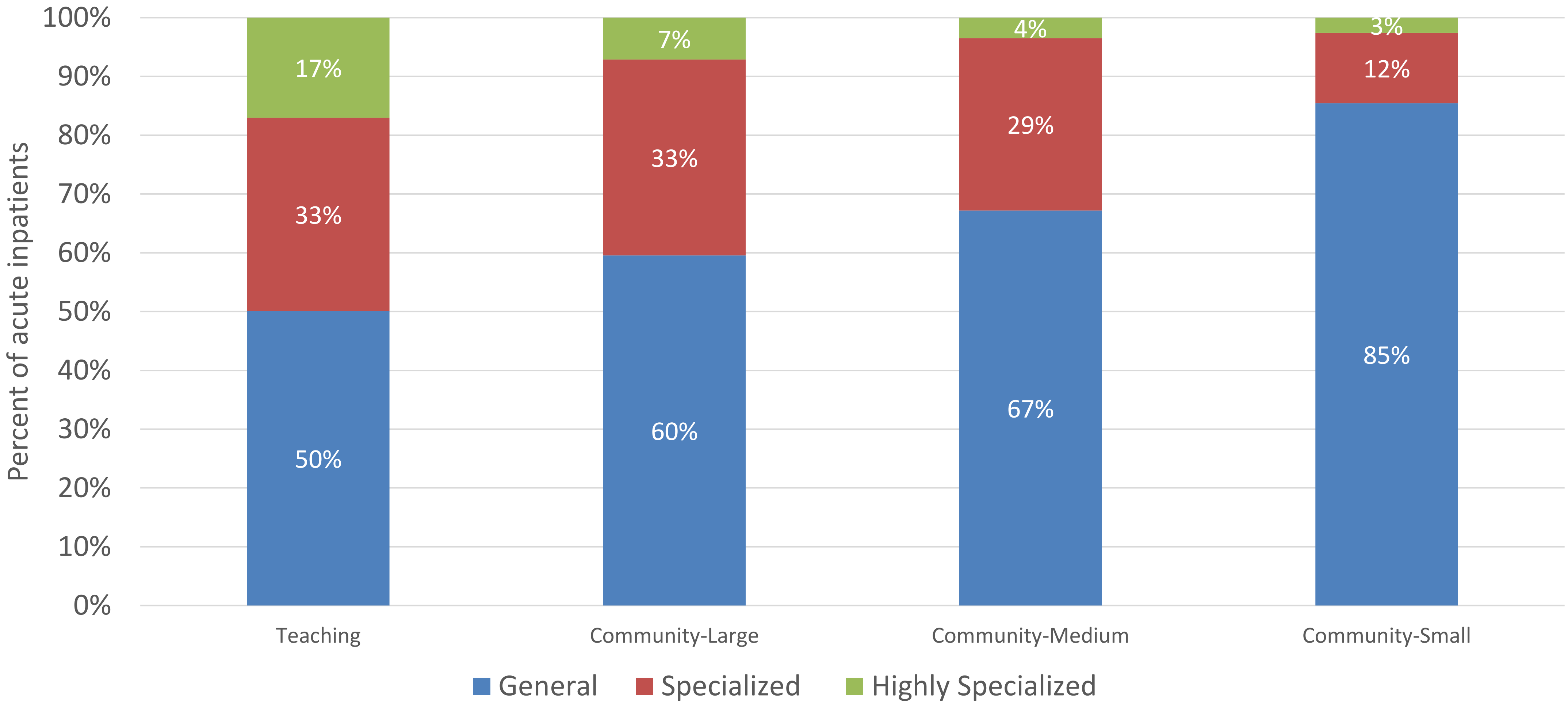

Modeling – many alternative approaches

- Hospital level or patient level
- Response variable:
  - Cost per patient, or cost per visit, or cost per weighted case
- Explanatory variables:
  - DRG
  - Cost weight
  - Case mix index (average cost weight for the facility)
  - Patient characteristics not captured by DRG and cost weights
  - Hospital characteristics ("structural effects")
- Fixed effects model or mixed (fixed and random) effects

Modeling adjustment factors – example alternatives

Model 1 (hospital level data)

$$\frac{avgcost_i}{CMI_i} = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \varepsilon_i$$

where

avgcost$_i$ = average cost per patient for hospital i

CMI$_i$ = case mix index for hospital i

x_{i1} = measure of teaching in hospital i

x_{i2} = measure of specialization in hospital i

Model 2 (patient level data)

$$\frac{cost_j}{cost\ weight_j} = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{j2} + \varepsilon_{ij}$$

where

cost$_j$ = the cost for patient j

cost weight$_j$ = cost weight for patient j

x_{i1} = measure of teaching in facility i

x_{j2} = measure of specialized care for patient j

Data for modeling – example model 1

Hospital level data

Hospital	Hospital average cost	Hospital CMI	Hospital CPWC	Teaching	Highly specialized
A	$6,000	1.5	$4,000	10	12
B	$6,000	0.8	$7,500	20	25
. . .	. . .	. . .	. . .	. . .	. . .
Z	$7,500	2.0	$3,750	85	30

For each hospital i

$$teaching_i = \frac{medical\ training\ days}{patient\ bed\ days} \times 100$$

$$LOC_i = \frac{\#\ of\ highly\ specialized\ cases}{total\ \#\ of\ cases} \times 100$$

Model 1: $$\frac{avgcost_i}{CMI_i} = \beta_0 + \beta_1 training_i + \beta_2 highspecialized_i + \varepsilon_i$$

Model 1 (hospital level data) exploratory analysis

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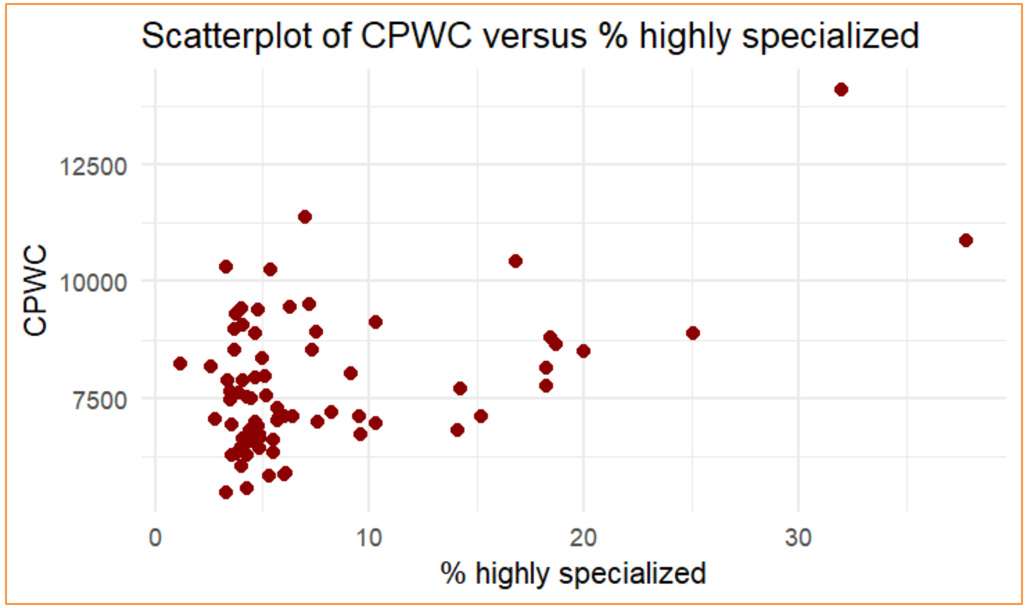

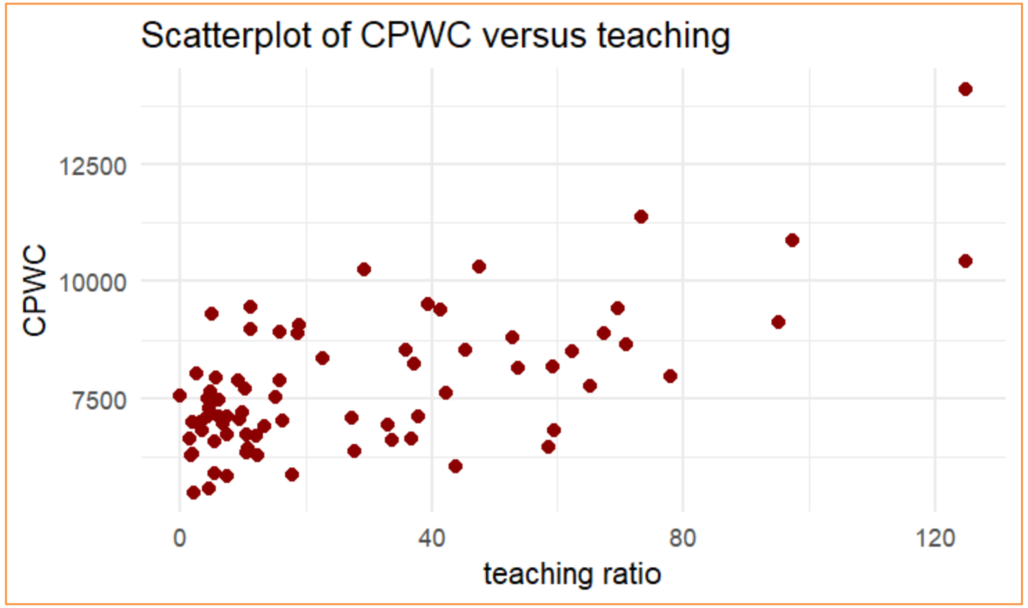

Correlation	
	CPWC
Teaching	0.644
Highly Specialized	0.697

Model 1 (hospital level data) results*

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Effect	β	Standard error	pvalue
Intercept	6702	168.56	0.0000
Teaching	15.8	5.57	0.0059
Highly specialized	64.9	14.83	0.0000395

$$\boxed{\$807 = (15.8 \times 10) + (64.9 \times 10)}$$

A	B	C	D	E	F	G	H
Hospital	Hospital average cost	Hospital CMI	Hospital average cost adjusted for CMI	Teaching ratio	% cases highly specialized	Factor adjustment	Hospital average cost adjusted for CMI and factors
A	$6,000	1.0	$6,000	0	0	$0	$6,000
B	$6,000	1.0	$6,000	10	10	$807	$5,193
C	$10,000	1.5	$6,667	10	10	$807	$5,859
D	$10,000	1.5	$6,667	20	20	$1,615	$5,052

*Results based on a mock sample of 78 hospitals

Model 1 (hospital level data) diagnostics

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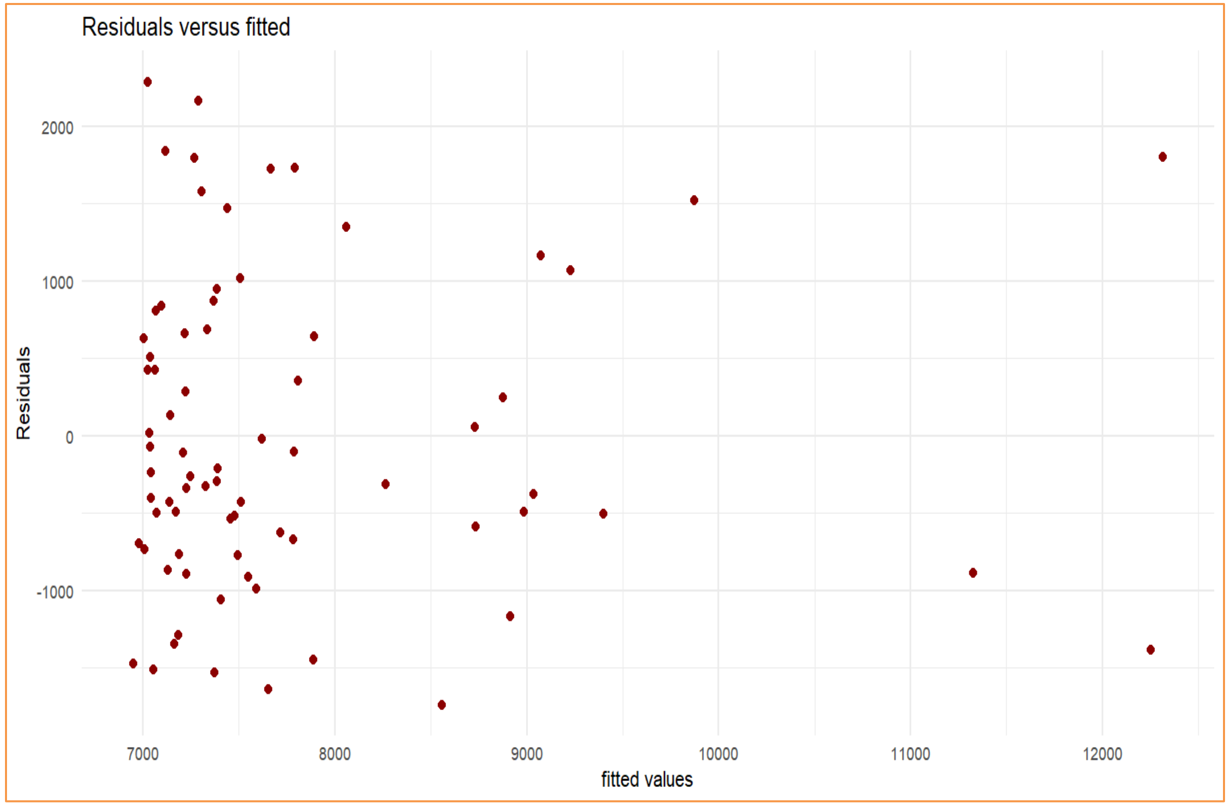

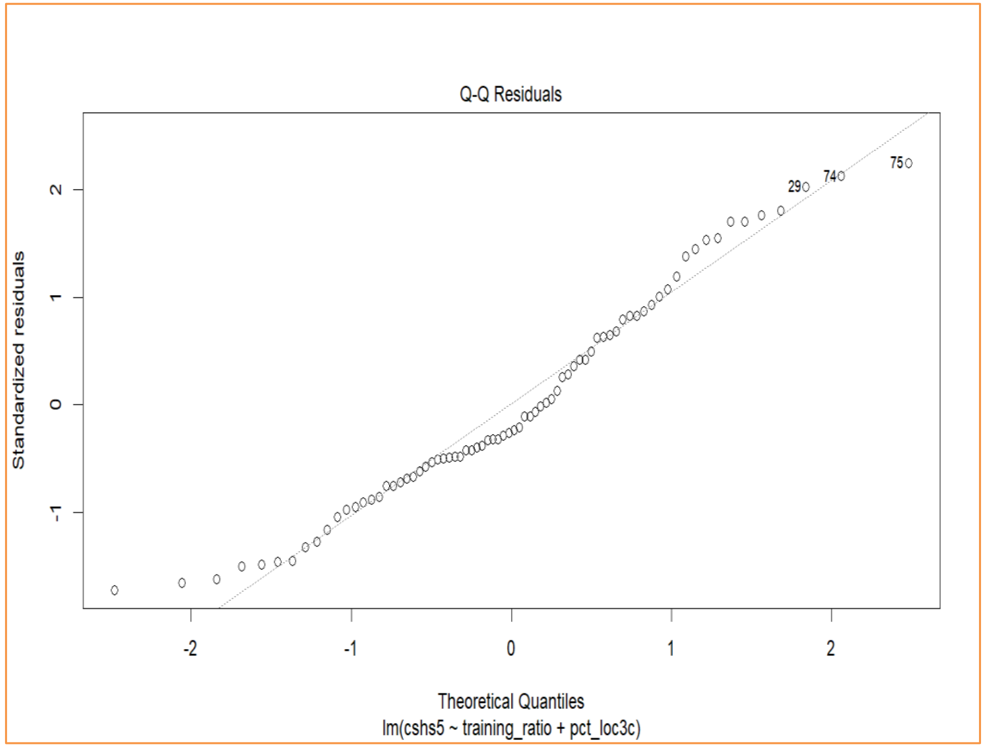

<u>Shapiro-Wilks test of non-normality</u>
H_0 (null): data are normally distributed
p-value 0.03

Data for modeling – example model 2

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Patient level data

Hospital	Training	Patient ID	Casemix group	Highly specialized	Patient actual cost	Patient cost weight	Patient risk-adjusted cost (RAC)
A	10	A0001	001	1	\$6,000	1.5	\$4,000
A	10	A0002	001	1	\$7,000	1.5	\$3,750
A	10	A0003	002	0	\$6,000	1.2	\$7,200
. . .	. . .			. . .	. . .	. . .	. . .
Z	85	Z0999	001	1	\$15,000	1.5	\$10,000
Z	85	Z1000	500	0	\$60,000	4.0	\$15,000

Model 2: $$\frac{cost_j}{cost\ weight_j} = \beta_0 + \beta_1 training_j + \beta_2 LOC_j + \varepsilon_i$$

Model 2 (patient level data) results*

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Effect	β	Standard error	pvalue
Intercept	8547	20.7741	0.0000
Teaching	9	0.4044	0.0000
Highly specialized	102	34.7076	0.0033

$$192 = (9 \times 10) + (102 \times 1)$$

Hospital	Patient ID	Casemix group	Patient actual cost	Patient cost weight	Patient cost risk-adjusted for casemix	Teaching	Highly Specialized	Factor adjustment	Patient cost risk-adjusted for casemix & factors
A	A0001	001	$6,000	0.8	$7,500	10	0	$90	$7,410
A	A0002	002	$7,000	0.8	$8,750	10	1	$192	$8,558
Z	Z0999	001	$15,000	1.5	$10,000	10	1	$192	$9,808
Z	Z1000	500	$30,000	3.0	$10,000	60	1	$642	$9,358

*Results based on a mock sample of 22 hospitals, 250,000 patients

Model 2 (patient level data) exploratory analysis

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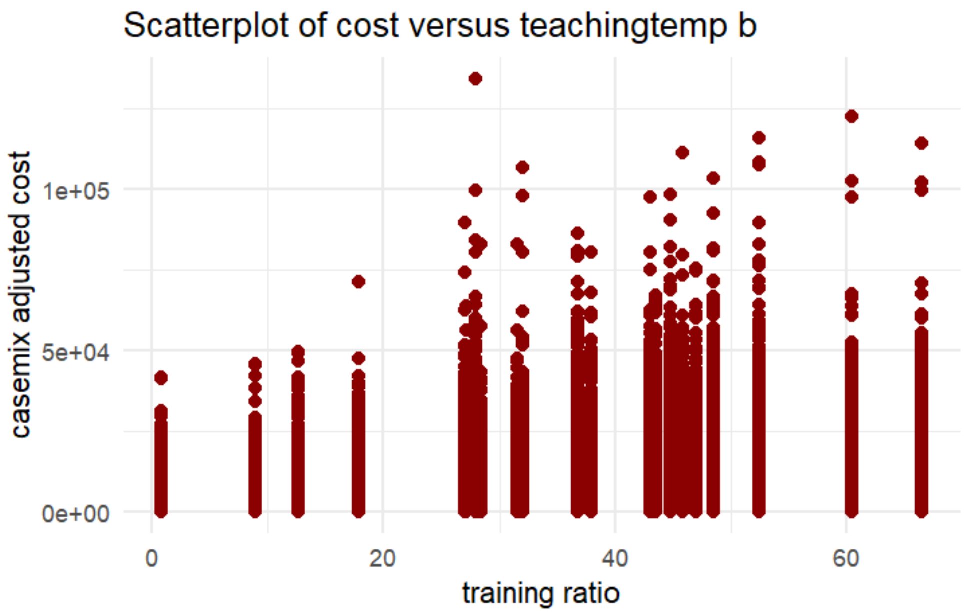

Correlation	Cost
Cost weight	0.783
Teaching	0.13
Highly Specialized	0.181

Correlation	Teaching
Highly Specialized	0.247

Characteristic	Highly Specialized	
	No	Yes
Cost	$7,287	$15,854
Adjusted cost	$8,891	$9,181
Teaching	39.0	60.3

Ordinary least squares (OLS)

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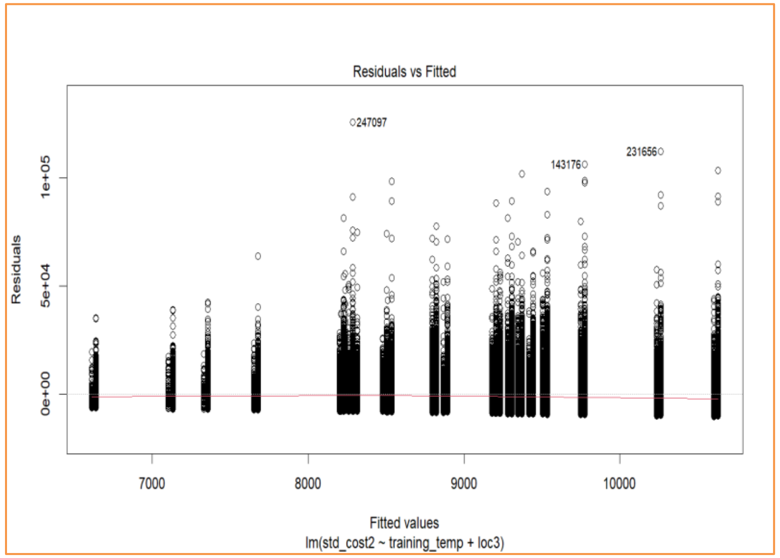

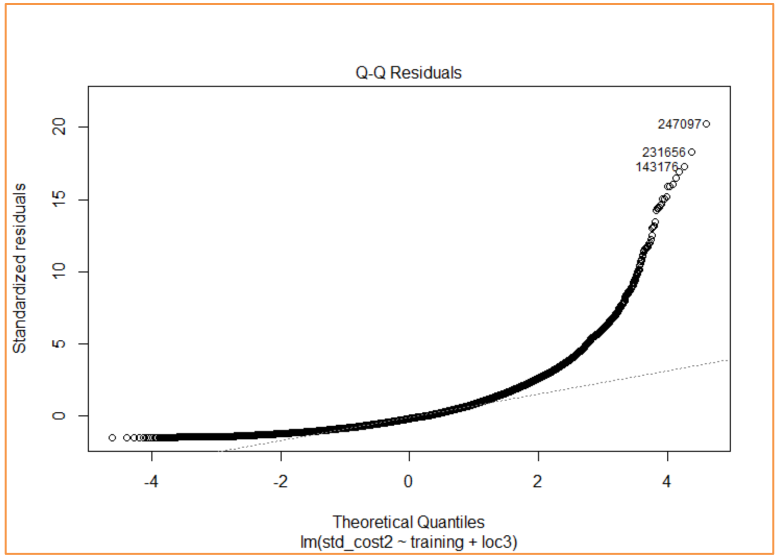

$$y_j = \beta_0 + \beta_1 x_{j1} + \beta_2 x_{j2} + \cdots \beta_p x_{jp} + \varepsilon_j \qquad \varepsilon_j = N(0, \sigma^2)$$

- For patient-level data the ε_i (i=1 to n) are usually not normally distributed, don't have constant variance and are not independent
- Statistical tests are asymptotically normal
- Non-constant variance? Solutions: robust standard errors or weighted least squares with $1/\hat{e_j}^2$ as weights.

$$\hat{e_i} = y_i - \hat{y}_i \qquad \hat{e_j}^2 = \alpha_0 + \alpha_1 x_{j1} + \alpha_2 x_{j2} + \cdots \alpha_q x_{jq}$$

- Patients clustered in hospitals. Variance estimates on model parameters may be underestimated and leading to false positive test results. Solution: mixed model or robust standard errors

Payment system price-adjusters

- Provider, patient or stay characteristics that adjust the base price in a casemix payment system
- Not captured by the grouper cost weights
- Affect the cost of providing care
- Help ensure equitable funding across providers
- Additional to the cost weights

Effect	β
Intercept	\$6,702
Teaching	\$15.8
Highly specialized	\$64.9

Example: Facility B has a teaching ratio of 10 and highly specialized cases is 10%

Payment price per weighted case:
$\$7{,}509 = 6702 + (15.8\ x\ 10) + (64.9\ x\ 10)$

Group discussion #2: Payment-system price adjusters

1. In your country/province/state/etc. is there a casemix/ABF payment system?
2. If yes, what risk adjusters are used in setting the payment prices?
3. In your country/province/territory/state/etc. is there modeling of payment adjustment factors?
4. Can you describe the data that is used?
   – Patient level for all hospitals?
   – Patient level for only some hospitals?
   – Only hospital level?
5. Can you describe the statistical methods used?

Analysis of casemix data to inform risk adjustment and payment policies

Part 2 - Analysing Variation in Length of Stay

Motivation – Why LOS still matters

Access and flow

- Longer stays block beds leading to ambulance ramping, ED crowding

Elective surgery backlog

- Fewer beds for planned procedures

Tangible capacity

- “Recoverable beds” resonate more with clinicians than abstract dollars

Policy debate

- Expand hospitals vs improve efficiency

'Absolutely packed': 101 aged care patients stuck in Illawarra hospitals when Mick needed surgery

Thousands on NSW elective surgery waitlists longer than recommended, data shows

By Joanna Woodburn and data journalist Catherine Hanrahan

Health

Tue 10 Jun

The number of people who waited longer than recommended times for elective surgeries has grown.

WA sets new ambulance ramping record as demand for hospital beds grows

By WA state political reporter Courtney Withers

State and Territory Government

Mon 1 Sep

Ambulances spent more than 7,000 hours ramped outside WA hospitals in August. *(ABC News: Keane Bourke)*

Problem - Hopewell General Hospital

Hopewell General Hospital

- Large metropolitan referral hospital
- Teaching hospital and referral centre for complex cases
- Provides specialist services: ICU, renal, oncology, major surgery

The issue

- Compared to peers, Hopewell patients stay longer
- Raises questions about efficiency and capacity use

Key questions for analysis

- Is the extra LOS due to patient complexity, higher rates of complications (HAC) or system / flow bottlenecks?

Note: Results are fictitious, simulated from real data for illustration.

Standardisation

- Raw average LOS (ALOS) can be misleading, hospitals treat different case mixes.
- Standardisation allows us to compare like-with-like.

$$SLOS = \frac{Observed\ LOS}{Expected\ LOS} = \frac{Observed\ ALOS}{Expected\ ALOS}$$

Hopewell illustration:

- Observed ALOS = 8.29 days
- Expected ALOS = 7.53 days
- Peer ALOS = 8.11 days
- SLOS = 1.10
  - SLOS > 1; patients stay longer than expected.
  - SLOS < 1; patients stay shorter than expected.

Standardisation (worked example)

How Expected LOS is calculated:

1. Take Hopewell's caseload (by DRG)
2. Apply peer mean LOS for each DRG
3. Sum across DRGs will give Expected LOS

DRG (example)	Hopewell cases	Peer mean LOS (days)	Expected bed-days
Chronic Obstructive Pulmonary Disease (DRG 139)	1,000	9.51	9,510
Cardiac (DRG 200)	800	6.80	5,440
Orthopaedics (DRG 500)	600	5.20	3,120
…	…	…	…
Total	–	–	Σ = Expected

Recoverable Beds

Recoverable beds are the number of hospital beds tied up by excess length of stay that could be freed if patients stayed only as long as expected.

1. Calculate LOS gap for each case i

$$\mathrm{Gap_i} = \max\left(0, \mathrm{Observed_i} - \mathrm{Expected_i}\right)$$

2. Sum excess bed-days across all cases
3. Convert to beds

$$\text{Recoverable Beds} = \frac{\text{Excess bed−days}}{365} = \frac{7}{365} = 0.02$$

Case	DRG	Observed LOS	Expected LOS (rounded)	Gap (days)
1	DRG 139	12	10	2
2	DRG 200	7	7	0
3	DRG 500	10	5	5
Total		–	–	7 excess days

Recoverable Beds (continued)

Hopewell totals (all cases)

- Observed ALOS = 8.29 days
- Expected ALOS = 7.53 days
- SLOS = 1.10

Calculated impact

- Excess bed-days: 58,025
- Recoverable beds: ~159
- ≈187 at 85% occupancy

Interpretation:

- Even small differences in LOS can create a large system impact.
- Equivalent to the bed base of a mid-sized hospital.

Making Excess LOS actionable

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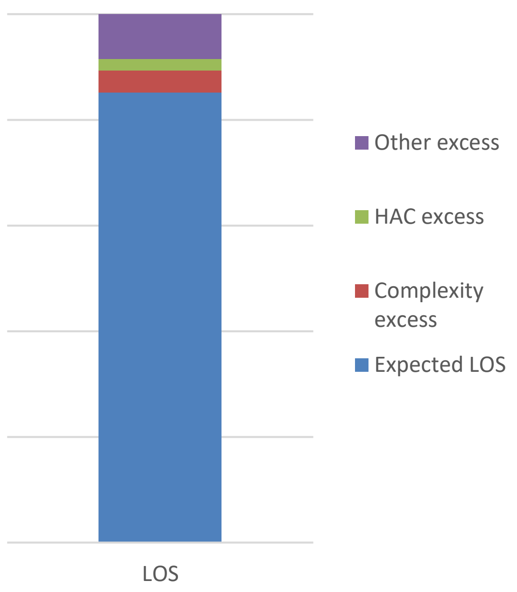
- Quantifying excess LOS shows scale
  - Hopewell: 58,025 excess bed-days (~159 beds)
- But numbers alone don't explain *why* patients stay longer
- To act, we need to segment excess LOS into drivers
  - Complexity (sicker or more comorbid patients)
  - Quality of care (hospital-acquired complications)
  - System/flow bottlenecks (delays in discharge, rehab, aged care access)



Complexity (MACSS)

What is MACSS?

- Multipurpose Australian Comorbidity Scoring System to adjust for comorbidity in analysis, uses ICD-10-AM diagnoses present on admission
- Covers a wide range of conditions (e.g. diabetes, renal disease, cancer, heart failure)
- Produces a single numeric score of patient complexity

Method

- Assign a MACSS score to each patient from their admission diagnoses
- Compare Hopewell’s distribution to peers
- Define “high complexity” = top 20% of peer distribution
- Attribute part of the excess LOS to these high-complexity cases

Holman, C D'Arcy J et al. “A multipurpose comorbidity scoring system performed better than the Charlson index.” *Journal of clinical epidemiology* vol. 58,10 (2005): 1006-14. doi:10.1016/j.jclinepi.2005.01.020

Complexity – worked example

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Hopewell calculation:

- Compare each patient's observed LOS with expected LOS.
- Gaps = excess bed-days, which can be converted into recoverable beds.
- High complexity cases (top 20% MACSS) are flagged.
- In this sample: 9 excess days (~0.02 beds).

Case	DRG	Observed LOS	Expected LOS (rounded)	Gap (days)	High complexity
1	DRG 139 – COPD	12	10	2	Yes
2	DRG 200 – Cardiac episode	7	7	0	No
3	DRG 500 – Orthopaedics	10	5	5	Yes
4	DRG 139 – COPD	9	10	0	No
5	DRG 200 – Cardiac episode	8	7	1	Yes
6	DRG 500 – Orthopaedics	6	5	1	No
7	DRG 139 – COPD	11	10	1	Yes
8	DRG 200 – Cardiac episode	6	7	0	No
9	DRG 500 – Orthopaedics	4	5	0	No
10	DRG 139 – COPD	13	10	3	No
	Total	—	—	9	—

Quality (HACs)

What are HACs?

- Hospital-acquired complications: conditions that arise during the hospital stay (not present on admission).
- Examples: pressure injuries, falls, infections, surgical complications

Why it matters:

- Complications prolong LOS unnecessarily, avoidable

Method

- Flag cases with ≥1 HAC
- Attribute excess LOS in these cases to quality-related drivers.
- Method is conceptually equivalent to MACSS

Segmentation Framework – Hopewell

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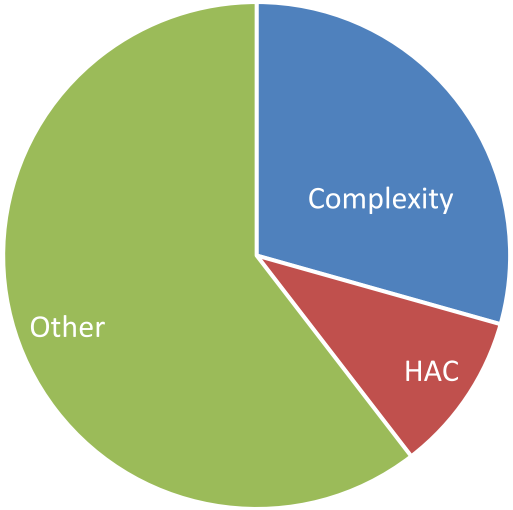
Excess LOS = 58,025 bed-days (~159 beds)

- Complexity (MACSS): 17,041 days (46.7 beds, ~30%)
  - Potentially justified – risk adjustment lever
- Quality of care (HACs): 5,911 days (16.2 beds, ~10%)
  - Potentially avoidable – quality improvement lever
- Other: 35,073 days (96.1 beds, ~60%)
  - Unexplained – further investigation needed, potential system and flow issues



Service Related Groups

What are SRGs?

- Aggregations of AR-DRGs into broader, service-based categories
- Group similar diagnosis-related cases into clinically meaningful bundles
- Designed to reflect services delivered during an episode of care
- Used in reporting to analyse hospital activity, map service needs, and plan for the future

Why they matter:

- Provide clinical context beyond DRGs.
- Enable drill-down analysis that is meaningful to clinicians.
- Support engagement and decision-making for planning, funding, and improvement.

Example: Respiratory Medicine SRG

Observed vs Expected (patients stay longer)

- Observed ALOS: 8.0
- Expected ALOS: 7.5
- SLOS: 1.07

Impact (small differences add up)

- Excess bed-days: 7,200
- Recoverable beds: ~20

Segmentation

- Complexity-related: 2,100 bed-days (~29%)
- HAC-related: 700 bed-days (~10%)
- Other: 4,400 bed-days (~61%)

Group Exercise

Scenario – Hopewell General Hospital

- Large metropolitan referral hospital.
- Compared to its peers, patients at Hopewell stay longer than expected.

Your task (in groups)

- Analyse Hopewell's results across SRGs.
- Identify where the excess length of stay is occurring, and why.
- Recommend actions that could reduce unnecessary LOS.

Group Exercise: Table A

SRG	Hopewell cases	Observed ALOS	Expected ALOS	SLOS = Obs ÷ Exp
Cardiology	3,000	7.5	6.9	
Respiratory medicine	3,600	8.0	7.5	
Neurology	2,400	9.2	7.5	
Gastroenterology	2,700	9.0	8.5	
Orthopaedics	2,200	6.0	5.2	
Oncology	1,900	12.1	12.0	
Renal medicine	1,800	7.8	7.2	
Endocrinology	1,700	6.2	5.9	
General medicine	3,400	8.7	7.9	
Geriatric medicine	1,500	9.0	8.2	

Group Exercise: Table B

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SRG	Total cases	Cases with excess LOS	Avg gap for those cases (days)	Excess bed-days	Recoverable beds
Cardiology	3,000	1,800	5.0		
Respiratory medicine	3,600	1,800	4.0		
Neurology	2,400	1,640	5.0		
Gastroenterology	2,700	1,800	3.5		
Orthopaedics	2,200	1,000	3.2		
Oncology	1,900	1,250	4.0		
Renal medicine	1,800	1,200	4.0		
Endocrinology	1,700	1,300	3.0		
General medicine	3,400	2,600	3.0		
Geriatric medicine	1,500	1,050	2.5		

Group Exercise: Table C

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SRG	Cases with high MACSS	Avg gap (days) – high MACSS	Complexity bed-days	Cases with ≥1 HAC	Avg gap (days) – HAC	HAC bed-days
Cardiology	540	5.0		150	4.0	
Respiratory medicine	500	4.2		200	3.5	
Neurology	440	5.0		130	5.0	
Gastroenterology	425	4.0		110	5.0	
Orthopaedics	200	4.0		100	3.0	
Oncology	320	5.0		100	5.0	
Renal medicine	280	5.0		90	5.0	
Endocrinology	275	4.0		100	3.5	
General medicine	700	4.0		225	4.0	
Geriatric medicine	320	2.0		260	3.5	

Group Exercise - Results

Thank You!

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