Multidisciplinary Insights into Health Care Financial Risk and Hospital Surge Capacity, Part 2:

High Population Density is Associated with Enhanced Year-to-Year Volatility in Many Aspects of Poor Health Including Health Care Worker Sickness Absence

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Abstract

The weighted population density for 349 English local government areas, and the raw population density for a further 58 areas from Northern Ireland and Scotland, were used to demonstrate the role of high population density in the volatility associated with year-to-year total deaths and of excess winter mortality (EWM). Volatility in EWM was measured as the standard deviation over a 20-year period while for total deaths looked at the absolute value of the year-to-year difference expressed as standard deviation equivalents. The volatility in EWM was almost double that of sparsely populated areas when weighted population density exceeded 8,000 persons per square Km. For total deaths, the year-to-year average difference was around 35% higher when population density exceeded 7,000 persons per square Km. Death culminates a six-month period of increasing admission to acute hospital which can account for 55% of a person’s lifetime use of a hospital bed. Hence the volatility in death is a good measure of volatile costs and capacity pressures. Volatility in costs will follow the year-to-year pattern while hospital capacity pressures will tend to follow the EWM pattern. Population density acts to facilitate the spread of infectious agents, which increasingly arrive via international air travel. Population density is also associated with air pollution which acts to increase systemic inflammation in the population, thereby rendering them more susceptible to infection and adverse outcomes. Dysregulation of the inflammatory response to infection in the elderly implies that infection(s) with otherwise seemingly ‘trivial’ pathogens can then lead to surges in admissions and deaths which are then reported as a variety of (secondary) diagnoses. Unexplained patterns in average length of stay and the gender ratio for admissions for common conditions, which have previously been ignored, support this explanation. Similar unusual trends in sickness absence among health care workers are also observed.
Key Points

- Population density is a proxy for air pollution and person-to-person contact, both of which enhance the transmission of infectious diseases
- Highest population density was associated with the highest volatility in year-to-year deaths and of Excess Winter Mortality (EWM)
- Transmissible infections work via the inflammatory immune response to promote acute illness and death in a variety of respiratory and pre-existing conditions, i.e. they act as the trigger for final demise
- Human pathogens are now known to interact in complex ways
- Multiple infections are far more common than realized
- Unexplained trends and spikes in hospital average length of stay and the proportion of male admissions seemingly arise from the network of such infectious outbreaks
- Unusual volatility in sickness absence rates among health care workers is also related to population density
- The higher volatility associated with population density implies that costs associated with the population of large cities will be more volatile than for least populated areas, i.e. there is higher financial risk and greater opportunity for insurance revenue to be out of sync with insurance costs, i.e. financial risk
- The foundations for the health insurance underwriting cycle appear to lie in the time patterns arising from this complex and ever-changing infectious landscape
- For the hospitals situated in large cities, this will manifest in more volatility in winter capacity pressures. However, this will be partly mitigated by larger hospital size necessitated in the more densely populated areas

Introduction

Earlier studies have shown that the year-to-year volatility in deaths, admissions and healthcare costs is both size and location specific, i.e. after adjusting for size some locations have intrinsically higher financial risk than others (Jones 2010a,b, 2012a-h, 2013a-c). This was assumed to be due to location-specific environmental factors including infectious outbreaks.

This study will first outline the fundamental biological/medical basis as to why some locations should show higher cost/capacity volatility. It will then give the corroborating evidence of a role for small-area population density, explore wider health care parameters showing unexplained volatility, and then conclude with the areas for further research.

Overview of infectious outbreaks

Modern society exists in a cocktail of infectious agents. In 2005, over 1,400 species of human pathogens had been identified (Woolhouse and Gowtage-Sequeria 2005). Of the human viruses alone, in 2012 it was estimated that between 89 to 265 new species remained to be identified (Woolhouse et al 2012). A study published in 2012 involving over 26,000 clinical samples specifically looking at bacteria identified 95 novel taxa, 111 novel genera, and 673 novel species (Schlaberg et al 2012). The figure of >1,400 species had suddenly jumped to >2,000 species in one leap.

A disturbing number of new species of bacteria causing human infection are emerging from those previously considered to be non-pathogenic (Sekowska and Gospodarek-Komkowska 2019). A search of
the term “new species in clinical samples” in Google Scholar restricted to papers published since 2016 yields hundreds of results.

In England, only 60 of these >1,400 species are ‘notifiable’ to Public Health Agencies (Public Health England 2020). High volume air travel and airports distribute these agents with disturbing ease (Kumala 2017, Pequeno et al 2020). Indeed, 1,400 species is the tip of the iceberg, since each species will have multiple strains and sub-types. Testing for atypical pathogens in something as common as pneumonia varies considerably between countries and hospitals (Gramegna et al 2018).

Indeed, outbreaks of different strains of the same species, i.e. the two coronaviruses SARS and COVID-19 can show markedly different spatiotemporal (space-time) patterns of infectious spread (Zhang et al 2020).

Accurate diagnosis of cause and effect is not simple. Up to 200 different species of virus can cause symptoms of the common cold (National Institutes for Health 2009). Rhinovirus, the most common cause of the cold, has 99 distinct types. This vast array of species/types/variants gives ample scope for health professionals to dismiss the potential implications of exactly why someone is feeling ‘unwell’.

No pathogen operates in splendid isolation and an increasing number of interactions between pathogens and between the intestinal microbiota are being identified (Brundage 2006, Xie et al 2020, Zuo et al 2020). In addition, humans accumulate a variety of persistent pathogens throughout their lifetime (Noppert et al 2019), called the ‘pathogen burden’, which has been implicated in the progress and severity of several diseases (Mundkur et al 2012, Sharma et al 2016). Active co-infection with multiple pathogens (different species and different strains of the same species) is far more common than appreciated (Seinost et al 1999, Rappe-Brooks et al 2020). This cocktail of infections has been linked to human mortality (O’Sullivan et al 2020).

Vaccination can diminish the impact of health services and a national rotavirus vaccination program in Finland led to large reduction in bed occupancy for acute gastroenteritis (Hartwig et al 2014).

Americans make 2.3 billion recreational journeys within the U.S. each year, they make a further 93 million journeys to other countries, while 80 international visitors arrive each year (Condor Ferries 2020). The opportunities to import and transmit pathogens are vast.

The specifics of how population density and other environmental factors interact will now be briefly covered.

**Population density and air pollution**

The spread of measles epidemics is profoundly influenced by population density (Tarwater and Martin 2001). As population density increases so also do the contact rates between individuals, however, this saturates at high density (Hu et al 2013). These authors noted that “in crowds with unusually large densities (e.g., transportation terminals, stadiums, or mass gatherings), the lack of organized social contact structure deviates the physical contacts towards a special case of the spatial contact model” (Hu et al 2013). Hence persons living in large cities will experience a mix of two types of exposure.

Population density has been linked with the spread of COVID-19 in both the USA and the UK (Jones 2020), Brazil (Pequeno et al 2020), and Japan (Hirata et al 2020). However, population density is also associated with air pollution which increases as a power-law function of population density (Lamsal et al 2013).
Air pollution acts to increase the potency of respiratory infections including COVID-19 (Domingo and Rovera 2020). Airborne particulate matter (PM10) may be implicated in the spread of COVID-19 (Setti et al 2020). Another study has concluded that long-term exposure to PM2.5 increases COVID-19 mortality (Wu et al 2020). Ambient NO2 increases systemic inflammation in COPD patients (Dadvand et al 2014), pollutants (PM2.5 and black carbon) also increase inflammation in Type 2 diabetes (O’Neill et al 2007). Another study demonstrated that different pollutants affected different inflammatory markers (Bind 2012). Long-term exposure to PM2.5 is also associated with risk of Alzheimer’s and other dementias (Wang et al 2020).

**Seasonality in deaths and the effect of temperature**

Deaths generally peak during the winter months, and in England and Wales, reach a minimum in August, and a maximum in January (around 60% higher than the daily minimum) (Jones 2013c). The winter peak is due to a mixture of cold, mainly due to physiological changes upon exposure of the respiratory tract to cold air (Mourtzoukou and Falagas 2007), seasonal gene expression (Shi et al 2009, Dopico et al 2015, Goldinger et al 2015), and lower levels of Vitamin D leading to impaired innate and adaptive immunity (Baggerly et al 2015, Aranow 2011), especially in the elderly (Meehan 2014), which be sensitive to cloud-free hours of sunlight during the summer (Garland et al 2016). In combination, these promote susceptibility to, and circulation of, winter infectious (typically respiratory) agents (Fleming et al 2005, Fleming and Elliot 2008).

Temperature is a well-recognized factor in the mortality rates for different diseases (Chen et al 2018, Bareca et al 2012). The effect of cold and heat on mortality has been characterized by a comprehensive Dutch study (latitude of Netherlands is 52.34 which is roughly the midlands of England) which showed that mortality reached a minimum around 17°C, but requires a +10 or -22 °C deviation from 17 °C to elevate daily mortality by 14% (Ekamper et al 2009). Hence it requires an extended period of unusual cold (relative to average at that time of the year) to make a large impact on deaths. The mortality risk of extreme cold lasts longer than that from extreme heat (Chen et al 2018), and the shape of the temperature-mortality profile varies considerably between countries, as does the temperature for minimum mortality (Gasparinni et al 2015).

In addition, one study has demonstrated that rates of consultation for inflammation-related diseases also varies with temperature. Low temperatures were associated with higher consultations for all types of inflammatory conditions, while high temperatures were only associated with gastroenteritis (Wang et al 2020). Cold air acts to increase inflammation in the lung (Larsson et al 1998). Interestingly, faster spread of COVID-19 in Brazil was associated with lower temperature (Pequeno et al 2020). The association of low temperature with inflammation is important since inflammation is identified as a risk for infection, followed by infection-induced additional inflammation. See next section.

**Role of infections and inflammation**

Infection is usually followed by a ‘protective’ inflammatory response which can become dysregulated, especially in the elderly, with lethal consequences (Levi et al 2003, Bauer and Wetzka 2020). With over 1,400 species of human pathogens, there is ample scope for local infectious outbreaks of unknown origin (Woolhouse and Gowtage-Sequeria 2005). The vast majority of these are not ‘notifiable’ pathogens and so will remain largely unreported and un-investigated.
Regarding influenza-like illness (ILI) one study identified that in addition to influenza(s) there are at least eight common viruses causing ILI (Taylor et al 2017). In another study, 44% of ILI respiratory swabs yielded multiple viruses (Dierig et al 2014). ILI can also be caused by bacteria, fungi, and parasites.

As mentioned above, the ensuing inflammatory response after initial infection becomes less regulated in the elderly (Boyd and Orihuela 2011). In the lung, this can lead to secondary bacterial pneumonia or direct damage to the lung by the inflammatory response (Jabr 2017). Around 30% of Influenza deaths arise from the effects of inflammation on pre-existing conditions outside of the lungs (Jabr 2017).

Few would realize that obesity is itself a serious inflammatory ‘disease’ (Karczewski et al 2018), which predisposes the obese to a higher risk of infection and poor outcomes from infection (Fernandes and Manuel 2017). Somewhat perversely some infections can also promote obesity (Akheruzzaman et al 2019). Elevated levels of C-reactive protein (CRP), which is a measure of inflammation, are associated with international travellers attending the ED due to overseas acquired illness (Herbinger et al 2016), and in detecting persons with viral and atypical bacterial infections (Duran et al 2016). However, chronic elevated CRP is also associated with disease progression and as an early biomarker of inflammatory disease onset (Luan and Yao 2018).

Numerous industrial, household, and agricultural chemicals promote chronic inflammation (Furman et al 2019). Hence it should come as no surprise that reasonably common conditions such as appendicitis in adults follow local trends influenced by air pollution (as an example of chronic inflammation) and common infections (Jones 2015).

**Age and inflammaging**

Aging is associated with chronic low-grade inflammation called inflammaging (Fulop et al 2018). The immune response to vaccination wanes with age especially in those who are infirm (Ciabattiani et al 2018). For these reasons, the elderly are more prone to disease and more specifically infectious disease (Ebihara 2011).

**The last year of life**

Healthcare demand depends far more on proximity to death than age. A score based on self-reported health rose from 3.46 at 15 years prior to death to 4.43 at one year prior to death (Stenholm et al 2016). Cognitive ability and wellbeing decline slowly with age but becomes more rapid 3-5 years prior to death (Stenholm et al 2016, Cohen-Mansfield et al 2018). Failure to account for nearness to death wrongly attributes decline to age per se (Rabbitt et al 2008), hence the sound bite “it’s all due to the aging population”. This is called the constant risk fallacy (Nicholl 2007).

The last year of life sees a transition from independence to requiring increasing help with the normal activities of life. For example, one study showed that 20% of persons in the last year of life had 6 limitations in the activities of daily living (ADLs) while only 6% of persons had 6 ADLs in the year prior to the last year of life. Some 63% of persons had no ADLs in the year before the last but 58% had 1 or more ADLs in the last year of life (Kalbarczyk-Steclik and Nicinska 2015). This decline is compressed in cancer patients (Kalbarczyk-Steclik and Nicinska 2015, Stenholm et al 2016). Admissions to hospital in the last year of life can account for 55% of lifetime bed occupancy (Hanlon et al 1998), and this occurs with increasing frequency in the last six months of life – irrespective of age (Larsson et al 2008, Thorn et al 2016, Jones et al 2016). It is of interest to note that a composite score based on common blood
biochemical tests shows a sudden shift to a higher (worse) score in the months prior to death (Jones et al 2016). This appears to be linked to the progressive increase in admissions in the last six months of life.

A functional aging index combined with frailty can predict entry into care and mortality (Finkel et al 2019). Elderly patients (aged 65+) with community-acquired pneumonia who were frail had a 2.9-times higher risk of death within one year of hospital discharge (Luo et al 2020).

A U.S. study conducted between 1998 and 2010 showed that the prevalence of pain, depression, periodic confusion, dyspnea, incontinence, severe fatigue, and anorexia all increased over time (Singer et al 2015). Many of these can be related to inflammation and infection so it could be possible that the susceptibility to infectious outbreaks is increasing with time.

As it were, those in the last year of life are waiting for any agent capable of precipitating final demise.

Results

Year-to-year variation in total deaths, U.S. States

Table 1 shows the top 15 U.S. states with the highest year-to-year volatility in deaths, relative to the state with the lowest volatility (Wyoming and Vermont, relative volatility = 1). These are mostly the states with highest weighted population density.

Table 1: Top 15 U.S. states with highest year-to-year relative volatility in the rolling 12-month total of deaths, 2007 to 2019.

<table>
<thead>
<tr>
<th>State</th>
<th>Relative volatility</th>
</tr>
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<tbody>
<tr>
<td>Florida</td>
<td>5.65</td>
</tr>
<tr>
<td>Texas</td>
<td>5.19</td>
</tr>
<tr>
<td>California</td>
<td>4.41</td>
</tr>
<tr>
<td>North Carolina</td>
<td>4.27</td>
</tr>
<tr>
<td>Ohio</td>
<td>4.05</td>
</tr>
<tr>
<td>Pennsylvania</td>
<td>3.89</td>
</tr>
<tr>
<td>Arizona</td>
<td>3.62</td>
</tr>
<tr>
<td>Georgia</td>
<td>3.58</td>
</tr>
<tr>
<td>Virginia</td>
<td>3.38</td>
</tr>
<tr>
<td>New York</td>
<td>3.24</td>
</tr>
<tr>
<td>Indiana</td>
<td>3.22</td>
</tr>
<tr>
<td>Massachusetts</td>
<td>3.19</td>
</tr>
<tr>
<td>Illinois</td>
<td>3.19</td>
</tr>
<tr>
<td>Maryland</td>
<td>3.10</td>
</tr>
<tr>
<td>New Jersey</td>
<td>3.04</td>
</tr>
</tbody>
</table>

Figure 1 compares the rolling year-on-year volatility in deaths between Florida (highest relative volatility) and Vermont (lowest). The chart starts at the difference between the sum of deaths during 2007 compared to 2008, move forward one month and repeat the calculation. Due to their difference in number of deaths, a 1 standard deviation difference due to Poisson- based chance equals ± 1.3% in Vermont but just ± 0.2% in Florida (Koehrsen 2019). Hence while the chart shows roughly similar percentage changes, the effect of size dramatically increases the relative volatility for Florida compared
to Vermont. Hence the use of size-adjusted volatility throughout this study. However, note the differences in shape and timing, and the peculiar absence of influenza-only features. In a rolling 12-month chart a ‘spike’ in deaths due to influenza shows up as a rectangular-shaped feature with a base which is roughly 12-months wide. This is because the spike in deaths enters the rolling 12-month total, stays there for 12-months, and then drops out of the rolling total. The significance of some of these trends will be discussed in Part 3 of this series.

While Public Health agencies seek to promote the simple ‘word bite’ story that major surges in deaths are due to influenza, the data in Figure 1 does not support such a simple explanation. Hence while influenza is important, it is not exclusively so and cannot explain the more nuanced trends over time, and between states. As explained above no pathogen operates in splendid isolation.

**Figure 1: Rolling year-to-year change in total deaths for Vermont and Florida based on a rolling 12-month sum of monthly data from January 2007 to March 2019.** Utah and the USA have been added to illustrate wider trends.

The problem with analysis at state level (above) is the huge size of the USA. For example, England has a surface area of 50,350 square miles, of which 21% is urban development. This is roughly the same size as Arkansas, Alabama, and North Carolina. On the other hand, Texas is 5-times the size of England (Wikipedia 2020a,b). From Poisson statistics, we need a spatial area with 500 to 1000 deaths per annum to achieve a degree of reliability that the differences are not due to chance (Koehrsen 2019). Local authority areas in the UK fit these criteria and have associated widely different weighted population densities.
Year-to-year variation in total deaths was plotted versus weighted population density for each local authority in England and Wales as shown in Figure 2. As can be seen, the average year-to-year volatility increases with weighted population density and appears to reach a maximum (saturates) around a population density of 7,000 per square Km (18,000 per square mile). A linear relationship may apply, although the high scatter after averaging using 10 consecutive local authorities indicate that other factors also influence the volatility. These could include weather patterns and social behaviors.

While average volatility is a useful measure, the standard deviation (STDEV) around the average is a better measure of the volatility in costs and capacity relating to the last year of life. This is shown in Figure 3.

**Figure 2: Average year-to-year difference (volatility) in deaths for English and Welsh local authorities, 2001 to 2020, versus weighted population density. Each point is the average of 10 local authorities ranked by weighted population density.**
Figure 3: Standard deviation (STDEV) associated with the year-to-year differences in total deaths, as per Figure 2.

As can be seen in Figure 3 a non-linear relationship may be possible up to a maximum (saturation) somewhere around 8,000 per square Km (21,000 persons per square mile). Many local authorities in London exceed this upper limit with 21,362 per square Km in Tower Hamlets, 20,430 in Westminster, i.e. up to 52,000 per square mile.

However, the key point has been established that population density is a key variable in volatility for costs and capacity associated with end-of-life. Also, that this relationship reaches a maximum (saturates) as predicted from theory (Hu et al 2013). Scatter in the relationship indicates that additional factors are involved at a local level. Recall that equal population density does not imply equal levels of air pollution.

Year to year variation in total deaths in 58 Scottish and Northern Ireland local authorities

Population density in Scotland and Northern Ireland is far lower than that in England. At the time of this study, small area population densities for these countries were not available and so unweighted (raw) population density has been used.

Figure 4 shows the relationship between the standard deviation in year-to-year deaths, after adjusting for the effect of size on the standard deviation (as above) and raw population density. Each point is an average of five local authorities. On this occasion, the standard deviation has been calculated relative to that expected for size (number of deaths). Recall that raw population density significantly underestimated the weighted population density (Decision Science News 2017). Volatility is around 20% higher at around 3,500 per square Km. However, even within the limitations of this data, the relationship between population density and volatility is still clear.
Figure 4: Relationship between raw population density and the adjusted standard deviation (STDEV) associated with year-to-year deaths in 58 Scottish and Northern Ireland local authorities, 2001 to 2020.

Volatility in Excess Winter Mortality

Since higher deaths occur during the winter months a measure called excess winter mortality (EWM) has been developed which compares average deaths in the four ‘winter’ months with the eight ‘non-winter’ months (Healy 2003). A study conducted in the South West Region of England between 1994 and 1998 at electoral ward level did not detect any association between Townsend deprivation score or population density and the average winter mortality (Lawlor et al 2002). This study did not note a strong association between average EWM and population density. This is because EWM is largely driven by multiple factors, the most important seeming to be indoor temperature (National Institute of Care Excellence 2009, Hamilton et al 2017, Ogbebor et al 2018, Thai et al 2019). These other factors would act to obscure any relationship. However, no one seems to have investigated the year-to-year volatility in EWM and any relationship with population density.

The standard deviation associated with raw EWM needs to be adjusted for size (number of deaths) since there will be greater statistical scatter associated with the smallest local authorities. This adjustment was made by fitting a power-law relationship to the raw data of STDEV in EWM versus average deaths in each local authority. STDEV was adjusted to the equivalent at 1,000 deaths per annum which is roughly the average size for local authorities. Each point is an average of 10 local authorities as above.

Figure 5 shows the resulting relationship between the standard deviation associated with EWM and population density. A non-linear relationship appears to apply up to a maximum (saturation) at around 8,000 per square Km. As above, volatility is roughly double in the most densely populated areas as that observed in least densely populated areas. A third-order polynomial has been used to explore the shape of the possible relationship. Multiple issues are involved in EWM (National Institute of Care Excellence 2009, Hamilton et al 2017, Ogbebor et al 2018, Thai et al 2019).
In conclusion, for deaths (end-of-life) both the average volatility and the standard deviation around the average show dependence on population density with implications to capacity and cost volatility. Any relationship with the average EWM is obscured by the multiple factors affecting the average, however, the standard deviation (Volatility) shows a clear relationship.

Based on the proposal that mini infectious outbreaks are occurring in different locations data relating to admissions from the English NHS will be used to explore if parameters such as length of stay and the gender ratio of admissions show unexplained year-to-year volatility. Finally, volatility in health care worker sickness absence across English regions will be explored.

**Length of stay shows ‘unexplained’ undulations**

Hospital average length of stay (LOS) has been a traditional measure of hospital efficiency which is presumed to be under the direct control of hospital managers (Buttigieg et al 2018). However, if we accept the hypothesis that multiple infectious outbreaks lie behind surges in admissions and deaths for many
common conditions, then it should follow that LOS should likewise show ‘unexplained’ peaks and undulations.

Figure 6: Deviation of financial year average length of stay for the medical group of specialties from the underlying trend for England, 2005/06 to 2019/20. The medical group includes all medical specialties, clinical specialties, hematology, oncology, rehabilitation, and palliative care.

Figure 6 shows evidence for such peaks and undulations for the average LOS in the medical group of specialties between 2005/06 and 2019/20. This is a large data set with 4.9 million admissions in 2005/06 rising to 8.5 million in 2019/20, i.e. changes in LOS are not due to sampling error in small samples. Rapid reduction in LOS over time prior to 2005/06 has meant that this period has been excluded from the analysis. Over this period the underlying trend to lower LOS (average of 5.8 days in 2005/06 falling to 3.5 days in 2018/19 and 2019/20) was fitted to a polynomial equation and the difference between trend and actual calculated. The medical group includes all the medical specialties, haematology, oncology, and various clinical specialties. The expected ‘unexplained’ trends emerge which are the combined result of subtle changes in case mix and patient illness severity arising from the multitude of infectious outbreaks which will have occurred across England over this period.

While this is not conclusive proof of the proposed cause, it nevertheless suggests that more detailed investigation is warranted.
Table 2: Top 15 specialties where the proportion of male admissions shows higher than expected variation (STDEV). England 1998/99 to 2019/20

<table>
<thead>
<tr>
<th>Specialty</th>
<th>Average male admissions</th>
<th>STDEV</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Specialties</td>
<td>7,166,888</td>
<td>2.21</td>
</tr>
<tr>
<td>Medical Oncology</td>
<td>95,397</td>
<td>1.63</td>
</tr>
<tr>
<td>Nursing</td>
<td>10,658</td>
<td>1.59</td>
</tr>
<tr>
<td>Allied Health Professional</td>
<td>5,633</td>
<td>1.56</td>
</tr>
<tr>
<td>General surgery</td>
<td>817,509</td>
<td>1.55</td>
</tr>
<tr>
<td>Clinical oncology (radiotherapy)</td>
<td>134,139</td>
<td>1.54</td>
</tr>
<tr>
<td>Mental illness</td>
<td>65,067</td>
<td>1.47</td>
</tr>
<tr>
<td>Urology</td>
<td>513,585</td>
<td>1.47</td>
</tr>
<tr>
<td>Tropical Medicine</td>
<td>506</td>
<td>1.31</td>
</tr>
<tr>
<td>Forensic psychiatry</td>
<td>2,200</td>
<td>1.28</td>
</tr>
<tr>
<td>General medicine</td>
<td>1,316,796</td>
<td>1.25</td>
</tr>
<tr>
<td>Accident &amp; Emergency (A&amp;E)</td>
<td>220,847</td>
<td>1.22</td>
</tr>
<tr>
<td>General Practice (mainly elderly)</td>
<td>31,794</td>
<td>1.16</td>
</tr>
<tr>
<td>Plastic surgery</td>
<td>123,989</td>
<td>1.08</td>
</tr>
<tr>
<td>General pathology</td>
<td>835</td>
<td>1.04</td>
</tr>
<tr>
<td>Rehabilitation</td>
<td>13,959</td>
<td>1.03</td>
</tr>
</tbody>
</table>

Table 3: ICD-10 chapters (body systems) where the proportion of male admissions shows higher than expected variation, England 1998/99 to 2019/20

<table>
<thead>
<tr>
<th>ICD-10 Chapter</th>
<th>Description</th>
<th>Average male admissions</th>
<th>STDEV</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Mainly bacterial</td>
<td>105,358</td>
<td>2.52</td>
</tr>
<tr>
<td>R</td>
<td>Signs &amp; Symptoms</td>
<td>845,902</td>
<td>2.21</td>
</tr>
<tr>
<td>S</td>
<td>Injuries &amp; fractures</td>
<td>347,468</td>
<td>2.05</td>
</tr>
<tr>
<td>J</td>
<td>Respiratory</td>
<td>580,129</td>
<td>1.83</td>
</tr>
<tr>
<td>N</td>
<td>Genitourinary</td>
<td>404,707</td>
<td>1.79</td>
</tr>
<tr>
<td>K</td>
<td>Digestive</td>
<td>921,397</td>
<td>1.51</td>
</tr>
<tr>
<td>Z</td>
<td>Health Services</td>
<td>488,230</td>
<td>1.41</td>
</tr>
<tr>
<td>C</td>
<td>Cancers</td>
<td>694,212</td>
<td>1.38</td>
</tr>
<tr>
<td>I</td>
<td>Circulatory</td>
<td>730,816</td>
<td>1.13</td>
</tr>
<tr>
<td>D</td>
<td>Blood forming</td>
<td>283,055</td>
<td>1.10</td>
</tr>
<tr>
<td>F</td>
<td>Mental &amp; behavioral</td>
<td>124,760</td>
<td>1.06</td>
</tr>
<tr>
<td>B</td>
<td>Virus, fungi, protozoa</td>
<td>63,538</td>
<td>0.97</td>
</tr>
<tr>
<td>H</td>
<td>Ear &amp; mastoid</td>
<td>284,874</td>
<td>0.96</td>
</tr>
<tr>
<td>M</td>
<td>Musculoskeletal</td>
<td>451,518</td>
<td>0.81</td>
</tr>
<tr>
<td>E</td>
<td>Endocrine &amp; metabolic</td>
<td>128,155</td>
<td>0.80</td>
</tr>
<tr>
<td>P</td>
<td>Neonatal</td>
<td>131,446</td>
<td>0.72</td>
</tr>
<tr>
<td>T</td>
<td>Burns, poisoning, etc</td>
<td>182,450</td>
<td>0.61</td>
</tr>
<tr>
<td>G</td>
<td>Nervous</td>
<td>161,028</td>
<td>0.55</td>
</tr>
<tr>
<td>L</td>
<td>Skin &amp; subcutaneous</td>
<td>173,277</td>
<td>0.53</td>
</tr>
<tr>
<td>Q</td>
<td>Congenital</td>
<td>65,423</td>
<td>0.48</td>
</tr>
</tbody>
</table>
Curious trends and fluctuations in the ratio of male to female admissions

The immune system in women has fundamental differences to it than in men, in that women must be able to avoid immune rejection of the foetus during pregnancy (Aghaeepour et al 2017). Interestingly, these changes are sensitive to the prevailing burden of infectious agents, i.e. location-specific (Hove et al 2020).

The genders differ in their response to and susceptibility to many diseases and infectious agents (Canadian Women’s Health Network 2012, Klein and Roberts (eds) 2015), which extends to differential infection with strains of the same pathogen (Long et al 2000). This author is not aware of any study which has followed the ratio of male or female admissions over time, however, given the differential susceptibility of the genders to inflammation and infection it would be expected that certain specialties may be more susceptible to the infectious landscape proposed in this study. This is an entirely neglected area of investigation (Jones 2011, 2012, 2013) and the unexplained trends have probably been dismissed as ‘statistical’ scatter or ‘poor’ coding. Tables 2 and 3 shows that this is indeed the case for both specialties and diagnoses within body systems.

Figure 7: Trend in the proportion of male admissions for diagnosis R69 (unknown and unspecified causes of morbidity and mortality) in England between 1998/99 and 2019/20. The standard deviation due to chance alone varies from ± 0.03% to 0.05% depending on the year, i.e. chance variation can be categorically excluded.

The specialties in Table 2 mainly involve medical care or surgery to remedy the outcomes of medical disease processes. Specialty A&E is mainly medical assessment. The presence of mental health specialties
is entirely consistent with the known relationships between immune function and mental health (Anisman et al 2019), and the fact that some pathogens are either neurotropic or associated with neuropsychiatric disorders (Tucci et al 2017, Munjal et al 2017, Ciurkiewicz et al 2020).

I have previously documented unusual trends in admissions for injuries and fractures as per Table 3, and the explanation lies in the fact that the inflammatory response to an infection will generally accompany headache and an associated increase in clumsiness; hence, an increase in falls, injuries and fractures. Most of these admissions are for the elderly as a medical admission, but more serious fractures are to trauma and orthopaedics. Note the difference between Chapters A and B in Table 3 which cover different groups of pathogens.

The entire list of ICD-10 chapters has been included in Table 3 (except Childbirth) to show the wide range in volatility between chapters. The situation at specialty level can be replicated for individual diagnoses and diagnosis R69 (unknown and unspecified causes of morbidity and mortality) is shown in Figure 7. Diagnosis R69 is a highly relevant diagnosis since it is indicative of “we know you are ill enough to get admitted but we don’t know what is wrong with you”. This is the type of diagnosis that would be expected to arise from the subtleties of undocumented infectious outbreaks and their medical consequences (as seen in Chapter R in Table 3).

In the U.S. commercial pressure to maximize income would mean that R69 would generally be up coded by conducting more investigations to find something ‘wrong’ with the patient. The general ambiguity resulting from multiple infections and inflammation would then be lost.

As a final comment, it is my belief that the current system of diagnostic coding is unable to reflect the nuances of multi-organism infection, inflammation, and immune function in the need for admission among the elderly.

Considering the above, it should come as no surprise to note that the gender ratio at birth also shows unexplained volatility (Jones 2017).

Having investigated the presence of curious patterns in LOS for admissions and the gender ratio of admissions, the issue of sickness absence rates among health care workers can now be explored.

**Sickness absence in health care workers**

Health care workers are directly exposed to patients and therefore are a high-risk group for the acquisition of a wide range of infections. If the proposed mechanism of infectious exacerbation of existing illness is correct, then the year-to-year volatility in sickness absence among health care workers should go from less volatile in the least densely populated region through to most volatile in the most densely populated region.

This relationship is confirmed in Figure 8 where the South West of England (Cornwall, Devon, Dorset, Somerset, Wiltshire, etc) is the least densely populated, followed by the East of England (Norfolk, Suffolk, Cambridgeshire, Essex, etc) with London being most densely populated. The North West contains the large Liverpool and Manchester conurbations. The South East of England forms a ring around London but does not contain any large cities and thus forms the third of the lowest population density regions.
The predicted upper limit to the effect of population density on disease transmission (Hu et al 2013) is seen in the only slightly higher volatility in London compared to the North West.

**Discussion**

It is often the ‘experts’ who are the last to accept the shift to a new paradigm (Greenwood 2019). Indeed as ‘everybody knows’ hospital LOS is a measure of efficiency/inefficiency and staff sickness absence rates are the responsibility of the employer. Among government agencies and politicians in the UK, there is a presupposition that periods of poor financial or operational performance are the direct result of poor management or the inability to manage demand.

This study has attempted to present such a new paradigm to explain why population density and associated pollution are important from an infectious/inflammatory perspective.

It goes without saying that while levels of pollution are influenced by population density they are also influenced by geography and industry. Studies are therefore required which link population density with directly measured levels of pollution. The exact role of population density is itself influenced by levels of household crowding and the health care behaviors of different social groups.

Even if the reader wishes to discount my explanation the fact remains that the volatility in health care admissions and costs remains highly location specific (Jones 2012b-f). Sickness absence represents a considerable cost to health care organizations and higher volatility in such costs makes the process of budgetary management even more difficult.
Further research

Further studies are required regarding the volatility in deaths, admissions, length of stay, gender ratio, and sickness absence where both small-area population density and levels of pollutants are known along with socio-demographic factors such as poverty, social group composition, and age.

Health insurers need to re-analyze their data to see if these concepts apply more widely. Hospitals need to be aware that the volatility in capacity pressures is indeed location specific and conduct deeper analysis of their own past trends.

Part 3 of this series will discuss the possibility that outbreaks of a novel type or kind of infectious disease is confounding traditional analysis of trends in capacity and costs. It will also present the possibility that these outbreaks are responsible for the health insurance underwriting cycle.

Data Sources and methods

Data sources

Monthly deaths in U.S. states were obtained from the National Center for Health Statistics (2020). Inpatient admissions in England 1998/99 to 2019/20 were obtained from NHS Digital (2020a). NHS staff sickness rates were also from NHS Digital (2020b).

Monthly deaths in England and Wales were from the Office for National Statistics (2020a), for Scotland from National Records of Scotland (2020a), and for Northern Ireland were by request from the Northern Ireland Statistics and Research Agency.

Data relating to mid-2019 population and population density at Lower Super Output Area (LSOA) in England and Wales were from the Office for National Statistics (2020b). Raw population density in Northern Ireland was from the Northern Ireland Statistics and Research Agency (2020), while that for Scotland was from National Records of Scotland (2020b).

Methods

Weighted population density (persons per square Km) for English and Welsh local authority areas were obtained by weighting the population density in each LSOA by the LSOA population, for each local authority area. Hence using the sum-product function (population, population density) divided by sum population. This was performed using Microsoft Excel. There is 2.59 square Km per square Mile.

Excess Winter Mortality (EWM) was calculated as a rolling percentage difference of eight months versus four months. Hence the percentage difference between average deaths September to December versus average deaths January to August. Move forward one month and recalculate. The maximum for the rolling EWM calculation usually occurs in the four months ending March, however, this calculation can peak between the four months ending February to the four months ending April. The maximum was chosen for each winter. The standard deviation (STDEV) of EWM was adjusted for local authority size by plotting the STDEV versus average deaths (2001 to 2020) and a power-law line of best fit calculated. STDEV was adjusted to the equivalent of 1,000 deaths per annum.

The year to year difference in total deaths was calculated by constructing a rolling 12-month total of deaths commencing the 12-months ending December 2001. This was compared to the 12-months ending December 2002 as the absolute value of the difference calculated as a standard deviation equivalent
assuming Poisson statistics for whole numbers. Hence the difference divided by the square root of the average deaths in year $n$ and $n+1$. Move forward one month and recalculate. This transformation is required to adjust for the effect of size. The standard deviation of the transformed differences was then calculated. Analysis of monthly sickness absence rates in NHS Regions was conducted in the same manner.

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Further Reading
Further studies relating to factors affecting financial and operational risk in healthcare can be found at http://www.hcaf.biz/2010/Publications_Full.pdf

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