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Multidisciplinary insights into health care financial risk and hospital surge capacity, Part 4:

What size does a health insurer or health authority need to be to minimise risk?

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Abstract

Death acts as a dual proxy for nearness to death (NTD) and related wider morbidity. Hospital bed use in the last year of life accounts for somewhere around 25 bed days of hospital resource consumption. The knock-on morbidity due to the agents promoting death also accounts for up to another 25 bed days of hospital resource consumption. This is approximately 50% of total bed consumption as a ratio of occupied beds per death (all-cause mortality). This explains why the trend in deaths alone can explain so much of medical bed utilisation. The volatility in the year-to-year difference in deaths can be used to determine the number of deaths in a population (health insurance members, health authority, health maintenance organisation, commissioning group, etc) at which this volatility reaches an asymptote. Data from 97 countries with more than 1,000 deaths per annum shows that at 1,000 deaths the standard deviation is high at between ± 5% to ± 10% depending on country. Somewhere around 20,000 deaths appear to be the size which minimises volatility (standard deviation) to an acceptable level of ± 2% to ± 3.5% depending on country. Volatility shows a small further reduction up to 100,000 deaths above which there is no further reduction. This is country specific and Australia, Canada, and the USA seem to have a lower volatility than UK local government areas. The maximum year-to-year increase is around 2- to 3.5-times higher than the standard deviation. The ability to forecast year-end deaths, and hence death associated costs, gives an acceptable tolerance at 20,000 deaths. This is illustrated using a month 6 forecast for 350 English and Welsh local government areas and regions. Countries with fewer than 20,000 deaths are free to subdivide the country into smaller health authorities, etc but must ensure that risk sharing between these units is done at national level. For example, New Zealand only has around 30,000 deaths per annum but has 21 Area Health Boards ranging from 300 to 3,000 deaths per annum (median 1,500). None of these are large enough to sustain the implied financial and capacity risk and this risk should be held at national level. Risk sharing based on deviation from funded number of deaths seems a sensible compromise with adjustment for costs associated with cause of death.

Key Points

- Death serves as a proxy for the number of persons in the last year of life and the related morbidity arising from the action of the agents promoting death (or precipitating final demise) among those who will survive longer than one year.
- It is estimated that such combined mortality/morbidity risk consumes up to 50% of the total bed days and as such is a significant source of risk in the marginal costs of health and social care.
- This raises the fascinating question as to how much of acute illness has a primary infectious trigger?
- The ratio of hospital bed occupancy in England per death has remained remarkably constant for around 20 years indicating that death is serving as an exceptionally good proxy for health care resource consumption in a far wider context.
- An area containing around 20,000 deaths per annum is required to minimize the associated volatility in deaths, associated admissions and costs.
- Many world countries and regions within countries have less than this required size and hence the resulting risk must be covered by flexibility in the health and social care budget via risk sharing arrangements.
- Government health agencies need to recognise that financial risk in health care is intrinsically high, is location specific, and is not primarily related to managerial incompetence.
- It is (variation in) the absolute number of deaths, cases, admissions, etc which drives financial and capacity risk, not the age standardized rates.

Introduction

As Arrow (1963) noted "the special economic problems of medical care can be explained as adaptations to the existence of uncertainty in the incidence of disease and in the efficacy of treatment". This is a statement regarding both capacity and financial risk. Size is one of the important factors relating to the financial stability of insurance companies (Chen and Wong 2007). The volatility in costs and capacity pressures arises from two sources, namely (Jones 2004):

1. Common cause volatility arising from statistical-based chance which can be approximated by Poisson statistics. This type of volatility is extremely high for small organisations since the standard deviation (a measure of volatility) of a Poisson distribution is equal to the square root of the (average) size (Science Direct 2020). Hence, as size increases the contribution from Poisson chance diminishes in an exponential manner.
2. Environment associated volatility in which (change in) the external environment (circadian and other cycles, temperature and other metrological variables, pollution and noise levels, and infections) all interact to influence human health.

The interaction of the two implies that the real-world volatility in health care costs is unacceptably high (Jones 2004, 2012a-c). The actual impact of this volatility then depends on the timing and magnitude of all the interacting factors. This implies that the impact of the volatility depends entirely on the (arbitrary) choice of the financial year. For example, in the USA the Federal government financial year runs October to September, most states run July to June and the corporate tax year runs January to December. The UK financial and tax year ends at the end of March while corporations can calculate their annual accounts at any point in the year. This has been called the calendar (or financial) year fallacy (Jones 2019).

Is the volatility in deaths a relevant metric?

The aim of this section is to demonstrate that a count of deaths not only is a measure of nearness to death costs but that it also encompasses significant morbidity associated with the action of the agents causing or precipitating death.

To do this it is first necessary to determine how many days a person occupies a hospital bed in the last year of life. This metric encompasses all the bed associated costs plus additional outpatient and emergency department costs. Then to establish that any agent causing death will also cause significant morbidity in others.

Hospital bed use in the last year of life

It is of interest to determine how many days a person occupies a hospital bed in the last year of life. A summary of studies conducted over the past four decades is given in Table 1. With respect to the Danish study of Vestergaard et al (2020) note that the average occupied bed days is always higher than the median and can be 3-4-time higher at age 65-74, 4-6-times higher at age 75-84, 5-9-times higher at age 85+ in the study of Henderson et al (1990), but around 4-times higher at age 0-24, to 2-times higher at age 25-85+ in the study of Dixon et al (2004).

For those who die, hospital episodes increased as death approaches. For example, 42% of all acute admissions (or 55% of bed days) took place within 12 months of death. Thirty-three per cent of admissions (48% of bed days) occurred during the last six months of life and 18% of admissions (34% of bed days) occurred within the last month (Hanlon et al 1998).

Table 1: Studies on the number of occupied bed days occurring in the last year of life

Year	Description	Bed days in last year	Comments	Reference
1976-1985	Deaths in Oxfordshire aged 65+	22 ± 1days age 65-74, 31 ± 1 days aged 75-84, 39 ± 3 days aged 85+	Persons admitted at least once have 1.3 to 1.6 (age dependent) higher occupied bed days. No appreciable change in bed days between 1976 and 1985, although the percent admitted at least once increased over time, especially for those aged 85+.	Henderson et al 1990
1989-1995	10% sample from a German insurance fund	Stay peaked at 41 days age 55-64.	24 days age 0-24, 23 days age 85+, maximum of 58 days (age 35-44) for persons admitted at least once.	Busse et al 2002
1999	Those dying in an English hospital in the financial year 1999/2000	30 days	Mental disorders 59 days, cancer/ palliative/ rehabilitation 54 days, nervous system 33 days.	Dixon et al 2004
2004-2008	All persons dying in England	30 days	Stroke 36 days, 18 days cardiovascular.	Lyons and Verne 2011
2009-2013	Persons with intellectual disability (ID) dying in Western Australia	22 days with intellectual disability, 26 days without	Those with intellectual disability also had higher use of critical care and higher emergency department visits.	Brameld et al 2018
2006-2015	***Median*** bed days all deaths in Denmark during the last six months of life	In 2015, 17 days cancer, 11 days heart failure or COPD	Median bed days is lower than the average. Only cancer bed days declined from 2006 (21 days) to 2015.	Vestergaard et al 2020
2016	UK ***emergency*** admissions only	29 days Wales, 25 days Scotland, 19 days England, 18 days Northern Ireland	Cancer can be 0-3 days longer depending on UK country. Days spent in hospital did not decline between 2013 and 2016 in England but did so in Wales from 29 days in 2012/2013 to 27 in 2015/2016. Between 2011 and 2016 in Scotland duration of stay declined by around 0.16 bed days per year.	Marie Curie 2018
2017	Deaths in England aged 75+	27.2 days average stay for people admitted at least once. 21.9 days per death for all deaths including not admitted.	19% did not have any admissions in the last year of life. Average of 9.2 days stay per admission. The proportion of utilization between emergency and elective admissions varies by age and gender. Persons aged 75+ in the last year of life account for 18% of total occupied beds. For all ages, there were 22.1 days per death including not admitted.	Dalrymple et al 2020

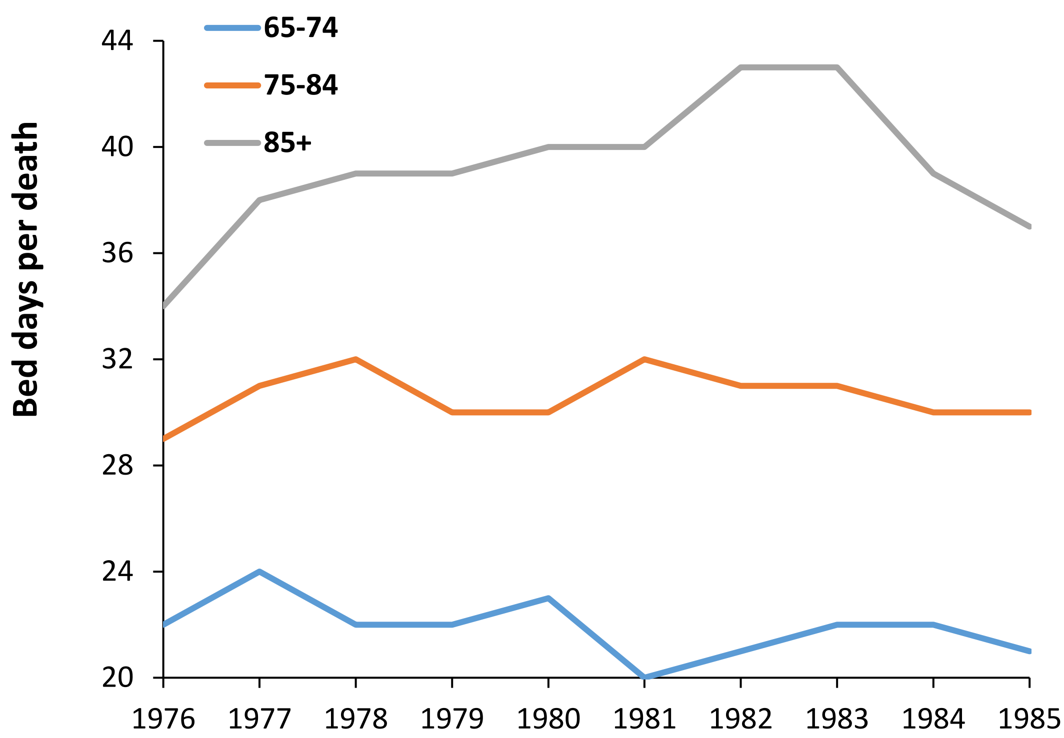
As is to be expected, lifetime bed occupancy increased from 55 days for death at age 20, 108 days for death at age 50, and 201 days for death at age 90 (Busse et al 2002). The balance in the last year changes with age at death.

Hence as a general summary, despite massive changes in length of stay and medical technology over 40 years the days spent in hospital in the last year of life remain remarkably constant at around 22-25 days per death (all-cause mortality) and 27-30 days per death for persons having one or more admissions in the last year of life.

The issue around length of stay (LOS) may be a red herring, since LOS is calculated across both the survivors and those who die. Whatever the case, the total number of days in hospital has remained relatively constant. The Marie Curie (2018) study does however demonstrate that the time spent over the last year depends on the health care system and alternatives to acute care during the period when wider palliative or nursing home care is needed in the last six months of life. From Table 1 it is also clear that cause of deaths is an important factor in bed use, and that cause of death will fluctuate from year to year.

Figure 1 explores the issue as to whether bed days per death in the last year of life shows volatility over time. The whole thesis of this series would indicate that it should do so, and this is indeed the case. The standard deviation around the average ranges from ± 3% to ± 7% depending on the age band (number of deaths).

Figure 1: Average number of bed days for all persons who died in Oxfordshire, by age group, 1976 to 1985 (from Henderson et al 1990)



Recall that these trends will also encapsulate any year-of birth, or birth cohort, effects as would be expected from age-period-cohort studies (Smith and Wakefield 2016), which will be partly hidden by using age bands. It will also encapsulate statistical and systematic variation in the proportion of persons with no hospital admissions in the last year of life. Hence the general principle holds that even bed days per death shows year-to-year volatility.

Death as a wider proxy for non-end-of-life bed use

The very fact that a combination of environmental factors (cold/heat, peaks in pollution, infections, etc) can cause death in some people implies that for each death others who are not in the last year of life will be admitted to hospital with an acute exacerbation of both related and seemingly unrelated illnesses.

For COVID-19 analysis of data from US states reveals that at the peak there were approximately 20 to 45 persons occupying a hospital bed per COVID-19 death (data from The COVID Tracking Project 2020). This ratio was between 13 to 28 occupied beds per death in an English hospital, depending on the region (data from NHS England 2020a,b). Clearly there are lags between bed occupancy and deaths, however, wider morbidity in terms of bed occupancy per death is clear.

For influenza, the US Centers for Disease Control and Prevention (CDC) estimates that, depending on the year, for every influenza death there are between 8 to 13 influenza hospitalizations (CDC 2020). Depending on the diagnosis the length of stay for influenza/pneumonia in England is between 5 to 10 days (NHS Digital 2020) giving 40 to 80 occupied beds per death. Among soldiers there are around 140 heat related hospitalizations per death (Carter et al 2005). For every cancer death there are multiple inpatient/outpatient admissions/attendances among the survivors plus additional palliative care among those who die (Jones 2012a).

Table 2 explores the issue of how total bed occupancy per death may depend on diagnosis or specialty group. The aim is to determine if the total bed days per death in Table 2 can be subdivided into:

1. bed days in the last year, as in Table 1,
2. bed days also encapsulated by wider morbidity influenced by agents promoting death,
3. the residue of bed days which are not associated with end-of-life but are related to human lifestyle, e.g., accidents, poor health behaviours, and 'wear and tear.'

Table 2 simply lists the total bed days from all three sources. From the previous section we have a figure of around 25 bed days per death due to admissions in the last year of life (point 1 above). This will be split across the mental health, surgical and medical bed pools. Recall from Part 3 of this series that the ICD-10 chapters covering falls, fractures and injuries will be susceptible to year-to-year volatility due to the clumsiness arising from a wide range of infections. Note from Table 2 that the two chapters covering infections (Chapters A and B) have an extremely high ratio of bed days per death implying that infections have high leverage in the issue of wider morbidity. Also highly leveraged are skin and subcutaneous conditions which would be exacerbated by infectious agents, and signs and symptoms which will often arise from hidden infectious sources.

Table 2 is itself a best estimate since the rules for coding mortality are different to those for morbidity. Hence cancer as a cause of death, may be coded to multiple morbidities as cancer patients are admitted for various reasons associated with diminished immune function. Hence cancer admissions per death in Table 2 will be lower than reality. Issues of uncertainty of allocation aside, Table 2 remains a useful starting point and its usefulness has been expanded by adding bed days per death (all-cause mortality) for several broad specialty groups. For simplicity, the specialty paediatrics has been added into the medical group. Obstetrics and maternity care have been excluded since these activities rarely lead to death.

Next, we need an estimate of the total bed days per death due to points 1+2. To derive this estimate, calculate the total bed days for the medical group in England for each financial year since 2001/02 to 2019/20. Then calculated total deaths in England in each financial year and then plot the successive differences in each. Hence 548,044 bed days difference between 2002/03 and 2001/02 versus 3,575 deaths difference between these two years, etc.

Table 2: Deaths, admissions, and occupied beds by ICD-10 chapter or by specialty group in England for 2019. Note that bed days per death for the specialty groups is a 20-year average ± 1 standard deviation. Mental health has been adjusted to current practice relating to care in the community.

Specialty group or ICD-10 Chapter	Deaths	Admissions	Occupied beds	Admissions per death	Bed days per death
Mental health specialties					9 ± 1
Surgical group of specialties					33 ± 1
Medical group of specialties					61 ± 3
All causes (Excl maternity)					**102 ± 4**
Cancers	138,132	1,712,690	9,051	12	24
Nervous	33,720	385,177	4,125	11	45
Circulatory	121,267	964,163	16,053	8	48
Respiratory	67,876	1,125,884	15,752	17	85
Mental & behavioural	44,227	171,757	11,376	4	94
Endocrine, nutritional, metabolic	8,314	328,467	2,980	40	131
Digestive	23,754	2,301,892	11,257	97	173
Congenital conditions	1,327	97,332	754	73	207
Genitourinary	9,791	923,091	7,016	94	262
Falls, fractures, Injuries	21,452	2,100,833	17,021	98	290
Signs & symptoms	12,846	1,857,670	12,743	145	362
Infections, mainly not bacterial	775	146,458	781	189	368
Infections, mainly bacterial	4,016	308,243	5,853	77	532
Skin & subcutaneous	1,926	382,182	2,825	198	535

There is considerable scatter using the successive differences method. An explanation for this is given in a recent study of the trends in occupied medical beds per death from 2000/01 to 2019/20. This trend shows systematic undulations rather than random distribution around an average (Jones 2021). The resulting maximum possible slope is somewhere around 45 ± 5 occupied bed days per death. The maximum possible slope was determined by successive removal of low values. This leaves somewhere around 20 additional bed days per death over and above that simply due to the last year of life. This is an initial estimate. However, due to the systematic undulations in the ratio of occupied beds per death the maximum estimated value of 45 does not apply to all years.

It is not possible to do this calculation for all specialties because there has been an ongoing shift of mental health out of hospital care over the period. Since 2010 the NHS budget was capped due to austerity imposed following the financial crash which meant that surgical demand was diverted into a rapidly growing elective waiting list. This was exacerbated by a lack of acute beds as managers closed beds in a desperate attempt to save costs, which meant surgical capacity was further eroded by medical patients placed in surgical beds. Hence the figure of 45 ± 5 only covers the medical group of specialties. For this same reason, the average of bed days per death for the Surgical group in Table 2 used corrected data (a polynomial curve fit) from 2014/15 onward. Excluding the corrected data gave the same average and standard deviation, hence the figures are robust.

The considerable scatter around the trend line using the differences between years method is also partly because deaths will lag admissions by around 1 to 2 months implying that financial year data may not exactly match, the mix of agents will vary from year-to-year, i.e. higher levels of influenza(s), or RSV, etc in some years, and that winter outbreaks can span financial years, and the fact that diagnoses like circulatory disease have been declining but are replaced by diagnoses such as dementia(s). The result is that there is considerable case mix volatility from year to year. This relationship requires far greater research.

However, 45 bed days represents a substantial 74% of total medical bed occupancy. The study of Hanlon et al (1998) established that there was a significant burden of mental health bed occupancy in the last year of life. Recent research has established that there are indeed huge overlaps between psychosocial and lifestyle factors and immune function (te Velde et al 2016), creating bidirectional relationships between the two (Maes et al 2012). Hence, it is possible that the last year of life plus associated morbidity could account for up to 50 bed days per death of the 102 ± 4 bed days of total hospital bed days, i.e., a maximum of approximately 50% of the total.

Recall from Part 2 of this series that any agent promoting inflammation will exacerbate a wider range of conditions leading to an admission for a diagnostic procedure, an elective or emergency intervention to correct the underlying medical condition, i.e., appendicitis, joint surgery, etc, or a medical admission for a flare up of rheumatoid arthritis, irritable bowel disease, COPD, asthma, etc.

Hence, the trend in deaths not only encapsulates acute hospital bed use during the last year of life expressed in the NTD effect but far wider morbidity. This raises the fascinating question as to how much of human disease has a primary infectious trigger (Jones 2010, Turabain 2017, Kung et al 2019, Skevaki and Thornton 2020)?

The key issue is whether deaths are highly volatile or stable from year to year. This explains why the seemingly simplistic ratio of occupied beds per 1,000 deaths gives such profound insight into medical bed demand (Jones 2020). Note that 82 occupied beds per 1000 deaths is equivalent to 30 bed days per death. This volatility will now be explored in greater detail in terms of the effect of organization size (as deaths) on the resulting volatility and consequent financial stability and the ability to forecast year-end outturn from a mid-year position.

In-hospital mortality

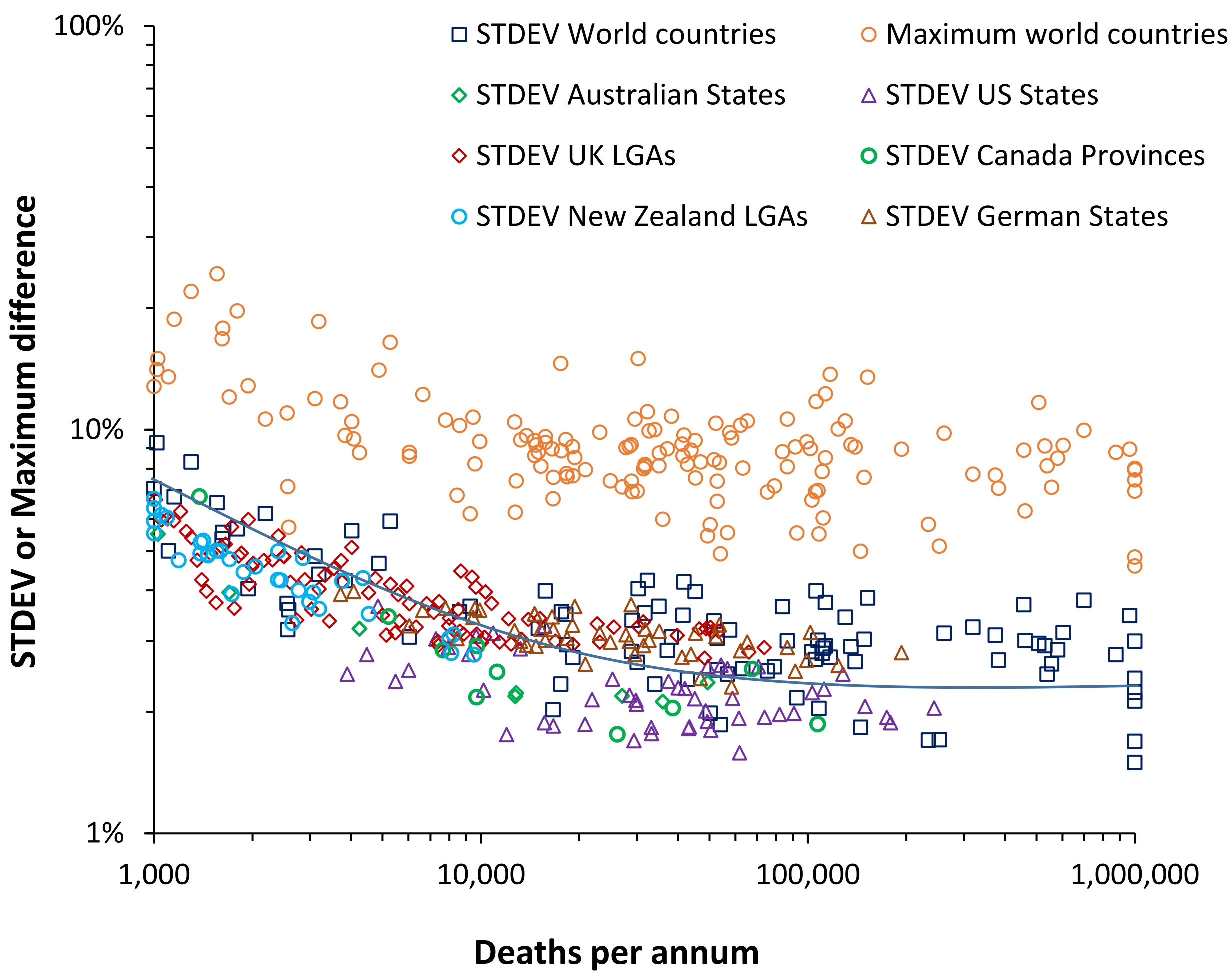
Attempts to determine if the quality of care in a hospital is of an adequate standard use the Hospital Standardized Mortality Ratio (HSMR) which has various modifications to adjust for risk factors. It is generally not widely appreciated that HSMR most often simply tracks the changes in the total number of deaths (all-cause mortality) in the wider community surrounding the hospital. To reiterate HSMR is not driving all-cause mortality rather all-cause mortality is driving HSMR (Jones 2015, 2016. 2017, 2018a,b). Hence HSMR is simply responding to all the complex small-area trends detailed in this series, and primarily has nothing to do with the quality of hospital care.

Organization size and volatility

Deaths represent a unique internationally comparable statistic since they are collected by most governments with a high degree of accuracy, as is also the case for births.

Figure 2 therefore shows a rolling 12-month calculated standard deviation and the maximum change in the difference in year-to-year deaths, versus the size of the spatial unit as average number of deaths per annum since 1990. These were calculated for 97 world countries with more than 1,000 deaths per annum. Also included in Figure 1 is data for Australian states, US states, Canadian provinces, German states (Länder) and UK local government areas (LGAs).

Figure 2: Standard deviation associated with a rolling year-to-year percentage difference in deaths for 97 countries having more than 1,000 deaths per annum and the value of the maximum year-to-year change, 1990 to 2019.



Several key points emerge from Figure 2, namely:

1. Year-to-year volatility is country specific.
2. Despite country specificity the volatility reaches an asymptote at 100,000 deaths per annum.
3. The volatility has declined considerably by 20,000 deaths per annum to suggest that this represents an acceptable compromise for the size required to minimize volatility and so achieve maximum financial stability.
4. A significant number of world countries lie below 20,000 deaths per annum including all the small Pacific states, most of the Gulf states, Cyprus, Iceland, Kuwait, Luxembourg, Malta, five out of eight Australian states, 16 of 52 U.S. states, Northern Ireland in the UK. Puerto Rico lies just at the 20,000 level.

5. As expected, the maximum year-to-year difference is 2- to 3.5-times higher than the standard deviation, and even at 20,000 deaths ranges from 6% to 15% depending on the country.
6. It is of interest to note that the volatility in the UK is higher than that seen in Australia, Bahrain, Canada, Costa Rica, Singapore, and the USA, but is similar to that in German states. Excess Winter Mortality (EWM) is also high in the UK although exactly why has never been adequately explained.
7. Table 3 explores the issue of volatility in more detail using data for US states over the interval 2007 to 2019. The standard deviation for each state has already been shown in Figure 2. As can be seen from Table 3 the rolling 12-month maximum difference occurs for some 24% of states occurs at the 12-month period ending July/August while 34% end at months April/May. Some 24% occur in 2013 while 57% occur in 2015. Multiple mechanisms for the volatility in deaths are required to explain this diversity. Table A1 in the Appendix gives a similar view for German states.
8. As for the ratio of maximum increase relative to standard deviation, an identical range of 2- to 3.5-times higher is seen as was the case for world countries (Figure 2).

Figure 3: Rolling year-on-year difference in total deaths for two US states of different size

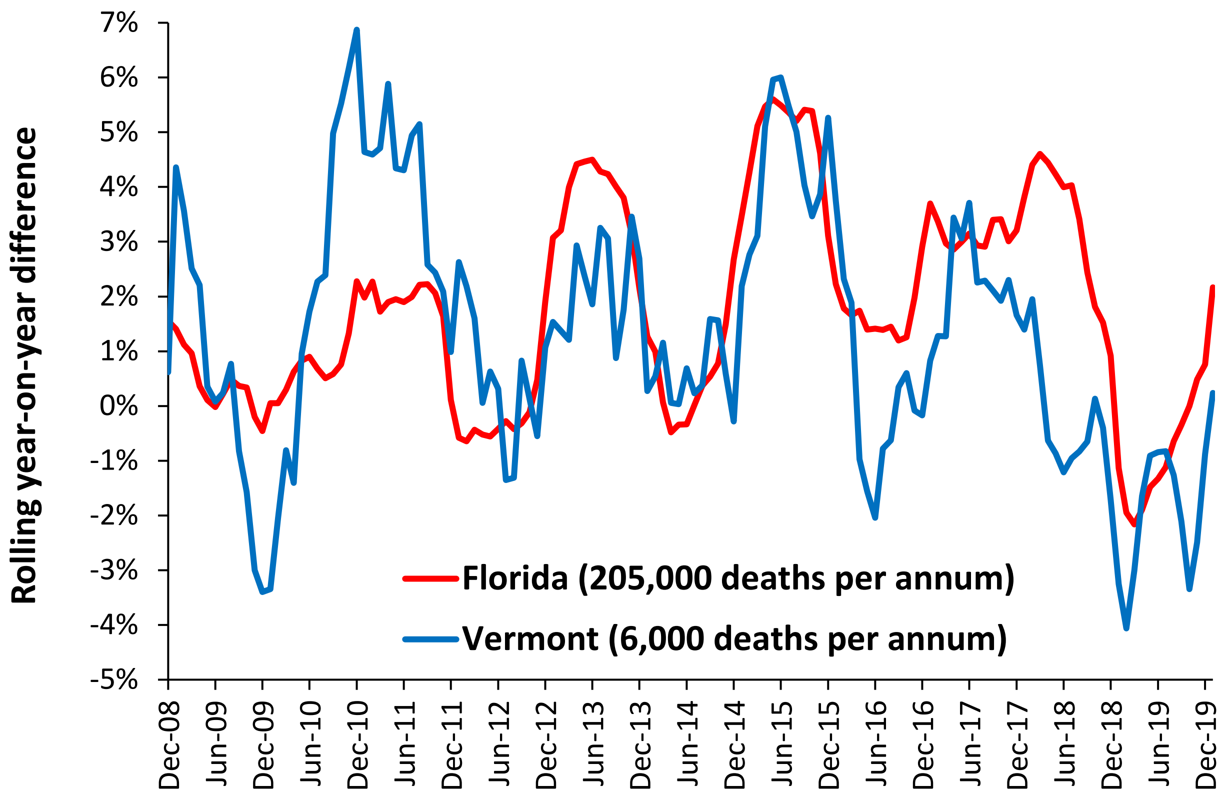


Table 3: Measures of the year-to-year volatility in deaths for US states, 2007 to 2019

State	Size (deaths per annum)	STDEV	Max-imum	Max /STDEV	When
Alaska	3,900	2.5%	8.7%	3.5	Sep-15
Wyoming	4,500	2.8%	10.1%	3.6	Apr-15
District of Columbia	4,900	3.7%	7.8%	2.1	Apr-15
Vermont	5,500	2.4%	6.9%	2.9	Dec-10

North Dakota	6,000	2.5%	7.1%	2.8	Jan-09
South Dakota	7,300	3.0%	8.4%	2.8	Jun-15
Delaware	8,000	2.9%	7.3%	2.5	Feb-15
Montana	9,200	2.8%	6.8%	2.5	Aug-13
Rhode Island	9,700	3.1%	6.2%	2.0	Nov-15
Hawaii	10,200	2.3%	5.6%	2.5	Oct-09
New Hampshire	10,900	3.1%	10.4%	3.3	Apr-15
Idaho	12,000	1.8%	6.5%	3.7	Aug-11
Maine	13,200	2.9%	8.6%	3.0	Sep-15
Utah	15,600	1.9%	6.4%	3.4	Aug-15
Nebraska	15,700	3.3%	8.1%	2.5	Aug-15
New Mexico	16,700	1.8%	5.2%	2.8	Jan-15
Nevada	20,800	1.9%	5.9%	3.2	Jan-17
West Virginia	21,900	2.1%	6.0%	2.8	May-15
Kansas	25,200	2.4%	4.8%	2.0	Jul-15
Iowa	28,500	2.2%	5.0%	2.3	Dec-08
Connecticut	29,400	1.7%	4.2%	2.5	Feb-15
Mississippi	29,800	2.1%	6.2%	2.9	Apr-13
Arkansas	29,900	2.1%	4.7%	2.3	Aug-15
Oregon	33,200	1.8%	5.1%	2.8	Jul-15
Colorado	33,200	1.8%	7.3%	4.2	Feb-15
Oklahoma	37,500	2.4%	5.1%	2.1	Nov-13
Minnesota	40,100	2.3%	6.0%	2.6	Oct-15
Louisiana	42,100	2.3%	7.5%	3.3	May-13
South Carolina	43,200	1.8%	6.1%	3.4	Apr-13
Kentucky	43,400	1.8%	6.5%	3.5	May-15
Maryland	45,100	2.2%	5.9%	2.7	Mar-17
Wisconsin	48,600	2.0%	5.1%	2.6	Jun-11
Alabama	49,300	1.9%	5.3%	2.8	May-13
Arizona	49,500	2.6%	7.2%	2.8	Mar-16
Washington	50,500	1.8%	5.2%	2.9	Sep-15
Massachusetts	54,300	2.6%	6.2%	2.4	Oct-15
Missouri	56,800	2.6%	5.8%	2.3	Apr-15
Indiana	58,900	2.2%	5.7%	2.6	Jan-09
Virginia	61,600	1.9%	5.5%	2.9	May-13
Tennessee	61,900	1.6%	4.8%	3.0	Jul-13
New Jersey	70,700	2.6%	5.5%	2.1	May-13
Georgia	73,700	1.9%	6.5%	3.3	May-13
North Carolina	82,000	2.0%	6.2%	3.1	Jul-15
Michigan	90,700	2.0%	5.3%	2.7	Apr-15
Illinois	103,100	2.2%	5.4%	2.4	Aug-15
Ohio	112,200	2.3%	6.0%	2.6	Aug-15
Pennsylvania	128,100	2.5%	5.2%	2.1	Apr-15
New York	149,600	2.1%	4.2%	2.0	Jul-13
Texas	174,300	1.9%	6.1%	3.1	Apr-13
Florida	179,000	1.9%	5.6%	3.0	May-15
California	243,400	2.0%	5.4%	2.6	Dec-15
USA	**2,554,000**	**1.8%**	**4.7%**	**2.7**	**Aug-15**

Note that in Part 3 it was established that 2015 marked an international tipping point when improvements in life expectancy and age standardized mortality suddenly seemed to stall in many Western countries. This was indeed the case in the US (Acciai and Firebaugh 2017). For men this was associated with changes in mid-life mortality, especially in accidental poisoning, homicide, and mental illness, but for women was due to changes in old age mortality especially in heart disease and mental illness. The magnitude of the effects differed across racial and ethnic groups. Especially refer to earlier comments regarding the bidirectional nature between mental illness and immune function. This is relevant since all three causes of higher male mid-life mortality can be linked to mental health implying a primary immune disturbance as the source.

The reader should note that a maximum change in say August 15 implies that the difference between years (as rolling 12-month totals) was highest for the 12-month period September 2014 to August 2015 versus the period September 2013 to August 2014, etc. This is not evidence for a predominantly winter phenomenon. These issues were discussed in greater detail in Part 3.

Clearly the maximum increase is not the only example of a large year-on-year change. Each state therefore faces the prospect of a variable maximum cost shock plus other cost shocks. See Table A1 in the Appendix for a similar example using German states. Figure 3 gives an example of a rolling 12-month difference using data for Florida and Vermont as random examples. As can be seen the shape of the rolling trend differs between the two states with differences in timing and magnitude for the multiple factors contributing to the trends. The far right of Figure 3 captures the start of the 2020 COVID-19 outbreak. Clearly Vermont will be more volatile than Florida due to its smaller size, however, smaller size allows for better detection of localized infectious outbreaks in the trend.

A shift-down in 2018 followed by shift-up in 2019 can be seen for Florida, as noted in the UK (see Part 3). Recall that each state is a composite picture of the smaller areas comprising that state (see Part 1). The overall trend will be greatly influenced by the number of large cities, their population density, age structure, the number and size of nursing homes, etc. The key point is that the trends are complex. Recall that in the Introduction the point was made that the effect of these cost shocks depends on when the financial year end occurs for organisations affected by such changes.

This raises the issue of the effect of size on the ability to forecast year-end outturn from cumulative mid-year totals. The obvious first step is for all organisations to construct rolling 12-month total and rolling 12-month difference charts to enable senior managers to see the trends in a wider perspective.

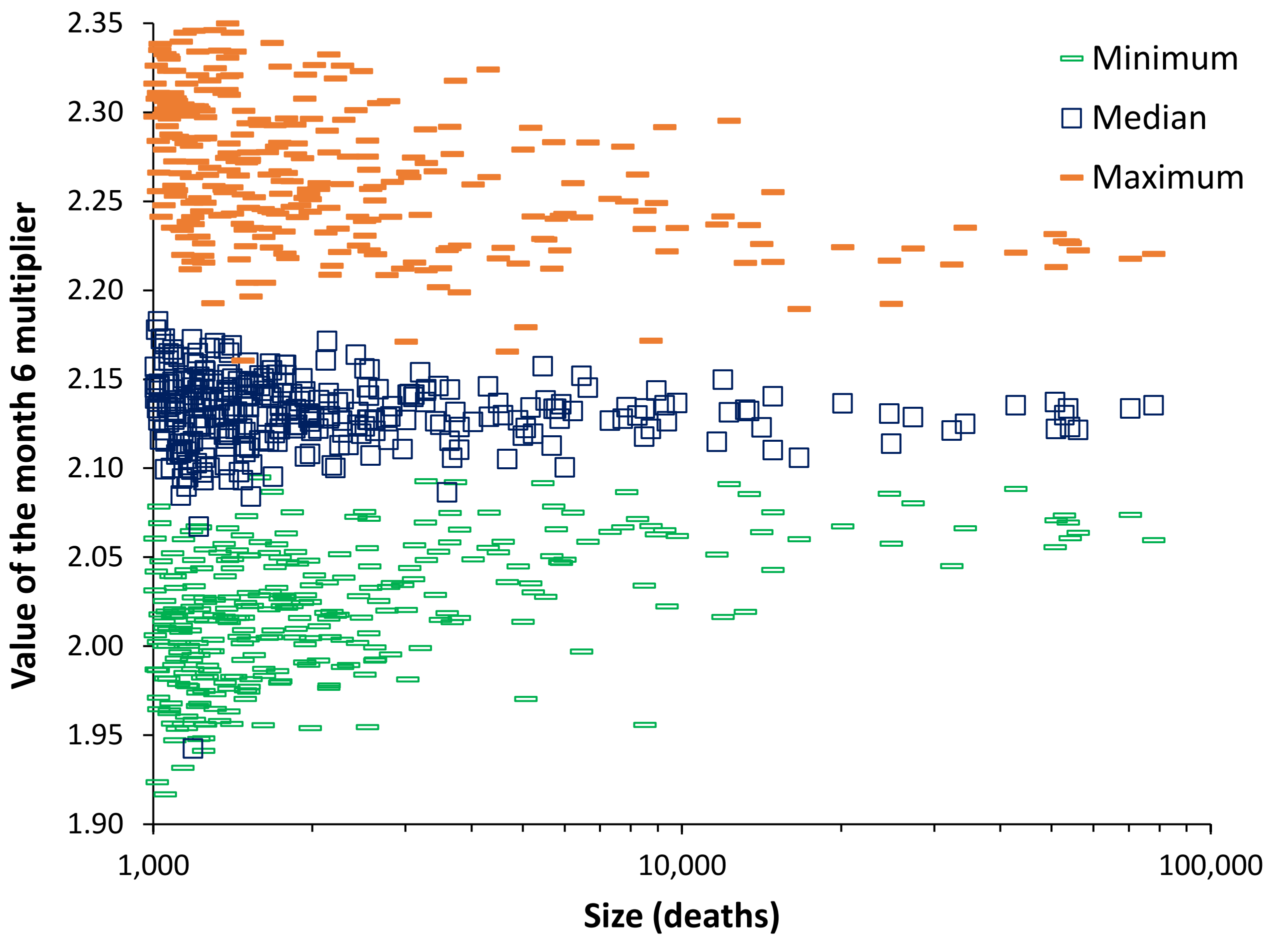
Size and forecasting year-end

Year-end can be forecast using the multiplier methodology (Jones 1996) in which monthly data is first corrected for the number of workdays or total days (for deaths). The cumulative number of deaths from previous years is used to construct a monthly multiplier which can be applied to forecast year-end at any point in the year. The forecast will have upper and lower limits determined from the volatility associated with however many years data is available.

Figure 4 demonstrates the importance of size using 350 English and Welsh local government areas (LGA) and regions over the interval 2001 to 2019. This analysis uses the UK financial year ending in March and hence month 6 occurs in September. The median value of the multiplier is higher than 2.0 because the winter (highest deaths) occurs at the end of the financial year. The maximum, median and minimum multiplier value for each LGA is calculated over a 19-year period and these are shown for the 350 LGAs in Figure 3. As can be seen even when using the median there is considerable size-related uncertainty between LGAs. Adding the 19-year maximum and minimum confidence intervals around the median only increases the uncertainty. Any area with less than the suggested 20,000 deaths per annum cannot forecast year-end at month 6 with any degree of certainty. Note how the uncertainty jumps to a higher level below the 20,000 deaths per annum boundary.

Consider the profound implications of this figure. Each data point is from 19 sperate calculations of the multiplier in that specific area. This is ***not*** an example of statistical scatter. This graphically illustrates the location-specific nature of small-area volatility. Both my published and unpublished work confirms this using very small-area data. See further reading at the end of the study. Most infectious outbreaks will only occur at small-area level. Many will be prompted by imported pathogens by those who have been overseas (Herbinger et al 2016). Each small area is a network of social and cultural person-to-person contacts overlaid by general population density.

Figure 4: Maximum, median, and minimum value of the month six multiplier to forecast year end outturn for 350 local government areas across England and Wales. Each point is from a nineteen-year period.



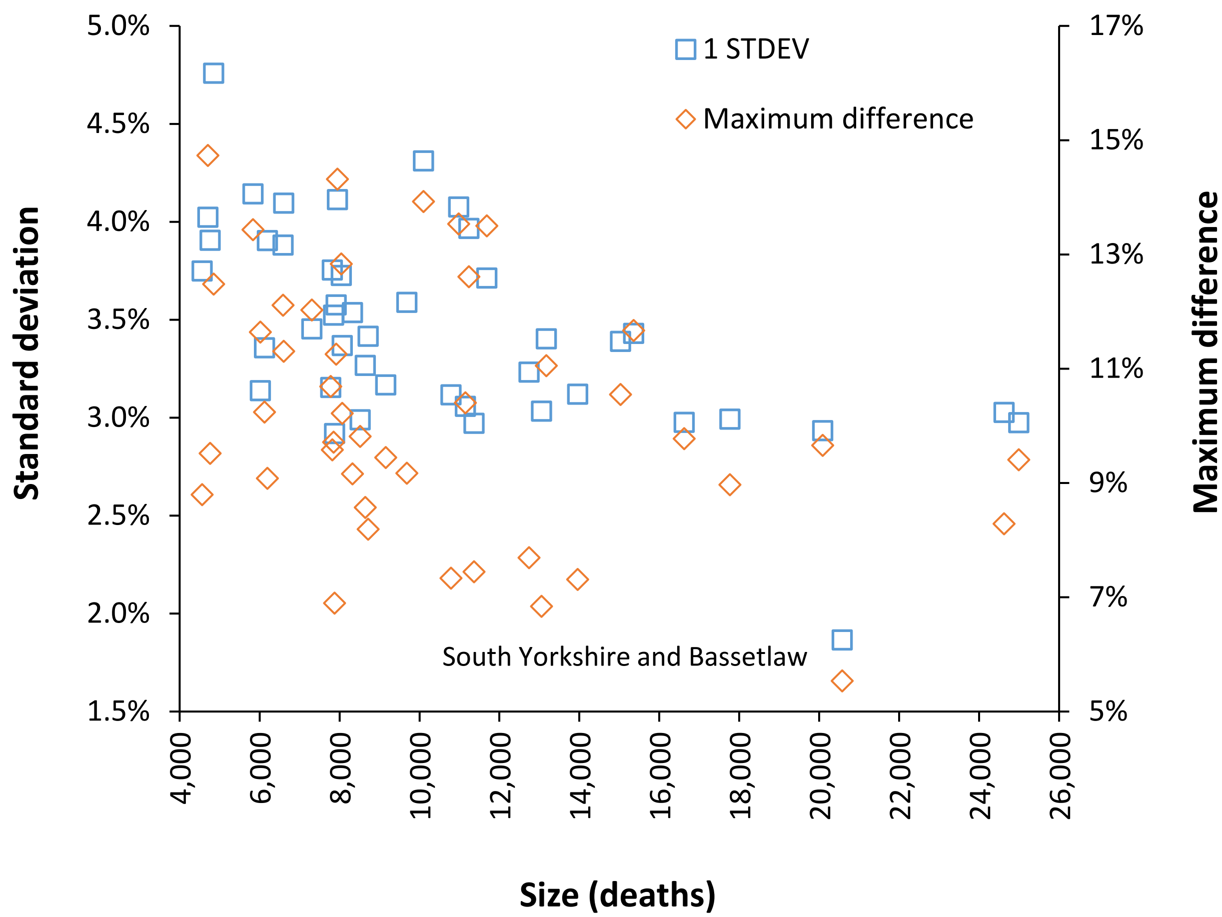
These small-area outbreaks have a cancelling-out effect as the spatial size and number of deaths increase. Hence the lower volatility as size increases. However, even large regions show consistent differences. Note that both health and social care costs relating to persons in the last year of life will follow the same pattern of risk.

Note from Figure 4 that the occasional 'lucky' small area can experience less volatility than far larger areas. This is simply the outworking of the location-specific nature of volatility.

Localization and the size of English Clinical Commissioning Groups

The Health and Social Care Act 2012 (Department of Health and Social Care 2012) introduced General Practitioner led Clinical Commissioning Groups (CCG) into England. The political ideal of localization was somewhat over-enthusiastically applied and CCGs were encouraged to be coterminous with local authorities. Most English local authorities only have around 1,000 deaths per annum which Figure 2 shows guarantees high financial risk. NHS England has been gradually merging these small CCGs and has recently announced a far higher level of mergers with CCG Sustainability Footprints (now called Integrated Care Systems)

Figure 5: Year-to-year volatility as the standard deviation and maximum rolling 12-month difference for CCG Footprints (2001 to 2020)



In Figure 5, the equivalent populations covered by these Footprints have been determined and the standard deviation (as above) associated with a rolling 12-month difference in deaths and maximum year-on-year increase have been calculated using monthly data from 2001 to 2020. As can be seen only four such footprints have sufficient deaths to fall near or above the suggested 20,000 deaths needed for financial stability. The two largest Footprints covering Greater Manchester and Cheshire and Merseyside have around 25,000 deaths per annum.

As can be seen, the South Yorkshire and Bassetlaw CCG Footprint has hit the jackpot for minimum possible volatility and risk with a standard deviation of just 1.9% and a maximum year-to-year difference of just 5.5%. As was determined back in 2012, financial risk is highly location specific and very high for small organisations (Jones 2012). At the other extreme the 'unlucky' CCG footprint in Dorset with around 5,000 deaths per annum experiences maximum risk with a standard deviation of 4.8% and a maximum increase of 12.5%. NHS England has seemingly not made a proper investigation regarding the financial risk implied by the 'larger' CCG Footprints and the implications regarding the gap in sizes.

The possibility of smaller STP footprints is not entirely precluded and apart from Greater Manchester and South Yorkshire & Bassetlaw several other STP Footprints have a 3% or lower standard deviation, namely, Durham/Darlington/etc, West Yorkshire, S.E. London, Kent & Medway, North Central London, Coast/Humber/Vale, Cheshire & Merseyside, Lancashire & South Cumbria. However, recall that a 3% standard deviation is a 20-year average, and that the maximum year-on-year difference is up to 3.7-times higher than the standard deviation. The potential for a very high year, or a series of higher years always creates scope for a significant financial challenge. Highs and lows do not always cancel out.

Implications to regional funding (capitation) formulae

Many countries use an allocation formula to distribute national funds to States, provinces, regions, and in England to CCGs (Howell 2008, Alonge et al 2017, Jones et al 2018). These are sometimes called capitation formula since the allocated funds are calculated based on the enrolled members or resident population (BMA 2020), and associated risk factors (Dixon et al 2011). A health insurer is therefore capitation funded by its members. Such allocation formula usually ignores the implications of total deaths as a measure of implied financial risk (Jones 2021). Earlier capitation funding used the age standardized mortality rate to forecast the effects of death (Raftery 1993), however this is a poor substitute for the absolute number of deaths. The problem is that Health Departments wrongly assume (at least publicly) that there is no risk associated with the formula (Howell 2008). Hence, in the English NHS, politicians seemingly assume that financial overspends are always due to poor management or the inability to control demand. A method is needed to equalize funds to cover those years when various regions experience higher/lower deaths than implied in the financial allocation.

It is suggested that deviation from the expected number of deaths in each year should be used to make retrospective adjustment (Jones and Kellet 2018c), with fine tuning for costs arising from cause of death and individuals with no admissions in the last year of life. See case study below.

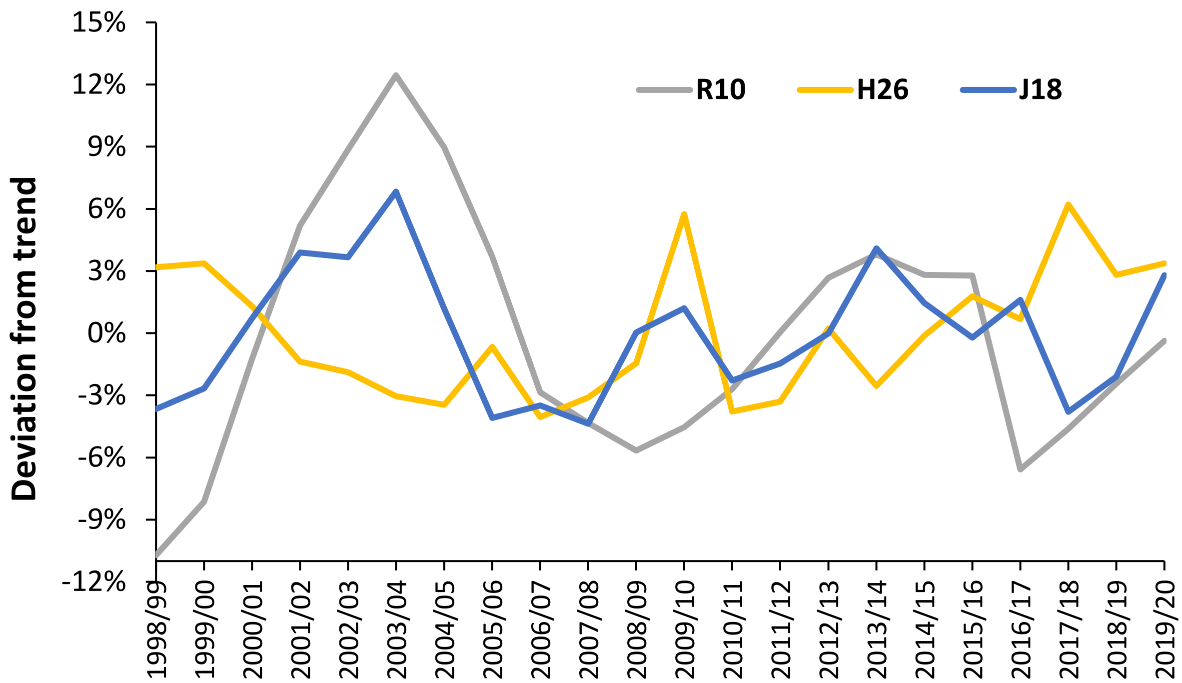
Fee-for-service HRGs, DRGs and financial risk

Many countries use a fee-for-service tariff to reimburse provider hospitals for admissions. England uses the Healthcare Resource Groups (HRG) and many other countries use Diagnostic Related Groups (DRG) (Mathauer and Wittenbecher 2013). Each HRG or DRG has a set price, which is incorrectly assumed to have no hidden flaws (Jones 2012d). The whole thrust of this series are that admissions and occupied bed days are volatile.

Figure 6 illustrates hidden volatility in the tariff using length of stay for three high volume diagnoses, namely R10 (abdominal and pelvic pain) 357,000 admissions in 2019/20, H26 (other cataract) 230,000 admissions, J18 (pneumonia, organism unspecified) 270,000 admissions. As can be seen there is systematic variation over time. The HRG tariff in England operates with a three-year lag, hence data for the 2016/17 year is used to calculate the tariff for the 2019/20 year. As can be seen from Figure 6 that there can be marked changes in length of stay related costs during this three-year interval. It should therefore come as no surprise to note that the price for each English HRG shows extreme year-to-year volatility (Jones 2011). The inherent complexity in the factors driving costs are essentially beyond the capacity of the architects of a simplistic tariff to anticipate. To multiply an uncertain number of admissions by an uncertain price is a recipe for financial risk. See Jones (2004) for an example of gross variation in income arising from chance using the HRG tariff.

Hence any system using a fee-for-service tariff enhances the underlying volatility in costs. Indeed, both HRGs and DRGs are a mix of NTD and non-NTD admissions, and this mix is assumed to remain constant across space and time, i.e., that there are no spatiotemporal effects. This incorrect assumption then adds further cost pressures into some locations or places. The risk does not go away, and governments need to intervene to ensure that it is equitably managed. Value based health care principles are a better approach (Salvatore et al 2020). Indeed, the artificial purchaser/provider split introduced into the English NHS in 1990 is long overdue to be consigned to history (Maynard and Dixon 2016). Given the evidence presented in this series it was doomed to failure before it started. In hindsight, the time would have been far better spent pursuing integrated care (NHS England 2020c).

Figure 6: Systematic deviation in length of stay from the underlying trend, 1998/99 to 2019/2020, England



Footnote: Data is from Hospital Episode Statistics (NHS Digital 2020). Length of stay is an average for both elective and emergency admissions. Same day stay admissions have been attributed an 8-hour length of stay. The underlying trend was calculated as a linear relationship for R10, a Power Law relationship for H26, and a second order polynomial for J18.

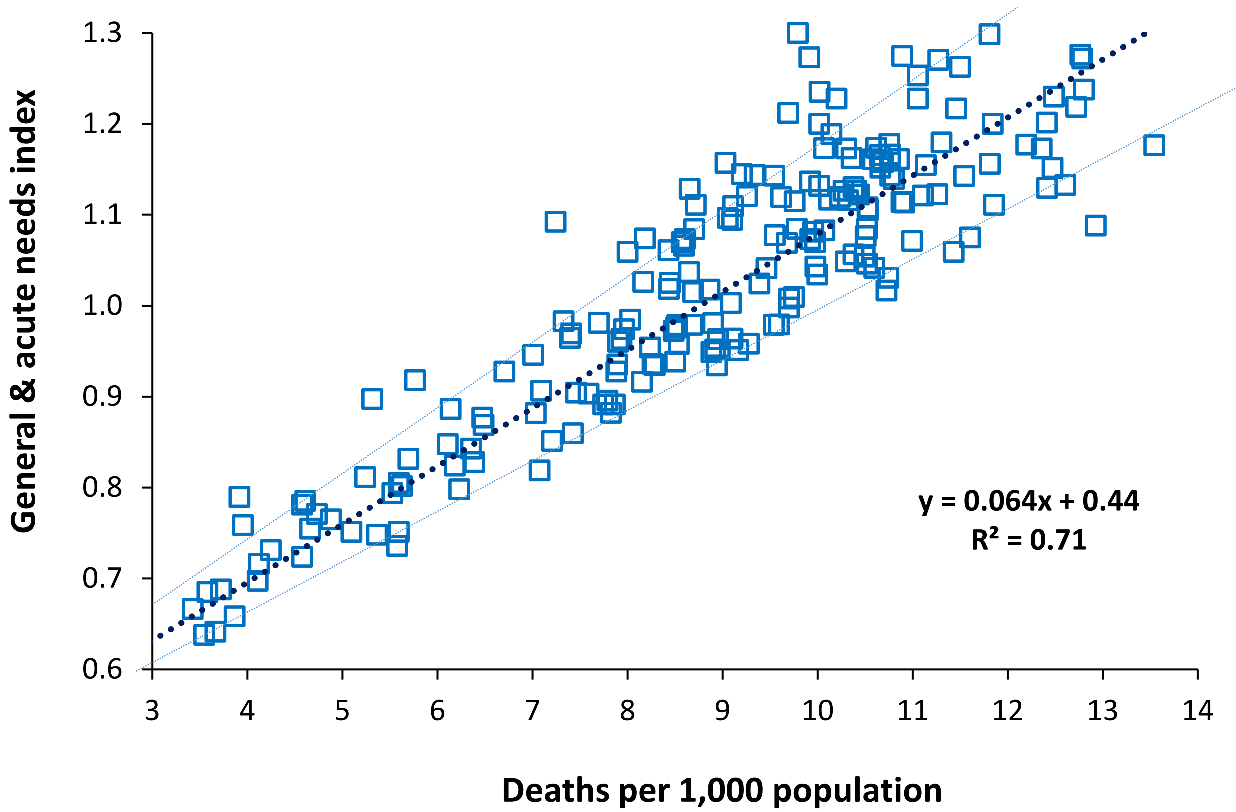
Case study: the English NHS general and acute needs index for Clinical Commissioning Groups (CCGs)

A long history of refinement of resource allocation formulas in the English NHS has led to a person-based formula for allocating general and acute costs to CCGs (Dixon et al 2011). This formula covers hospital costs for inpatient, outpatient, and the emergency department contact (excluding maternity and mental health) and has since undergone continuous development (NHS England 2020). This is a complex formula with multiple pages of technical documents. However, this formula completely omits to acknowledge the reality of the NTD effect.

The general and acute needs index has a national average of 1.0 with a value of 0.6 implying that a CCG would receive only 60% of the national average funding per head of population (or 40% less per head), while a value of 1.3 implies 30% more funds per head of population.

Despite its vast complexity Figure 7 shows how a simple ratio of deaths per 1,000 population can explain over 71% of the variation in the general and acute needs index. This is a remarkable achievement for a single parameter model versus the output from a model with hundreds of parameters.

Figure 7: Role of deaths per 1,000 population as a neglected explanatory variable in the 2018/19 general and acute needs index formula for English CCGs. Data is from spreadsheet C1 (NHS England 2020), while deaths in 2018 are from the ONS Number of death registrations by clinical commissioning group, England: 2017 to 2018 - Office for National Statistics**.**



To create Figure 7 the actual CCG needs index for 2018/19 was matched to CCG deaths in 2018. Deaths per CCG ranges from 13,240 for the Birmingham & Solihull CCG down to 540 for the Bradford City CCG. Hence some of the scatter will also arise from simple Poisson statistical variation in the number of deaths, i.e., ± 0.3 deaths per 1,000 population for Bradford City, to ± 0.1 for Birmingham & Solihull. These are somewhat minor technical points.

The relationship is seemingly linear with the intercept indicating the approximate non-end-of-life component. However, the greatest scatter seems to occur for those CCG which have a needs index above the national average. There is also a tendency for more CCG to lie appreciably higher than the trend line than below (see dotted lines). Is this scatter an artefact of the NHS model omitting to include a key variable? Recall that the shift-up shift-down mechanisms in deaths identified in Part 3 will be operating regarding end-of-life costs for each CCG.

CCG lying below the trend line are highly likely to be under-funded and those above it are likely to be over-funded. Deaths partly adjust for the effects of social deprivation in that persons in more deprived areas tend to die younger. CCGs outside of the dotted lines are probably grossly over- or under-funded.
The key point is that a very sophisticated model appears to contain a serious and possibly catastrophic flaw simply due to the omission of the well-researched reality of the NTD effect upon costs (Seshamani and Gray 2004, French et al 2017, van der Plas et al 2017, Stoye 2019, Luta et al 2020). How did the obvious get overlooked?

Conclusions

A simple common-sense view of financial and capacity risk would indicate that smaller organisations would be subject to higher volatility and consequent risk. Given the small area volatility demonstrated in this series it is not surprising that an area with greater than 20,000 deaths per annum is required to achieve maximum financial stability.

If the principle of localization is to be upheld, then central government must ensure that the inevitable financial risk is equalized. Variation in the absolute number of deaths is the most obvious way to achieve this end (Jones and Kellet 2018c), with suitable adjustment for costs associated with cause of death. Primary and social care follow the same principles, however, the NTD transition in these settings occurs over three to four years.

Finally, to conclude this four-part series. Financial and capacity risk in health care is brutally high, always has been and always will be. This risk is completely unfairly distributed in a location-specific manner, always has been and always will be. Governments must change the way that this risk is shared and avoid the blame culture that has arisen out of misunderstanding of the nature and origins of the risk.

Materials and Methods

Data sources and methods have been detailed in earlier parts of this series. Monthly deaths for world countries were from the United Nations Data repository (2020). Data for German states is from GENESIS-online (2020). Methods are the same as detailed in the earlier parts.

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Further reading

Details of wider research in the areas of financial risk, capacity planning and forecasting demand can be found at http://www.hcaf.biz/2010/Publications_Full.pdf

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Appendix

Table A1: The equivalent to Table 3, but for German states, including separate male/female analysis, 1990 to 2020. Note the high frequency of maximum year-to-year difference in 2015, as per Part 3.

State	Gender	Average Deaths	STDEV	Maximum	Max/ STDEV	When
Baden-Württemberg	Male	46,904	2.4%	8.3%	3.4	Aug-15
	Female	52,325	3.1%	10.4%	3.4	Sep-15
	Total	99,229	2.7%	9.3%	3.5	Sep-15
Bayern	Male	58,426	2.3%	9.5%	4.1	Sep-15
	Female	65,280	3.0%	10.5%	3.5	Sep-15
	Total	123,706	2.6%	10.0%	3.9	Sep-15
Berlin	Male	15,750	3.0%	9.3%	3.1	Sep-15
	Female	19,349	3.6%	8.5%	2.3	Nov-15
	Total	35,099	3.2%	8.8%	2.8	Nov-15
Brandenburg	Male	13,790	2.9%	9.7%	3.3	Sep-15
	Female	14,622	3.5%	8.6%	2.5	May-15
	Total	28,413	3.0%	9.1%	3.0	Sep-15
Bremen	Male	3,722	3.9%	11.7%	3.0	Jun-15
	Female	4,076	4.0%	9.5%	2.4	Jun-15
	Total	7,799	3.6%	10.6%	2.9	Jun-15
Hamburg	Male	8,444	3.0%	6.9%	2.3	Apr-03
	Female	9,907	3.6%	9.3%	2.6	May-15
	Total	18,351	3.0%	7.7%	2.5	May-15
Hessen	Male	29,588	2.8%	10.6%	3.8	Nov-15
	Female	32,657	3.0%	9.9%	3.3	Nov-15
	Total	62,245	2.8%	10.3%	3.6	Nov-15
Mecklenburg-Vorpommern	Male	9,467	3.4%	10.7%	3.1	Jul-15
	Female	9,587	3.6%	8.2%	2.3	Sep-15
	Total	19,054	3.3%	9.1%	2.8	Dec-15
Niedersachsen	Male	41,194	2.7%	9.2%	3.4	Jun-15
	Female	45,272	3.1%	7.6%	2.4	Jul-15
	Total	86,466	2.9%	8.1%	2.8	Jul-15
Nordrhein-Westfalen	Male	91,481	2.5%	9.1%	3.6	Jul-15
	Female	101,758	3.1%	9.0%	2.9	Aug-15
	Total	193,239	2.8%	9.0%	3.2	Jul-15
Rheinland-Pfalz	Male	20,863	2.6%	8.0%	3.0	Sep-15
	Female	23,066	3.1%	9.9%	3.1	Oct-15

State	Gender	Average Deaths	STDEV	Maximum	Max/ STDEV	When
	Total	43,929	2.8%	8.9%	3.2	Aug-15
Saarland	Male	6,035	3.3%	8.6%	2.6	Nov-15
	Female	6,644	3.6%	12.2%	3.4	Nov-15
	Total	12,679	3.2%	10.5%	3.3	Nov-15
Sachsen	Male	24,840	3.0%	7.5%	2.5	Sep-15
	Female	28,778	3.7%	9.2%	2.5	Jul-15
	Total	53,618	3.3%	8.3%	2.5	Sep-15
Sachsen-Anhalt	Male	15,260	3.2%	8.1%	2.5	Nov-15
	Female	16,496	3.4%	9.0%	2.6	Sep-15
	Total	31,757	3.2%	8.1%	2.5	Sep-15
Schleswig-Holstein	Male	14,742	2.9%	9.2%	3.2	Dec-15
	Female	16,664	3.2%	7.6%	2.4	Jun-15
	Total	31,406	2.9%	8.0%	2.7	Dec-15
Thüringen	Male	13,218	3.0%	9.4%	3.2	Jul-15
	Female	14,573	3.5%	9.4%	2.7	Sep-17
	Total	27,791	3.1%	9.0%	2.9	Nov-15