Novel Diagrammatical Analyses of Turnover of Cancer Patients

TITLE PAGE

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Accepted Version

Abstract

Aim: The *Inverted Nomogramma di Gandy* is a diagrammatical method successfully applied to evaluating staff turnover in large organisations. This exploratory research investigated whether it could be applied to cohorts of ‘active’ cancer patients (i.e. those within the first five years after diagnosis) and provide additional insights into the underlying dynamics of cancer incidence and prevalence, given that net changes can mask very different patterns. It covered each of the main five cancers.

Methods: The method was applied using relevant data for all Clinical Commissioning Groups in England in 2017. This article details the data and results for breast and lung cancer. To evaluate the method’s usefulness to service practitioners a report was circulated throughout the Cheshire & Merseyside Cancer Alliance, with an associated electronic survey.

Results: There were wide variations in incidence and prevalence across England. The diagram showed dispersed patterns for Cancer Alliances and readily identified individual outlier locations, thereby revealing the underlying dynamics. The patterns for breast cancer and lung cancer were very different. Even within the Cheshire & Merseyside Cancer Alliance there were some marked variations between locations. The evaluation found a positive response to the method from service practitioners.

Conclusions: This diagrammatical method provides useful and novel analyses that are complementary to incidence and prevalence, and helpful to practitioners. It demonstrates varying patterns, identifies outliers, and highlights the underlying dynamics behind incidence and prevalence that would otherwise not necessarily be appreciated from net figures. Because it uses existing available data it could be speedily introduced.

250 words

Introduction

Traditionally incidence and prevalence have been the main epidemiological indices for measuring trends in cancer (and other diseases); with inferences drawn about past and future pressures on related health services. Intuitively there is a correlation between incidence and prevalence, but the strength of such correlation varies between different cancers, and there can be large variations between different locations. It is generally taken that the 'active' period for cancer care is the first five years after diagnosis, with survival rates beyond 5-years being an often-used measure. If the cohort of 'active' patients for a given cancer service is therefore taken as being all patients with the disease who are alive within five years of diagnosis, then an important question is what are the dynamics of the turnover of such patients? This is because two locations could both show, say, a net percentage increase of 5% in the number of prostate cancer patients over a year; yet one might have arrived at this figure by 'gaining' 10% new cases whilst 'losing' 5% of existing cases (through death or having survived 5+ years), whilst the other may have 'gained' 25% new cases and 'lost' 20% of existing cases. The implications for their respective cancer services would be very different given most treatments are 'front-loaded' after diagnosis; consequently, the latter location would likely see much greater service demand than the former.

There are arguably parallels between measuring the turnover of patients in such cohorts and measuring staff turnover in large organisations. Certain methods have been successfully applied to the latter, and therefore research examined whether they could also be appropriately applied to cancer data. Data was acquired for all English Clinical Commissioning Groups (CCGs) for the five main cancers.

Methods

Data and formulae

The chosen diagrammatical methodology was the *Inverted Nomogramma di Gandy* which has been successfully applied to staff turnover. It had the number of staff lost as a percentage of average numbers (for a given period) as its X axis and the number of new staff as a percentage of average numbers as its Y axis. Detailed research for one large university showed widely varying patterns for different departments, which served to underline the importance of benchmarking and how this could inform management's strategic aims and objectives (Gandy et al, 2018a; 2018b).

To investigate whether this method could be applied for cancer services, data was acquired from Public Health England for 2017 for each of the 195 English CCGs in place during that year; with certain figures not shown if they were so small they risked the unlawful disclosure of personal information[1]. The data set out below was provided for: Colorectal Cancer (C18-C20); Female Breast (C50); Lung Cancer (C33-C34); Male Prostate (C61); and Melanoma (C43). For reasons of space results are shown for breast and lung cancers only, with those for the other cancers (and the evaluation survey) available on the Journal website.

A. The number of existing cancer cases (where the time since diagnosis is less than 5 years) at the beginning of 2017
B. The number of new cancer cases diagnosed during 2017 (excluding Death Notice Only cases)
C. The number of cancer deaths (where the time since diagnosis is less than 5 years) during 2017 (excluding Death Notice Only cases)
D. The number of individuals whose survival passed the 5 years' mark during 2017
E. The number of existing cancer cases (where the time since diagnosis is less than 5 years) at the end of 2017

It should be noted (E) is equal to (A)+(B)-(C)-(D).

The diagram involves two axes, which are equivalent to the axes quoted above for staff turnover:

X= The number of patients who died or survived more than 5 years as a percentage of the average number of patients during the year

Y= The number of newly diagnosed patients as a percentage of the average number of patients during the year

Using the above data these formulae become:

X=((C+D) x 100)/((A+E)/2) and Y=(B x 100)/((A+E)/2)

There is a diagonal on the diagrams (from the point (0,0) to the point (100,100)) which enables the reader to straightaway distinguish which CCGs/Alliances have net 'gains' and net 'losses' of cancer patients – those above the diagonal have net 'gains' whilst those below have net 'losses'. As would be anticipated the variations in the calculated values for each cancer site are not huge, and usually concentrate around the means. It is the shape of these patterns and the degree of dispersal that are of most interest and therefore the axes are truncated to make patterns as clear as possible. Accordingly, the range of values of the axes in the diagrams should always be noted.

The tables associated with the diagram include values of 'Y/X' and the 'Percentage of the cases that were "lost" that involved the death of the patient'. A value greater than one for the former indicates a net increase in the number of cases (i.e. above the diagonal); whilst a value less than one indicates a net decrease (i.e. below the diagonal). The percentage of cases 'lost' to deaths is a simple descriptive statistic, where it might be assumed there should be a reasonable degree of consistency.

Additional data used were the mid-2017 populations of the CCGs (Office of National Statistics,2018) to calculate incidence and (5-year limited-duration) prevalence. The data supplied gave the number of cases at both the beginning and end of 2017. Therefore a ‘Prevalence Mean’ was calculated for the year to ensure consistency.

Whilst the method could be applied to CCGs it could not be applied to hospital Trusts because of variations in how different cancer services are delivered across the country and the fact patients can travel to different centres, particularly for rarer cancers. Also, hospitals do not serve fixed populations.

Engagement

It was important to establish whether the method was useful for practitioners involved in cancer services. Therefore, the lead author contacted his local Cheshire & Merseyside Cancer Alliance to this end. The Alliance welcomed the opportunity, with initial thinking being to give a presentation and use focus group methodology at one of its member events. This was agreed in late 2019 but then the Covid-19 pandemic struck with unavoidable consequences. It was subsequently agreed the only practical way forward was to circulate a report detailing the method, data and analyses to all members of the Alliance and then invite them to complete a survey seeking views on whether the method provides additional, complementary insights to the local dynamics of the epidemiology and/or demands on the delivery of cancer services. Likert scales were utilised for most responses (1=Strongly Disagree to 5=Strongly Agree). The online survey took place in May 2021 using Qualtrics software, with no inducements to complete it.

Results

It is worth first looking at the relationship between CCGs’ incidence and prevalence (per 100,000 population), with Figures 1 & 2 showing the respective patterns for breast and lung cancers. All individual CCGs are represented by a blue diamond, with Cheshire & Merseyside CCGs denoted with red squares. It is seen there were wide variations in incidence and prevalence across the country and Cheshire & Merseyside CCGs; with a notably higher regression coefficient value for lung cancer. It is inferred that CCGs with the higher levels of incidence will have seen greatest demands on local services, with associated clinical and financial consequences.

[INSERT FIGURE 1 HERE]

[INSERT FIGURE 2 HERE]

Breast Cancer

Table 1 shows the 2017 data and analyses for the 12 (anonymised) Cheshire & Merseyside CCGs (represented by letters A-L) and Figures 3 & 4 show the *Inverted Nomogramma di Gandy* diagrams for all English Cancer Alliances and all individual English CCGs respectively. The latter denotes the Cheshire & Merseyside CCGs with red squares.

It is seen that all Alliances bar one (Greater Manchester) showed increases with the three London Alliances and Kent & Medway having the greatest percentage increases. Alliances' figures are more likely to concentrate around the national mean because they are aggregates of individual CCGs. Figure 4 highlights the diversity of individual CCGs with some being clear outliers, and a substantial minority having net reductions in the numbers of cases. Overall, the number of Cheshire & Merseyside cases went up 0.8% during 2017; 'gaining' 2138 new cases (23.0%) and 'losing' 2065 (22.2%); but with comparatively wide variations and identifiable outlier CCGs. It was evident several net percentage increases and reductions in the numbers of cases 'masked' underlying dynamics: for example, Group 'B' had by far the largest percentage increase in cases (7.3%), but this was in part because it had the second lowest number of cases 'lost' within the Alliance (20.4%). Comparatively, Group 'J' had a very low percentage of its patients 'lost' due to death (11.6%).

Table 1 **Analysis of Turnover in Cohort of Patients with Breast Cancer who are within 5 Years of diagnosis: Cheshire & Merseyside Cancer Alliance (2017)**

Clinical Commissioning Group in Cheshire & Merseyside	Cases at start of 2017	New Cases in 2017	Deaths during 2017 (where less than 5 years since diagnosis)	Cases whose survival passed 5 years during 2017	Cases at end of 2017	% Change in Number of Cases				% Deaths of 'Lost'
	A	B	C	D	E		X	Y	Y/X	
CCG 'A'	896	201	38	158	901	0.6%	21.8	22.4	1.03	19.4%
CCG 'B'	436	124	19	73	468	7.3%	20.4	27.4	1.35	20.7%
CCG 'C'	495	130	29	76	520	5.1%	20.7	25.6	1.24	27.6%
CCG 'D'	1416	316	79	227	1426	0.7%	21.5	22.2	1.03	25.8%
CCG 'E'	713	144	37	110	710	-0.4%	20.7	20.2	0.98	25.2%
CCG 'F'	603	154	29	107	621	3.0%	22.2	25.2	1.13	21.3%
CCG 'G'	541	93	29	90	515	-4.8%	22.5	17.6	0.78	24.4%
CCG 'H'	615	136	30	95	626	1.8%	20.1	21.9	1.09	24.0%
CCG 'I'	396	102	25	83	390	-1.5%	27.5	26.0	0.94	23.1%
CCG 'J'	742	181	21	160	742	0.0%	24.4	24.4	1.00	11.6%
CCG 'K'	1008	258	61	157	1048	4.0%	21.2	25.1	1.18	28.0%
CCG 'L'	1402	299	86	246	1369	-2.4%	24.0	21.6	0.90	25.9%
Total	9263	2138	483	1582	9336	0.8%	22.2	23.0	1.04	23.4%

[INSERT FIGURE 3 HERE]

[INSERT FIGURE 4 HERE]

Lung Cancer

Table 2 shows the 2017 data and analyses for the twelve (anonymised) Cheshire & Merseyside CCGs, and Figures 5 & 6 show the *Inverted Nomogramma di Gandy* diagrams for all English Cancer Alliances and all individual English CCGs respectively. Some data for Groups ‘I’ & ‘J’ were so small they risked unlawful disclosure of personal information and were not provided (as with some other English CCGs)[1].

The patterns for lung cancer are more distributed than those for breast, with some CCGs in Figure 6 having very high values and almost a complete change of their patient cohorts. All Alliances saw increased numbers of cases but the turnover in patients varied considerably, with high turnover for the East Midlands, West Midlands and Kent & Medway, and comparatively low turnover for two London Alliances and Cheshire & Merseyside. To illustrate the additional insights this method gives, it is seen that Kent & Medway and North West & South West London had net increases of 4.5% and 4.6% respectively. Yet Kent & Medway’s increase involved 82.0% ‘gains’ and 77.6% ‘losses’, which was very different to North West & South West London’s 63.3% ‘gains’ and 58.7% ‘losses’.

Cheshire & Merseyside Alliance saw variations between the individual CCGs, with some clear outliers: Group ‘G’ had the highest percentage new cases (79.5%) but ‘lost’ 85.8% cases, so there was a net reduction of 6.1%; which compared with seven of the other CCGs having an increased caseload despite much lower figures for percentage new cases. Group ‘B’ had almost the same percentage new cases (79.1%) but because it only ‘lost’ 64.8% of its cases the net increase was 15.4%; the highest within the Alliance. Interestingly an adjacent Group had a similar percentage ‘lost’ cases (61.5%) but showed a net reduction of 8.1% because it had one of the lowest percentage new cases nationally (53.1%).

Table 2 **Analysis of Turnover in Cohort of Patients with Lung Cancer who are within 5 Years of diagnosis: Cheshire & Merseyside Cancer Alliance (2017)**

Clinical Commissioning Group in Cheshire & Merseyside	Cases at start of 2017	New Cases in 2017	Deaths during 2017 (where less than 5 years since diagnosis)	Cases whose survival passed 5 years during 2017	Cases at end of 2017	% Change in Number of Cases				% Deaths of 'Lost'
	A	B	C	D	E		X	Y	Y/X	
CCG 'A'	189	146	107	17	211	11.6%	62.0	73.0	1.18	86.3%
CCG 'B'	149	127	94	10	172	15.4%	64.8	79.1	1.22	90.4%
CCG 'C'	273	139	132	29	251	-8.1%	61.5	53.1	0.86	82.0%
CCG 'D'	754	498	429	68	755	0.1%	65.9	66.0	1.00	86.3%
CCG 'E'	173	128	95	14	192	11.0%	59.7	70.1	1.17	87.2%
CCG 'F'	259	176	153	26	256	-1.2%	69.5	68.3	0.98	85.5%
CCG 'G'	131	101	99	10	123	-6.1%	85.8	79.5	0.93	90.8%
CCG 'H'	226	167	136	13	244	8.0%	63.4	71.1	1.12	91.3%
CCG 'I'	128	74	:	:	123	-3.9%	-	59.0	-	-
CCG 'J'	220	151	:	:	224	1.8%	-	68.0	-	-
CCG 'K'	272	199	153	17	301	10.7%	59.3	69.5	1.17	90.0%
CCG 'L'	407	285	225	29	438	7.6%	60.1	67.5	1.12	88.6%
Total	3181	2191	1836	246	3290	3.4%	64.3	67.7	1.05	88.2%

The symbol "**:**" denotes small numbers where publication risks unlawful disclosure of personal information[1]

[INSERT FIGURE 5 HERE]

[INSERT FIGURE 6 HERE]

Evaluation Survey

Twenty-five people responded to the evaluation survey. Twelve respondents (50%) were male and 12 (50%) were female (one declined to say); with 12 (48%) aged 30-49 years and 13 (52%) aged 50 years & over. Eleven (44%) were from secondary care, 5 (20%) were from tertiary care, and 2 (8%) were from primary care. Four (16%) were Cancer Alliance staff, 2 (8%) were from Public Health, and 1 (4%) was based in a university. In relation to profession, 16 (64%) were doctors, 4 (16%) were non-clinical managers, 3 (12%) were nurses, and 2 (8%) were information specialists. The responses to each question were scored in line with the above Likert scales, with their means and standard deviations calculated. All mean agreement scores were positive (greater than neutral) with the highest being 4.36 (The first year of a (typical) cancer patient’s treatment and care is the most resource-intensive). The others were (in descending order): Knowing the underlying dynamics of the numbers and percentages of 'gains' and 'losses' of patients was better than simply looking at net changes (3.84); The analyses and diagrams were clear and understandable (3.76); The analyses and diagrams prompted questions about what might be happening in certain Cheshire & Merseyside CCGs (3.72); I would like to see these analyses and diagrams provided annually (3.64); Is was conceptually helpful to draw parallels between the turnover of staff in a large organisation and the turnover of cases in 5-year cohorts of cancer patients (3.52); The analyses and diagrams provide additional complementary insights to those currently available nationally about cancers (3.48); The analyses and diagrams provide additional complementary insights to those currently available within the Cheshire & Merseyside Alliance (3.40); and, Some of the observed patterns in the diagrams surprised me (3.16). A final question asked if the method might be better/more helpful if it focused on a cohort of cancer patients who are alive within fewer than five years of their diagnosis? Thirteen (52%) said ‘No’ whilst 7 (28%) had no opinion. Of the 5 (20%) who thought a shorter period better, 3 said 2 years and 2 said 3 years. There were a small number of additional positive and negative comments. The former found it ‘helpful additional interpretation’, ‘added another layer of understanding’ and ‘useful in a wide range of contexts’. The latter thought it ‘academic’, ‘didn’t add a lot’, ‘not particularly helpful’, and questioned how the analyses could ‘translate into real-life outcomes for patients’.

Discussion

The results served to highlight that looking at the turnover of patients in the ‘active’ (5-year) cohort of cancer patients, using this diagrammatical method, provides insights to the dynamics of local cancer epidemiology which are complementary to simple incidence and prevalence statistics. Examples demonstrated how very different scenarios can result in similar net changes which could mask locations that have experienced comparatively greater demand for services; the Y axis involves new cases and so higher values reflect relatively higher demands on local services, given most treatments are delivered within the first year.

The method is practical, requires minimal, readily available data, and has the advantage it can compare many geographical areas in one presentation. By allowing a visual scan of a number of data points and their relative juxtapositions, the diagram enables many common thinking errors to be minimised, if not completely avoided (Levy, 1997). Therefore, it can be used to explore potential issues through questioning individual values (i.e. the “Whats”) and their juxtaposition to each other (i.e. the “Whys and Wherefores”). It points to where more detailed, localised analysis may be required, and supports the approach used in Action Learning (Teare and Prestoungrange, 2004).

The diagram showed some wide variations between locations (and the tables showed differences in percentage deaths) which should stimulate local work to understand why such variations occur, and whether remedial action might be necessary. There were different patterns for different cancers: lung cancer patients tend to die, but if new medications increase survival this could correspondingly impact on palliative and supportive services; breast cancer is more about better overall survival, and so commissioners need to appreciate any consequences of increasing numbers living with and beyond cancer.

The figures for the Alliances were not as extreme as for individual CCGs because they were themselves aggregates of their CCGs, but outlier CCGs could be readily identified. Some national outliers involved CCGs with very small populations (some of which may have subsequently merged); they ranged from 69,540 to 1,175,256, with a mean of 285,228. (Alliances’ populations ranged from 1,379,839 to 6,459,083, with a mean of 2,927,338). Although the data and analyses cannot be applied directly to hospital Trusts, as stated above, it should be possible for Alliances to make inferences and judgements about how the varying patterns between CCGs might impact on the local networks of hospital services.

The 25 responses to the evaluation survey would, on face value, represent 5.2% of the Alliance members emailed. However, its wide membership encompasses lay patient representatives to professorial researchers; many of whom would have little interest in considering the circulated report. It was estimated probably no more than one third of members would be inclined to read the report, which would then give a survey response of 15.6%. As the survey took place at a very difficult time for many practitioners due to the Covid-19 pandemic, and because the number of responses was consistent with the likely size of the originally envisaged focus group, the authors were satisfied with this size of the response. The survey results were positive about the diagrammatical method, suggesting it is helpful to service practitioners, with the majority satisfied with the patient cohort relating to 5-years.

Trends over time can be presented in primarily three ways. The first, and simplest, is to create the diagram for each of however many time periods are being studied, place them consecutively alongside each other, and then look for any trends in the patterns. The second option is to use one diagram and show the patterns for (preferably) two periods using two sets of symbols. The third option is to use arrows, sequentially linking the relevant points on the diagram (Gandy et al, 2011). However, it is important not to overload such diagrams with too many points and symbols; and therefore, it is likely such trend analyses would best suit a single Alliance.

There are inevitably some limitations with the method. One is that the annual distribution of the surviving cases across the 5-year period will likely differ between CCGs and for different cancers. Any (significant) variations in these distributions cannot be determined from the data, and so this potential issue should be borne in mind. Also, by design the diagram focuses on percentages, which by definition mask relative size. Consequently, it does not indicate the relative numbers of cases and so tables showing the actual data and calculations should be presented alongside.

It is recommended that national and regional organisations that monitor cancer trends should add this diagrammatical method to their arsenal of regular analyses. This should not involve any real cost as it utilises existing data and should be straightforwardly programmable.

Conclusions

This diagrammatical method provides useful and novel analyses that are complementary to incidence and prevalence, and helpful to practitioners. It readily demonstrates varying patterns and identifies outliers. It also highlights the underlying dynamics behind incidence and prevalence that would otherwise not necessarily be appreciated from net figures. Because it uses existing available data it could be speedily introduced.

1 Note: The small number policy of Public Health England (now NHS Digital (2021)) is part of its protective data management; which is the overall management of data, taking account of applicable legislation and procedures, to maximise its statistical use while minimising the risk of unlawful disclosure of personal information. Depending upon the subject area, a minimum number is set below which the presentation of data is ‘suppressed’, i.e. not shown, because the potential risk of individuals being identifiable is deemed too great. In the data provided by Public Health England for this research the minimum numbers quoted for individual CCGs for data A, B, C, D & E were 12, 12, 5, 5 & 10 respectively.

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Notes Section

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Key Points:

- Investigating turnover of cancer patients can highlight pressures on local services
- Net incidence and prevalence changes can mask different underlying local dynamics
- Diagrammatic method reveals varying patterns, outliers and underlying dynamics
- Method provides useful analyses complementary to incidence and prevalence
- Because method uses existing available data it could be speedily introduced

Key Words:

Cancer Incidence; Cancer Prevalence; Diagrams; *Nomogramma di Gandy*; Patient Turnover

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