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A fundamental flaw in person-based funding?

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Abstract

A long time series of surgical emergency admissions is used to demonstrate that bed occupancy (and costs) fluctuates in a manner which is far greater than expected from simple random variation. Periods of adverse environmental conditions can be discerned which presumably act to exacerbate existing conditions. Somewhere around 20% of cost variation between Clinical Commissioning Groups (CCGs) may be explained by the wider environment (weather, air quality, infectious outbreaks). Future generations of the capitation formula will need to incorporate a greater proportion of environmental factors and at a local level some form of yearly risk payment (or risk equalisation via larger financial risk pools) may be needed to account for adverse events not experienced elsewhere.

Key Points

- Cost variation over time for emergency admissions to a surgical group of specialties is relatively high despite the relative insensitivity of this group to the seasonal fluctuation in admissions seen in medicine, paediatrics and trauma.
- It is highly likely that somewhere up to 20% of cost variation between CCGs may arise from the environment rather than from person-based factors
- Failure of the existing versions of the resource allocation formula to reflect this important contribution to cost is perversely leading to inequality and promulgation of the so-called post code lottery.

Introduction

With the move towards person-based health budgets the impact of variation on health care costs has never been so important. As series of articles in BJHCM have demonstrated that environmental factors, such as the weather, air quality and infectious outbreaks appear to play a far greater role in the variation associated with health costs than has been previously recognised, possibly even as important as personal factors such as gender, age, health status and socio-economic factors (Jones 2009a-b, 2010c, 2011 a-c, 2012 a-i).

It is widely recognised that many medical conditions show seasonal variation (Flemming et al 1991, Damiani & Dixon 2001, Upshur et al 2005), i.e. if the environment only played a minor role in health there would be no basis for seasonal effects. While seasonality is an important expression of the environment upon health, especially in an infectious context (Dowell 2001), this does not imply that all expressions of the environment are necessarily seasonal. In this respect a person-based formula for predicting the expenditure on acute health problems for GP practices has been recently developed to extend the previous capitation formula (Dixon et al 2011). The various person-based models developed to predict acute costs all explained around 77% of the observed cost variation. While this does not imply that the different models predict the same level of funding for each practice (Jones 2010d) it offers the possibility that this study has inadvertently measured the extent to which the combined and interactive effects of the wider environment influences the variation in costs, i.e. the 23% of residual unexplained variation. This hypothesis is tested using a long time series of surgical emergency hospital admissions, where such admissions are fairly non-seasonal, but still open to a range of environmental effectors.

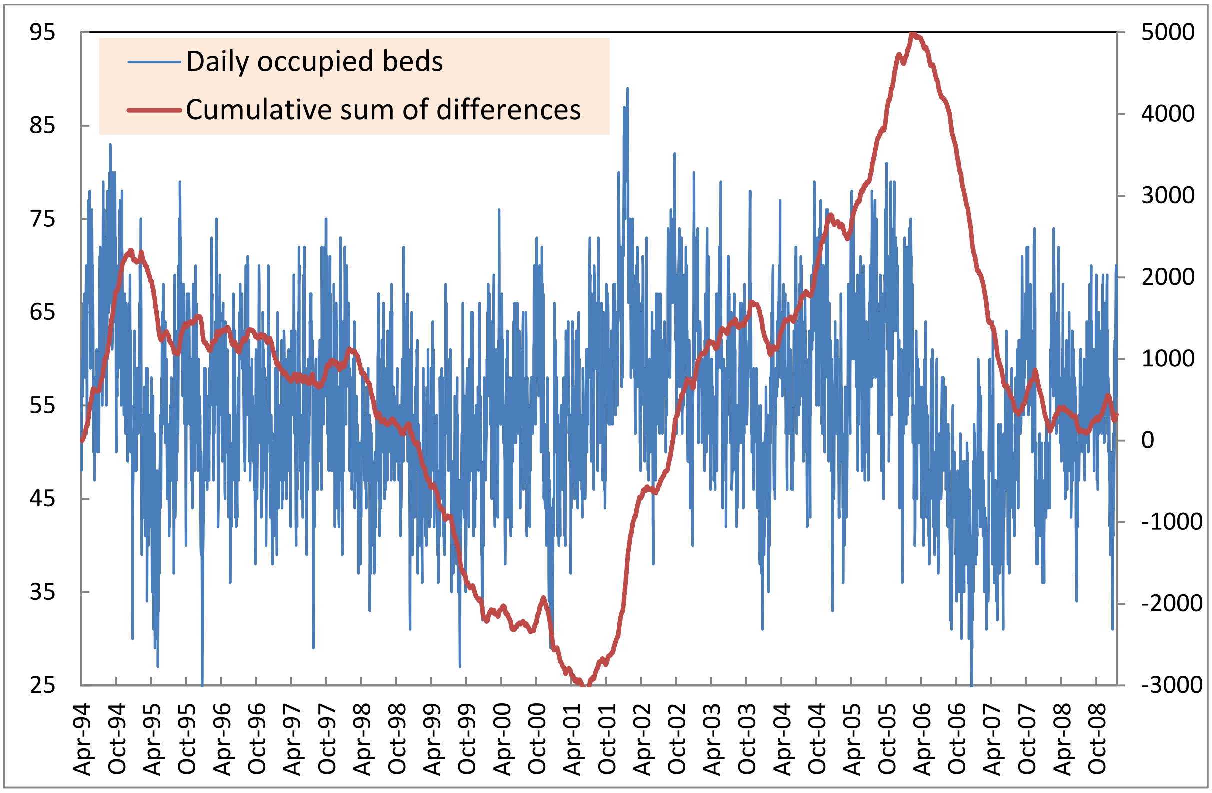
Bed Occupancy

Bed occupancy offers a simple way to test the relationship between costs and the environment in that occupied beds (via their association with admissions) are a direct measure of costs and have the additional advantage that they exclude zero or same day stay admissions which can arise as an artefact of the four hour A&E target and the operation of emergency assessment units (Jones 2010b). Since medical, paediatric and trauma admissions are known to be seasonal whilst surgical admissions tend not to show such behaviour (Jones 2009a) the hypothesis regarding wider environmental effects beyond simple seasonal variation can be tested using emergency admissions to a surgical group of specialties. General Surgery, Urology and Gynaecology can be grouped due to the natural overlaps between these specialties. While these are surgical specialties there will still be some element of a 'medical' basis for admission (i.e. appendicitis, etc), however sensitivity to the environment should be more general in nature rather than specifically seasonal as observed in medicine. The aim is to obtain a conservative estimate for the role of the wider environment in admissions and bed occupancy and hence upon costs.

Methods & Results

Figure 1 presents a time series of daily occupied beds (calculated from the admission and discharge dates of all patients) for emergency surgical admission to a large acute hospital based in Reading, Berkshire. Over the 15 year period there was no discernable trend in annual bed occupancy (mean, median, mode were 55, 55, 53 occupied beds respectively), hence no adjustment to the daily numbers were needed to account for growth. Of this total the mode for Urology and Gynaecology were 8 and 4 occupied beds respectively. The catchment population for this hospital has been stable over the 15 year period since there have been no configuration changes at other nearby hospitals to alter the pattern of surgical patient flows. Some 80% of patients live within a 9 km radius and the closest alternative is Frimley Park Hospital some 21 km away in Camberley. Apart from the (variable) transient dip in occupied beds over the Christmas to New Year period the occupancy appears to follow a complex time-trend. An attempt to characterise this complexity has also been made in Figure 1 where what is called a CUSUM, i.e. cumulative sum of difference (to the average), has been calculated. This line is best understood when it is recognised that every change in slope represents a shift in the average bed occupancy (Burns et al 2005). Hence a period of generally high average occupancy, say 60 occupied beds (5 more than the long term average of 55), will generate a straight line upward with a slope of 5 per day. Bed occupancy near to the average generates a line of slope equal to zero, etc. The key point to note is the multitude of times that the slope changes, i.e. bed occupancy is constantly shifting in response to the external environment.

Figure 1: Daily occupied beds time series

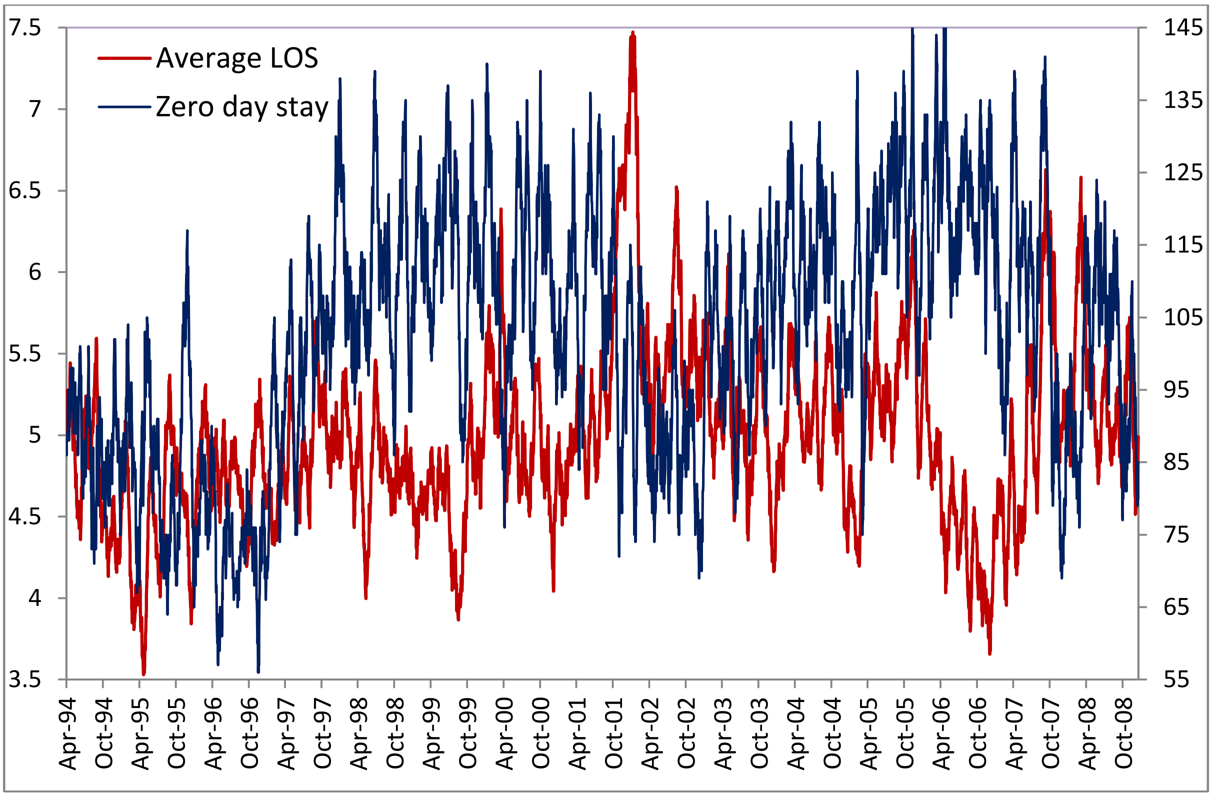


Footnote: Data over the 15 year period 1994/95 to 2008/09 was kindly supplied by the Royal Berkshire Hospital NHS Foundation Trust and includes daily occupied beds in General Surgery, Urology and Gynaecology. The average over the time period is 55 occupied beds. To create the cumulative sum of differences (CUSUM) the average of 55 was subtracted from each daily value, the differences were then cumulatively summed. The CUSUM is displayed on the right hand axis.

The alternative argument is that the threshold to admission is changing. This view has been somewhat popularised by the recent Nuffield Trust report (Blunt et al 2010) where the increase in emergency admissions was suggested to be (partly) due to reductions in the admission threshold due to increasing ‘efficiency’. There are several reasons to doubt this explanation. Firstly, a study conducted in the USA has demonstrated that the case mix adjusted admission threshold stays constant in spite of fluctuating demand. Hospitals adapt to periods of high bed demand by earlier discharge rather than modifying the admission threshold *per se* (Sharma et al 2008). Secondly, there are so many changes in the slope of the CUSUM line that almost constant changes in admission threshold would be implied and this is highly unlikely and the impact of a constantly changing environment upon the expression of poor health is a more likely explanation (see references in Jones 2011c) and this will be discussed later.

As further evidence that we are not dealing with an admission threshold phenomenon Figure 2 shows the trend in average length of stay (LOS) and zero day stay admissions, both calculated as a running 28 day average. The average LOS is calculated after excluding zero or same day stay admissions which are excluded from the calculation of total bed days. As a result this average may at first appear to be high since typical average LOS calculations include zero day stay admissions in the denominator. In theory average LOS should be increasing over time due to the increasing complexity of an ageing population, although increasing efficiency will offset this trend. Indeed this hospital has been in the best 10% of hospitals for length of stay for many years. Contrary to expectation the average has remained relatively constant over the entire 14 year period since reducing average LOS is often an artefact of zero day stay admissions, however, the key point is that it remains relatively constant except for periods of deviation around the average. Indeed there is no correlation between average LOS and zero day stay admissions (R^2 = 0.0002) indicating that the two are independent processes, i.e. case mix and severity. As discussed elsewhere both zero day stay admissions and occupied beds follow complex long-term cycles around a nominal average (Jones 2009a, 2011b,c, 2012a,c, 2013). These periods of deviation reflect the environment-induced changes in case mix and severity which this article is seeking to highlight.

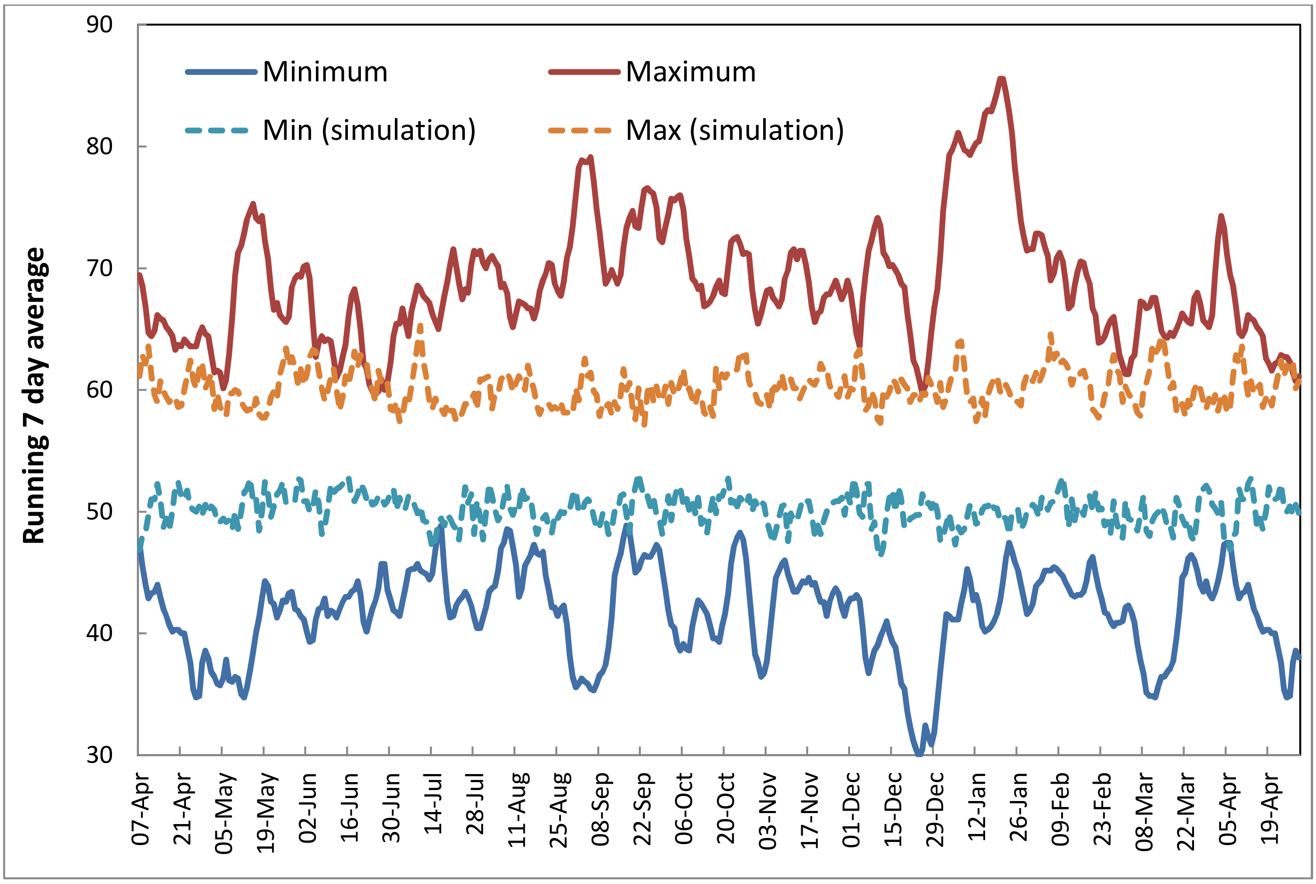
Figure 2: Running 28 day average length of stay and zero day stay admissions



Footnote: The running 28 day average LOS is calculated after excluding zero or same day stay admissions. The figure for zero day stay admissions is a running 28 day total.

The extent of the volatility in bed occupancy was further characterised by comparing bed occupancy on the same day in each of the 15 years. To do this a running 7 day average was calculated (to avoid any day of the week occupancy patterns) and the average occupancy was then compared for each year commencing 7th April (Figure 3). To provide a reference point for simple statistical variation in bed occupancy a Poisson simulation was performed (see Jones 2011c for details) and the data was manipulated exactly as per the actual data. As can be seen the real world exhibits far higher volatility than simple statistical variation around an average. There are periods of time when the actual maximum and minimum lines come very close to that determined by simple statistical randomness (Figure 3) and in these periods it would seem that the collective effects of the environment are minimal. Since the range of potential environmental effectors is changing throughout each day, such periods of minimum effect are fairly infrequent.

Figure 3: Range in weekly average occupied beds for a surgical group of specialties



Footnote: The minimum and maximum bed occupancy was determined comparing the same week day of the year for each year over a 15 year period. Simple statistical variation was simulated using a Monte Carlo Simulation (Oracle Crystal Ball software) using a Poisson distribution with an average of 55 - see Jones 2011c. Such a simulation assumes constant case mix. This data was then processed in the same way as the actual data using 15 simulated years of daily bed occupancy.

Implications

If we assume that the average of 55 occupied beds in Figure 1 represents the funding predicted by a person-based formula then the actual line represents significant periods of higher and lower costs relative to this 'average'. Hence periods of time in 2002 through to 2005 were generally high cost while most of 2006 and 2007 was low cost, etc. These periods of systematic deviation from the average can falsely 'assure' managers that admission avoidance schemes have been 'successful' or a 'failure' and demonstrate the powerful effect of the environment on costs. The implications to initiatives such as Quality, Innovation, Productivity and Prevention (QIPP), where every deviation from the expected average is scrutinised for significance, should be apparent.

The simplest way to disentangle the additional contribution from the environment is to calculate the range between the maximum and minimum occupied beds at the same time of the year and turn this into a percentage value by dividing the range by the maximum value. Using this calculation the average range for the actual data is 39.1% while that for simple statistical variation was 16.6%. Hence the difference between these two values gives us a figure of 22.5%

as the residual contribution from the environment. This is close to the figure of 23% for the residual variation in costs not explained by the person-based models (although different methods and time periods have been used to measure the 'variation'). The key point is that the two methods point to a significant potential role for the environment in cost fluctuation.

In England there are around 3 occupied beds per 1,000 head of population and the surgical pool in this study represents an equivalent population of around 18,000 which is roughly the size of a large GP practice. Calculating the variability over yearly periods gives a standard deviation of ± 7.5% which is lower than the figure of 21% by virtue of the larger annual total. However acute costs are far wider than just the conservative surgical group chosen here and after including the higher environmental sensitivity of medical, paediatric and trauma admissions against the lesser sensitivity of elective admissions (although lesser in numbers than emergency admissions) it would not be surprising if the net effect of the environment on total inpatient costs was somewhere around 20% of annual cost variation as per the study on person based funding.

Indeed, based on a two decade career in forecasting health care demand the author has concluded that infectious outbreaks (in their widest sense) have a far greater impact on general health than has hitherto been acknowledged (Jones 2009a, 2010b, 2011a, 2012 a-g). With over 1,400 human pathogens (of which >220 are viruses) and with around 58% of these being zoonotic (Woolhouse & Gowtage-Sequeria 2005); the scope for local infectious outbreaks is considerable. This is supported by recent research in the USA where 26,000 clinical isolates were screened for 'novel' bacteria (novel = not previously characterised) using a method based on detection and analysis of 16S rRNA which is unique to bacteria. This identified 111 novel (new) genera and 613 novel (new) species isolated mainly from blood, wounds and the respiratory tract. Bacteria most commonly encountered were family members of Actinomyces (43%), Corynebacteria (20%) Nocardia (18%) and Micobacteria (11%) which are all well known in a clinical context (Schlaberg et al 2012). Infants, the elderly, those receiving treatment for cancer, diabetics, and so on will be susceptible to such infectious challenges (Jones 2012h). Another study has demonstrated that simultaneous bacterial and viral infection in those who are hospitalised leads to a higher risk ratio for death (6.6-times), multi-organ failure (8.2-times) and septic shock (271.2-times) (Miggins et al 2011). Such outbreaks may not be perceived as the primary cause for the admission, however, in reality they have acted to exacerbate pre-existing conditions which then lead to an acute admission where the diagnosis may only be given as that of the immediately apparent condition (i.e. appendicitis, asthma, etc). The local maximum seen between the 7th May and the 5th June (which occurred in 1994) in Figure 3 is probably an example of such a localised outbreak. Similar peaks can also be seen along the maximum and these relate to specific periods of time in particular years. The two large peaks in December & January arose from presumed event(s) occurring from 5th December 2001 to 22nd February 2002. These also correspond to unique periods in the CUSUM plot and a peak in average LOS in Figure 2. Further detailed research will be required to determine the exact timing of infectious as opposed to other environmental effects.

Indeed recent research has demonstrated the existence of some form of infectious spread across the UK associated with events occurring in 1996, 2002 and 2007 relating to approximate 15% increases in medical admissions and GP referrals (Jones 2012g). Given the fact that full spread across the UK takes two years the resulting spatial cascade in cost pressures is entirely outside of the remit of the current resource allocation formula. However it is of interest to note that zero day stay admissions (Figure 2) show three cycles initiating in 1996, 2002 and 2007 which appear to align with the medical cycle documented in Reading and surrounding hospitals

(Jones2009a, 2012g), although bed occupancy (overnight stay admissions) appears not to show these cycles. It would be interesting to see if zero day stay admissions were more medical in nature than the corresponding overnight stay admissions.

Returning to the issue of non-infectious health determinants a recent study relating to ambulance journeys in Hong Kong has demonstrated that temperature alone was the most significant predictor especially for the elderly, patients with higher triage acuity, those progressing to inpatient admission and the most deprived (Wong & Lai 2012). In this reasonably tropical location ambulance journeys reached at minimum at 27 C and increase by 50% at 9 C, i.e. an 18 C difference in average temperature. Another study in Spain has demonstrated that noise 'pollution' can also be an important factor in determining the level of daily emergency admissions and by extrapolation to lower admissions in more 'peaceful' locations (Tobias et al 2001). While these examples are more likely to influence medical admissions, they are only several among a multitude of environmental factors whose effects are usually only studied in isolation.

If we add together fluctuations in the infectious and other environmental influences (weather, air quality, etc) we can conclude that the environment does have a significant role in the observed variation in local health care costs (as demonstrated to apply in Reading). Attempts to model health care costs based purely on person-based indices will fail to capture the full range in cost variation at GP practice level (subject to local environmental fluctuations) and will then inadvertently lead to what is called the post code lottery as the trajectory of local costs will deviate from that predicted using a person-based formula.

Additional national gradients in sunlight intensity (and vitamin D production), exposure to radon gas (second highest cause of lung cancer), etc will lead to long-term bias against a national average and hence the proposal that the wider environment is responsible for up to 20% of cost variation (both as a long-term general bias and as environment-induced short-term volatility) across all national GP practices seems highly plausible. Hence some areas will suffer from unavoidable higher/lower expenditure due to the more fixed aspects of the local environment (sunlight intensity, air/noise quality in cities, radon gas, etc) while all areas will suffer from additional random variation due to the more variable aspects of the environment (weather, air quality as a daily variable, infectious outbreaks, etc) and therefore research into the environment-sensitive aspects of a person-based formula is desperately required to ensure genuine fair funding for all.

Indeed the weakness of the funding formula coupled with the high inherent volatility in healthcare costs (Jones 2012a-f) implies that CCGs will be exposed to the same flawed assumptions around financial performance as were PCTs.

Priming the Formula

Having demonstrated that even surgical admissions show characteristic deviations from the average over time, the issue of priming the formula needs some consideration since calculation of resource allocation based on different years may well lead to different levels of funding based on different weightings within the formula. The recently discovered cycle in medical admissions is a good example. The last occurrence of this infectious-like outbreak appeared to commence around February 2007 in the Tayside Health Board area of Scotland (Jones 2012g) spreading across the whole of the UK with full extent of spread leading to outbreaks in parts of the East of England toward late 2008 (Jones 2010a, 2011a, 2012d,i). Since each outbreak can lead to a 10% (or more) increase in medical admissions and between 15% to 25% increase in

GP referral for particular specialties it should be fairly obvious that attempts to prime the formula using data from 2006/07 or earlier will give a different picture to data from 2007/08 to 2008/09 and then from 2009/10 onward – depending on where each location lies with respect to the extent of spread. Research has also revealed that emergency admissions to different surgical and medical specialties show their own characteristic long-term cyclic patterns in *volatility* around the average (Jones 2011c) and this re-enforces the observation that cost behaviour is not stable over time. It would seem that far more research is needed into the stability of the person-based and other types of capitation formula over longer time intervals and at different geographic locations.

Conclusions

While this article cannot give answers to all possible questions it has demonstrated that even in a group of specialties where seasonal effects are minimal there is still considerable sensitivity to the cumulative and interactive effects of the external environment. Zero day stay admissions have been shown to follow a different pattern to overnight admissions. Long term changes in total cost will therefore arise which are unique to each location. While further research is required to unravel cause and effect behind the complex patterns and interactions it is suspected that infectious outbreaks (especially in synergy) play a greater role than weather-related effects. In this respect it would be useful to repeat this work using data from hospitals in disparate locations over the same time period to determine the magnitude of the effect arising from location. However, it would seem that the funding formula needs to be modified to incorporate environmental effects, since in their absence it becomes a tool for inequality and the promotion of the so-called post code lottery.

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