# "The use of Hospital Standardised Mortality Ratio (HSMR) in monitoring quality of care: Strengths and weaknesses

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#### Mortality as a performance indicator

#### **WANTED**

A single indicator that can discern good or poor quality of care







#### Mortality as a performance indicator

#### **WANTED**

A single indicator that can discern good or poor quality of care



#### **HAVE**

A tool for surveillance purposes when considered along other information and data









#### Mortality as a quality indicator

- it is unambiguous
- often undesired
- recorded accurately
  - However, most deaths in hospital are neither unexpected nor consequences of sub-optimal care
  - HSMR cannot directly distinguish between inevitable and potential preventable deaths !!!
- HSMR encompasses a wide-range of diagnoses, providing a more expansive insight than metrics based on single diagnoses





#### **HSMR** in brief

Measure for hospital-related mortality based on primary diagnoses leading to 80% of all hospital-related deaths

Overall measure of mortality and thus fundamentally different from disease or procedure specific mortality measures

Large number of deaths, statistically robust

Allows for some variation in coding

By *indirect standardisation* adjusted for diagnosis, age, sex, admission type, comorbidity, marital status, and quarter of admission....



The included diagnoses

80 diagnoses accounted for 80% of hospital related deaths in 2008

ICD code	Description
DJ18	Bronchopneumonia, unspecified organism
DZ03	Medical observation and evaluation for suspected diseases and conditions
DA41	Other septicaemia
DJ96	Respiratory failure, not elsewhere classified
DC34	Malignant neoplasm of bronchus and lung
DS72	Fracture of femur
DE86	Volume depletion
DJ44	Other chronic obstructive pulmonary disease
DI21	Acute myocardial infarction
DI50	Heart failure
DI61	Intracerebral haemorrhage
DI46	Cardiac arrest
DJ15	Bacterial pneumonia, not elsewhere classified
DI64	Stroke, not specified as haemorrhage or infarction
DI63	Cerebral infarction
DC18	Malignant neoplasm of colon



#### **HSMR** in brief

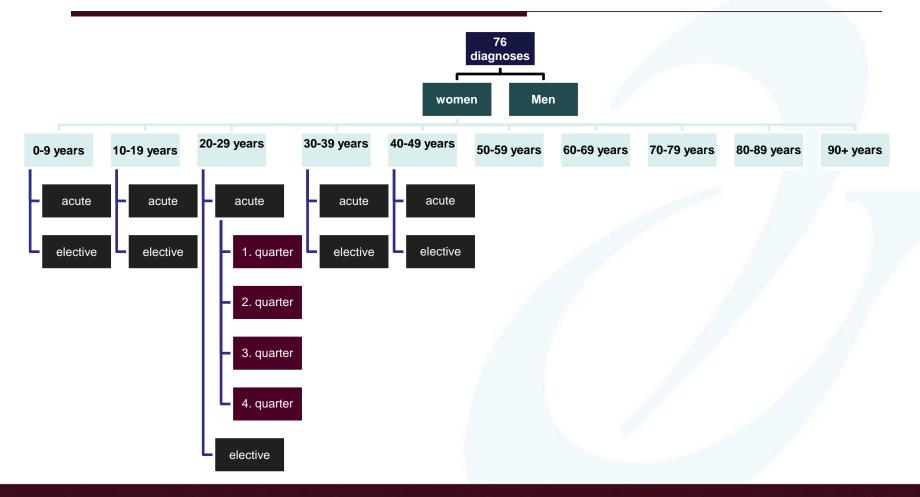
How to find the expected number of deaths?







#### **HSMR** – at first





**HSMR** – at first

For the included diagnoses, we calculated the national mortality:

- number of deaths within 30 days / number of hospitalized patients
- Stratified by age group, sex, mode of hospitalization (acute / elective), quarter of hospitalization

For each region and each hospital, we calculated

#### the expected number of deaths:

number of admissions for each of selected diagnoses in each combination of age, sex, quarter and mode of hospitalization multiplied by the national mortality rate







#### **HSMR** – next

Comorbidity and marital status also included as covariates

- → TOO MANY strata
- Create a model instead (logistic regression):
   p<sub>i</sub> is the risk of dying within 30 days after admission for patient *i*

$$logit(p_i) = log(p_i/(1-p_i)) = l_i,$$

I<sub>i</sub> is depending on patient i's diagnosis, age, sex, mode of hospitalisation, comorbidity, transferral, marital status, and quarter of admission







#### **HSMR** in brief





#### **Indirect standardisation**

#### Limitations

When comparing more than one hospital to the reference rates ("national average") HSMRs are adjusted to different standards



Comparisons of HSMR may thus be inappropriate!!!



# Indirect standardisation

Mortality in reference population: Young: 30% Elderly: 40%

Hospital A: treated 10 young/4 deaths (40%), treated 100 elderly/40 deaths (40%)

Hospital B: treated 100 young/40 deaths (40%), treated 100 elderly/40 deaths (40%)

Mortality in hospital A and B is the same!

Hospital A: Observed number of deaths: 4 + 40 = 44

Expected number of deaths: 3 + 40 = 43

HSMR  $44/43 \times 100 = 102$ 

Hospital B: Observed number of deaths: 40 + 40 = 80

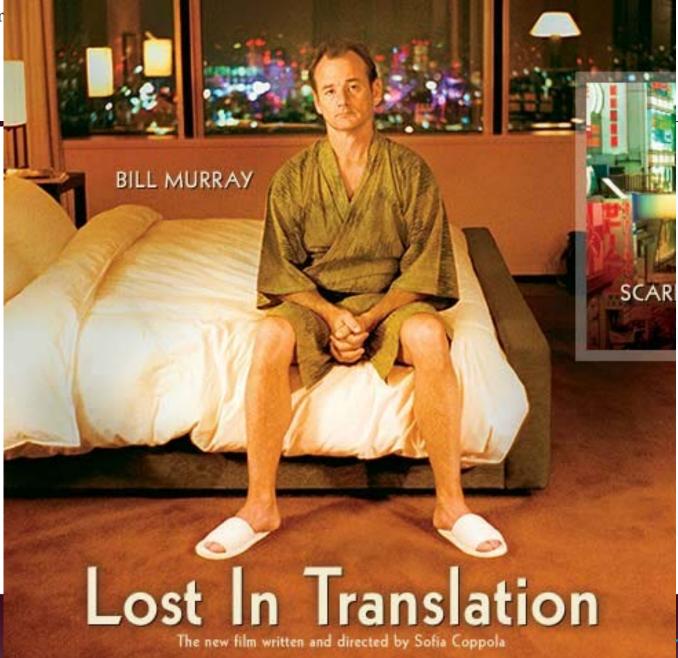
Expected number of deaths: 30 + 40 = 70

 $HSMR 80/70 \times 100 = 114$ 

Despite similar mortality rates, HSMRs are not the same



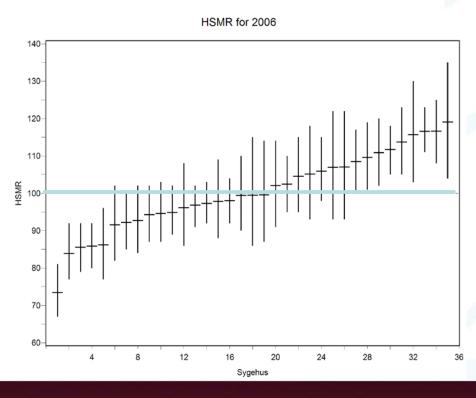






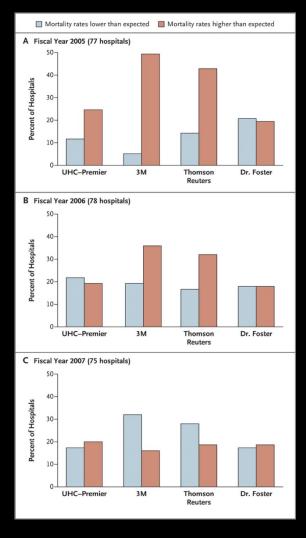


# **Comparison**





# Percentages of Hospitals with Mortality Rates Higher or Lower Than Expected for Fiscal Years 2005 through 2007, According to Four Measurement Methods.



Shahian DM et al. N Engl J Med 2010;363:2530-2539.

The NEW ENGLAND

JOURNAL of MEDICINE

### Comparison with the national average

Each of the 80 diagnoses predicted mortality rates are based on the national average

Curative intent Complications

Palliative intent



## Comparison with 2008 – year of reference

Diagnoses are used differently in 2013 than in 2008

 Unspecific diagnoses DZ03 are increasingly being used as the first primary diagnosis at admission because of medical acute care centers have been implemented in most hospitals

 Observed mortality has become higher than predicted mortality in this group of patients



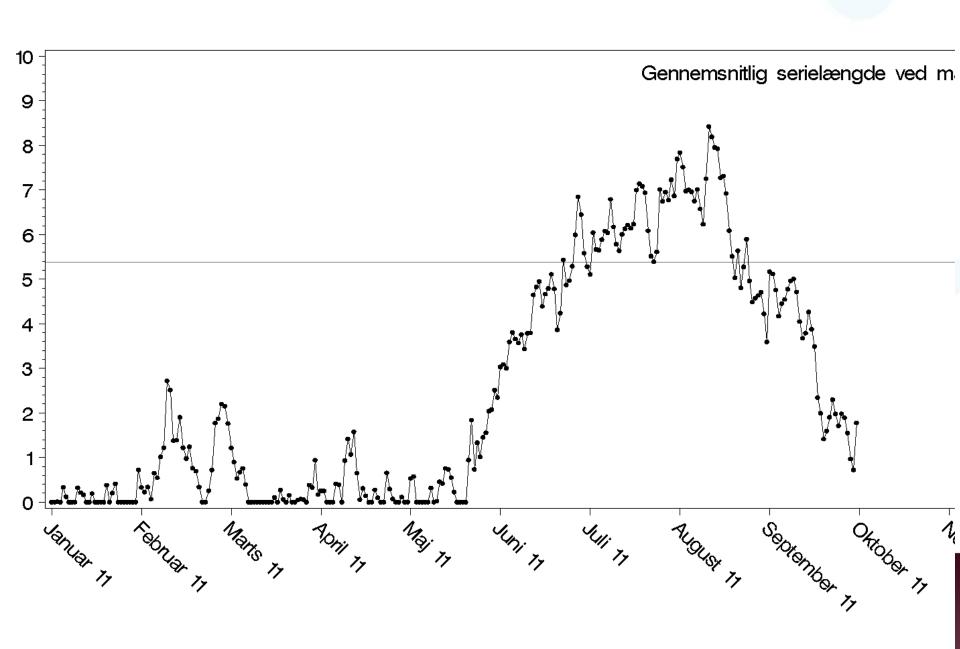


## **Monitoring HSMR**

"When should we react on our HSMR?"

Time period	HSMR
4. quarter 2010	119 (98;146)
1. quarter 2011	116 (95;142)
2. quarter 2011	140 (115;169)
3. quarter 2011	145 (119;176)







#### What was found?

DZ03 increased:

35% in January 1 – May 15 51% in May16 – June 30

No substantial changes in the pattern of covariates

Mortality of DZ03 increased:

in January 1 – May 15 expected deaths = 51.6 (4.5%)

observed deaths 62 (5.4%)

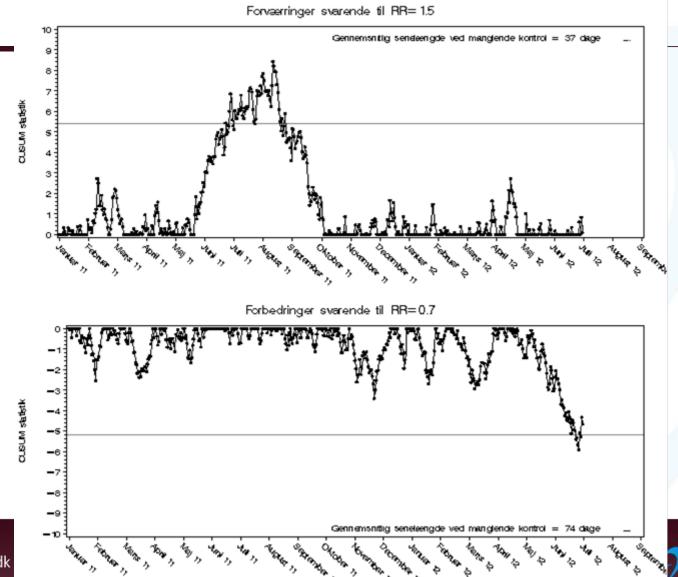
in May16 – June 30 expected deaths 30.8 (4.4%)

observed deaths 62 (8.9%)









Tid (målt i dage)

#### In conclusion

HSMR is an overall measure comparing hospitals with the national average

HSMR includes several common diagnoses that are not routinely monitored in other quality programmes

High HSMR is not equivalent to low quality but is a signal of potential low quality and should be followed by other types of quality measures

Cusum charts may be useful for each hospital to identify periods with high (or low) mortality.







#### What to do?

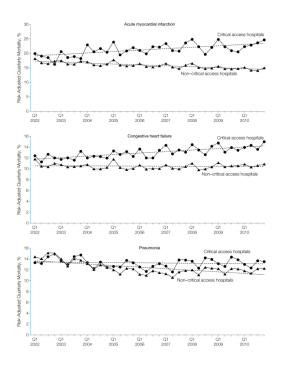
- The HSMR could be accompanied by other types of information
- Identify subgroups of diagnoses with a clearer link between mortality and quality





From: Mortality Rates for Medicare Beneficiaries Admitted to Critical Access and Non-Critical Access Hospitals, 2002-2010

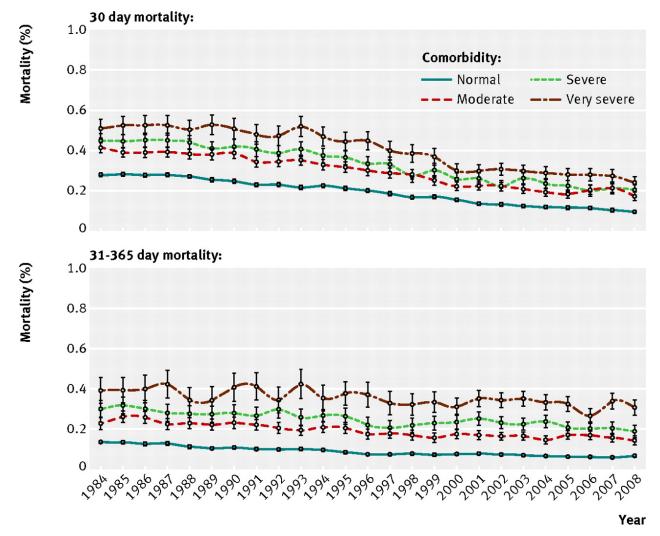
JAMA. 2013;309(13):1379-1387. doi:10.1001/jama.2013.2366



#### Figure Legend:

Dashed lines indicate linear trends. Y-axis segments shown in blue indicate interval from 0% to 16%.

Fig 4 30 day and 31–365 day mortality after first time hospitalisation for myocardial infarction between 1984 and 2008, according to comorbidity category.



Schmidt M et al. BMJ 2012;344:bmj.e356





# Are Mortality Differences Detected by Administrative Data Reliable and Actionable?

John P. A. Ioannidis, MD, DSc

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JAMA. 2013;309(13):1410-1411. doi:10.1001/jama.2013.3150.

Text Size: A A A

Article References

Administrative data offer impressive amounts of information that can be readily analyzed. However, how credible are the results derived from these behemoth data sets? Moreover, how prudent is it to translate those results into policy actions, and, if this is done, what should that translation path involve?

In this issue of JAMA, Joynt and colleagues¹ report the results of an interesting analysis that exemplifies these challenges. The authors used administrative data from almost 10 million admissions of Medicare patients in 2002-2010 to evaluate the change in 30-day mortality rates for acute myocardial infarction, congestive heart failure, and pneumonia in critical access hospitals (CAHs) vs non-CAHs. Critical access hospitals fared worse by 0.3% per year, such that by 2010, CAHs had higher mortality rates compared with non-CAHs (13.3% vs 11.4%). The nominal statistical significance also was maintained in analyses matching CAHs against other rural non-CAHs, although the absolute difference in mortality declined to 0.1% (95% CI, 0.0%-0.2%) per year. This means that only a small portion of the variation in mortality risk was explained by CAH status. Numerous sensitivity analyses also demonstrated a relatively consistent pattern.





Editorial | April 03, 2013

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- 1. Over powered
- Information in administrative data sets is spurious by default
- Measurement errors also can affect the ability and approaches used to adjust for important confounders
- Differential misclassification of the measured covariates in the compared groups cannot be excluded
- 5. Are the covariates modelled correctly?
- What about unmeasured covariates?
- Are the observed differences caused by modifiable features?











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