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Long-term cycles in the volatility associated with average bed occupancy for emergency admissions and implications to hospital design

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Key Words: optimum bed occupancy, emergency admissions, bed occupancy margin, volatility in bed occupancy, long term cycles, health care planning, demand forecasting, environment, weather.

Abstract

The volatility associated with the average bed occupancy for emergency admissions is shown to follow complex long term patterns. The pattern wavelength and amplitude are specific to each specialty, i.e. to the range of diagnoses which are associated with the specialty of admission. Such patterns in volatility arise from the interaction between the environment (weather and infectious agents) and human physiological and immunological processes. Hospital average bed occupancy should be sufficient to cope with the periods associated with maximum amplitude in volatility and it is at this point that current methods for sizing hospitals are woefully inadequate. By implication hospitals should be built with a higher numbers of available beds than is current practice and supporting methodologies need to be developed to allow hospital managers to staff the occupied beds (in a predictive manner) rather than the available beds, i.e. to minimise staff costs but maximize patient care.

Key Points

- Bed occupancy is subject to considerable time-dependant volatility and by implication bed management and the allocation of staff is a more difficult task than is at first apparent
- The known sensitivity of a wide range of conditions to the weather and other environmental variables explains this intrinsic high volatility and may provide a basis to understand the very long-term patterns in the volatility associated with bed occupancy
- The above imply that hospitals need to be built with excess capacity over and above that implied by simple statistical variation
- Supporting health forecasts not only need to forecast anticipated numbers of admissions but also the anticipated average bed occupancy and the associated volatility around the average

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Introduction

There is now widespread agreement that the principal cause of crowding in the emergency department is the inability to move patients requiring an admission into a hospital bed (Lattimer et al 2004, Rathlev et al 2007, Hoot & Aronsky 2008, Hoot et al 2008, Hillier et al 2009, Khare et al 2009, Lucas et al 2009, Moskop et al 2009, Jones 2011h). It has been observed that the current methods used to size hospitals and the constituent bed pools are subject to methodological bias leading to a perception of fewer beds than are actually needed (Jones 1997, 2001, 2002, 2003, 2009c,e, 2010m, 2011g,i) and that very long-term cycles may also play an important part in the expression of bed demand (Jones 2009a-d, 2010a-c, e-l, 2011a-d).

It is becoming apparent that the forces regulating bed demand may be far more complex than the simplistic methods used to calculate bed requirements. While average occupancy is a useful indicator it is the volatility around the average which determines the operational bed requirement and associated occupancy margin - not the average per se (Baker et al 1999, Harper & Shahani 2002). Since emergency admissions are environment-sensitive the observed volatility can be up to three-times higher than that expected from simple statistical variation around an average (Jones 2004, 2006).

The mechanism behind volatility in bed demand is contained in the relationship between the exacerbation of a wide variety of diagnoses by shifts in the external environment, i.e. temperature, pressure, dew point, humidity, pollutants, ozone, regional weather types, viruses and other communicable infections, etc (Hill 1989, Danet et al 1999, Lieberman et al 1999, Anderson et al 2001, Diaz et al 2001, Jones et al 2002, Makie et al 2002, Rusticucci et al 2002, Galan et al 2003, Hughes et al 2004, Patz et al 2005, Mangtani et al 2006, Marno et al 2006, Rising et al 2006, Dawson et al 2007, Baldi et al 2008, Ford et al 2009). Specific shifts in environmental parameters lead to changes in the level of admissions for selected diagnoses and will therefore affect bed demand via the typical length of stay profile associated with the diagnosis.

For example, a rise in temperature over a 24 hour period lead to an increase in ischaemic stroke, a fall in pressure over a 48 hour period lead to an increase in haemorrhagic stroke while higher maximum daily temperature over an extended period led to an increase in lacunar stroke (Dawson et al 2007). Hence a shift in the environment will (after an appropriate lag) lead to an influx of admissions leading to a step up to higher bed occupancy and then after a characteristic length of stay these patients will leave the hospital at roughly the same time leading to a step down in bed occupancy. These steps are then replicated across the multiple diagnoses making up an individual specialty.

It is this step up/down behaviour in bed occupancy that will feed through into the volatility experienced in bed demand. This volatility around the average bed demand will drive the need for available beds and it is at this point that the current models for determining the number of acute beds are inappropriate in that a single average occupancy is usually assumed to apply at all times (Jones 2001, 2002, 2003, 2009c, 2011g). There do not appear to have been any studies on the very long-term volatility associated with bed demand for emergency admission in different specialties and this work will attempt to address this gap in understanding.

Methods

Daily (midnight) bed occupancy at the Royal Berkshire Hospital (Reading, Berkshire) a very large acute hospital in England was calculated over a fifteen year period from the admission and discharge dates of all admitted patients. To avoid the known day-of-the-week cycle in bed occupancy (Baillie et al 1997, Fullerton & Crawford 1999) the measure of volatility in bed occupancy was chosen as a paired difference in occupied beds for the same day in one week compared to the next, i.e. Monday occupancy in week one compared to Monday occupancy in week two, etc.

The volatility in bed demand was calculated as the difference in occupancy divided by the square root of the average occupied beds for the two days (see discussion). An index of volatility was calculated using the absolute value of the transformed paired differences. The average index of volatility was calculated on a 28 and 365 day basis throughout the 15 year period to reveal medium and long term trends in volatility.

The emphasis here is around occupied beds rather than available beds since the nominally allocated available beds for a particular specialty may or may not be adequate and may be supplemented by borrowing beds from other specialties.

Results

Figure 1 presents typical results for a Paediatric department. Over the 15 year period the average is around 23 occupied beds with 76 (during a period of high bed demand in Oct/Nov 2007) and 4 (in August 2008) occupied beds as the maximum and minimum respectively. Paired differences between the same day of the week lie mostly in the range of ± 10 beds and represents considerable fluctuation around the average as is expected for a relatively small bed pool (Jones 2009c, 2011g). The proposed transform (Index of Variation) which divides the absolute value of the paired difference in bed occupancy by the square root of the average occupied beds does indeed give an average value close to 1.0 which indicates that the most common difference in occupancy from one week to the next is around one standard deviation away from the average (see discussion).

The existence of both medium- and longer-term trends can be discerned in Figure 1 but is obscured by the high background variation. As is demonstrated for the specialty General & Elderly Medicine (Fig. 2) a running 28 day average can be used to dampen the short-term weekly variation in order to reveal these hidden trends. As can be seen there are medium term seasonal cycles in the volatility associated with bed occupancy (higher in winter lower in summer). The winter peaks in volatility generally occur in November/December. There also appear to be even longer-term cycles over periods of many years. For example, a period of minimum possible volatility can be seen between 2000 to mid 2002.

The possibility of even longer-term cycles is explored in Figures 3 and 4 by employing a running 365 day average which should remove the bulk of variation associated with the shorter-term seasonal patterns. As can be seen each specialty follows its own particular pattern of long-term trends in the volatility associated with bed occupancy. The range in volatility for a number of inpatient specialties has been summarised in Table 1 and can be seen to be more marked in particular specialties. For example, the ratio of the maximum to the minimum average volatility in Rheumatology ranges from 12- to 2.5-times for the 28 and 365 day averages respectively while that for General Medicine ranges from 9.5- to 1.7-times.

In Table 1 the column headed 'Frequency of Identical Occupancy' is an indicator of the size of the bed pool since specialties with fewer beds will have greater opportunity for occupied bed numbers to be the same.

Discussion

Within the UK issues surrounding hospital design have been dominated by the prohibitive cost of capital arising from the private finance initiative (PFI) which was introduced in 1992 as a means of substituting private for public funding of large capital projects (Pollock et al 2002, Dunnigan & Pollock 2003, Palmer et al 2006, Hellowell & Pollock 2007, 2010). It would appear that this has inadvertently led to the situation where hospitals have been built too small in order to be PFI affordable (Dunnigan & Pollock 2003, Hellowell & Pollock 2007, Jones 2009e).

Unfortunately the current methods for sizing hospitals are far too easily manipulated to give whatever answer is 'desired' rather than needed (Jones 2002, 2003, 2010m, 2011g,h) and assumed average occupancy of around 85% has been shown to be inappropriately high (Jones 2010m, 2011g,h). To a large degree the volatility associated with healthcare demand and average bed occupancy can be described by queuing theory, Poisson statistics and the Erlang equation(s) (Bain et al 2010, Jones 2010m); however, healthcare demand and associated volatility are additionally characterised by a unique reliance upon the environment as human physiology and immunology responds in countless time-dependant adaptive ways to changes in temperature, pressure, pollutants, ozone, etc. Even fluctuations in the average length of stay have been shown to be environmentally sensitive (Jones 2009f, 2010f).

The Erlang equation and its relationship with Poisson statistics has been shown to apply to the occupancy of hospital bed pools and explains why smaller bed pools show the highest volatility around the average (Jones 2002, 2003). This intrinsic relationship with Poisson statistics suggests that a transformation which divides the paired differences in occupancy by the square root of the average occupancy could provide a constant which should be independent of bed pool size and which measures the fundamental volatility in bed occupancy. This constant should convert the paired differences into the equivalent to a difference expressed in terms of standard deviations away from the average.

Hence in many ways the highly volatile nature of bed occupancy shown in Figures 1 to 4 is entirely consistent with the concept of a physiological/immunological response to an ever changing environment. The problem is that such a fundamental and obvious reality has not to date been reflected in the models describing future hospital bed requirements and the need for a suitable occupancy margin. Indeed such fundamental environment-linked causes for bed occupancy is the basis for a number of weather/environment-based forecasts of various aspects of inpatient demand (Met Office 2001, 2009, Jones et al 2002, My Weather & Health Forecast 2009, Baldi et al 2009) which should be available to the health services to enable them to efficiently allocate scarce resources in the most cost effective manner possible. Such a scheme was commenced in the UK in 2002 but later became subscription based when the Department of Health declined to provide funding on behalf of the wider NHS (http://www.metoffice.gov.uk/health).

Issues of appropriate supporting technology aside, the seasonal basis for volatility in bed demand should be fairly obvious; however, the very long term cycles may be less so. A recent series of papers has sought to explore both the existence and causes of such long-term cycles (Jones 2009a-g, 2010a-m, 2011a-d, i-j). The medical cycle has attracted particular interest and it is relevant to note that the cycle in volatility appears to mirror a proposed cycle of infectious outbreaks. The move to higher volatility after each outbreak has also been documented in Northern Ireland (Jones 2010l) and Queensland, Australia (Jones 2011i) and a move to higher volatility in admissions has also been observed after something very similar to the 2002 outbreak in Athens, Greece (Boutsioli 2009). It would appear that this cycle has an international basis and additional research is required.

The fluctuations in volatility may lead the situation where studies conducted at different times may reach different conclusions. For example, one study which used air temperature and levels of influenza-like-illness to forecast bed occupancy 32 days in advance was conducted in the period 2000 to 2001 (Jones et al 2002) and the observation that the volatility associated with medical admissions reached a minimum over the period 2000 to mid-2002 (Fig. 2) may have been an enabling factor in this study, i.e. the ability to forecast 32 days into the future may not always be possible.

Based on the known relationship between size and the standard error associated with the mean, a move from a 28 to a 365 day should reduce the Index of Volatility by a factor of 3.6, however, the actual reduction in Table 1 ranges from 3.6 (Elderly Care) down to 1.4 (Oral Surgery). This indicates that additional environmental factors are operating in most specialties.

The lower volatility in bed occupancy observed in Rehabilitation and Elderly Care is consistent with how these bed pools are run from an operational perspective. In these two specialties patients tend to be transferred from another specialty as and when a bed becomes available, i.e. the size of the bed pool is the rate determining step. Under these circumstances the volatility will be reduced since the bed pool will be operating close to 100% occupancy.

Conclusions

The science behind the planning of hospital size and associated bed occupancy has been largely based on an assumed relationship with demography and the application of a standard occupancy, usually around 85%. The author has argued that these assumptions are both incorrect and misleading and that factors such as death rather than demography are the key drivers for bed demand - excluding Obstetric, Paediatric & Neonatal where trends in birth are the obvious driving force (Jones 2011e,f,k). The figure of 85% occupancy has likewise been shown to be based on a flawed understanding of the role of bed pool size and optimum occupancy for maximum clinical efficiency (Jones 2011g,h,j,l). This study has added to this body of work and has demonstrated that the volatility in occupancy is higher than has been appreciated and this explains why running a hospital is such a complex and difficult task; made only more difficult by attempting to operate with too few beds (Jones 2009g, 2011l). The application of more sophisticated methodologies such as wavelet analysis will be required to understand the full complexity behind these cycles. Indeed analysis of a long time series of daily emergency admissions to Trauma & Orthopaedics (a specialty which is relatively immune to day of week effects) using a fourier transform (a mathematical operation which decomposes a pattern into its constituent frequencies) reveals a series of sub-patterns behind the long-term time series (unpublished analysis). Overlapping of these sub-patterns can generate periods of higher volatility.

Indeed the same forces leading to volatility in acute bed demand will impact on attempts to shift acute demand into a community setting, i.e. unexpected volatility in the demands on staffing capacity will simply be transferred into this context. This is not an argument against such a move but simply a suggestion that the intrinsic behaviour is regulated by the environment and this implies the need for high levels of flexibility in staffing and physical resources (Jones 2009g, 2011j,l). To ignore reality is to invite operational inefficiency, chaos and unnecessary disillusionment as flawed financial targets are missed.

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Table 1: Range in the Index of Variation (IoV) over a 15 year period

Specialty	Frequency of Identical Occupancy (1)	15 year average in IoV	28 day average		365 day average	
			Maximum	Minimum	Maximum	Minimum
Rehabilitation	29%	0.31	1.41	0.10	0.57	0.23
Elderly Care	5%	0.63	3.56	0.20	0.98	0.46
Neurology	33%	0.74	2.00	0.20	0.94	0.46
Oncology	12%	0.75	1.58	0.27	0.91	0.64
Medical Group	2%	0.79	2.48	0.27	0.98	0.57
Haematology	25%	0.78	1.99	0.17	1.01	0.61
General & Elderly Medicine	3%	0.79	2.46	0.28	0.96	0.56
Neonatal	10%	0.79	1.81	0.27	1.08	0.65
Trauma & Orthopaedics	5%	0.79	1.99	0.34	0.97	0.64
Gastroenterology	21%	0.87	2.24	0.12	1.06	0.67
Rheumatology	19%	0.89	2.35	0.20	1.32	0.53
All Specialties	2%	**0.88**	**2.62**	**0.33**	**1.01**	**0.70**
Cardiology	8%	0.91	2.31	0.37	1.02	0.73
General Medicine	4%	0.92	2.70	0.28	1.13	0.66
Urology	12%	0.92	2.12	0.41	1.17	0.73
General Surgery	5%	0.94	1.91	0.42	1.17	0.75
Thoracic Medicine	24%	0.95	2.61	0.43	1.42	0.75
ENT	17%	1.03	2.09	0.48	1.18	0.85
Paediatrics	7%	1.04	2.55	0.40	1.38	0.84
Gynaecology	12%	1.09	2.09	0.39	1.37	0.88
Ophthalmology	22%	1.12	2.10	0.15	1.29	0.93
Oral Surgery	17%	1.27	2.11	0.26	1.52	0.92

Footnote (1): Proportion of times during the 15 year time series that successive same-day-of-week occupied numbers of beds are identical. In general this proportion is higher for smaller bed pools.

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Figure 1: Index of variation for paediatrics

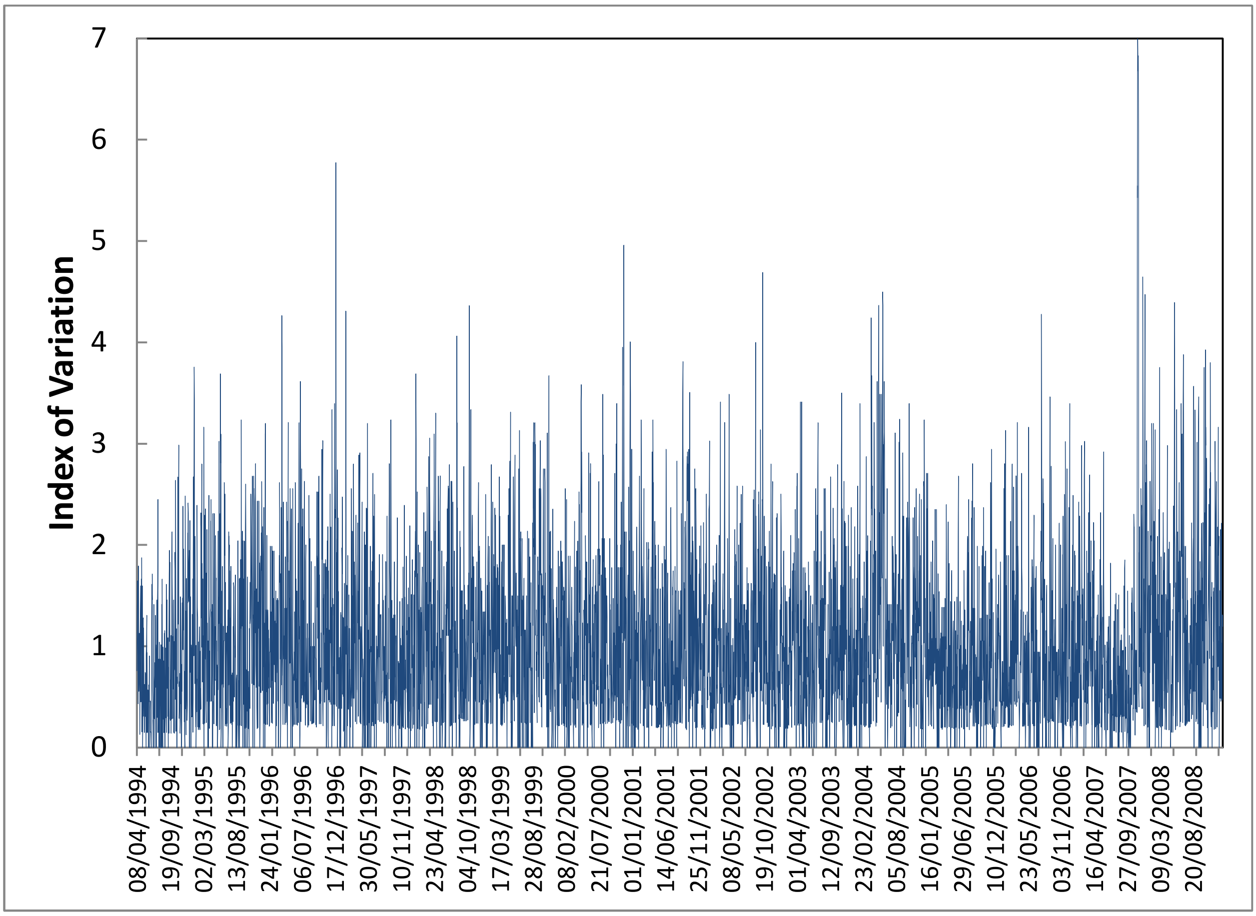

Figure 2: Index of variation for general & elderly medicine (running 28 day average)

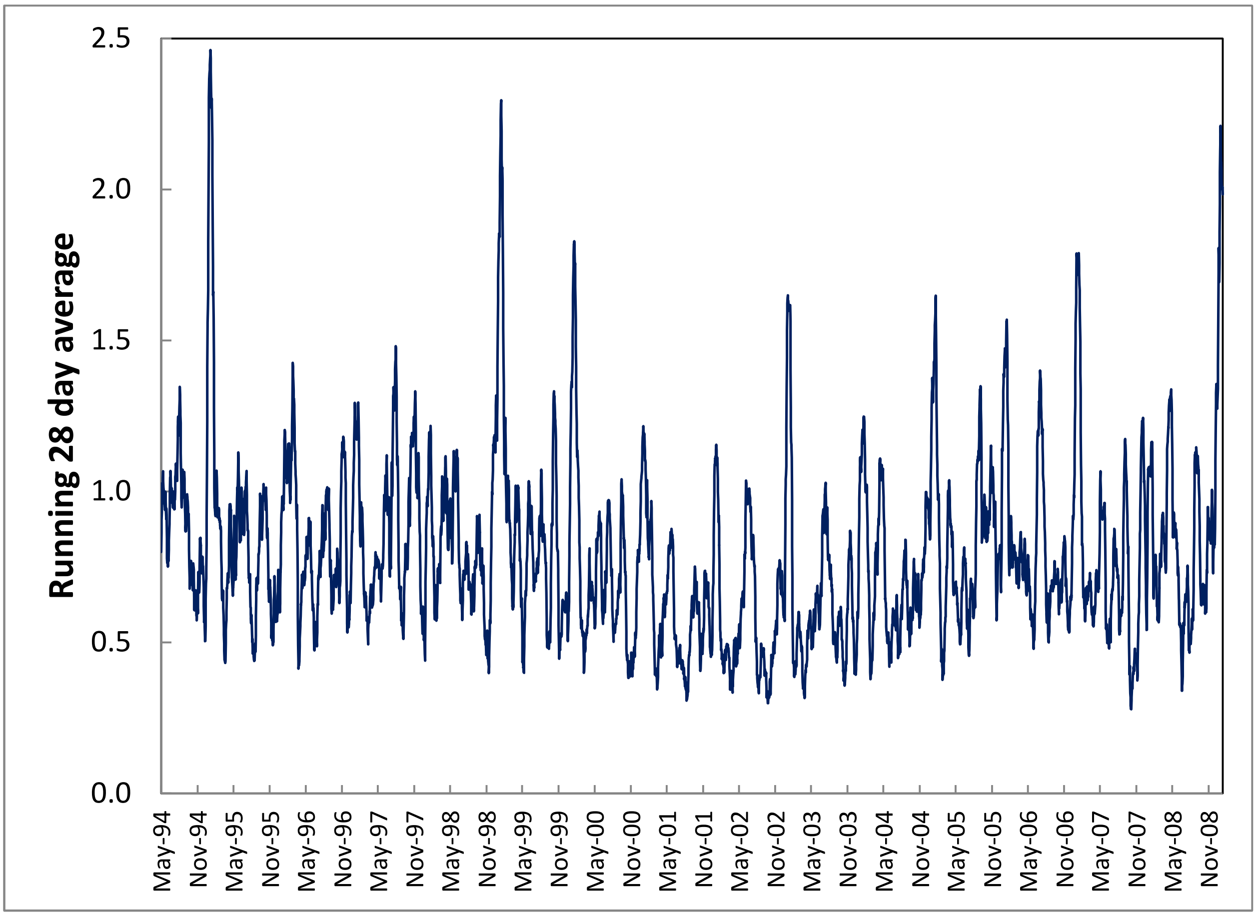

Figure 3: Underlying longer-term cycles in the index of variation

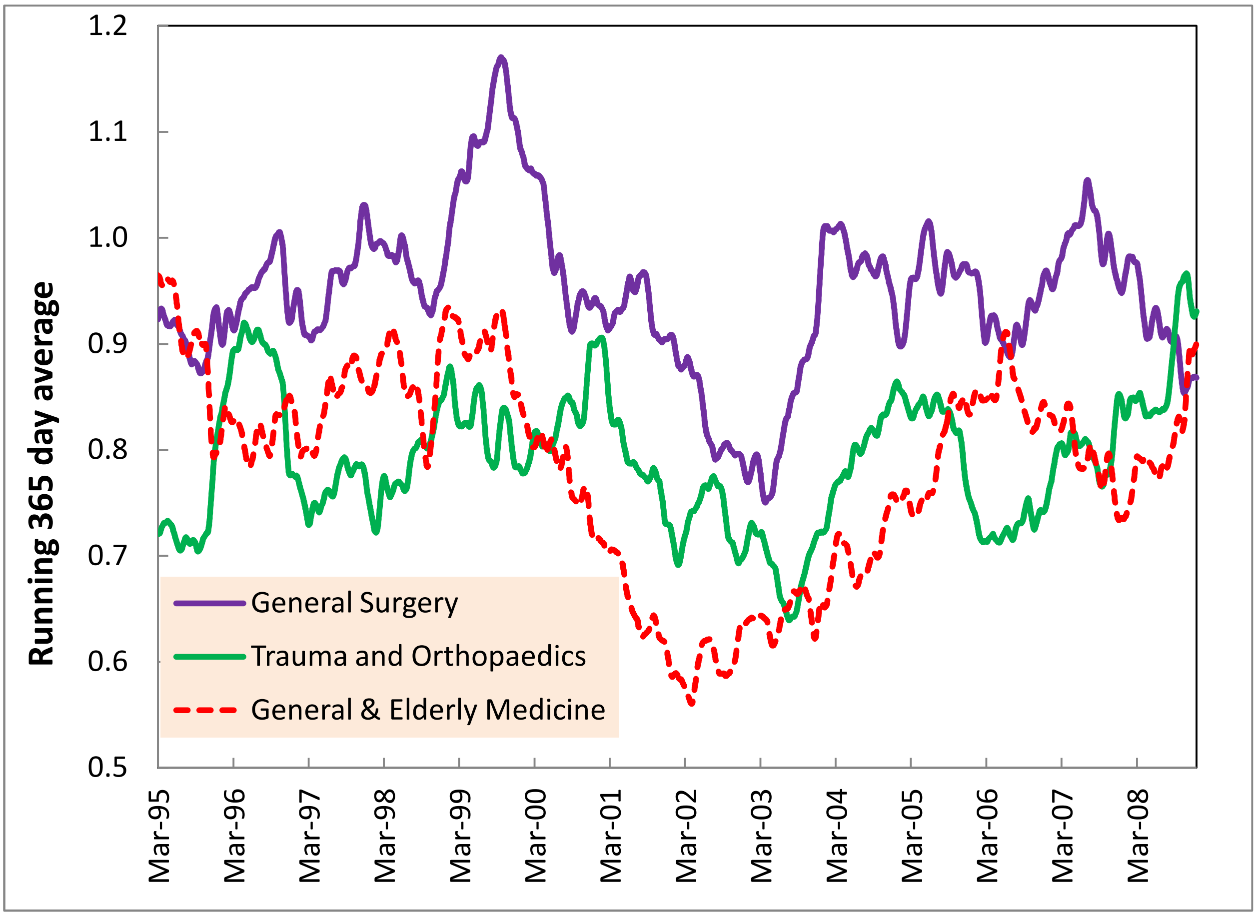

Figure 4: Underlying longer-term cycles in the index of variation