Cambridge Judge Business School

Job Talk • Emory University, Goizueta Business School • January 2017

Economies of Scale and Scope in Hospitals:

An Empirical Study of Volume Spillovers

Michael Freeman

Jan 6, 2017

Joint work with
Nicos Savva, London Business School
Stefan Scholtes, Cambridge Judge Business School

UNIVERSITY OF CAMBRIDGE
Judge Business School

Existing and ongoing research

Patient routing and flow

- Gatekeepers at Work: An Empirical Analysis of a Maternity Unit, *Management Science (Forthcoming)*.
- Gatekeeping Under Uncertainty: An Empirical Study of Referral Errors in the Emergency Department, *Working paper*.

Hospital service redesign

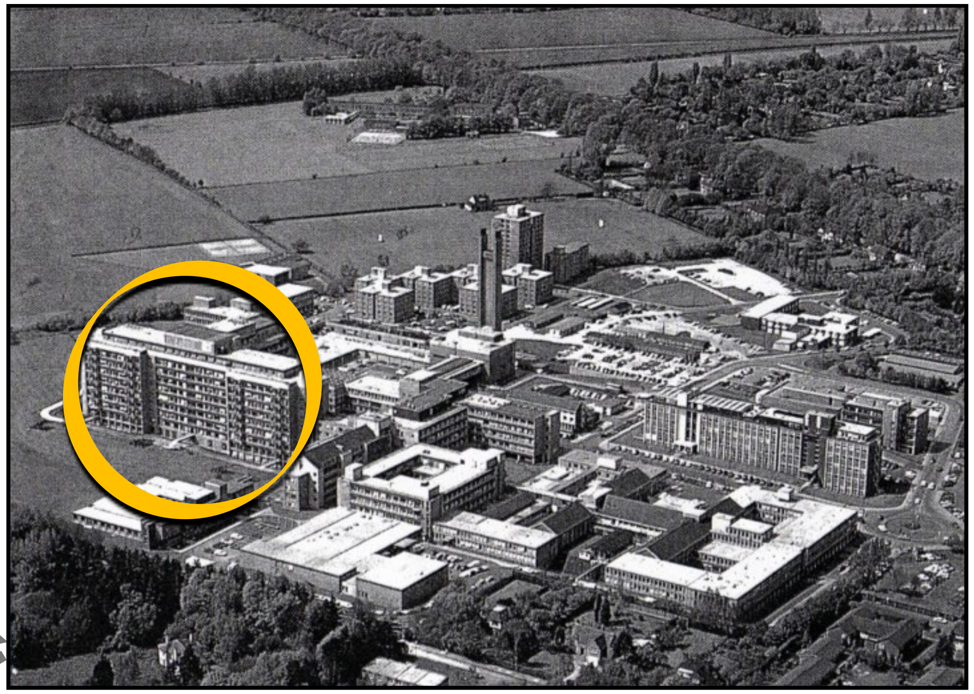
- Economies of Scale and Scope in Hospitals: An Empirical Study of Volume Spillovers, *Management Science (Under Revision)*.
- Fat-Tails in Patient Costs: Evidence and Implications for Tariff-Based Compensation Systems, *Work-in-progress*.

Cambridge University Hospital — 2016

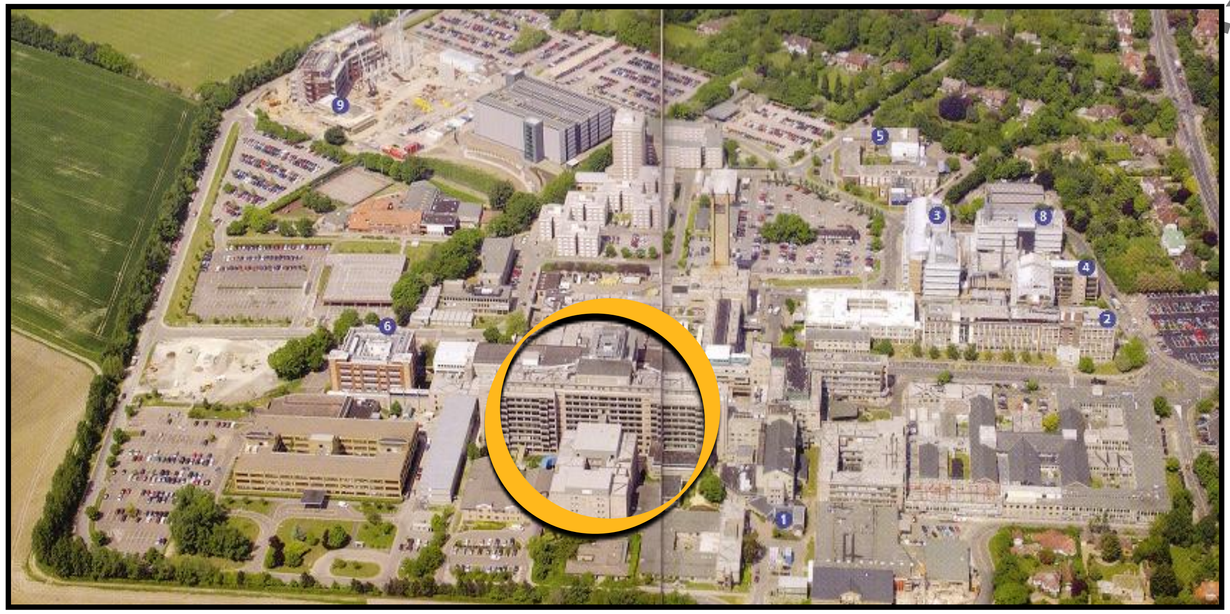
Hospitals have followed a path of growth

Main hospital building

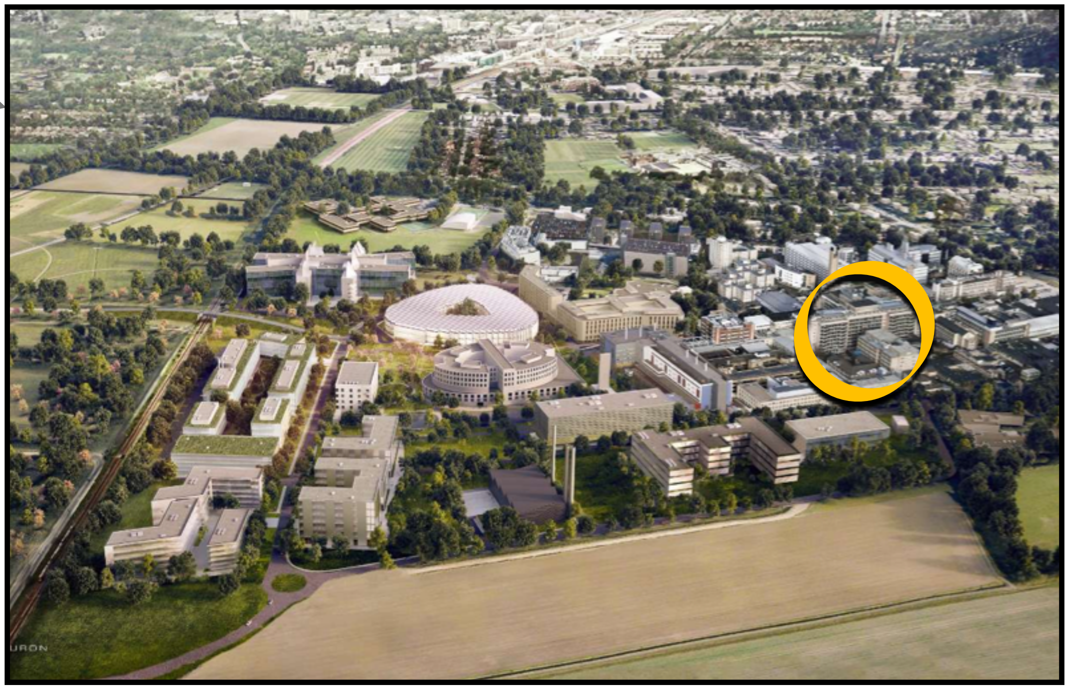
1964



1983



2007



2016

Is this the most productive way of delivering care?

To answer, need to know whether hospitals experience economies of **scale** and/or **scope**…

Economies of scale and scope industry specific

Economies of **scale**

- Production costs **reduce** with increased volume of the **focal** activity
  - Theory: *e.g. Debreu (1959); Lancaster (1968); Mansfield (1970)*
  - Empirics: *Banks (Saunders & Walker 1994); electric power (Christensen & Greene 1976); …*

Economies of **scope**

- Production costs **reduce** with increased volume of **other** activities
  - Theory: *Teece (1980); Panzar & Willig (1981)*
  - Empirics: *Advertising (Silk & Berndt 1993); multi-industry (Villalonga 2004); drug R&D (Henderson & Cockburn 1993); …*

Diseconomies of **scope** (benefits of operational focus)

- Production costs **increase** with increased volume of **other** activities
  - Theory: *Skinner (1974); Heskett (1986)*
  - Empirics: *Airlines (Tsikriktsis 2007); automobile assembly (Fisher & Ittner 1999); manufacturing plants (Brush & Karnani 1996; Schoar 2002); …*

Are there economies of scale and scope in healthcare?

> Given the importance of economies of scale and scope *[in healthcare]* it is perhaps surprising that **so little is known about their extent and importance**. A systematic literature survey as part of this study revealed very little evidence (either positive or negative) about the issue. Many of the existing studies **focus on the "whole hospital"** rather than particular services and even those studies are often very **limited by poor data and methodologies**.

— *"Economies of scale and scope in healthcare markets," Monitor (2012).*

The fully integrated general hospital

The fully integrated general hospital accommodates:

- Multiple **types** of urgency, *e.g.* ***Emergencies*** *and* ***Electives***
- Multiple **service-lines**, *e.g. Orthopedics, Cardiology, Neurology,…*

The fully integrated general hospital

Benefits of the integrated model

Asset amortization
(e.g. Moore 1959; Panzar & Willig 1981)

Variation buffers
(e.g. Schuster et al. 2011; Freeman et al. 2016)

Meet diverse customer needs
(e.g. Bagozzi 1986; Cravens & Woodruff 1986)

The fully integrated general hospital accommodates:

- Multiple **types** of urgency, *e.g.* ***Emergencies*** *and* ***Electives***
- Multiple **service-lines**, *e.g. Orthopedics, Cardiology, Neurology,…*

Integrated hospitals are complex organizations

Hospitals have become:

> *"some of the most managerially intractable institutions in the annals of capitalism"*

— Christensen et al., The Innovator's Prescription (2009, p.75)

An alternative to the integrated model?

HARVARD | BUSINESS | SCHOOL

JAMES HESKETT

9-683-068

REV: JUNE 2, 2003

Shouldice Hospital Limited

Papworth Hospital

MEMORIAL SLOAN-KETTERING CANCER CENTER · ESTABLISHED 1884 ·

Memorial Sloan-Kettering Cancer Center

Massachusetts Eye and Ear

The specialist hospital

Shouldice Hospital

The specialist hospital treats a subset of patients, e.g.:

- with specific **types** of urgency, *e.g.* ***Emergencies*** *or* ***Electives***
- in specific **service-lines**, *e.g. Orthopedics or Cardiology or Neurology…*

The specialist hospital

Shouldice Hospital

<u>Benefits of the focused model</u>

Organizational simplicity
(e.g. Argote 1982; Birtan 1988)

Learning and experience
(e.g. Pisano et al. 2001; KC & Staats 2012)

Development of specialized expertise
(e.g. Hopp & Lovejoy 2012; Argote 2013)

The specialist hospital treats a subset of patients, e.g.:

- with specific **types** of urgency, *e.g.* ***Emergencies*** *or* ***Electives***
- in specific **service-lines**, *e.g. Orthopedics or Cardiology or Neurology…*

Which model is better?

Integrated model

- Asset amortization
- Variation buffers
- Meet diverse customer needs

Focused model

- Organizational simplicity
- Learning and experience
- Specialized expertise

Do the benefits of pooling across patient **types** and/or **service-lines** in the integrated model outweigh the cost of reduced focus?

Research questions

Integrated model

Focused model

Do costs reduce with increased volume of patients:

[scale]	of the same type and from the same service-line?
[type-scope]	of the other type and from the same service-line?
[service-scope]	of the same type and from the other service-lines?
[other-scope]	of the other type and from the other service-lines?

Do effects depend on whether the focal patient type is emergency or elective?

Data

Condition level **cost** and inpatient **activity** data:

- ↳ For the **9** financial years from 2006/07 to 2014/15
  - ↳ For **130** acute hospital trusts operated by the NHS in England
    - ↳ Corresponding to **~105 million** inpatient admissions

Cost and volume data are reported in each year by each hospital, broken down into one of

<u>~2000 HRGs (treatment/conditions groups)</u>

HRGs: Healthcare Resource Groups

Patients within an HRG are clinically similar and require a relatively homogeneous bundle of resources for their treatment *(Fetter 1991)*

HA11A	Major Hip Procedures for Trauma, Category 2, with Major CC
HA11B	Major Hip Procedures for Trauma, Category 2, with Intermediate CC
HA11C	Major Hip Procedures for Trauma, Category 2, without CC
HA12B	Major Hip Procedures for Trauma, Category 1, with CC
HA12C	Major Hip Procedures for Trauma, Category 1, without CC
HA13A	Intermediate Hip Procedures for Trauma, with Major CC
HA13B	Intermediate Hip Procedures for Trauma, with Intermediate CC
HA13C	Intermediate Hip Procedures for Trauma, without CC

HRG assignment: Automated process, with each patient episode assigned to a unique HRG using information from discharge notes: *(DH 2013)*

- ICD-10 medical diagnosis codes
- OPCS procedure codes
- Contextual information, e.g. patient age and gender
- Any complications or comorbidities

Main data set

Each hospital in each year submits data to government, aggregated to the HRG level, containing:

- The **volume** of patients treated from each HRG
- The average **cost** of treating patients within each HRG
- The average length-of-stay (LOS) of these patients
- Reported separately for **electives** and **emergencies**

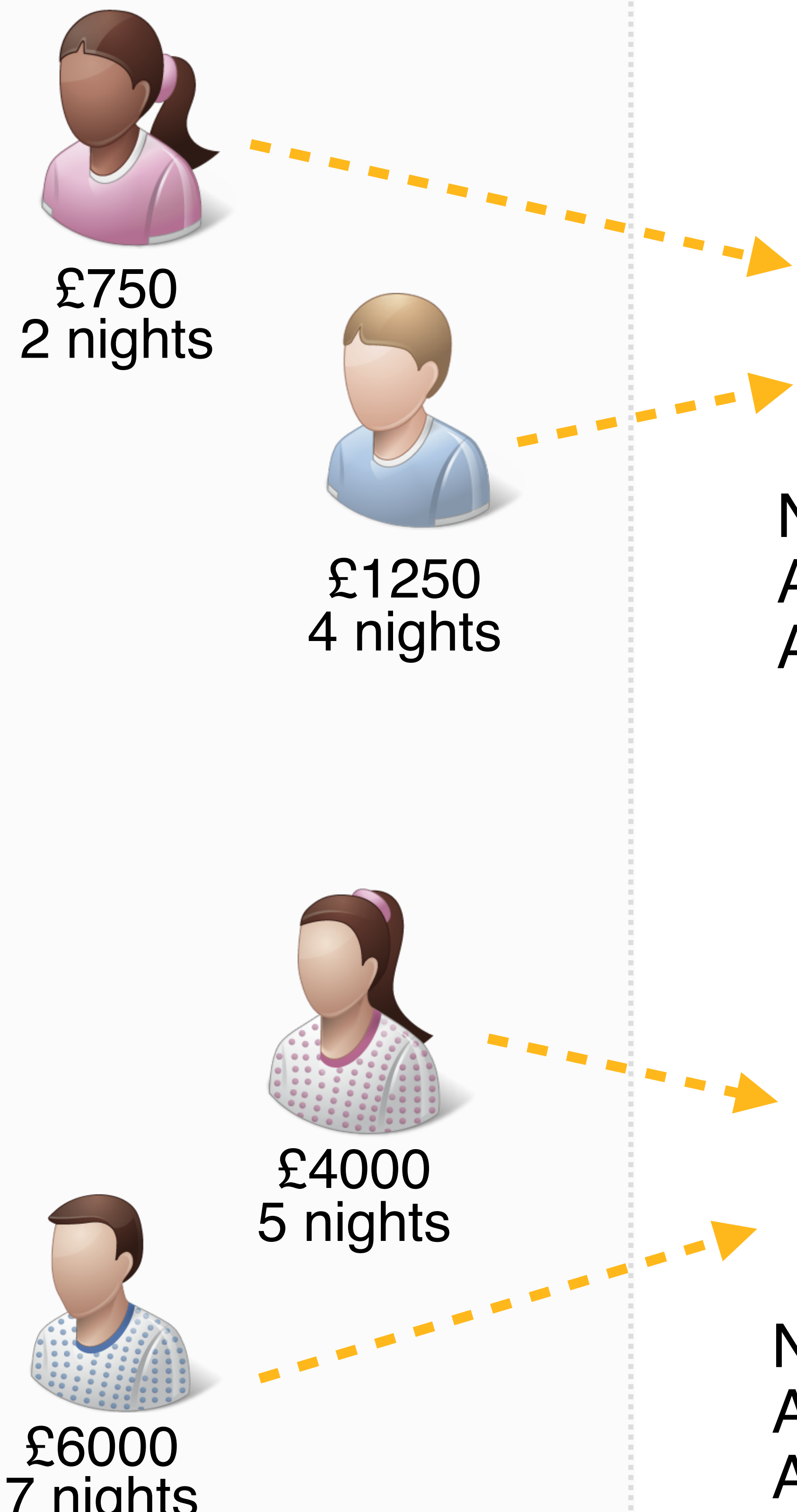
Main data set

Each hospital in each year submits data to government, aggregated to the HRG level, containing:

- The **volume** of patients treated from each HRG
- The average **cost** of treating patients within each HRG
- The average length-of-stay (LOS) of these patients
- Reported separately for **electives** and **emergencies**

Our data set ~**7.2 million** observations

Main data set



Emergency
Wrist fracture

Num. patients = 2
Avg. cost = £1000
Avg. stay = 3 nights

Emergency
Hip fracture

Num. patients = 2
Avg. cost = £5000
Avg. stay = 6 nights

Each hospital in each year submits data to government, aggregated to the HRG level, containing:

- The **volume** of patients treated from each HRG
- The average **cost** of treating patients within each HRG
- The average length-of-stay (LOS) of these patients
- Reported separately for **electives** and **emergencies**

Our data set ~**7.2 million** observations

Aggregate HRG-level data to the service-line level

£750
2 nights

£1250
4 nights

£4000
5 nights

£6000
7 nights

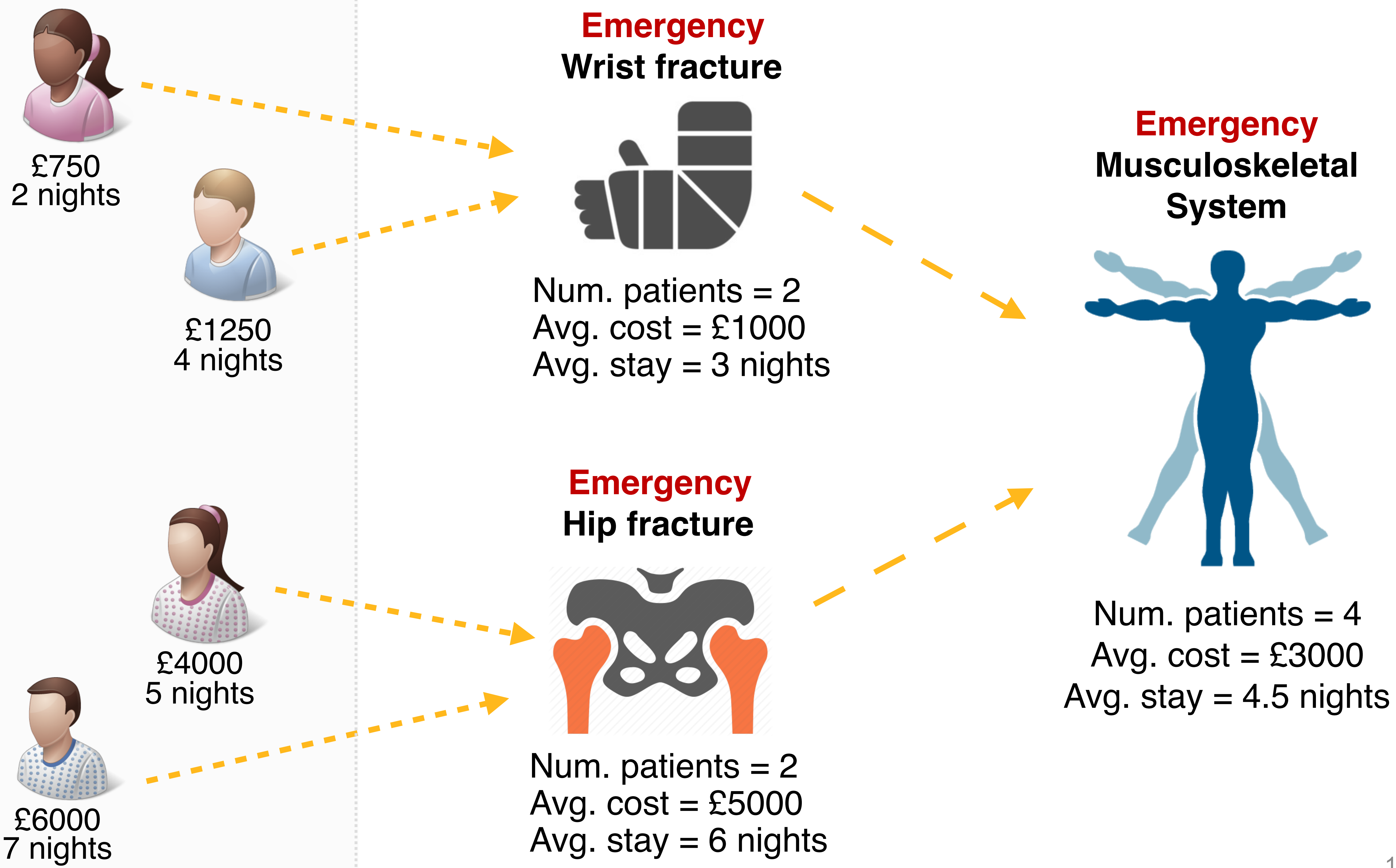
Emergency
Wrist fracture

Num. patients = 2
Avg. cost = £1000
Avg. stay = 3 nights

Emergency
Hip fracture

Num. patients = 2
Avg. cost = £5000
Avg. stay = 6 nights

Aggregate HRG-level data to the service-line level



Service-lines: HRG chapters

14 service-lines

Nervous System
Eyes and Periorbita
Mouth, Head, Neck and Ears
Respiratory System
Cardiac Surgery and Primary Cardiac Conditions
Digestive System
Hepatobiliary and Pancreatic System
Musculoskeletal System
Skin, Breasts and Burns
Endocrine and Metabolic System
Urinary Tract and Male Reproductive System
Female Reproductive System
Diseases of Childhood and Neonates
Vascular System

HRG chapters correspond to major body systems or medical specialties

Unit of analysis

In each of the **130** hospitals *h*

↳ in each of the **9** years *t*

↳ in each of the **14** service-lines *s*:

— **Volume** of elective inpatient admissions
— Average **cost** of treating those electives
— Average **length-of-stay** of those electives

15,339 observations

— **Volume** of emergency inpatient admissions
— Average **cost** of treating those emergencies
— Average **length-of-stay** of those emergencies

15,354 observations

Methods

We use

- Dependent variable: **Costs** — emergency and elective
    - Within service-line case-mix adjustment
    - Across service-line normalization

- Independent variables: **Volumes**
    - Four effects: scale, type-scope, service-scope, other-scope
    - Within-between volume decomposition *(Mundlak 1978)*

- Econometric model
    - Multi-level (hierarchical) model *(Gelman & Hill 2007)*

Methods

We use

- Dependent variable: **Costs** — emergency and elective
  - Within service-line case-mix adjustment
  - Across service-line normalization

- Independent variables: **Volumes**
  - Four effects: scale, type-scope, service-scope, other-scope
  - Within-between volume decomposition *(Mundlak 1978)*

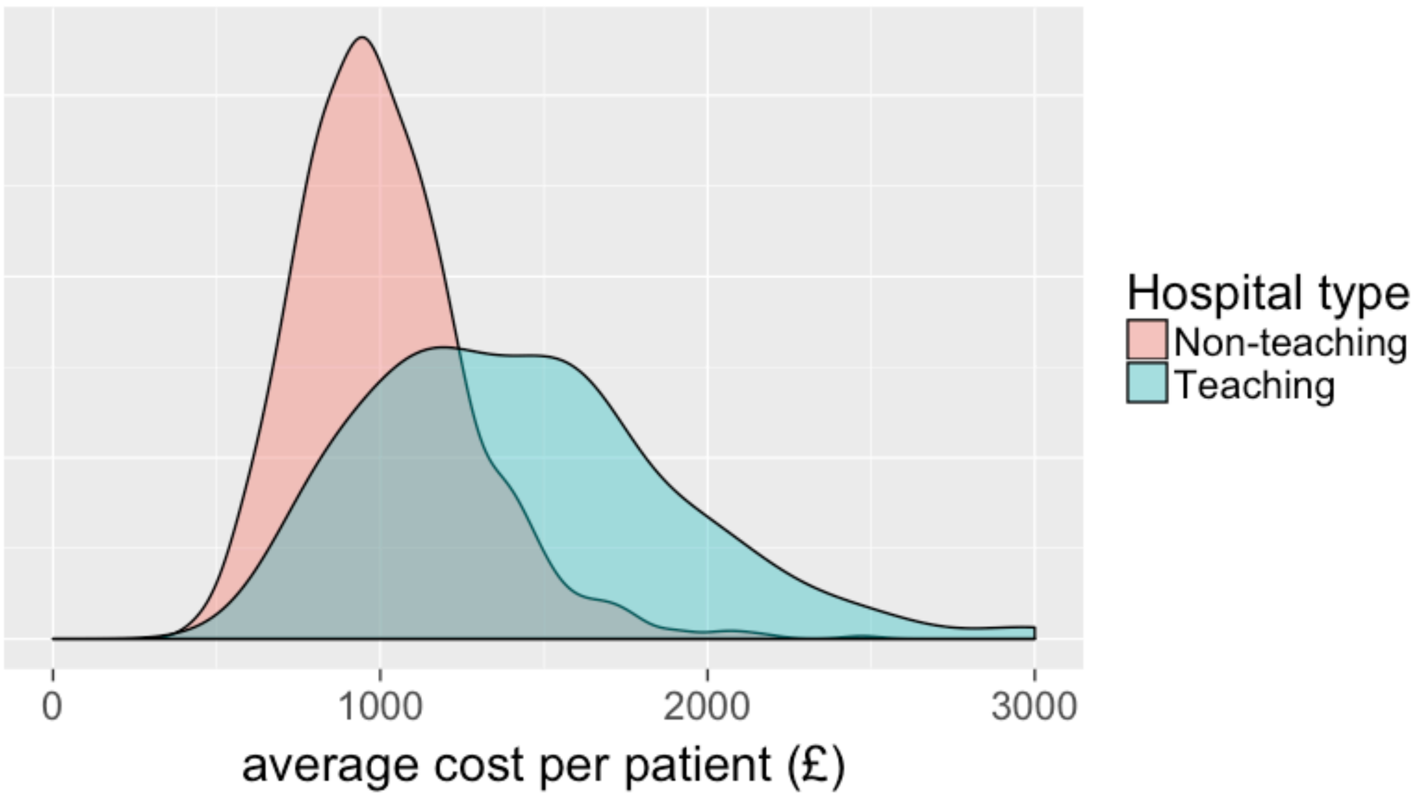
- Econometric model
  - Multi-level (hierarchical) model *(Gelman & Hill 2007)*

Case-mix adjust costs to reduce estimation bias

- Costs confounded by case-mix variation across hospitals
- Granularity of data set (HRG-level) enables cost case-mix adjustment

↳ Calculate cost of treating the same "average elective" and "average emergency" patient within a service-line *s* in each hospital *h* and year *t*

Average cost per patient,
emergency cardiac conditions

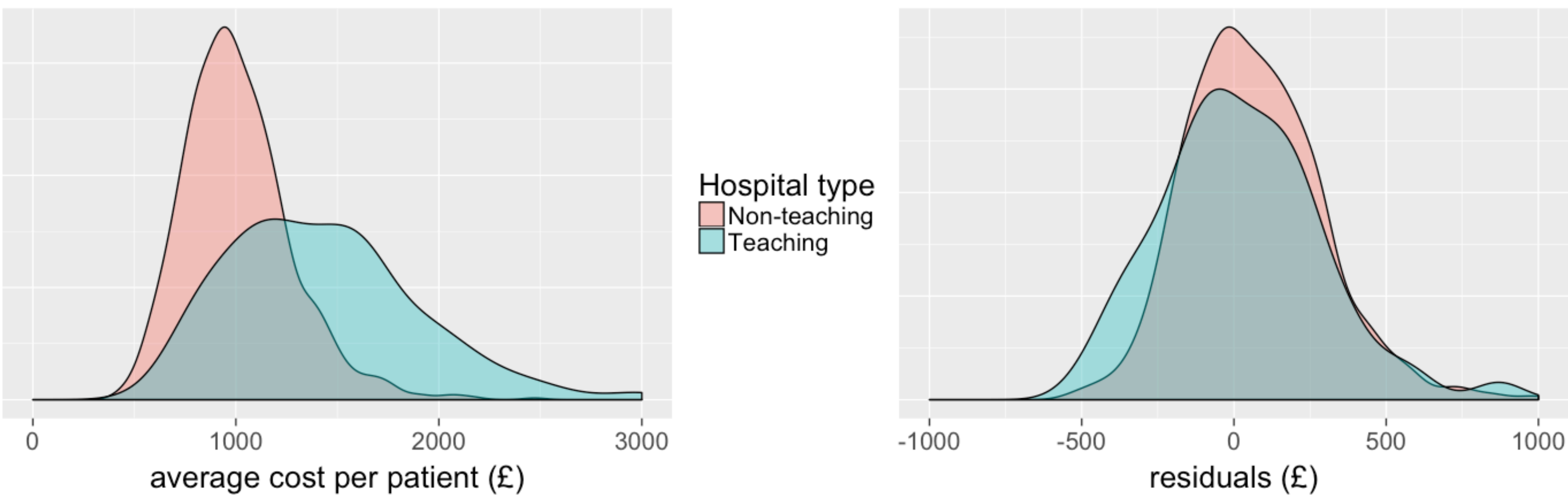


Case-mix adjust costs to reduce estimation bias

- Costs confounded by case-mix variation across hospitals
- Granularity of data set (HRG-level) enables cost case-mix adjustment

↳ Calculate cost of treating the same “average elective” and “average emergency” patient within a service-line *s* in each hospital *h* and year *t*

Average cost per patient, emergency cardiac conditions → after case-mix adjustment and w/ hospital-type fixed effect



Methods

We use

- Dependent variable: **Costs** — emergency and elective
  - ✓ - Within service-line case-mix adjustment
  - - Across service-line normalization

- Independent variables: **Volumes**
  - - Four effects: scale, type-scope, service-scope, other-scope
  - - Within-between volume decomposition *(Mundlak 1978)*

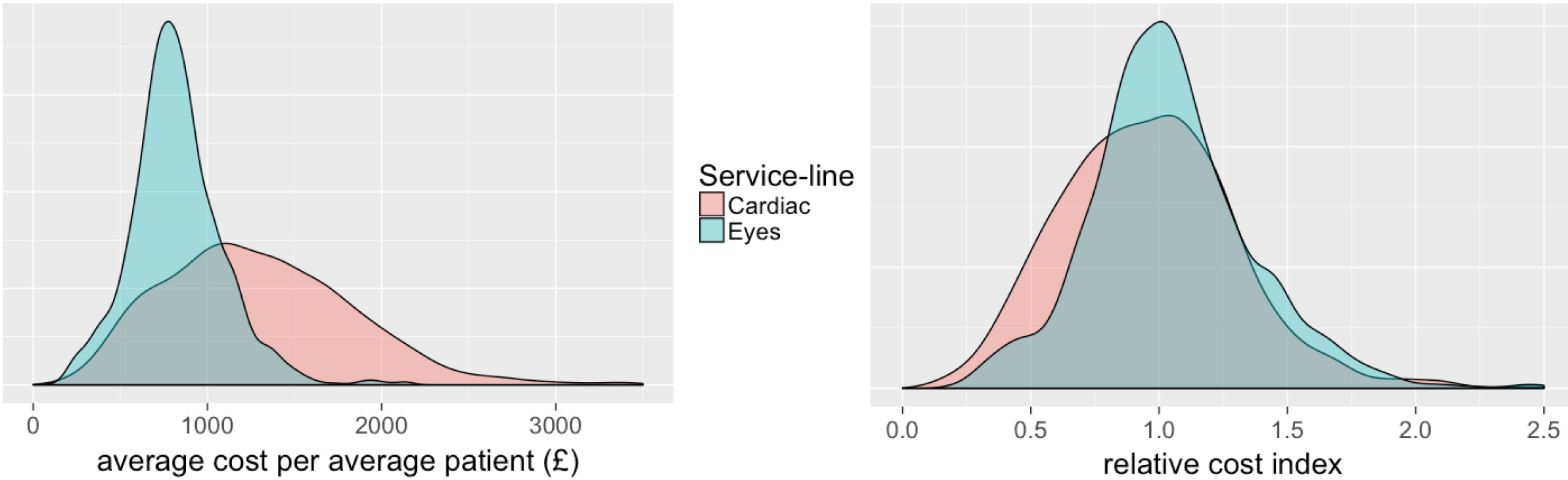
- Econometric model
  - - Multi-level (hierarchical) model *(Gelman & Hill 2007)*

Normalizing costs reduces across service-line heterogeneity

Average cost per patient higher in some service-lines than others

↳ Normalize costs by dividing by the average cost of treating a patient of the same type and from the same service-line

Average cost per patient, elective service-lines → after dividing by same service-line, same-type average cost



Methods

We use

- Dependent variable: **Costs** — emergency and elective
  ✓ - Within service-line case-mix adjustment
  ✓ - Across service-line normalization

- Independent variables: **Volumes**
  - Four effects: scale, type-scope, service-scope, other-scope
  - Within-between volume decomposition *(Mundlak 1978)*

- Econometric model
  - Multi-level (hierarchical) model *(Gelman & Hill 2007)*

Volume measures

Data

Volume of **emergency** and **elective** patients in each **service-line *s***

Legend:

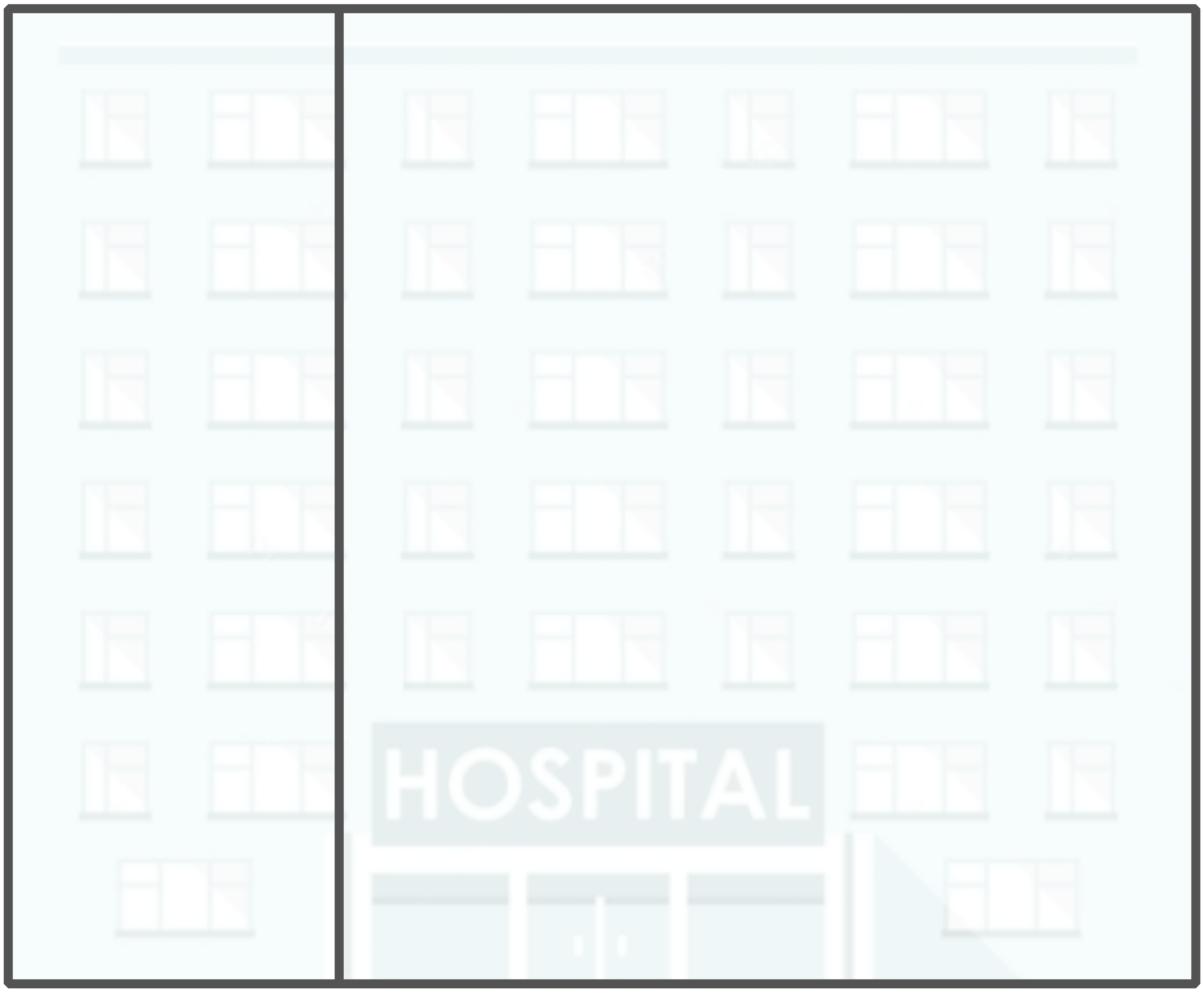
***FS** = Focal service-line*

***OS** = Other service-lines*

Volume measures

Focal service-line

Other service-lines



<u>Data</u>

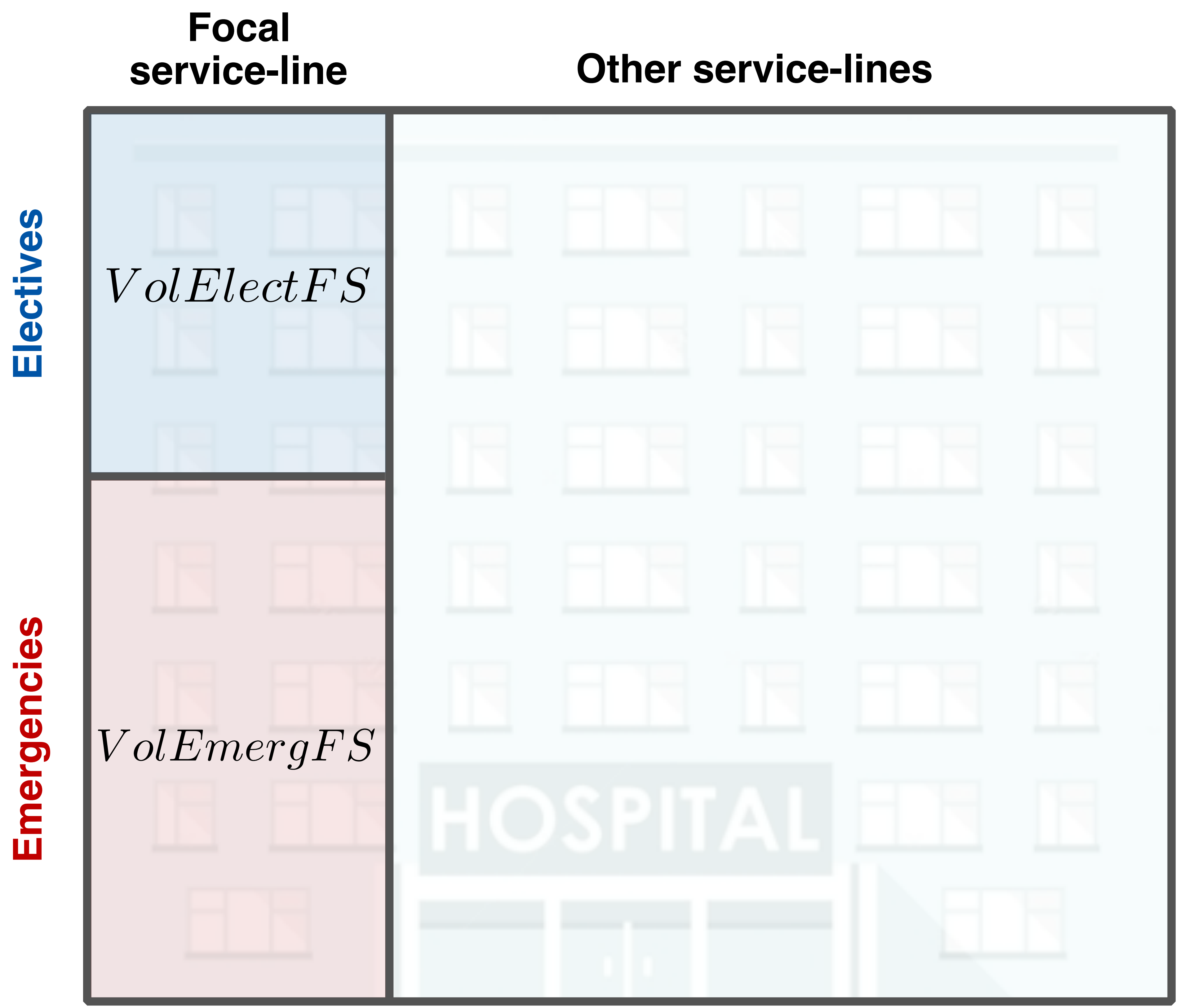
Volume of **emergency** and **elective** patients in each **service-line *s***

<u>Legend:</u>

FS *= Focal service-line*

OS *= Other service-lines*

Volume measures



Data

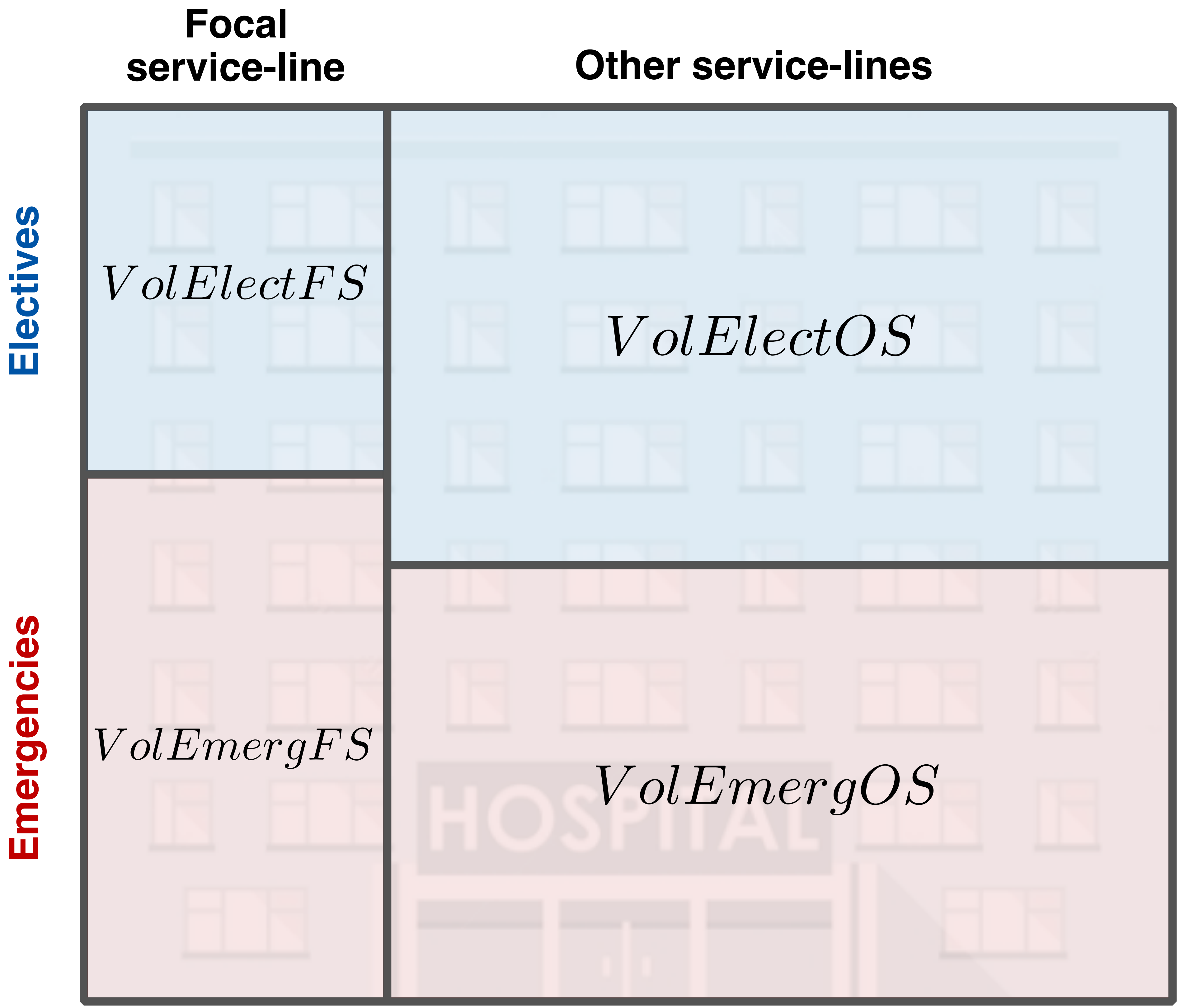
Volume of **emergency** and **elective** patients in each **service-line *s***

Legend:

FS *= Focal service-line*

OS *= Other service-lines*

Volume measures



Data

Volume of **emergency** and **elective** patients in each **service-line *s***

Legend:

FS *= Focal service-line*

OS *= Other service-lines*

Base model

$$\begin{aligned} EmergCost_{hst} = &\alpha_0 + \alpha_1 VolEmergFS_{hst} + \alpha_2 VolElectFS_{hst} + \\ &\alpha_3 VolEmergOS_{hst} + \alpha_4 VolElectOS_{hst} + \vec{\alpha_5} Controls_{hst} + \delta_{hst} \end{aligned}$$

$$\begin{aligned} ElectCost_{hst} = &\beta_0 + \beta_1 VolElectFS_{hst} + \beta_2 VolEmergFS_{hst} + \\ &\beta_3 VolElectOS_{hst} + \beta_4 VolEmergOS_{hst} + \vec{\beta_5} Controls_{hst} + \epsilon_{hst} \end{aligned}$$

$$\text{where} \quad \delta_{hst} \sim \mathcal{N}(0, \sigma_\delta^2) \quad \text{and} \quad \epsilon_{hst} \sim \mathcal{N}(0, \sigma_\epsilon^2)$$

Legend:

FS *= Focal service-line*

OS *= Other service-lines*

Base model

[scale] **[type-scope]**

$$EmergCost_{hst} = \alpha_0 + \boxed{\alpha_1} VolEmergFS_{hst} + \boxed{\alpha_2} VolElectFS_{hst} +$$
$$\boxed{\alpha_3} VolEmergOS_{hst} + \boxed{\alpha_4} VolElectOS_{hst} + \vec{\alpha_5} Controls_{hst} + \delta_{hst}$$

[service-scope] **[other-scope]**

[scale] **[type-scope]**

$$ElectCost_{hst} = \beta_0 + \boxed{\beta_1} VolElectFS_{hst} + \boxed{\beta_2} VolEmergFS_{hst} +$$
$$\boxed{\beta_3} VolElectOS_{hst} + \boxed{\beta_4} VolEmergOS_{hst} + \vec{\beta_5} Controls_{hst} + \epsilon_{hst}$$

[service-scope] **[other-scope]**

$$\text{where} \quad \delta_{hst} \sim \mathcal{N}(0, \sigma_\delta^2) \quad \text{and} \quad \epsilon_{hst} \sim \mathcal{N}(0, \sigma_\epsilon^2)$$

Legend:

FS *= Focal service-line*

OS *= Other service-lines*

Methods

We use

- Dependent variable: **Costs** — emergency and elective
  - ✓ - Within service-line case-mix adjustment
  - ✓ - Across service-line normalization

- Independent variables: **Volumes**
  - ✓ - Four effects: scale, type-scope, service-scope, other-scope
  - - Within-between volume decomposition *(Mundlak 1978)*

- Econometric model
  - - Multi-level (hierarchical) model *(Gelman & Hill 2007)*

Longitudinal versus cross-sectional effects

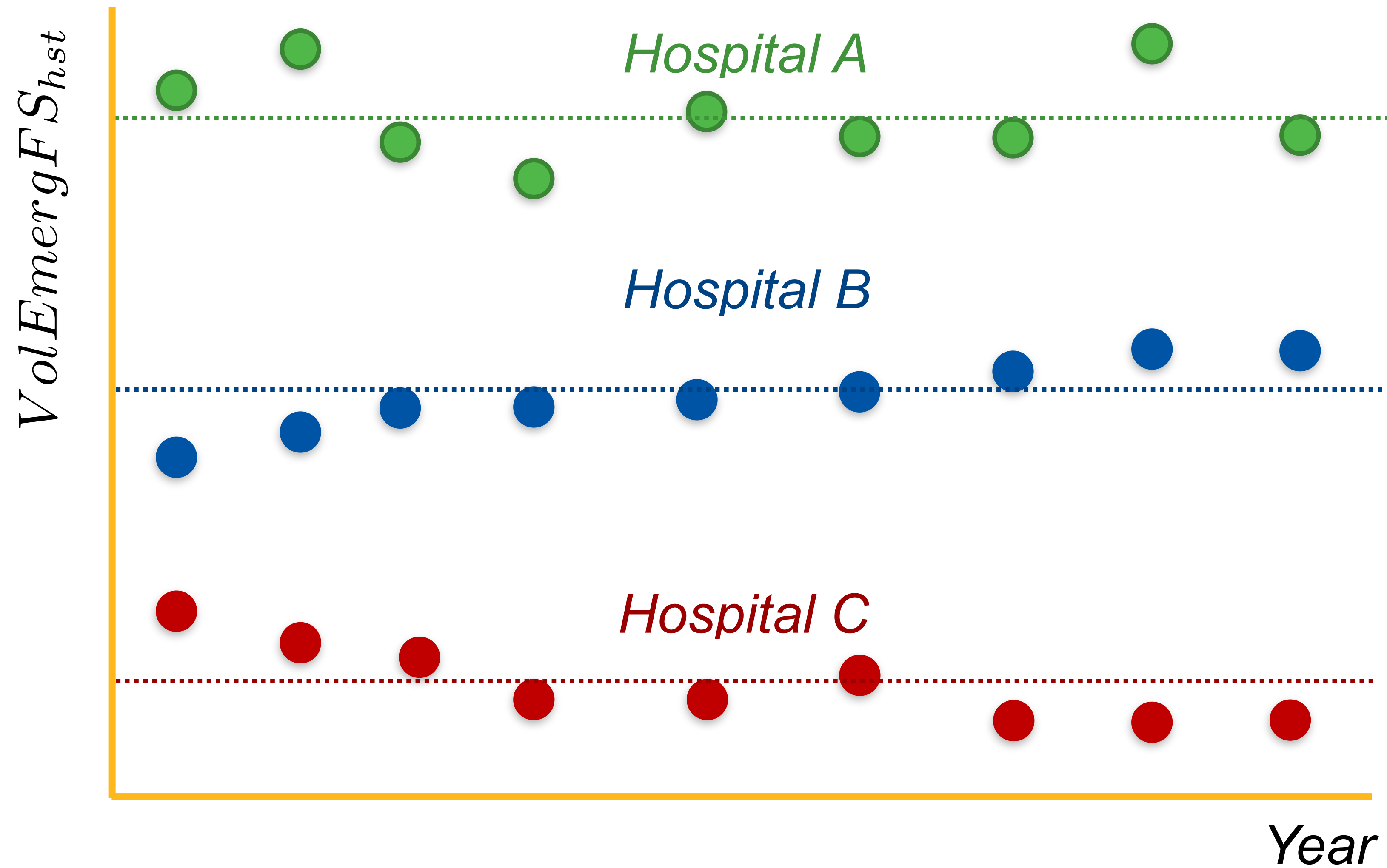
- For each of the four volume measures, observe 9 observations per hospital

e.g. volume of emergency orthopedics

Longitudinal versus cross-sectional effects

- For each of the four volume measures, observe 9 observations per hospital

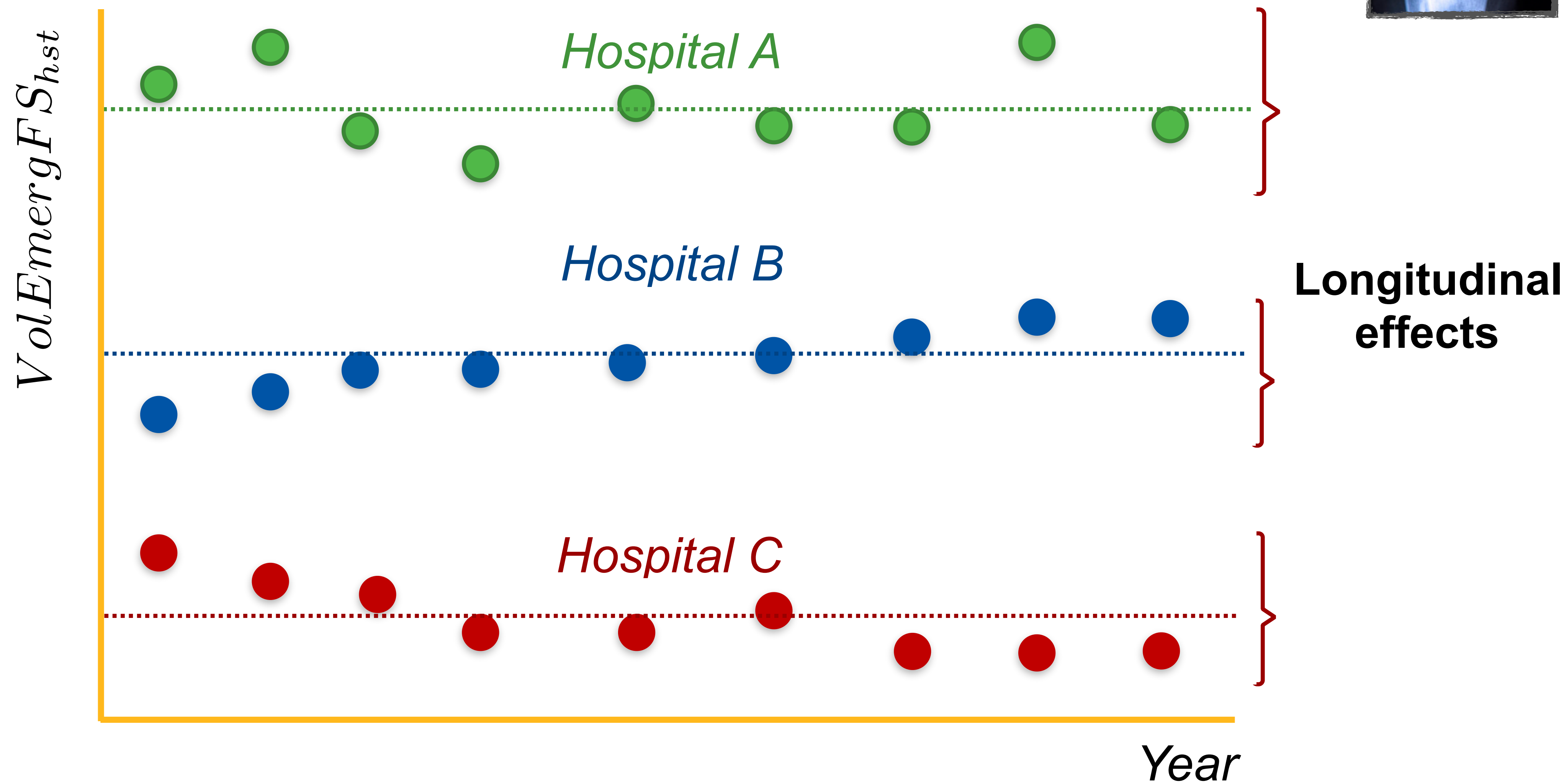
e.g. volume of emergency orthopedics



Longitudinal versus cross-sectional effects

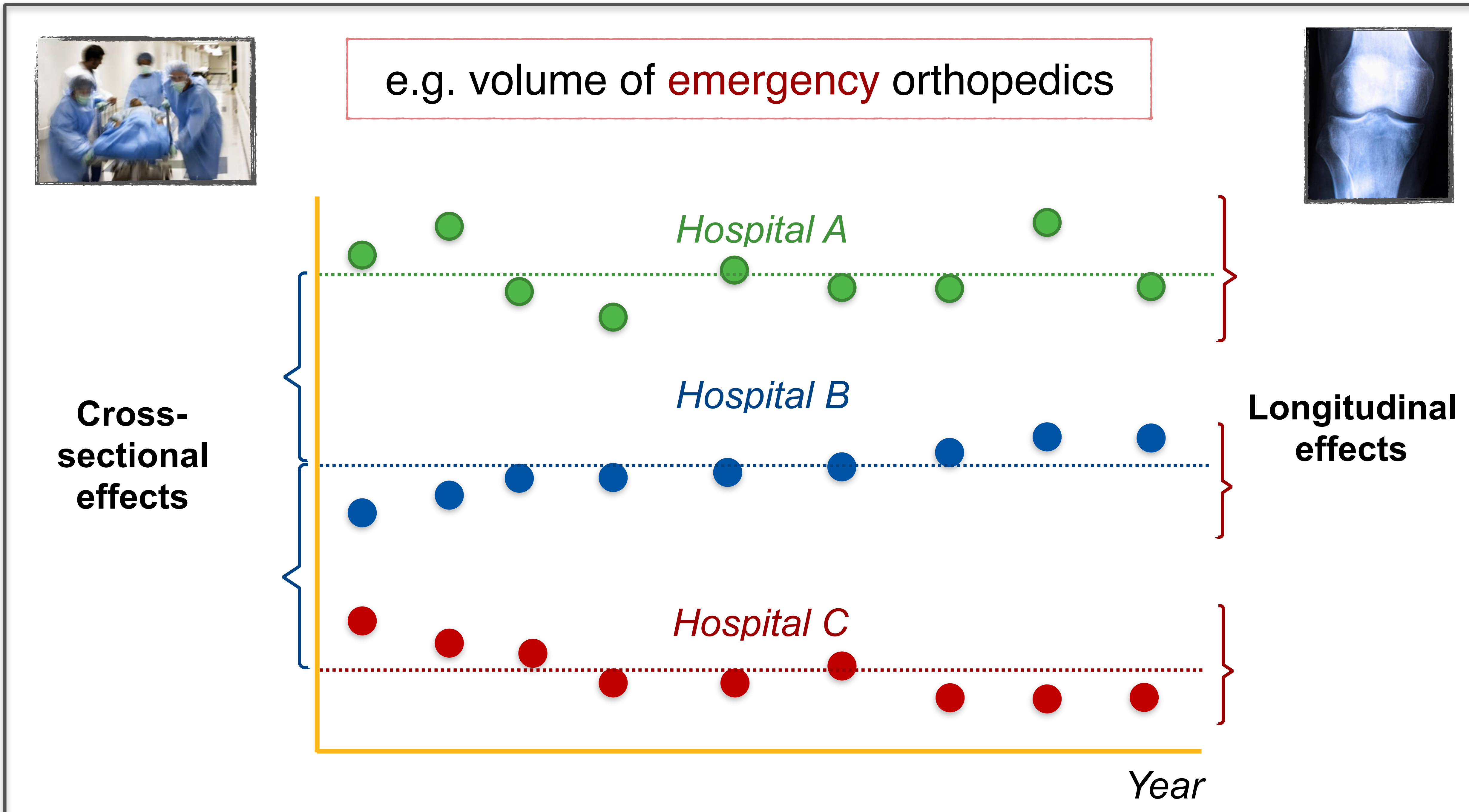
- For each of the four volume measures, observe 9 observations per hospital

e.g. volume of emergency orthopedics



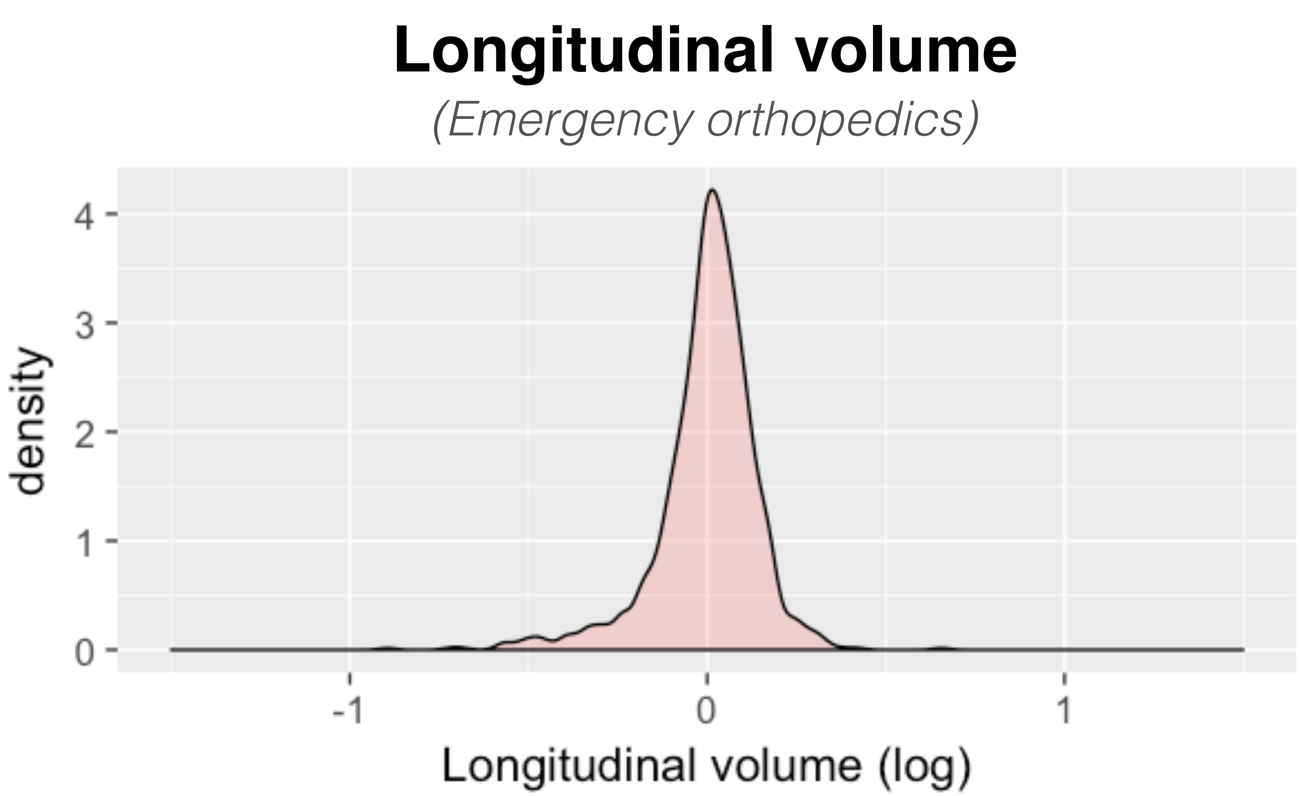
Longitudinal versus cross-sectional effects

- For each of the four volume measures, observe 9 observations per hospital



Volume decomposition

- Volume in hospital *h*, service-line *s*, year *t* : $VolEmergFS_{hst}$
- Average volume in hospital *h*, service-line *s* : $\mu(VolEmergFS)_{hs}$



$VolEmergFS_{hst} - \mu(VolEmergFS)_{hs}$

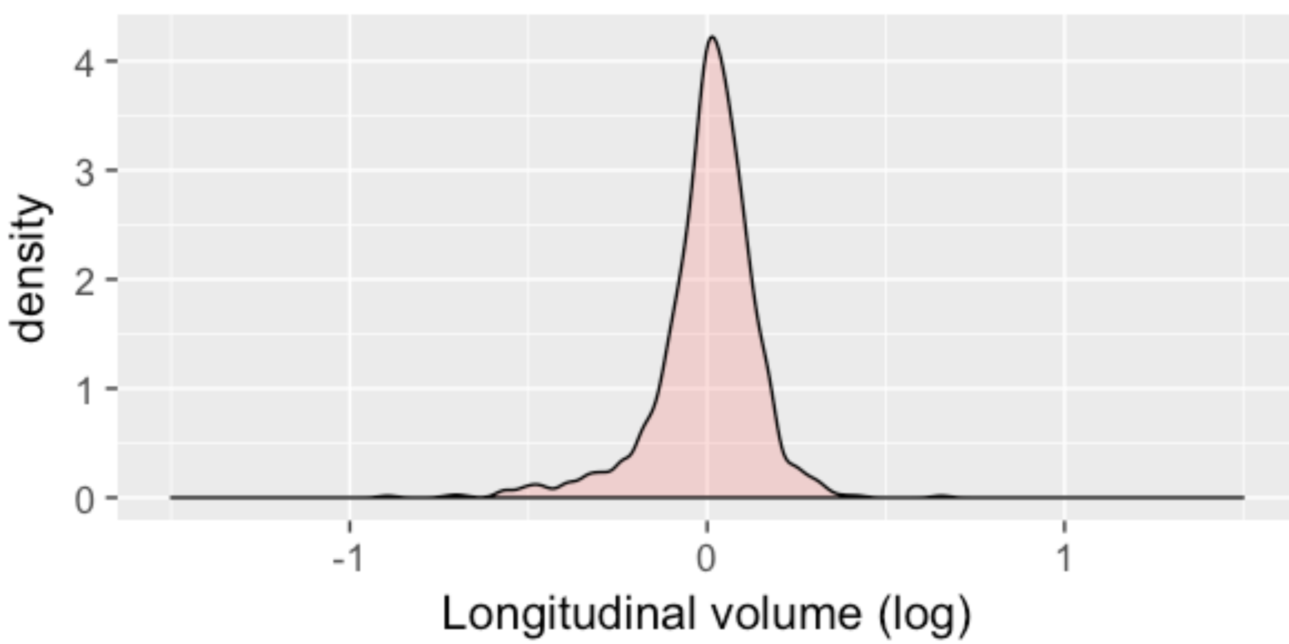
- Captures change in utilization

Volume decomposition

- Volume in hospital *h*, service-line *s*, year *t* : $VolEmergFS_{hst}$
- Average volume in hospital *h*, service-line *s* : $\mu(VolEmergFS)_{hs}$

Longitudinal volume

(Emergency orthopedics)

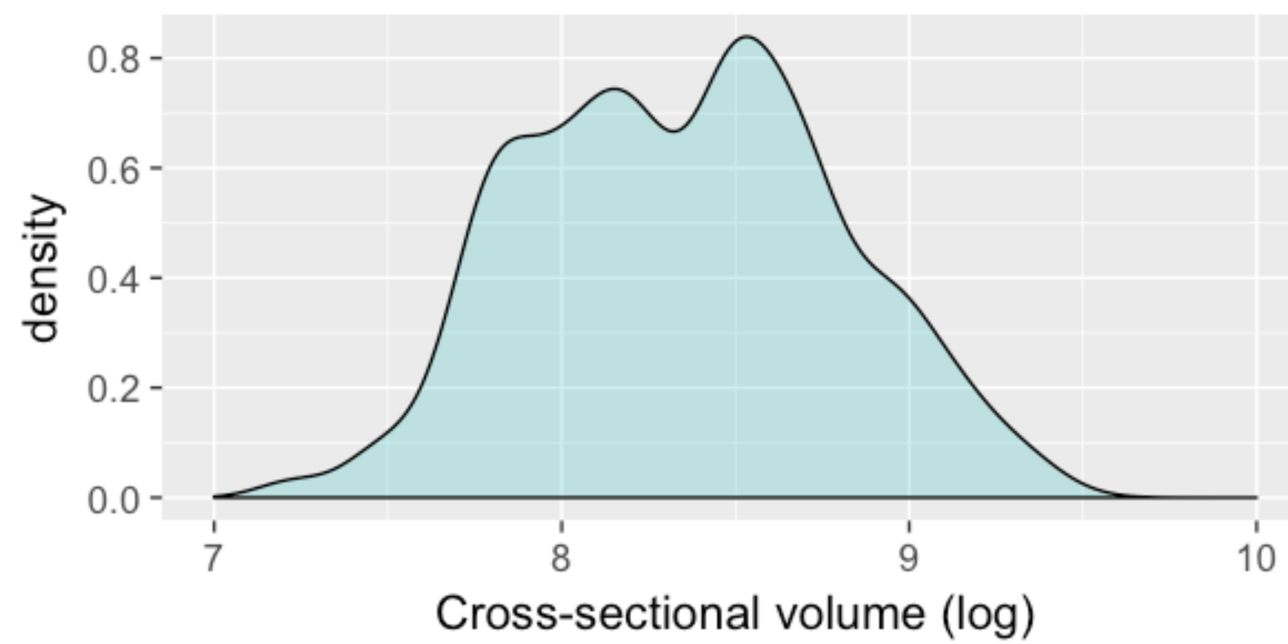


$VolEmergFS_{hst} - \mu(VolEmergFS)_{hs}$

- Captures change in utilization

Cross-sectional volume

(Emergency orthopedics)



$\mu(VolEmergFS)_{hs}$

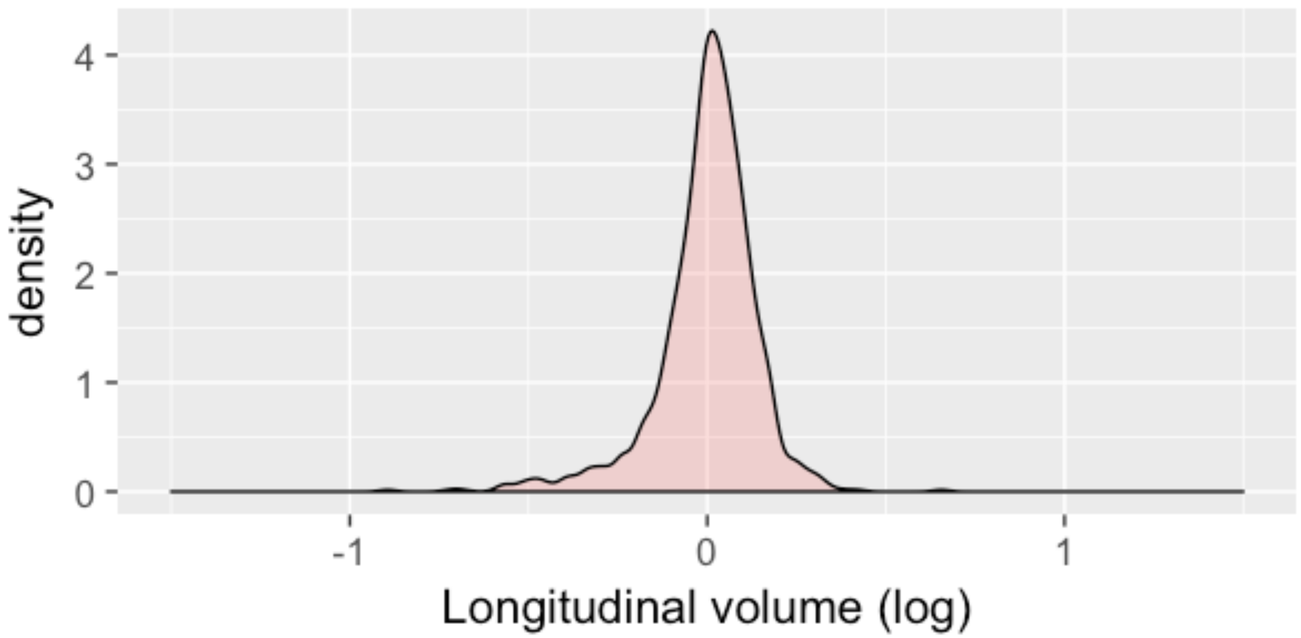
- Captures structural variation

Volume decomposition

- Volume in hospital *h*, service-line *s*, year *t* : $VolEmergFS_{hst}$
- Average volume in hospital *h*, service-line *s* : $\mu(VolEmergFS)_{hs}$

Longitudinal volume

(Emergency orthopedics)

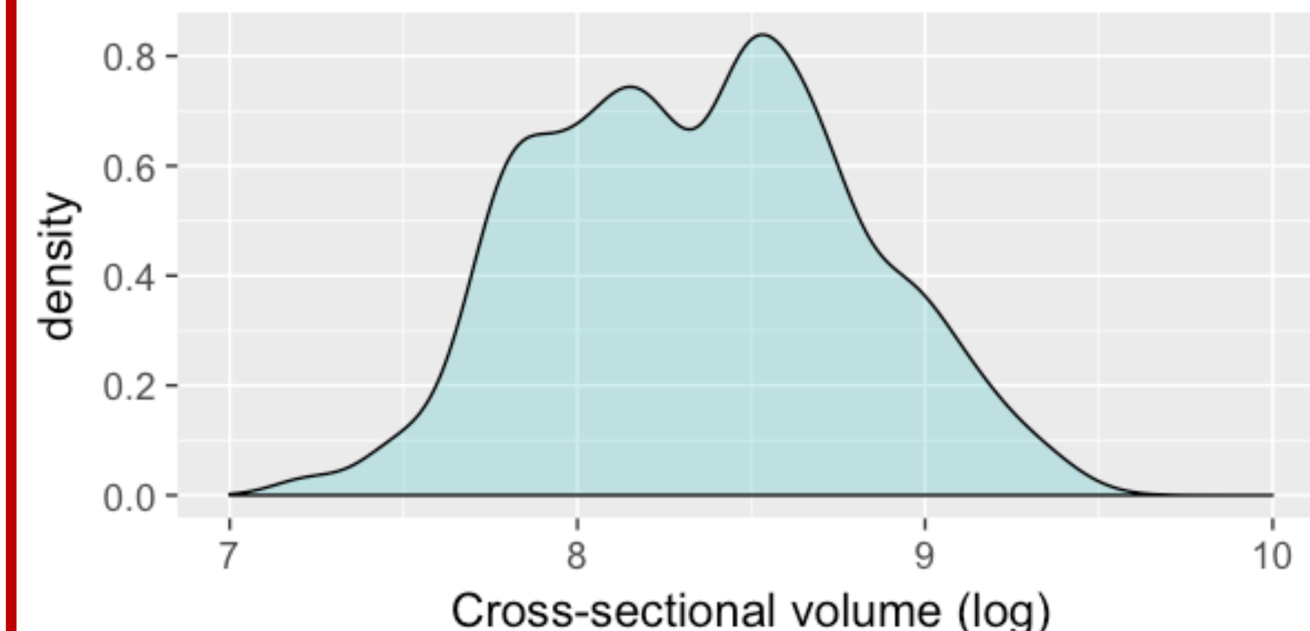


$VolEmergFS_{hst} - \mu(VolEmergFS)_{hs}$

- Captures change in utilization

Cross-sectional volume

(Emergency orthopedics)



$\mu(VolEmergFS)_{hs}$

- Captures structural variation

Main effect of interest

Methods

We use

- Dependent variable: **Costs** — emergency and elective
  ✓ - Within service-line case-mix adjustment
  ✓ - Across service-line normalization

- Independent variables: **Volumes**
  ✓ - Four effects: scale, type-scope, service-scope, other-scope
  ✓ - Within-between volume decomposition *(Mundlak 1978)*

- Econometric model
  - Multi-level (hierarchical) model *(Gelman & Hill 2007)*

Multi-level (hierarchical) model

$$EmergCost_{hst} = \alpha_{hs} + (Hosp)_h + (Service)_s + (Yr)_t + (HospYr)_{ht} + (ServiceYr)_{st} +$$
$$\gamma_1 VolEmergFS^{Lgt}_{hst} + \gamma_2 VolElectFS^{Lgt}_{hst} +$$
$$\gamma_3 VolEmergOS^{Lgt}_{hst} + \gamma_4 VolElectOS^{Lgt}_{hst} +$$
$$\vec{\alpha_5} Controls_{hst} + \delta_{hst}$$

[controls]

[scale] **[type-scope]**

where $$\alpha_{hs} = \alpha_0 + \alpha_1 VolEmergFS^{Cross}_{hs} + \alpha_2 VolElectFS^{Cross}_{hs} +$$
$$\alpha_3 VolEmergOS^{Cross}_{hs} + \alpha_4 VolElectOS^{Cross}_{hs} + \nu_{hs}$$

[service-scope] **[other-scope]**

with $$\delta_{hst} \sim \mathcal{N}(0, \sigma^2_\delta)$$
$$\nu_{hs} \sim \mathcal{N}(0, \sigma^2_\nu)$$

Legend:

FS *= Focal service-line*

OS *= Other service-lines*

Multi-level (hierarchical) model

[random intercept]

$$EmergCost_{hst} = \alpha_{hs} + (Hosp)_h + (Service)_s + (Yr)_t + (HospYr)_{ht} + (ServiceYr)_{st} +$$
$$\gamma_1 VolEmergFS^{Lgt}_{hst} + \gamma_2 VolElectFS^{Lgt}_{hst} +$$
$$\gamma_3 VolEmergOS^{Lgt}_{hst} + \gamma_4 VolElectOS^{Lgt}_{hst} +$$
$$\vec{\alpha_5} Controls_{hst} + \delta_{hst}$$

[controls]

[scale] **[type-scope]**

where $$\alpha_{hs} = \alpha_0 + \alpha_1 VolEmergFS^{Cross}_{hs} + \alpha_2 VolElectFS^{Cross}_{hs} +$$
$$\alpha_3 VolEmergOS^{Cross}_{hs} + \alpha_4 VolElectOS^{Cross}_{hs} + \nu_{hs}$$

[service-scope] **[other-scope]**

with $$\delta_{hst} \sim \mathcal{N}(0, \sigma^2_\delta)$$
$$\nu_{hs} \sim \mathcal{N}(0, \sigma^2_\nu)$$

Legend:

FS *= Focal service-line*

OS *= Other service-lines*

Multi-level (hierarchical) model

[random intercept]

$$
\begin{aligned}
EmergCost_{hst} = \alpha_{hs} &+ (Hosp)_h + (Service)_s + (Yr)_t + (HospYr)_{ht} + (ServiceYr)_{st} + \\
&\gamma_1 VolEmergFS^{Lgt}_{hst} + \gamma_2 VolElectFS^{Lgt}_{hst} + \\
&\gamma_3 VolEmergOS^{Lgt}_{hst} + \gamma_4 VolElectOS^{Lgt}_{hst} + \\
&\vec{\alpha_5} Controls_{hst} + \delta_{hst}
\end{aligned}
$$

[controls]

[scale] **[type-scope]**

where

$$
\begin{aligned}
\alpha_{hs} = \alpha_0 &+ \alpha_1 VolEmergFS^{Cross}_{hs} + \alpha_2 VolElectFS^{Cross}_{hs} + \\
&\alpha_3 VolEmergOS^{Cross}_{hs} + \alpha_4 VolElectOS^{Cross}_{hs} + \nu_{hs}
\end{aligned}
$$

[service-scope] **[other-scope]**

with

$$\delta_{hst} \sim \mathcal{N}(0, \sigma^2_\delta)$$

$$\nu_{hs} \sim \mathcal{N}(0, \sigma^2_\nu)$$

Models correlation in cost over time within the same hospital—service-line

Legend:

***FS** = Focal service-line*

***OS** = Other service-lines*

Multi-level (hierarchical) model

[random intercept]

$$EmergCost_{hst} = \alpha_{hs} + (Hosp)_h + (Service)_s + (Yr)_t + (HospYr)_{ht} + (ServiceYr)_{st} +$$
$$\gamma_1 VolEmergFS^{Lgt}_{hst} + \gamma_2 VolElectFS^{Lgt}_{hst} +$$
$$\gamma_3 VolEmergOS^{Lgt}_{hst} + \gamma_4 VolElectOS^{Lgt}_{hst} +$$
$$\vec{\alpha_5} Controls_{hst} + \delta_{hst}$$

[controls]

[scale] **[type-scope]**

where $$\alpha_{hs} = \alpha_0 + \alpha_1 VolEmergFS^{Cross}_{hs} + \alpha_2 VolElectFS^{Cross}_{hs} +$$
$$\alpha_3 VolEmergOS^{Cross}_{hs} + \alpha_4 VolElectOS^{Cross}_{hs} + \nu_{hs}$$

[service-scope] **[other-scope]**

with $$\delta_{hst} \sim \mathcal{N}(0, \sigma^2_\delta)$$
$$\nu_{hs} \sim \mathcal{N}(0, \sigma^2_\nu)$$

Models correlation in cost over time within the same hospital—service-line

<u>Legend:</u>

***FS** = Focal service-line*

***OS** = Other service-lines*

- Adjustment: take *ln()* of the cost and volume effects to reduce skewness

Recap: research questions

Integrated model

Focused model

Do costs reduce with increased volume of patients:

[scale]	of the same type and from the same service-line?
[type-scope]	of the other type and from the same service-line?
[service-scope]	of the same type and from the other service-lines?
[other-scope]	of the other type and from the other service-lines?

Do effects depend on whether the focal patient type is emergency or elective?

Results: coefficient estimates

Log-log model interpretation:

- every doubling in the volume of patients from the corresponding row results in an ~x% change in costs / length-of-stay

	Costs		LOS	
	Elective	Emergency	Elective	Emergency
Elect. vol. (focal SL)	-0.057^{***}	0.020^{***}	-0.022^{***}	0.006^{*}
	(0.009)	(0.004)	(0.004)	(0.003)
Emerg. vol. (focal SL)	0.007	-0.121^{***}	0.021^{***}	-0.081^{***}
	(0.014)	(0.011)	(0.006)	(0.008)
Elect. vol. (other SLs)	0.043	0.135^{***}	-0.005	0.069^{**}
	(0.030)	(0.028)	(0.014)	(0.026)
Emerg. vol. (other SLs)	-0.008	-0.099^{**}	0.015	$-0.052^{\dagger}$
	(0.034)	(0.031)	(0.015)	(0.028)

Results: economies of scale **[scale]**

Marginal effects at the mean:

- a 1,000 patient increase in the number of admissions p.a. to the "average" hospital results in an ~x% change in costs / length-of-stay

	Costs		Length-of-stay		"average" hospital
	Elective	Emergency	Elective	Emergency	
Cross-sectional effects					
Elect. vol. (focal SL)	-0.022^{***}	0.008^{***}	-0.008^{***}	0.002^{*}	2,640 p.a.
Emerg. vol. (focal SL)	0.002	-0.040^{***}	0.007^{***}	-0.027^{***}	2,990 p.a.
Elect. vol. (other SLs)	0.001	0.004^{***}	−0.000	0.002^{**}	38,210 p.a.
Emerg. vol. (other SLs)	−0.000	-0.002^{**}	0.000	$-0.001^{\dagger}$	51,540 p.a.
Model fit					
Observations	15,339	15,354	15,339	15,354	
Conditional R^2	0.513	0.623	0.463	0.739	

$^{\dagger}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Results: economies of scope **[type-scope]**

***Marginal effects at the mean*:**

- a 1,000 patient increase in the number of admissions p.a. to the "average" hospital results in an ~x% change in costs / length-of-stay

	Costs		Length-of-stay		"average" hospital
	Elective	Emergency	Elective	Emergency	
Cross-sectional effects					
Elect. vol. (focal SL)	-0.022^{***}	0.008^{***}	-0.008^{***}	0.002^{*}	2,640 p.a.
Emerg. vol. (focal SL)	0.002	-0.040^{***}	0.007^{***}	-0.027^{***}	2,990 p.a.
Elect. vol. (other SLs)	0.001	0.004^{***}	-0.000	0.002^{**}	38,210 p.a.
Emerg. vol. (other SLs)	-0.000	-0.002^{**}	0.000	$-0.001^{\dagger}$	51,540 p.a.
Model fit					
Observations	15,339	15,354	15,339	15,354	
Conditional R^2	0.513	0.623	0.463	0.739	

$^{\dagger}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Results: economies of scope **[service-scope]**

***Marginal effects at the mean*:**

- a 1,000 patient increase in the number of admissions p.a. to the "average" hospital results in an ~x% change in costs / length-of-stay

	Costs		Length-of-stay		"average" hospital
	Elective	Emergency	Elective	Emergency	
Cross-sectional effects					
Elect. vol. (focal SL)	-0.022^{***}	0.008^{***}	-0.008^{***}	0.002^{*}	2,640 p.a.
Emerg. vol. (focal SL)	0.002	-0.040^{***}	0.007^{***}	-0.027^{***}	2,990 p.a.
Elect. vol. (other SLs)	0.001	0.004^{***}	-0.000	0.002^{**}	38,210 p.a.
Emerg. vol. (other SLs)	-0.000	-0.002^{**}	0.000	$-0.001^{\dagger}$	51,540 p.a.
Model fit					
Observations	15,339	15,354	15,339	15,354	
Conditional R^2	0.513	0.623	0.463	0.739	

$^{\dagger}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Results: economies of scope **[other-scope]**

***Marginal effects at the mean*:**

- a 1,000 patient increase in the number of admissions p.a. to the "average" hospital results in an ~x% change in costs / length-of-stay

	Costs		Length-of-stay		"average" hospital
	Elective	Emergency	Elective	Emergency	
Cross-sectional effects					
Elect. vol. (focal SL)	-0.022^{***}	0.008^{***}	-0.008^{***}	0.002^{*}	2,640 p.a.
Emerg. vol. (focal SL)	0.002	-0.040^{***}	0.007^{***}	-0.027^{***}	2,990 p.a.
Elect. vol. (other SLs)	0.001	0.004^{***}	-0.000	0.002^{**}	38,210 p.a.
Emerg. vol. (other SLs)	-0.000	-0.002^{**}	0.000	$-0.001^{\dagger}$	51,540 p.a.
Model fit					
Observations	15,339	15,354	15,339	15,354	
Conditional R^2	0.513	0.623	0.463	0.739	

$^{\dagger}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Endogeneity concerns

- **Reverse causality**: more productive hospitals may be referred a higher volume of patients (or patients may self select)
  - Health services in the UK are free at the point of care ⇒ little incentive
  - Little evidence that patients or physicians exercise such choice, or even account for quality (Gaynor et al. 2004; Gowrisankaran et al. 2006)
    - *Recent survey: only half of patients in UK offered choice of hospital, 70% chose nearest provider (Dixon et al. 2010)*
  - Re-run analysis on geographically isolated hospitals (for which travel to another provider more inconvenient for patients): no reduction in effect size on this subsample
- **Endogeneous service-line formation**: hospitals may choose to offer a subset of elective services, selecting only the most profitable.
  - If this were the case, lower volume hospitals would be more productive (we find the opposite)
  - Re-run analysis on only hospitals that treat >90% of HRGs, no change in results
- *Little concern for endogeneity associated with emergency volume effects, since emergency activity is largely exogenous*

Other robustness checks

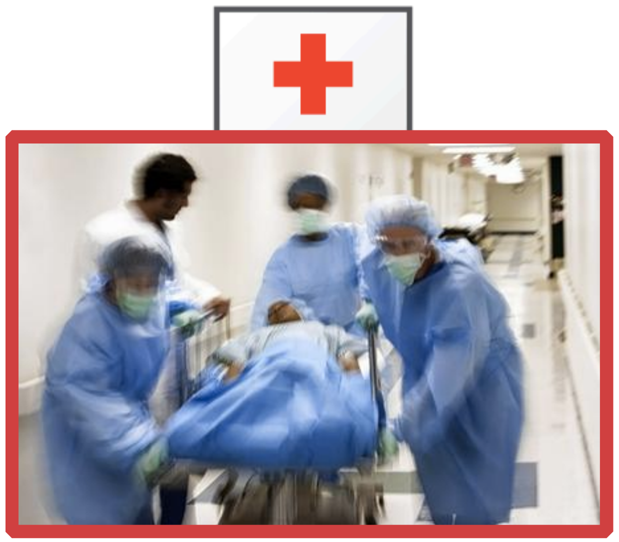
- Cost accounting issues: repeated analysis using length of stay data
- Autocorrelated errors: no evidence
- Non-linear volume effects: no evidence (*log*-*log* formulation already captures diminishing returns to scale/scope)
- Influence of cost outliers: cap extreme costs and re-estimate, consistent
- Rare conditions: re-estimate for set of most common conditions, consistent
- Outliers/Limited service: re-estimate for high volume hospitals (e.g. >.25 median)

Implications

- Pooling electives and emergencies increases cost of emergencies

Implications

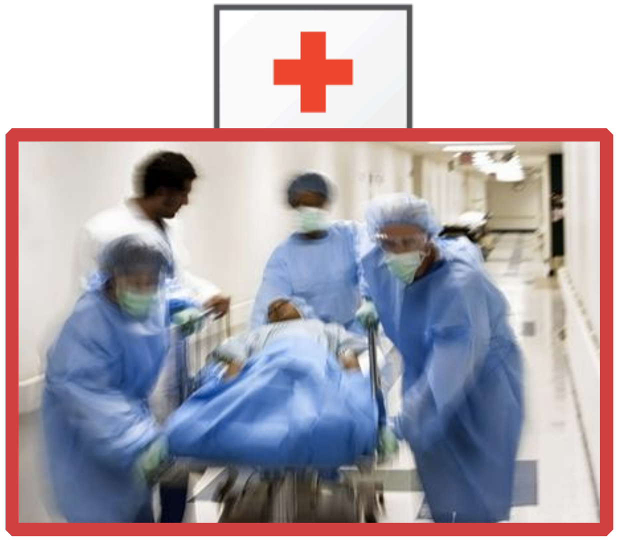
- Pooling electives and emergencies increases cost of emergencies



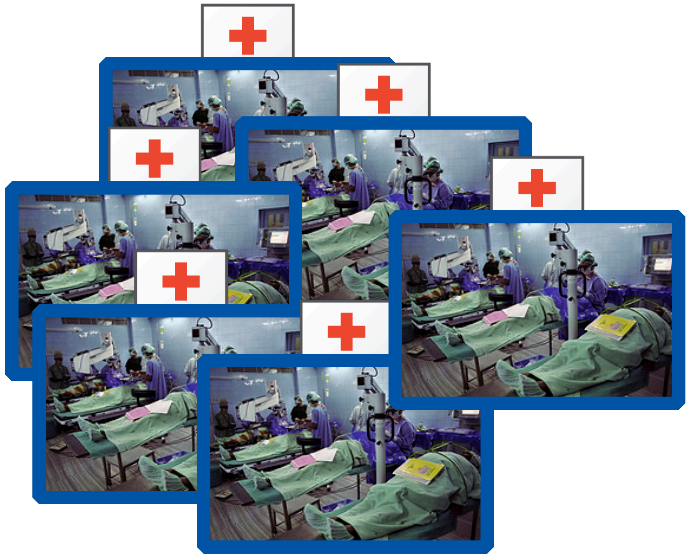
- Pooling service-lines within emergencies reduces costs of emergencies

Implications

- Pooling electives and emergencies increases cost of emergencies



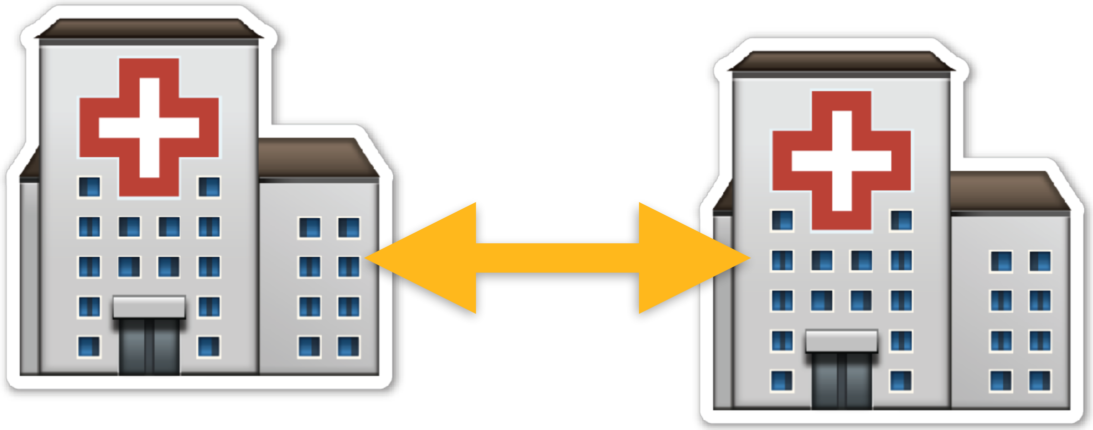
- Pooling service-lines within emergencies reduces costs of emergencies



- No evidence that pooling service-lines within electives has an effect on cost of electives
- Costs reduced from operating focused elective hospitals at high volume

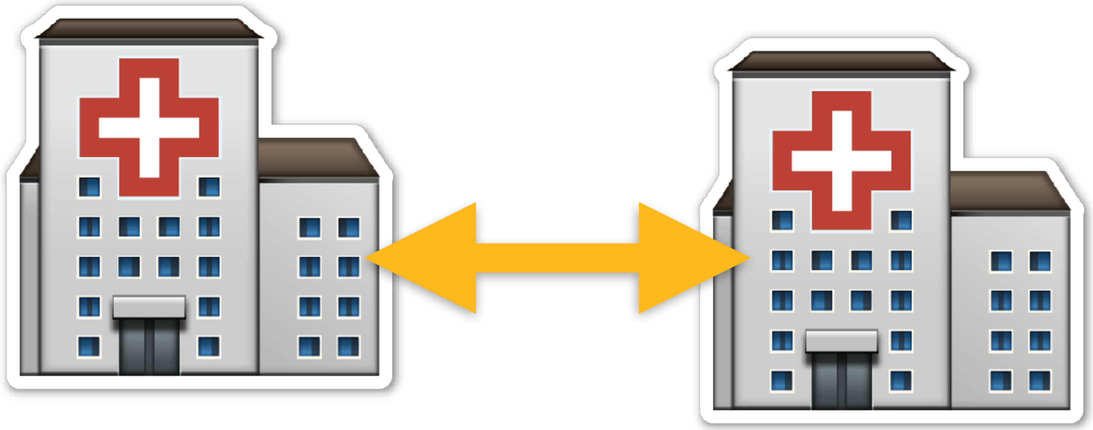
Counterfactual: Potential cost savings

- If pairs of hospitals in London split elective service-lines then:
    - Cost reduction of ~4%, saving **£300m+** over sample period
    - Limits need for new capacity

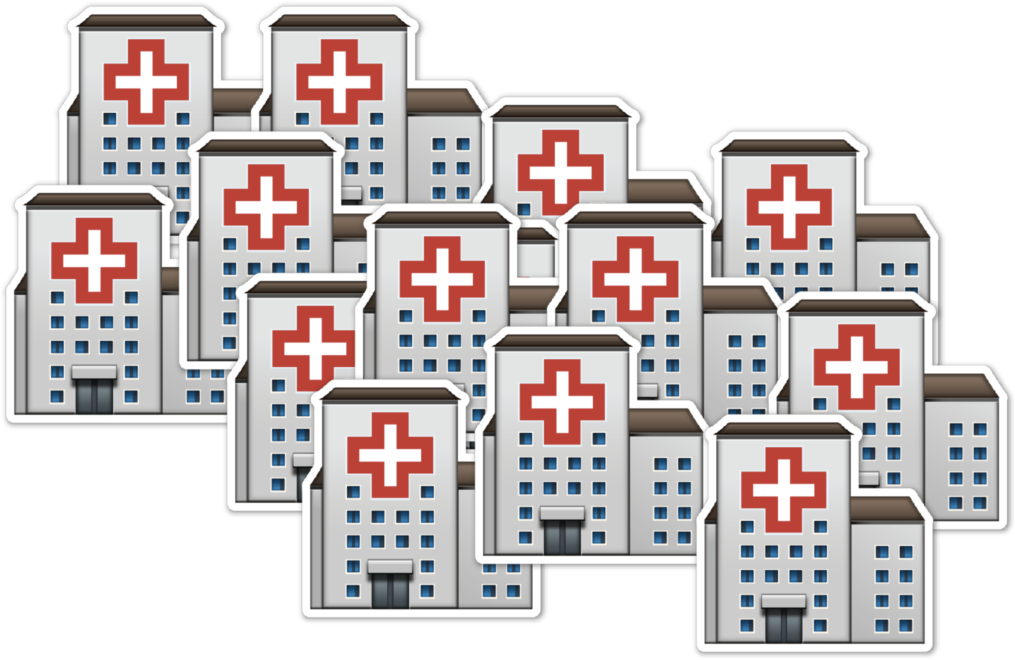


Counterfactual: Potential cost savings

- If pairs of hospitals in London split elective service-lines then:
    - Cost reduction of ~4%, saving **£300m+** over sample period
    - Limits need for new capacity



- Establishing one "focused" specialist hospital for each service-line:
    - Cost reduction of ~15%, saving nearly **£1.2bn** over sample period
    - Plus cost savings for the leftover emergency activity in other hospitals



Summary

Find support for a new hospital business model that separates activity into:

Integrated emergency hospitals

- High volume;
- High complexity, customized;
- Multi-specialty;
- Mainly emergency care

Specialist hospitals for elective care

- High volume;
- Standardizable;
- Specialty-specific;
- Mainly elective care

Summary

Find support for a new hospital business model that separates activity into:

Integrated emergency hospitals

- High volume;
- High complexity, customized;
- Multi-specialty;
- Mainly emergency care

Specialist hospitals for elective care

- High volume;
- Standardizable;
- Specialty-specific;
- Mainly elective care

- Evidence suggests there may also be quality benefits *(e.g. Kuntz et al. 2016)*

Thank you!

Questions?

Appendix

Full results

	Costs		LOS	
	Elective	Emergency	Elective	Emergency
Within-effects				
Elect. vol. (focal SL)	-0.117^{***}	0.007	-0.062^{***}	0.001
	(0.007)	(0.004)	(0.003)	(0.003)
Emerg. vol. (focal SL)	-0.011	-0.162^{***}	$0.010^{\dagger}$	-0.083^{***}
	(0.012)	(0.008)	(0.006)	(0.005)
Elect. vol. (other SLs)	-0.129^{***}	0.070^{*}	-0.039^{*}	0.114^{***}
	(0.031)	(0.029)	(0.016)	(0.027)
Emerg. vol. (other SLs)	0.049	-0.162^{***}	$0.027^{\dagger}$	-0.117^{***}
	(0.032)	(0.031)	(0.016)	(0.029)
Between-effects				
Elect. vol. (focal SL)	-0.057^{***}	0.020^{***}	-0.022^{***}	0.006^{*}
	(0.009)	(0.004)	(0.004)	(0.003)
Emerg. vol. (focal SL)	0.007	-0.121^{***}	0.021^{***}	-0.081^{***}
	(0.014)	(0.011)	(0.006)	(0.008)
Elect. vol. (other SLs)	0.043	0.135^{***}	-0.005	0.069^{**}
	(0.030)	(0.028)	(0.014)	(0.026)
Emerg. vol. (other SLs)	-0.008	-0.099^{**}	0.015	$-0.052^{\dagger}$
	(0.034)	(0.031)	(0.015)	(0.028)
Control structure				
Year	Y	Y	Y	Y
Service line	Y	Y	Y	Y
Hospital	0.072	0.076	0.031	0.073
Hospital:Service line	0.153	0.094	0.065	0.070
Hospital:Year	0.034	0.016	0.020	0.011
Service line:Year	0.080	0.088	0.041	0.092
Residual std. error	0.206	0.138	0.105	0.087
Model fit				
Observations	15,339	15,354	15,339	15,354
Marginal R^2	0.096	0.179	0.107	0.100
Conditional R^2	0.513	0.623	0.463	0.739
Bayesian inf. crit.	481.0	-11,166.4	-20,650.8	-23,870.5

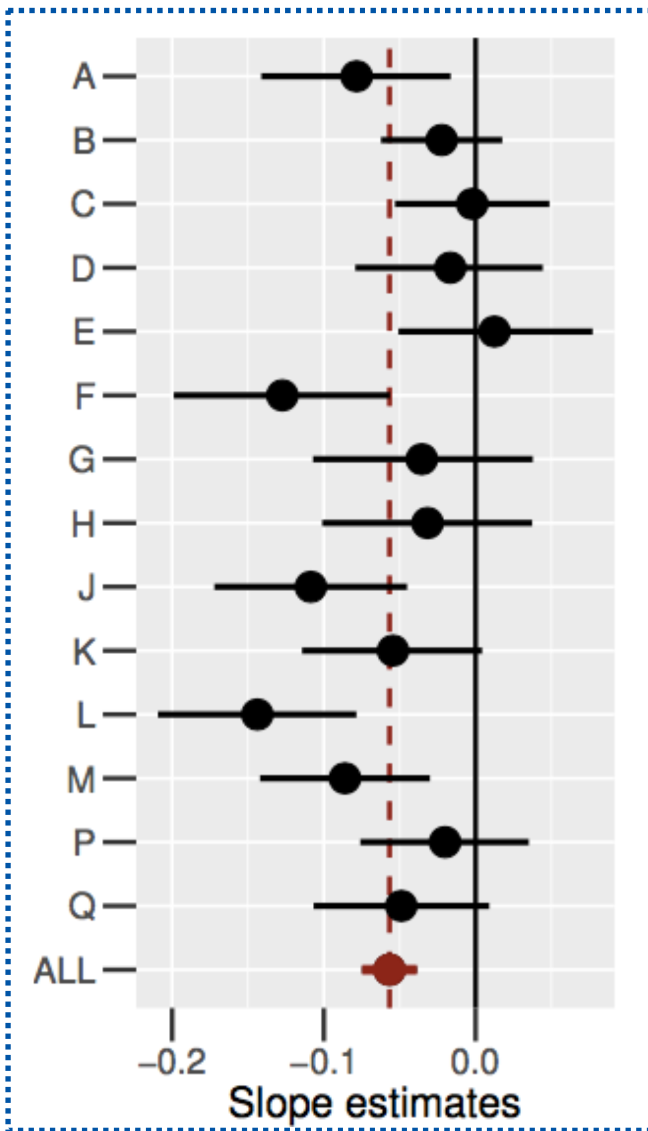
Appendix
Service-line dependency

Service-line dependency of scale effects

- Scale effects consistent in <u>direction</u> and similar in <u>scale</u> *across* service-lines

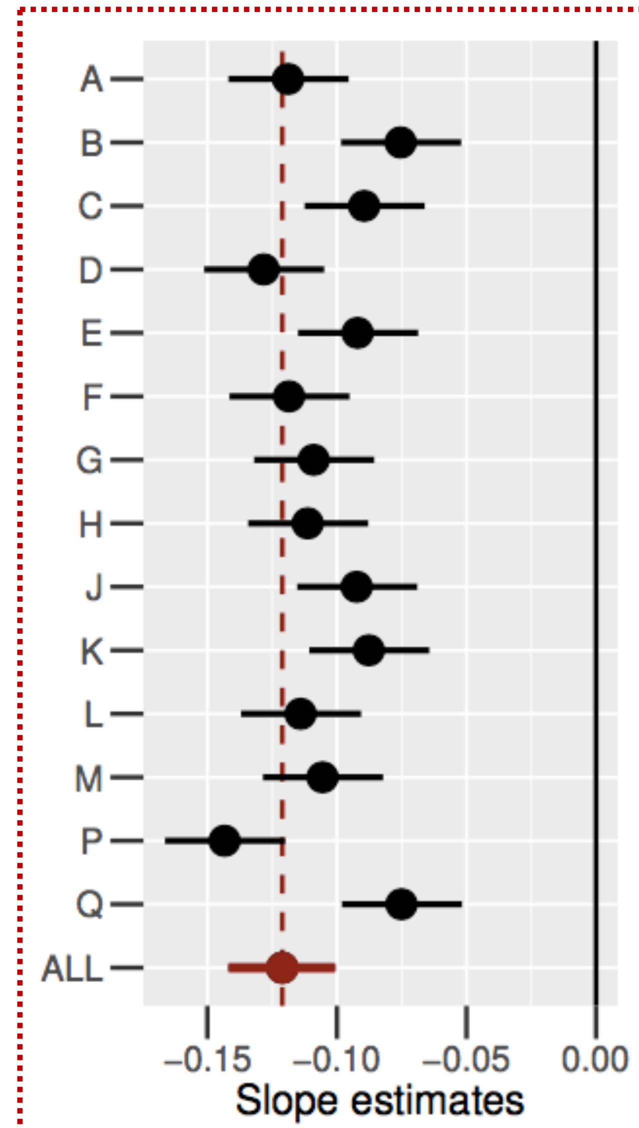
[scale]

Focal elective service-line



[scale]

Focal emergency service-line

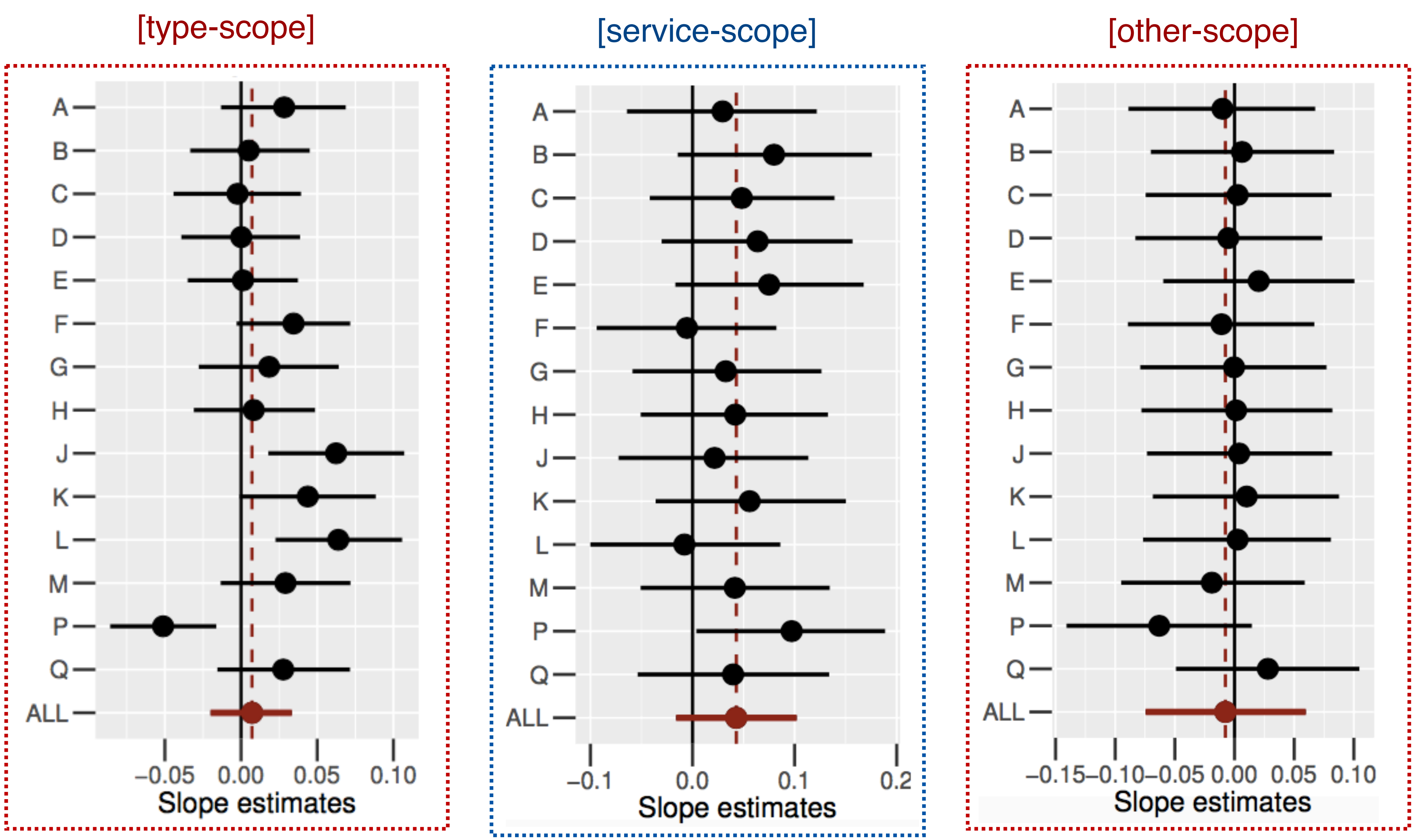


Note. A – nervous system; B – eyes and periorbita; C – mouth, head, neck, and ears; D – respiratory system; E – cardiac surgery and primary cardiac conditions; F – digestive system; G – hepatobiliary and pancreatic system; H – musculoskeletal system; J – skin, breast and burns; K – endocrine and metabolic system; L – urinary tract and male reproductive system; M – female reproductive system; P – diseases of childhood and neonates; Q – vascular system.

Electives: Service-line dependency of scope effects

- Scope effects consistent in <u>direction</u> and similar in <u>scale</u> *across* service-lines

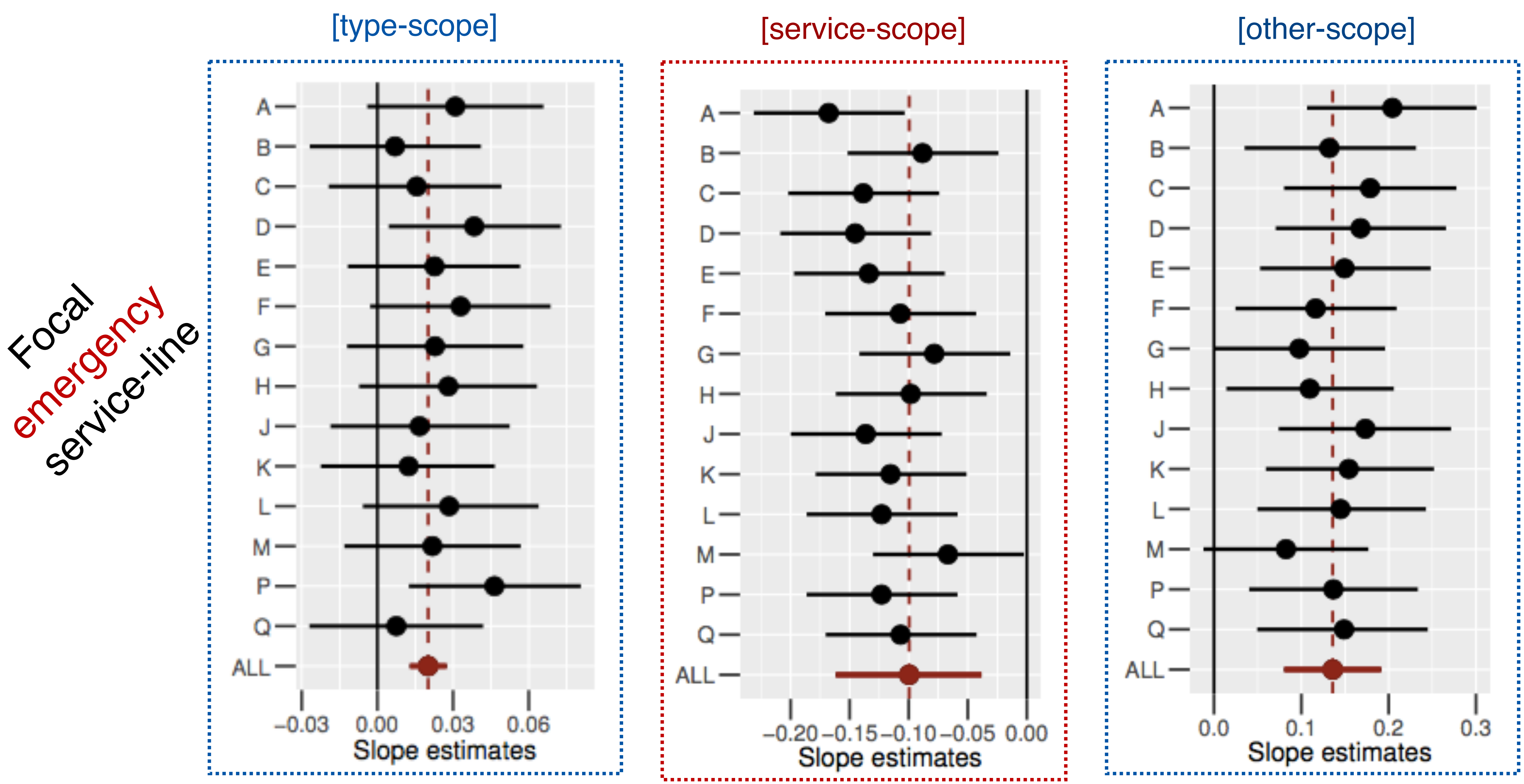
Focal elective service-line



Note. A – nervous system; B – eyes and periorbita; C – mouth, head, neck, and ears; D – respiratory system; E – cardiac surgery and primary cardiac conditions; F – digestive system; G – hepatobiliary and pancreatic system; H – musculoskeletal system; J – skin, breast and burns; K – endocrine and metabolic system; L – urinary tract and male reproductive system; M – female reproductive system; P – diseases of childhood and neonates; Q – vascular system.

Emergencies: Service-line dependency of scope effects

- Scope effects consistent in <u>direction</u> and similar in <u>scale</u> *across* service-lines



Note. A – nervous system; B – eyes and periorbita; C – mouth, head, neck, and ears; D – respiratory system; E – cardiac surgery and primary cardiac conditions; F – digestive system; G – hepatobiliary and pancreatic system; H – musculoskeletal system; J – skin, breast and burns; K – endocrine and metabolic system; L – urinary tract and male reproductive system; M – female reproductive system; P – diseases of childhood and neonates; Q – vascular system.

Appendix

Multi-level modeling

Why a MLM?

MLM estimator

$$y_{it} = \alpha_i + \beta(x_{it} - \bar{x}_i) + \epsilon_{it} \quad \text{where} \quad \alpha_i = \alpha_0 + \gamma\bar{x}_i + \nu_i \;\; \text{and} \;\; \nu_i \sim \mathcal{N}(0, \sigma_\nu^2)$$

longitudinal effect

cross-sectional effect

Fixed effects estimator

$$\begin{aligned} y_{it} &= \alpha_i + \beta x_{it} + \epsilon_{it} \\ (y_{it} - \bar{y}_i) &= \beta(x_{it} - \bar{x}_i) + \epsilon_{it} \\ y_{it} &= \bar{y}_i + \beta(x_{it} - \bar{x}_i) + \epsilon_{it} \end{aligned}$$

longitudinal effect

Random effects estimator

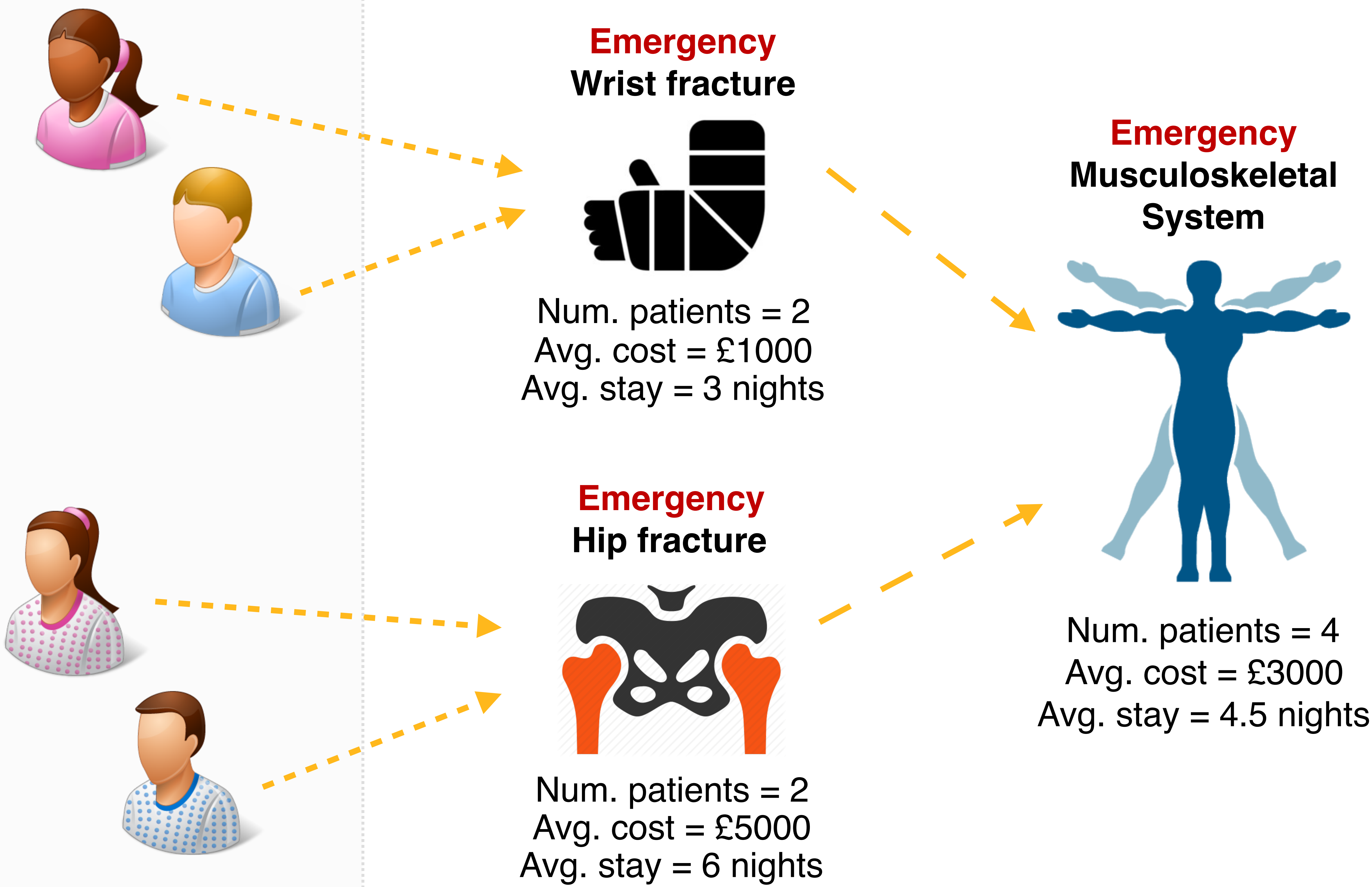
$$\begin{aligned} & y_{it} = \alpha_i + \beta x_{it} + \epsilon_{it} \\ \text{where} \quad & \alpha_i = \alpha_0 + \nu_i \\ \text{and} \quad & \nu_i \sim \mathcal{N}(0, \sigma_\nu^2) \end{aligned}$$

longitudinal & cross-sectional effect

Appendix

Case-mix adjustment

Example of data aggregation process



Within service-line case-mix confounding

Hospital A

Num. patients = **2**
Avg. cost = £1000

Num. patients = **2**
Avg. cost = £5000

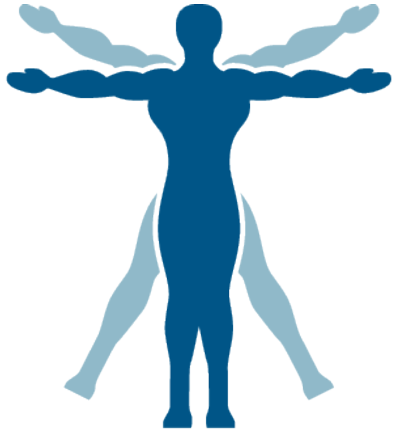
Num. patients = 4
Avg. cost = **£3000**

Within service-line case-mix confounding

Hospital A

Num. patients = **2**
Avg. cost = £1000

Num. patients = **2**
Avg. cost = £5000

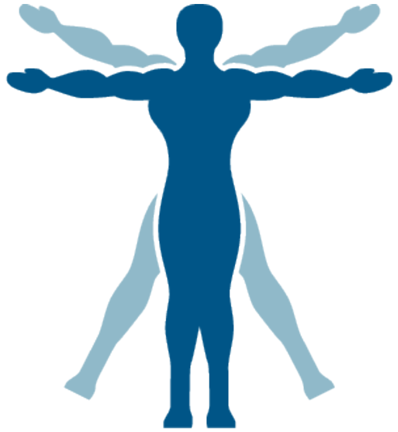


Num. patients = 4
Avg. cost = **£3000**

Hospital B

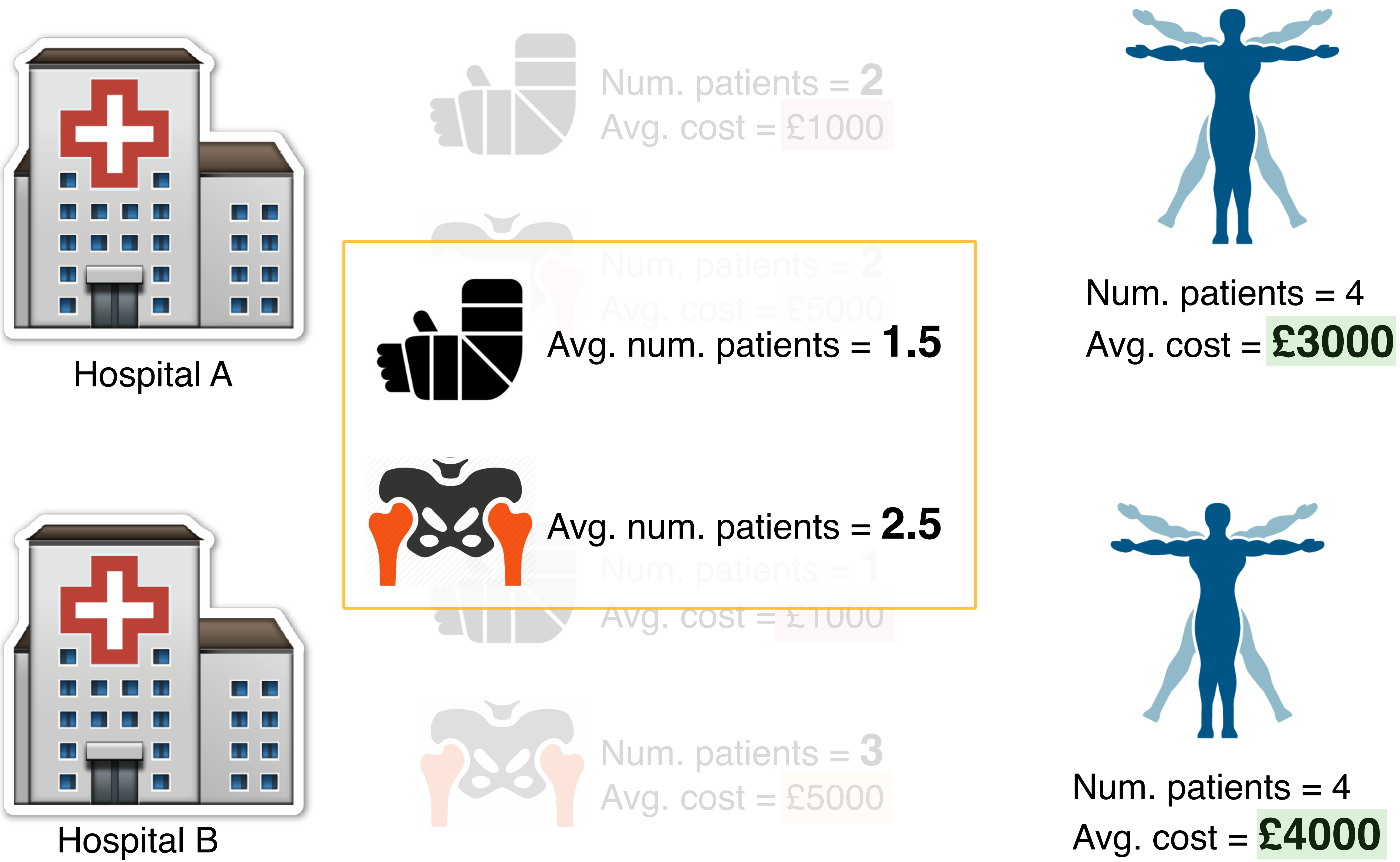
Num. patients = **1**
Avg. cost = £1000

Num. patients = **3**
Avg. cost = £5000



Num. patients = 4
Avg. cost = **£4000**

Within service-line case-mix confounding

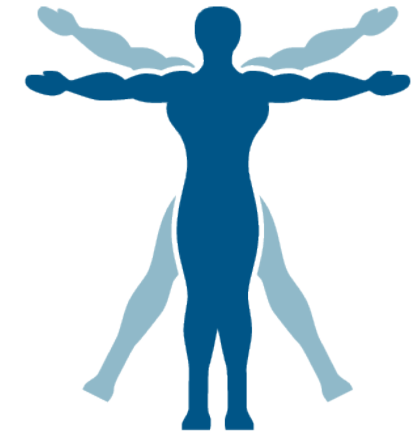


Cost of treating an “average” patient

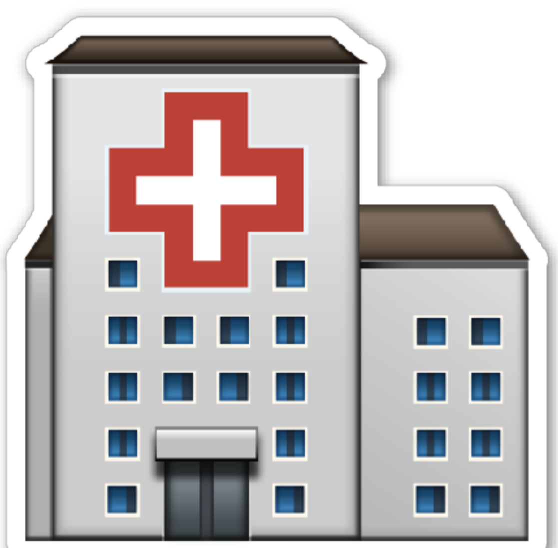
Hospital A

Avg. num. patients = **1.5**
Avg. cost = £1000

Avg. num. patients = **2.5**
Avg. cost = £5000



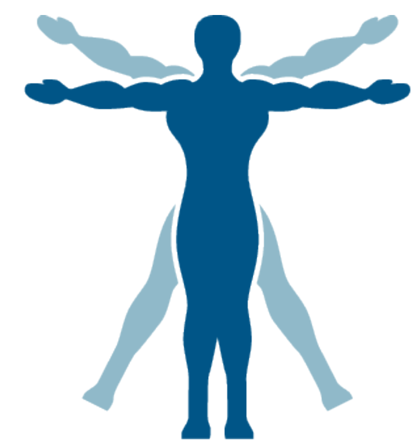
Num. patients = 4
Avg. cost = **£3500**



Hospital B

Avg. num. patients = **1.5**
Avg. cost = £1000

Avg. num. patients = **2.5**
Avg. cost = £5000



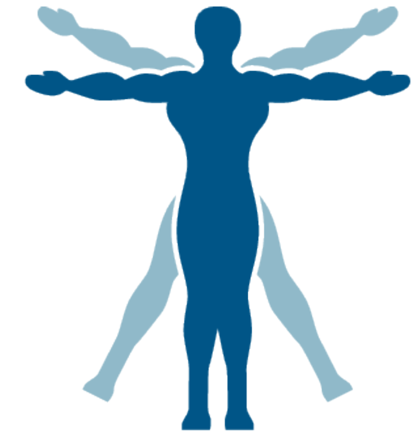
Num. patients = 4
Avg. cost = **£3500**

Cost of treating an “average” patient

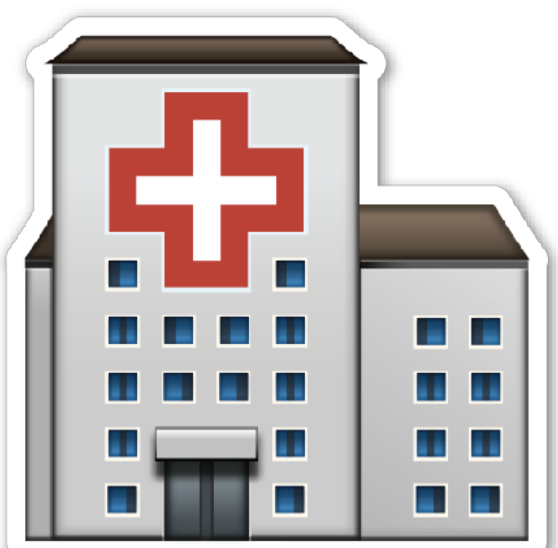
Hospital A

Avg. num. patients = **1.5**
Avg. cost = £1000

Avg. num. patients = **2.5**
Avg. cost = £5000



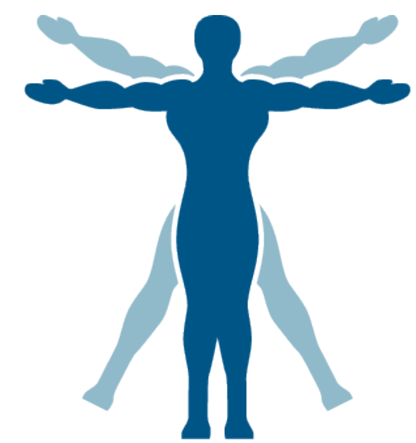
Num. patients = 4
Avg. cost = **£3500**



Hospital B

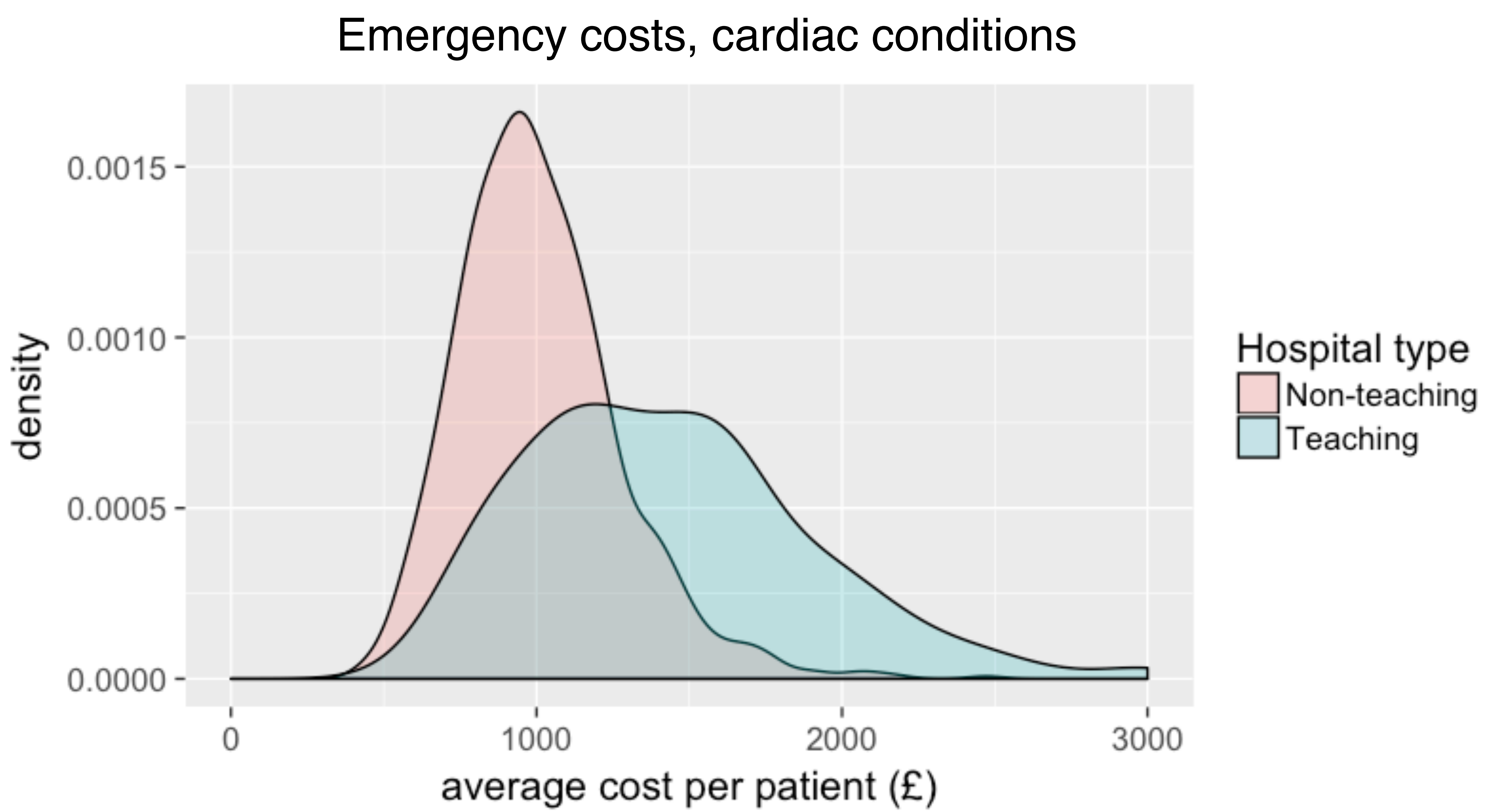
Avg. num. patients = **1.5**
Avg. cost = £1000

Avg. num. patients = **2.5**
Avg. cost = £5000



Num. patients = 4
Avg. cost = **£3500**

Within service-line case-mix confounding in the data



Problem:

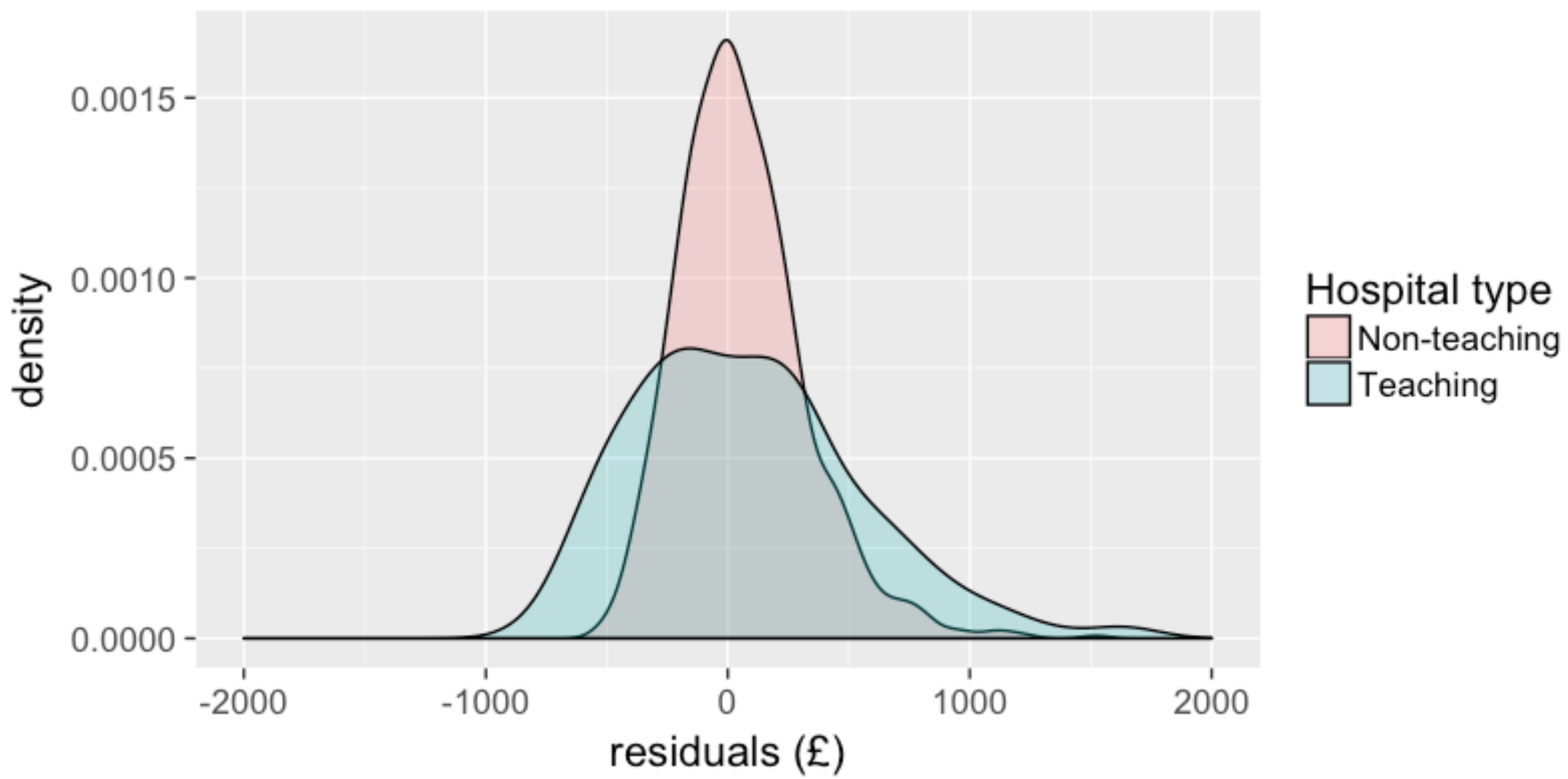
- Teaching hospitals treat more complex mix of patients → higher cost
- Teaching hospitals are also larger → higher volume

spurious relationship

Solution?? Add a fixed-effect to control for average cost differences across hospitals?

Heteroskedastic errors

Emergency residuals, cardiac conditions — w/ hospital type fixed-effect



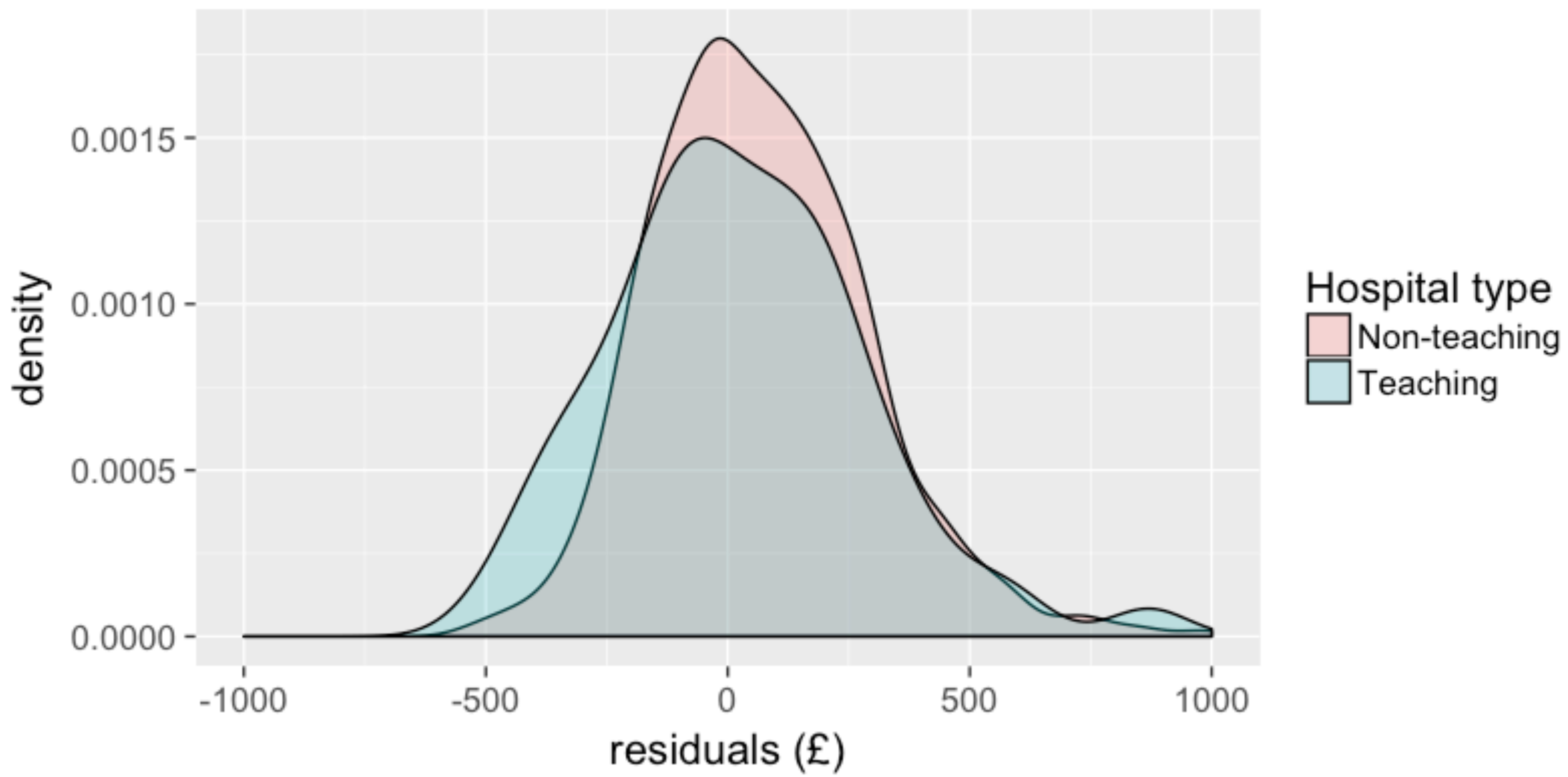
Problem:

- Errors (residuals) are heteroskedastic across hospital types → violation of IID assumption
- If error term is misspecified, can bias model coefficient estimates *(King & Roberts 2014)*

Solution: Case-mix adjust costs to remove within service-line heterogeneity

Homoskedastic errors after case-mix adjustment

Emergency residuals, cardiac conditions —
after case-mix adjustment and w/ hospital type fixed effects



⇒ compare hospitals based on the cost of treating an “average” patient within the specified service-line