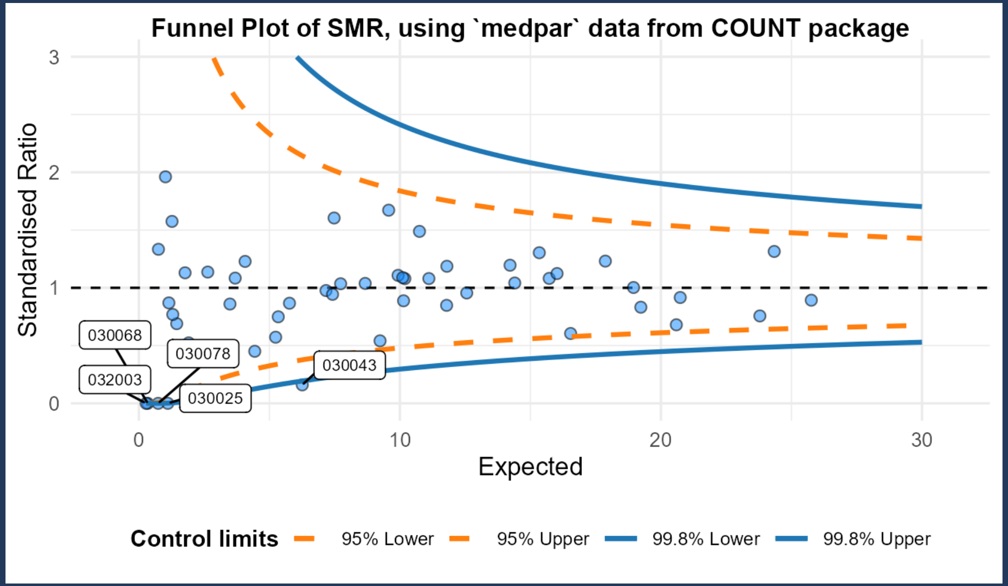
Understanding Standardised Mortality Ratios (SMRs)

SHMI and HSMR



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Presentation and code available: **https://github.com/chrismainey/understanding_standardised_mortality**

Measuring death

Why do we do it?

- 'Smoke alarm for the quality of care' - (Keogh, 2013)
- Tacit assumption that high mortality is bad

Does it work?

- **Yes:**
  - Increases power of comparison by reducing confounding.
  - Monitoring them has effects on hospital's vigilance and culture (Jarman, Bottle, Aylin, et al., 2005; Wright, Dugdale, Hammond, et al., 2006)
- **No:**
  - Poor proxy of avoidable death: (Girling, Hofer, Wu, et al., 2012)
  - Case-mix adjustment can exaggerate biases it tries to address: (Deeks, Dinnes, D'Amico, et al., 2003)

Desceptive argument:

"...of course we should be monitoring deaths": - but is this too simplistic a view? Is it a measure of 'quality?'

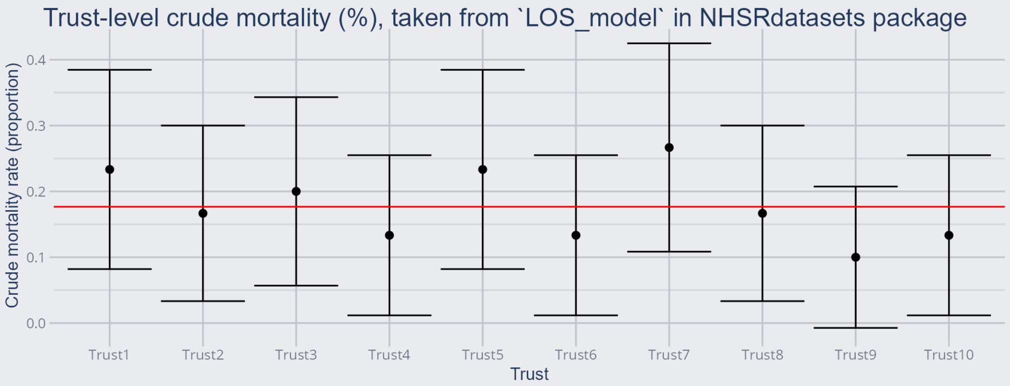
Crude Mortality

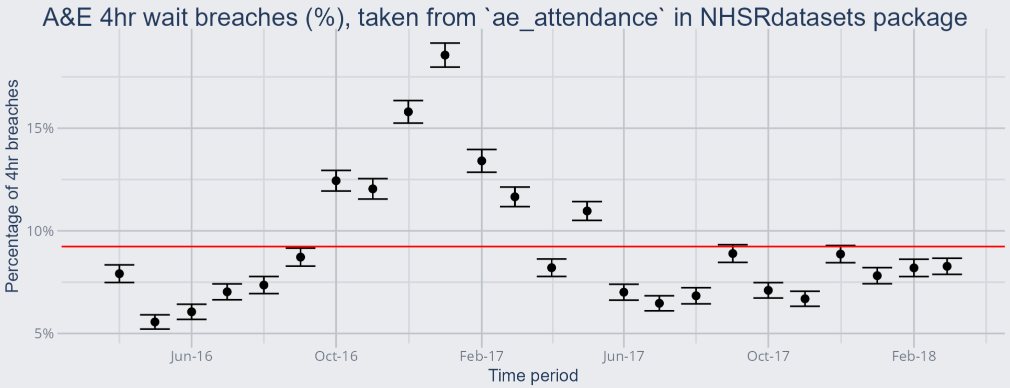
Crude mortality Rate

- Count the numbers of deaths? - Not a rate
- Give it some sort of scale: proportion
  - In hospital, patients, discharges, bed-days etc.
  - Often adjusted to a larger standard, e.g. per thousand

$$Crude\ Rate(p) = \frac{\Sigma Deaths}{n}$$

- **Strengths:**
  - Easy to calculate
  - Directly linked to real deaths
- **Weaknesses:**
  - Not really comparable across organisations
  - Case-mix confounds rate





Standardising mortality

Aim: reduce confounding and increase power of comparison

Direct standardisation

- Take our data and map them to a common population/structure.

- Example: Age-standardisation:

  - Calculate age-specific rates in groups (e.g. 10-year bands)
  - Identify a relevant standard population in corresponding groups. E.g. European Standard Population
  - Multiply age-specific rates by standard population bins
  - Sum and adjust to desired multiplier (e.g. per 100, per 100,000 etc.)

- Commonly used in public health cases, such as cancer incidence and mortality rates.

- **Strengths:**
  - Directly comparable between units/group/sites/countries
  - Does not require statistical model

- **Weaknesses:**
  - Harder to relate to local/observed numbers
  - Challenging to do for anything more than age and sex

Indirect standardisation

- Compare our data to expected averages
- E.g Calculate average rate, per-patient, across the dataset
    - Per trust, calculate 'expected rate': $average\ rate * n$
    - Present as grouped ratios of Observed / Expected
- Commonly uses a regression model
    - Predict risk of event, based on case-mix factors (predictors)
- **Strengths:**
    - Directly comparable between units/group/sites/countries
    - Usually require statistical model, e.g. regression
- **Weaknesses:**
    - Usually requires a statistical model, e.g. regression to calculate 'expected rate'
    - Susceptible to more forms of bias (Iezzoni, 1997; Deeks, Dinnes, D'Amico, et al., 2003)
    - Can be challenging to understand what changes in rates mean

Example SMR:

```r
# Load 'medpar' dataset from COUNT package.
data("medpar")

# build logistic regression for risk of death
mod1 <- glm(died ~ los + factor(type) + age80
            , data=medpar
            , family = "binomial")

# Predict risk of death back into data frame.
medpar$pred <- predict(mod1, type="response")

# SMRs
medpar %>%
  group_by(provnum) %>%
  summarise(Observered = sum(died),
            Expected = sum(pred),
            SMR = sum(died) / sum(pred))
```

```
## # A tibble: 54 x 4
##    provnum    Observered Expected   SMR
##    <labelled>      <int>    <dbl> <dbl>
##  1 030001             16    19.2  0.832
##  2 030002             19    20.7  0.916
##  3 030003              2     1.77 1.13
##  4 030006             23    25.8  0.893
##  5 030007              2     4.44 0.451
##  6 030008              5     9.24 0.541
##  7 030009              4     5.34 0.749
##  8 030010             22    17.9  1.23
##  9 030011             12    12.6  0.955
## 10 030012             12     7.48 1.60
## # ... with 44 more rows
```

SMR = 1: observed=predicted, >1: observed>predicted, <1: observed <predicted

Common (indirectly standardised) SMRs:

Summary Hospital-level Mortality Indicator (SHMI)

Dr Foster Hospital Standardised Mortality Ratio (HSMR)

Hospital Standardised Mortality Ratio (HSMR)

- Work in USA as early as 1970s demonstrated ability to calculate theses metrics.
- Prof. Sir Brian Jarman and others adapted these methods to English health care system, data coding standards and structures.
- Methods were heavily impacted and applied in aftermath of Bristol and Mid-Staffs enquiry.
- Controversy on some issues:
    - Commercial exploitation of method by Dr Foster Intelligence - accused of 'black box methods'
    - University of Birmingham and others published criticism
    - Imperial rebutted criticism, and won NIHR funding to build national monitoring system
    - Until recently, sent alerts to CQC and trusts for high mortality.

Key References:

- Original paper: (Jarman, Gault, Alves, et al., 1999)
- Birmingham's criticism: (Mohammed, Deeks, Girling, et al., 2009)
- Paul Taylor's long-form article on history and controversy: (Taylor, 2014)

Summary Hospital-level Mortality Indicator (SHMI)

With growing controversy, then NHS Medical Director, Prof. Sir Bruce Keogh, commissioned a review.

Recommended creating a new, NHS owned and transparently published indicator, however:

- Changed the remit to in-hospital or within 30-days of discharge
- Applied to all acute activity (except still birth)
- Cruder case-mix model deliberately to avoid controversial measure such as:
    - Palliative care coding
    - No adjustment for deprivation - political context
    - Co-morbidity score 'binned' rather than continuous to reduce change of gaming
    - Fewer, larger diagnosis groups

Key References:

- Review: National Quality Board (in national web archives)
- Sheffield paper: (Campbell, Jacques, Fotheringham, et al., 2012)
- NHSD SHMI: www.digital.nhs.uk/SHMI

Case-mix factors:

Factor	HSMR	SHMI
Inclusion	~20-30% inpatient activity	All inpatient activity excluding still births
Diagnosis Stratification	260 CCS groups	142 SHMI groups, groups of CCSs
Transfers considered as CIPS	Yes	No
Predictors / casemix variables:		
Age	5-year bands	5-year bands
Sex	Categorical	Categorical
Admission Method	Elective/Non-elective/ Transfer/Unknown	Elective / Non-elective /Unknown
CCS-sub group	Yes	No
Co-morbidity Score	Charlson score (continuous)	Charlson score (binned: 0, 1-5, >5)
Emergency admission in last 12-months	Yes	No
Admission Source	Yes	No
Deprivation	Yes	No
Specialist Palliative Care	Yes	No
Year of admission / index	Yes	Yes
Seasonality	No	Monthly
Birth Weight	No	Categorical for neonatal groups

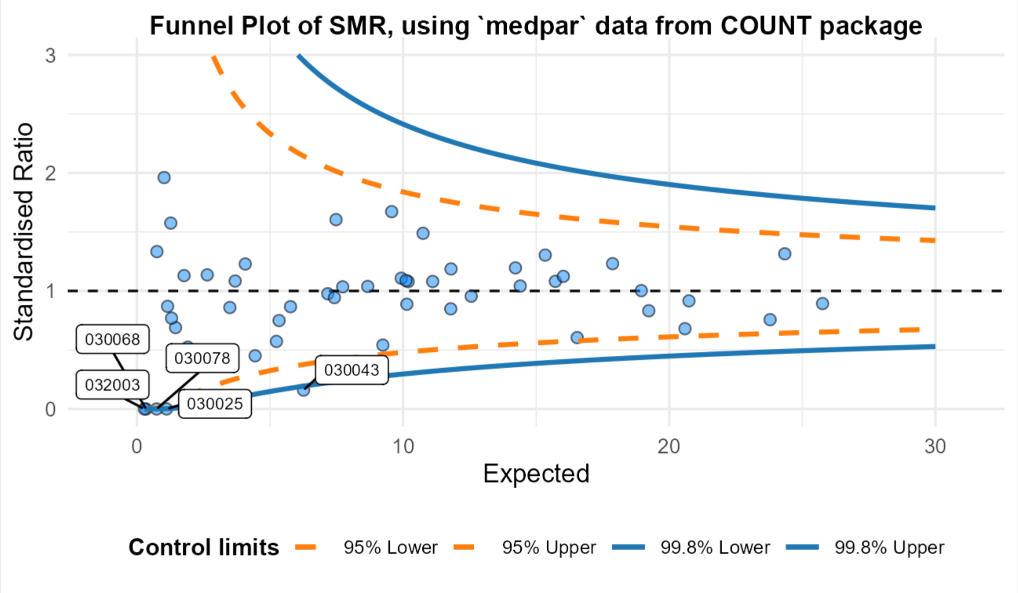
Criticisms (HSMR and/or SHMI)

- Link to quality of hospitals unclear,
  - For: (Cecil, Bottle, Esmail, et al., 2020; Cecil, Bottle, Esmail, et al., 2018)
  - Against: (Lilford and Pronovost, 2010; Black, 2010)
- They do not directly relate to avoidable death (Girling, Hofer, Wu, et al., 2012; Hogan, Zipfel, Neuburger, et al., 2015)
- Single number does not convey nuance
- Insensitive to who patients who survived
- Susceptible to 'gaming' - (Hawkes, 2013)
- Covid-19 pandemic, these models assume stability
- Case-mix adjustment fallacy (Mohammed, Deeks, Girling, et al., 2009)
- Constant risk fallacy (Mohammed, Deeks, Girling, et al., 2009; Nicholl, 2007)
- Potential for Simpsons paradox (Marang-van de Mheen and Shojania, 2014)

Cross-sectional

Comparison at single point in time

- Both HSMR and SHMI report on the final year of their modelling period.
- Snapshot of performance against expected
- League-tables are bad, as measure is relative (Goldstein and Spiegelhalter, 1996; Lilford, Mohammed, Spiegelhalter, et al., 2004)
- SPC principles applied in using funnel plot (Spiegelhalter, 2005a)
- Overdispersion



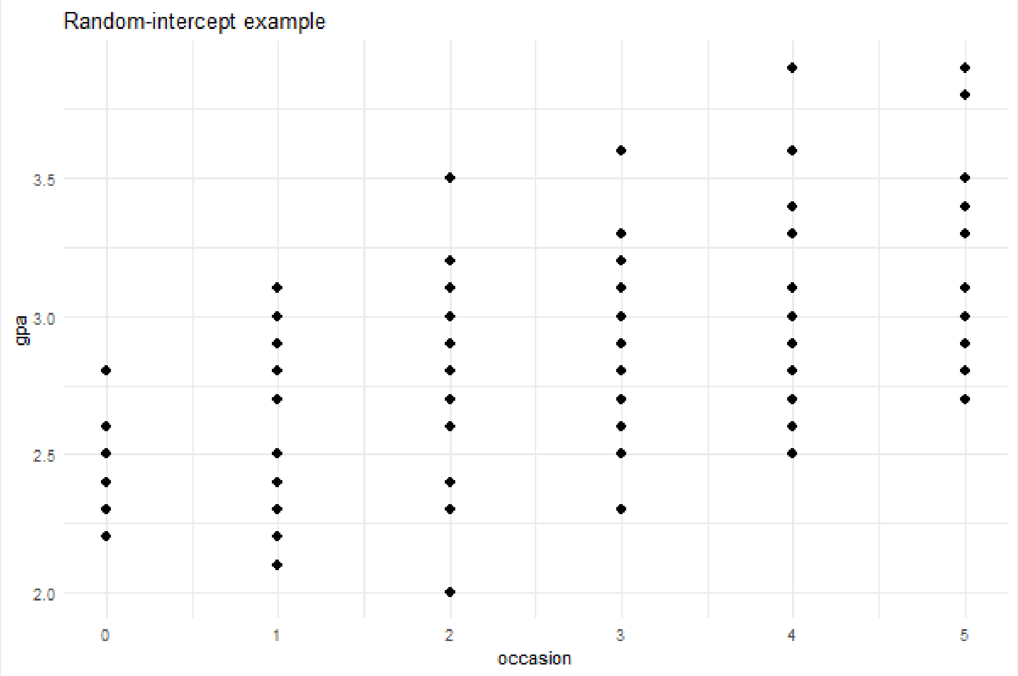
Overdispersion

Overdispersion, where conditional variance is greater than conditional mean, occurs when:

1. Aggregation / Discretization
2. Mis-specified predictors/model
3. Presence of outliers
4. Variation between response probabilities (heterogeneity)

Repeated measures (correlation)

- Regression assumes all points independent
- Sampling from same organisations repeatedly
- Clustered: - local means



Dealing with overdisperion

- Ignore it: use-case dependent. False alarm rate too high here, as error is underestimated
- Improve the model with more information: Some room for this.
- Build a model with clustered assumption (Mainey, 2020):
  - Quasi-likelihood methods (with multiplicative scale factor) (Wedderburn, 1974)
  - Compound distribution model: beta binomial (Skellam, 1948)
  - Random-intercept model: model 'within' and 'between' variance
- Apply tools based on meta-analysis methods: (Spiegelhalter, Sherlaw-Johnson, Bardsley, et al., 2012)
  - Designed to summarise studies fo different size
  - Akin to hospitals of different sizes
  - Additivity assumption - more like random-intercept than scale factor

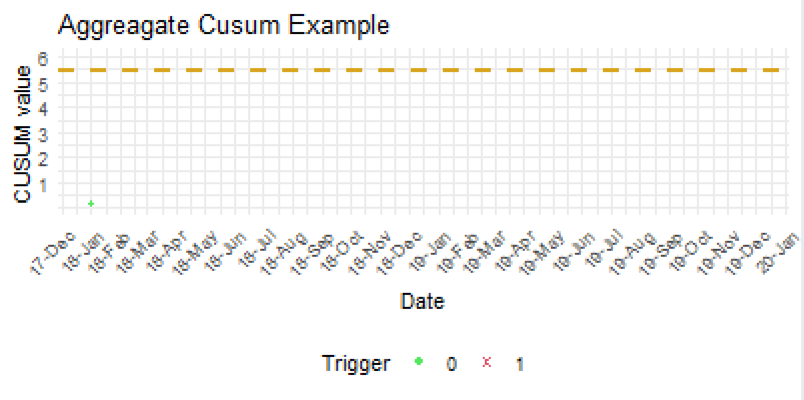
Longitudinal

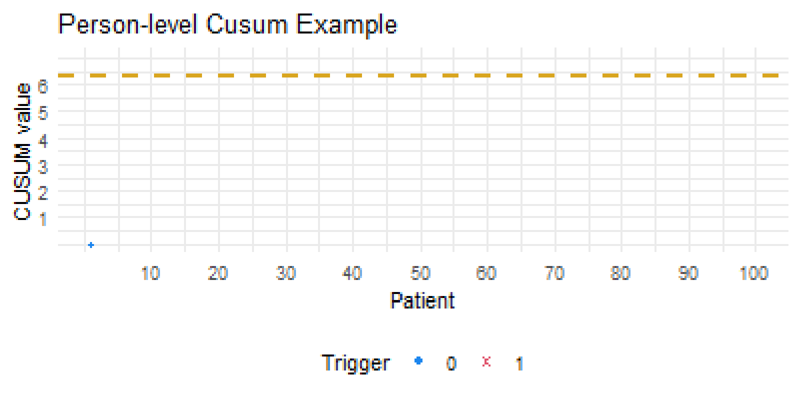
How?

- Can't simply plot in XmR chart, as risk-adjustment forms denominator (and overdispersion)
- Can use the observed and predicted in risk-adjusted control chart
- Common is 'risk-adjusted CUSUM'
  - Continuous log-likelihood ratio test

$$C_t = max(C_{t-1} + w_t, 0)$$

- C CUSUM value at time-point t (e.g. a monthly at a trust)
- w is a weighting, in this case the log-likelihood ratio (observation v.s. England) to calculate the CUSUM weight/value (C) at time point (t)





Differences in CUSUM methods

Until recently, mortality outlier programme and Imperial college sent monthly alerts to Trusts.

CQC - (aggregated)

- Data are transformed to z-scores
- Overdispersion adjustment based on additive model (Spiegelhalter, Sherlaw-Johnson, Bardsley, et al., 2012)
- Can convert average run-length to FDR, and set threshold (Grigg and Spiegelhalter, 2008; Care Quality Commission, 2014)
- Global trigger (5.48) - set to marginal 0.01% FDR.
- Applicable to other indicators and groupings, subject to same transformation

DFI/Imperial - (person-level)

- Binomial assumption and threshold set through simulation of average run-length to false positives. (Bottle and Aylin, 2011)
- Unique to each trust / group / reporting period.
- Intractable to calculate each month, and authors fitted a set of descriptive equations give a decent approximation for conditions where mortality rate 30% or lower.
- Formula can then be solved through optimisation methods and give threshold value for each group.

Problem with CUSUM charts

- A common criticism of CUSUMs is that the are opaque and hard to interpret
- What does the CUSUM value mean?

Variable Life-Adjusted Display (VLAD)

- Originally used to visualise surgical outcome more intuitively (Lovegrove, Sherlaw-Johnson, Valencia, et al., 1999)
- Can actually add limits to plot using cusums (Sherlaw-Johnson, 2005)

$$Vn = \sum_{i=1}^{n} y_n - \sum_{i=1}^{n} X_n$$

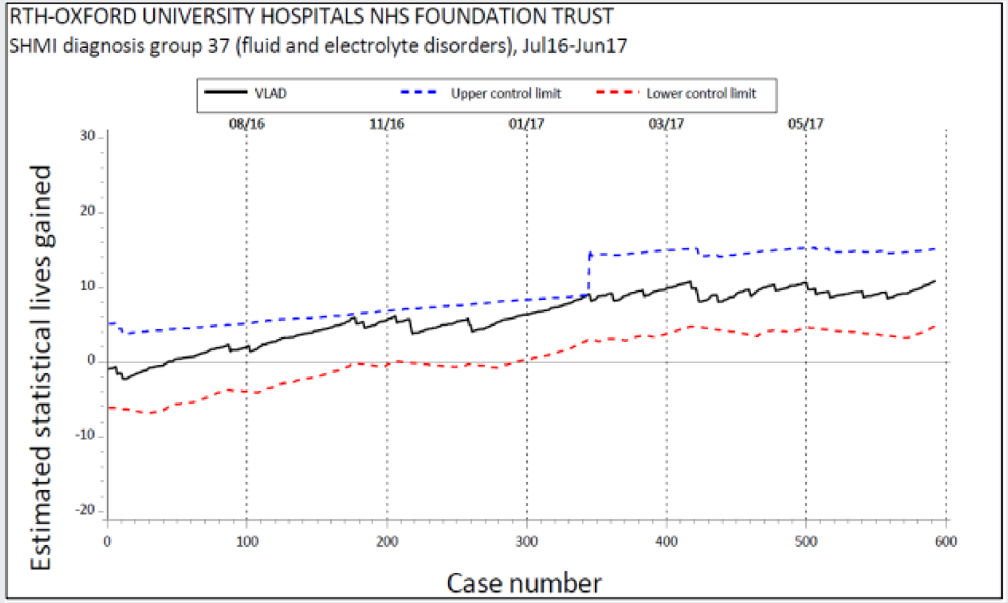


Chart sourced from https://www.ouh.nhs.uk/about/trust-board/2018/january/documents/MRG2017.149a-shmi-update.pdf

Summary

- Mortality monitoring is common, but it's use as a global measure (rather than specific conditions) is unclear.
- Not directly linked to avoidable deaths
- Crude mortality can be sensibly used in some cases, but confounded by case-mix
- Case-mix adjusted mortality is usually done by indirect standardisation, with regression model
- SMRs as grouped sums of observed / 'expected' (or 'predicted')
- HSMR was first national measure in UK - narrow scope and extensive case-mix adjustment
- SHMI is NHS-owned indicator - wider scope and less case-mix adjustment
- Criticisms remain of both - and SMRs broadly
- Cross-sectional comparisons usually by funnel plot, longitudinal with cusums and vlad.

Worth knowing history and limitations of indicators before using them

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