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Age-Period-Cohort model : trends in mortality from lung cancer in women, Belgium 1971-1990

by

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Abstract

Mortality from lung cancer becomes an important cause of death among women. In Belgium, there is an increase in the age-adjusted mortality rate. We have examined which impact age, periods and cohorts had on the mortality between 1971 and 1990.

Poisson models (GLIM) were used. The deviance of the nested models were compared, so that the simplest model still was compatible with the data. The adequacy of the models was checked using residuals plots.

The "drift" model was considered after the model without temporal variation (the age-only model). The "drift" model is a regular trend which cannot be ascribed to either period or cohort influences. At last the specific effect of cohort or/and period over and above the "drift" was evaluated.

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In the specific case of lung cancer mortality among women no specific period or cohort effects over and above the regular evolution in time could be identified. However there is evidence that the trend was different between the regions.

In the Walloon region, the mortality increased more than twice as fast by time (R.R. (relative risk) = 1.19 every 5 years (C.I. (confidence interval 95%): 1.16-1.22)) than in the Flemish region (R.R. = 1.08 (C.I.: 1.06-1.10)). In 1971, the mortality was higher in the Flemish region and in 1990, the mortality in this region was the lowest. The mortality in Brussels increased with a factor 1.16 (C.I.: 1.11-1.20)) every 5 years.

Key-words

APC-model, Belgium, drift, lung cancer mortality, nested model, Poisson model, trend, woman.

1. Introduction

Lung cancer appears to be one of the most important public health issues of the latter part of the twentieth century. With a few exceptions, there is no indication that this epidemic will decrease, especially among women. There is evidence that the epidemic just started. The mortality rates from lung cancer among women are rising throughout the developed world. This tendency has been most pronounced in Canada, the Netherlands and Norway, where the mortality from lung cancer rose with more than 6% per year between 1980-1984 and 1985-1989. Substantial increases in lung cancer, between 3 and 5%, were also recorded during the 1980s among women in the U.S.A., Belgium, Denmark, France, Germany, Hungary, Poland, Sweden and Switzerland (1). In some of those countries, lung cancer becomes the most important cause of cancer mortality. In Belgium, this is not yet the case. Breast cancer remained the first cause of cancer mortality (2). We have analysed the mortality of lung cancer among women at the age of 20 years and older for the period 1971-1990 in Belgium.

The second objective of this paper is to provide the reader with a step by step approach for temporal and more specific age, period and cohort analysis. We used a trend analysis to describe and to interpret the variance in mortality over the time interval, paying particular

attention to the influence of the variables age, birth cohort and period of death on mortality (3-5). Descriptive and statistical age-period-cohort (APC) analysis methods have received considerable attention in the literature. The statistical modelling of APC data often involves the popular multiple classification model, a model containing the effects age groups (rows), periods of observation (columns) and birth cohorts (diagonals of the age-by-period table) (6). Age, period and cohort are related to each other: the cohort can be calculated from the age and the period. We discuss the use of this model when the temporal variations are due to purely secular (period) influences and when they are attributable to generation (cohort) influences. Also we demonstrate the serious difficulties in the interpretation of regular trends (drift) (7).

2. Materials and methods

2.1. *The dataset*

Both the mortality and the population data were made available by the National Institute for Statistics. These data were subdivided by year of death, age group, gender and region. For the mortality data, also the cause of death was added. From these data, we have selected the females who died from lung cancer (ICD-8 (1971-1978) / ICD-9 (1979-1990) classification = 162)) and who had the age of 20 years or more for the years 1971-1990.

Exploration of the dataset is necessary, such that statistical analysis is possible. This can be done by (re)coding and/or (re)grouping the data. From the variable "year of death", we created a new variable "period of death". Each period consist of 5 years: 1971-1975, 1976-1980, 1981-1985 and 1986-1990. Age was also categorised in 5 year age groups (20-24, 25-29,..., 85+). Knowing the age of death and the date of death determines the date of birth: the birth cohort was calculated by subtracting the age at which death occurred from the year of death (8, 9). A descriptive APC analysis of epidemiological data first assembles mortality rates in a two-way table with the rows representing categories of age at occurrence and the columns defining categories of period of death of occurrence. The diagonals of Table 1 (going from upper left to lower right) define the lung cancer mortality rate patterns for females born together and hence age together. The birth cohorts extend over 10-year intervals, and each birth cohort is typically identified by its central birth year: ex. 1886 (1881-1890), 1891

(1886-1895)... and 1966 (1961-1970). The birth cohorts will "overlap" (i.e. will have certain years of birth in common) when defined in this manner, such overlap is typically ignored when fitting statistical models to APC data. Birth cohorts corresponding to diagonals at the extremes of the tables will involve very few data points (6). When fitting APC models, the assumption is that the mortality rate, estimated in each cell of the table, is constant.

TABLE 1

Age specific mortality rate (/100 000) by period, Belgium 1971-1990.

	1971-1975	1976-1980	1981-1985	1986-1990
20-24 years	**0.39**	0.16	0.05	0.21
25-29 years	0.31	**0.55**	0.21	0.20
30-34 years	0.57	0.56	**0.85**	1.02
35-39 years	1.65	1.36	1.26	**1.87**
40-44 years	3.33	3.86	3.55	5.28
45-49 years	6.21	7.61	7.97	9.68
50-54 years	10.90	11.74	13.33	14.45
55-59 years	15.33	17.76	19.32	25.27
60-64 years	18.96	23.68	28.99	35.39
65-69 years	25.35	33.22	34.85	43.95
70-74 years	38.49	40.12	46.41	49.37
75-79 years	47.47	44.45	51.13	55.51
80-84 years	57.40	51.60	60.81	61.36
85+ years	50.90	59.43	69.54	68.58
Total	13.31	14.69	16.80	19.27

2.2. *Statistical methods*

2.2.1. *Introduction*

Statistical models are simplified descriptions of data, usually constructed from some mathematically or numerically defined relationships. By including a sufficient number of parameters in our model, we can make the fit as good as we please. By using as many parameters as observations, we make the fit perfect. But this way, we have no reduction in complexity and no simple model. However, dropping crucial variables makes the model totally useless. Hence, the purpose of the statistical analysis is to extract from data the maximum information in an as parsimonious and comprehensive manner as possible (10). A parsimonious model is the simplest possible model, still giving a good description of the data. This means that a balance should be made between interpretation and precision.

2.2.2. *Exploratory data analysis*

In the first place, the age specific and the age adjusted mortality rates (according to the direct method (11)) were calculated. This calculation was executed by the computer package SPSS (12). Standardisation for age was done to compare the different regions and periods with each other. The European standard population was used as the reference population (13).

2.2.3. *Statistical models/Poisson models*

We defined Poisson regression models (14) using the Generalised Linear Interactive Models (GLIM) package (14, 15). In the specification of Poisson models, it is assumed that the dependent variable (observed events) follows a Poisson distribution. Maximum likelihood estimates of the parameters were obtained (5). The corresponding regression model is multiplicative and usually it is represented in the logarithmic form:

$$\log(\mu_i) = \log E(D_i) = \log(P_i) + \sum_j \beta_j x_{ij}$$

which :

$\mu = E(D)$: the expected number of deaths

P : the population

x : the explicative variables recorded in the model

β : the parameter which has to be determined, where e^{β} is

2.2.4. *Drift*

The main concern is the interpretation of the temporal variations. This is not evident, because of the mathematical link between the three time-variables age, period and cohort: when two of them are given, then the other one can be derived. Temporal variations can be due to purely secular (period) influences and/or generation (cohort) influences. However, if the trend is regular, it can be shown it is impossible to disentangle the time evolution in a cohort or a period effect in an unique way. This situation is described in literature as drift, which is a systematic change of the rate which cannot be ascribed to cohort or period effects (7). Only if the evolution of the rate is irregular,

sufficient clues are available to discriminate between cohort and period effects.

2.2.5. *Screening*

As stressed by Clayton and Shifflers (Fig. 1) (10), because of these identification problems, it is very important to follow a strict strategy to model time evolution. As usual age should be introduced in the model, because this is an important confounder in most epidemiological studies. Next one should test for a regular time component or drift. This is done by introducing period or cohort (it does not matter which

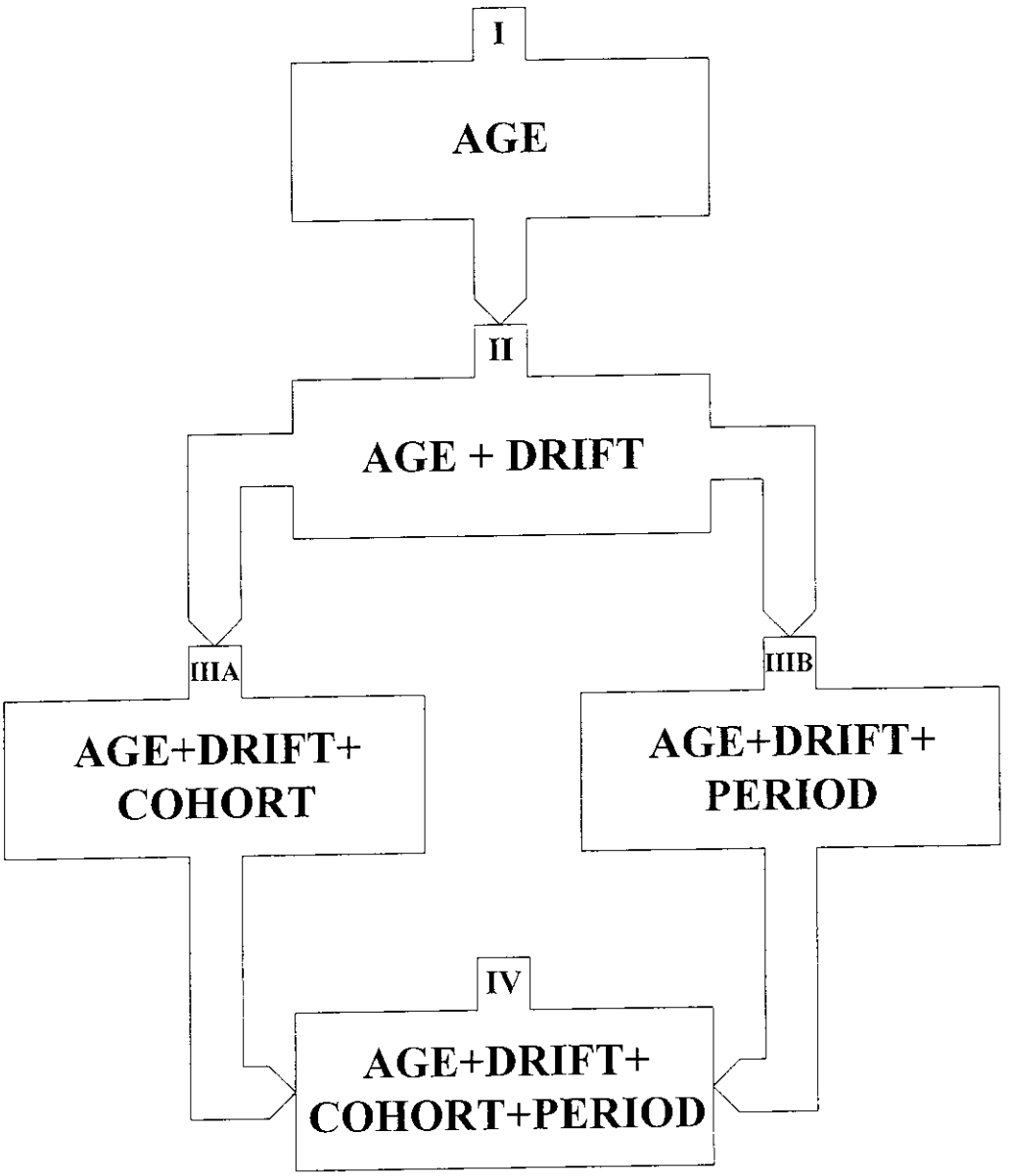

Fig. 1: Screening process in APC models (10).

to choose) as a continuous variable. Then it should be looked for irregularities by introducing the period or cohort as a class variable (factor), which allows to describe irregularity in time. Finally it should be controlled if the introduction of period and cohort further improves the model.

To test if a variable gives an important contribution to the model, we looked at the decrease in deviance derived by the number of degrees of freedom associated with that variable. If this value was large, the variable was introduced in the model, if not, the variable was rejected. As a threshold we took a value of 3 for the change for 1 degree of freedom (d.f.), because we were mainly interested in the global aspects of the data.

2.2.6. *Residual analysis*

We used the standard residuals to test the goodness of fit of the model. Residuals are the difference between the observed numbers and the expected numbers. To interpret them appropriately they should be standardised by dividing them by the standard error (for a Poisson variable this is the square root of the expected numbers) (7). Such standard errors are calculated automatically as part of the computer output from the model fitting program (GLIM).

The acceptability of a model depends upon whether the residual variability is small enough to be of little practical importance (7). First, we have been testing this by quantile plots. Normal QQ-plots are used to compare the ordered standardised residuals with their expected values. If the fit of the model is good, then approximately a straight line must be found. In a next step, we explored the residuals for outliers, residuals outside the boundaries $(-2; 2)$. The standardised residuals give the statistical distance of the observations from their expected values. If the model is appropriate, 95% of the residuals is expected to be within a range of ± 2. Much larger values indicate there is maybe something particular with some of the data or the model may not be totally appropriate. It is also possible that the residuals may exhibit a systematic pattern. If a systematic pattern is observed in the residual plot, it can be an indication that the form of the covariates in the model is not optimal and should be transformed. or the introduction of a new variable may be necessary.

2.2.7. *Prediction of the data*

Another way to test the goodness of the fit of the model is to compare the observed and the expected or predicted rates. The observed rate is the age specific mortality rate. The expected rate can be calculated by dividing the fitted value (expected number of deaths), which is also a result of the model fitting program (GLIM), by the population. For each period we have plotted both rates by region.

3. Results

3.1. *Mortality rates*

The age standardised mortality rate (Fig. 2) in Belgium for the period 1971-1990 shows an increasing trend. The rates increased from 9.40/100 000 in 1971 to 17.01/100 000 in 1990. The evolution in time was different for the regions in Belgium: the age adjusted mortality rate in the Brussels Region is the highest and the most unstable; in the first decade of the observation, the age adjusted mortality rate was in the 0Flemish Region higher than in the Walloon Region, but since 1982 we observe the opposite.

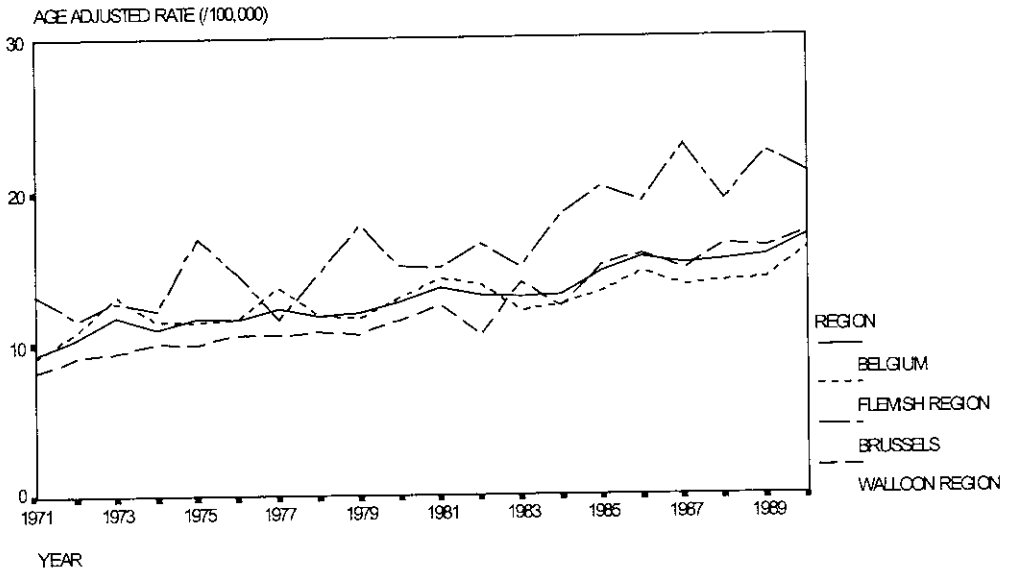

Fig. 2: Age adjusted rate by year and region – lung cancer mortality. Belgium, 1971-1990, females.

The age specific mortality rate by period of death (Table 1) increased with age. In addition there was, with the exception of the two youngest age groups, an increase of the mortality in the same age group for each period. The birth cohorts for lung cancer mortality give a regular pattern (Fig. 3): for the same age group, the mortality increased with more recent birth cohorts: e.g. for the age group 60-64 years the age specific mortality rate for the birth cohort 1911 is 18.96/100 000 and for the birth cohort 1926 35.39/100 000.

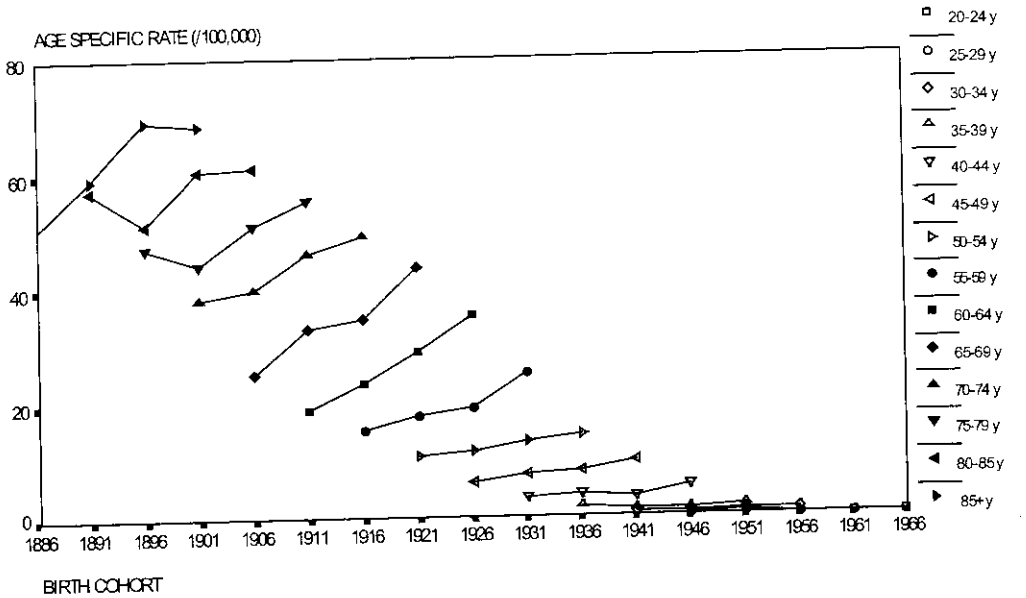

Fig. 3: Age specific rate by birth cohort – lung cancer mortality. Belgium, 1971-1990, females.

3.2. *Deviance analysis of the data*

Table 2 illustrates the goodness of fit of various log-linear models. The first column gives the variables in the model and the last column will be used as a criterion to decide whether a new term should be included or not. The full line and dotted line are used to indicate which models are nested. By adding the age parameter to the 0-model, there is a loss of 13 degrees of freedom (d.f.) for a difference in deviance of 15 360. For 1 d.f. this gives a change in the deviance of 1 182. This is a very high value (very significant), so we can conclude that age is an important factor and must be included in the model. In the second step, we evaluated which time parameter is important. By adding the

drift parameter, there was a difference in deviance of 199 for 1 d.f., which is still very high and hence drift should be included in the model. Then we test whether cohort or period are also important: the introduction of cohort gives a change in deviance of 46.11 for 15 d.f. Strictly speaking (e.g. using a χ^2 table) this change in deviance is marginally statistically significant. However the gain in precision by the model remains rather small (on average 3.07 for 1 d.f.) in comparison with the increase in the complexity of the model, especially compared to the gain in precision obtained by the introduction of the age and drift variable. For the period, this value is even lower: 0.5 for 1 d.f. To control whether cohort and period together explain much more than the simple terms alone, we tested the influence of period in the age + drift + cohort model and the influence of cohort in the age+drift+period model. The results found were similar to the previous stage. Hence, we can conclude that the parameter "drift" gives an appropriate description of the time-evolution.

TABLE 2

Lung cancer mortality in Belgium females, 1971-1990
Goodness of fit of various log-linear models

Model	Deviance	Degrees of freedom (d.f.)	Difference in deviance	Difference in d.f.	Deviance for 1 d.f.
0	15908	167			
Age	548.51	154	−15360	−13	1181.54
Age + drift	349.51	153	−199	−1	199
+ cohort	303.39	138	−46.11	−15	3.074
+ period	303.01	136	−0.383	−2	0.192
+ period	348.53	151	−0.975	−2	0.488
+ cohort	303.01	136	−45.52	−15	3.035
Age + drift + region	236.81	151	−112.7	−2	56.35
+ age . region	163.07	125	−73.74	−26	2.836
+ drift . region	212.19	149	−24.62	−2	12.61
+ age . drift	186.44	138	−50.37	−13	3.875

Screening model: age + drift + region + drift . region.

Referring to Figure 2 with the age standardised rates, which provides evidence that there is a different trend for the regions in Belgium, we add this parameter to the age-drift model. This variable has also a significantly effect: a loss of 2 d.f. for a difference in deviance of 113, which gives a change in deviance of 56 for 1 d.f. This

indicates the importance of the region in the model. Finally, we investigated the interactions between the different parameters. The possibilities are: interaction between age and region, between drift and region and between age and drift. Comparing the change in deviance for 1 d.f., identifies the value of the interaction between drift and region as the most pronounced, namely 12.6. For the other interaction terms this value is around 3, which is of the same order of magnitude as for the cohort term. Based on the deviance analysis, we concluded that age + drift + region + drift . region may be an appropriate model to describe the evolution of lung cancer mortality among females in Belgium.

3.3. *Residual-analysis*

The normal QQ-plot (Fig. 4) shows approximately a straight line, indicating that there is a good fit of the residuals. This means that the standard residuals are close to the expected normal values. Plotting the standard residuals by region, period and age (Fig. 5), allows to identify the extreme values (outliers), which are mainly situated in the Flemish region. It is also important to notice that these are cases from the youngest or oldest age groups. In the youngest age groups, the number of cases are low, such that the standardisation is insufficient.

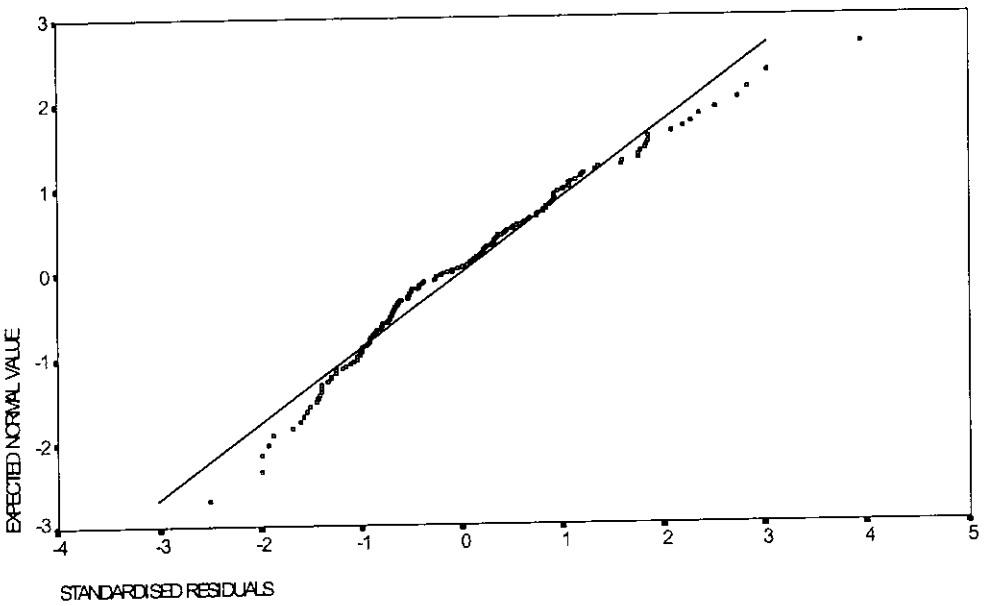

Fig. 4: Normal QQ-plot of the residuals: age + drift + region + drift . region.

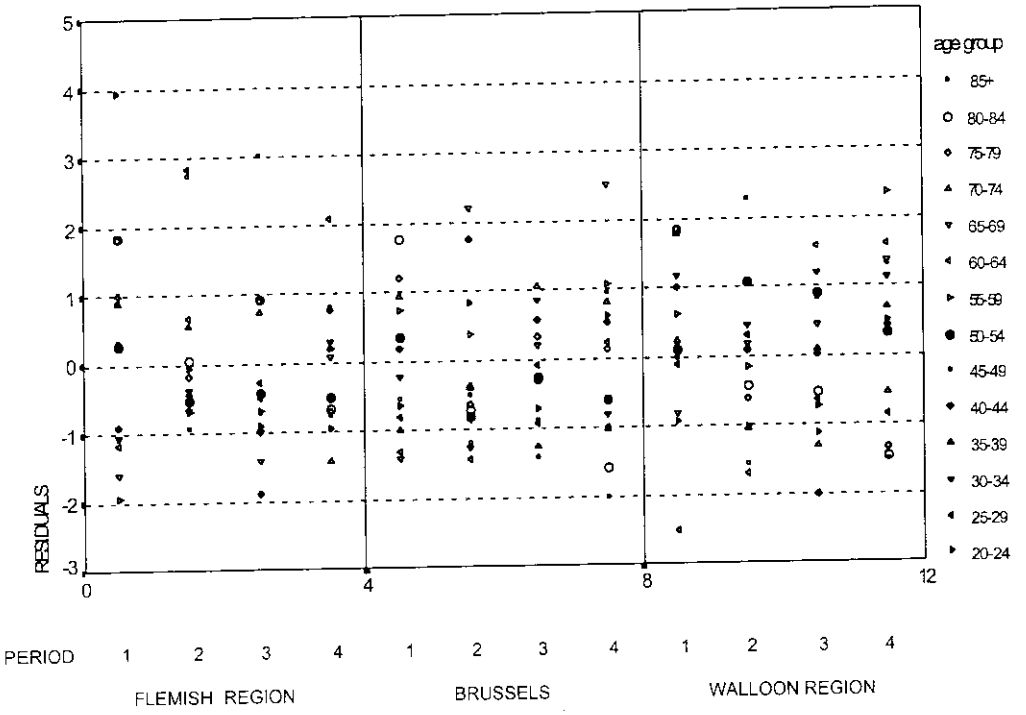

Fig. 5: Standardised residual plot by period and region. Model: age + drift + region + drift . region.

Overall, the residuals are well distributed between −2 and 2, without any systematic pattern. This is another indication for the goodness of fit of the model. For Brussels and the Walloon region there are no specific patterns. For the Flemish region there is also no real pattern; most of the residuals are lying between 1 and −2, and there are a few outliers that are lying around 3 and 4. This may be an indication that the mortality as a function of age is different in the Flemish region than in Brussels and the Walloon region. No further variable were introduced and no alternative model was evaluated, because no specific outliers were observed and no pattern was detected.

3.4. *Interaction between the variables*

In the deviance analysis, we saw that there was an interaction between drift and region. This means that there is a different trend of mortality in each region (Fig. 6). The factor of the relative evolution was calculated by taking the exponential value of the estimates. In the Flemish region, the mortality increased with a factor of 1.08 (95% confidence limits: 1.06-1.10) between each period of 5 years. The mortality of lung cancer among women in the Walloon region had the highest factor of increment (1.19 (1.16-1.22)). Brussels had a smaller

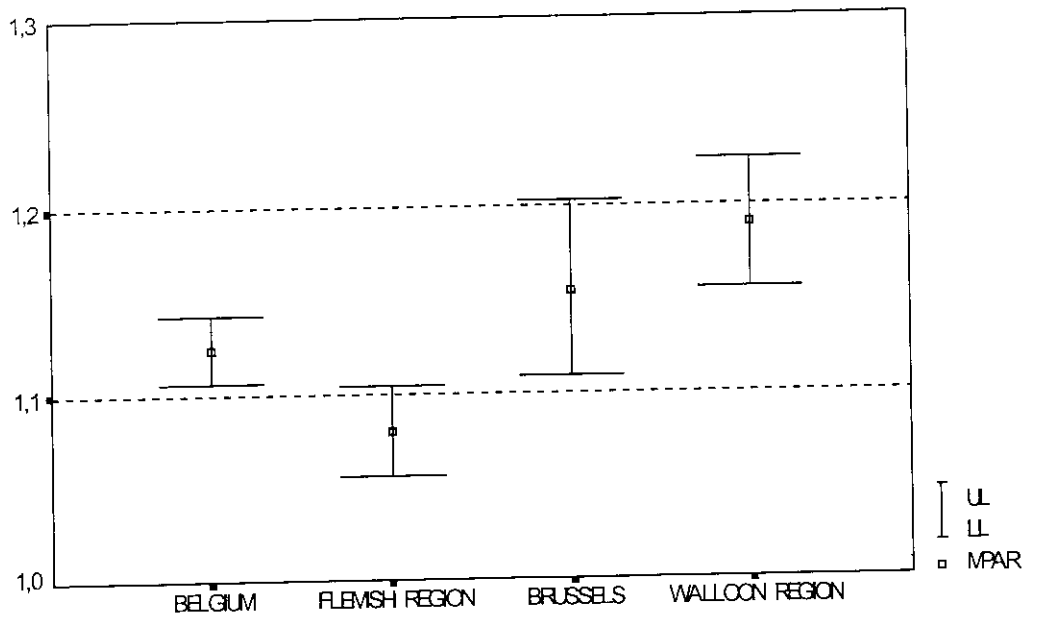

Fig. 6: Relative evolution of the mortality rate by 5 year period.

increment factor than the Walloon region, but it is still high (1.16 (1.11-1.20)). The trend in the Flemish region is significantly different from the one in the Walloon region and Brussels. The trend in Brussels is not significantly different from the one in the Walloon region. This observation confirms the conclusion drawn from the age standardised mortality rates.

3.5. *Observed and expected rates*

In each region of Belgium there was an increasing trend in the mortality rate of lung cancer among women (Fig. 7). We notice that in the first period (1971-1975) the mortality rate was higher in the Flemish region than in the Walloon region. In Brussels, the mortality rate is the highest. But over the time, the mortality rate in the Walloon region increased faster than in the Flemish region and during the last period the mortality rate in the Walloon region was higher than in the Flemish region.

When comparing the observed rates with the expected rates, there is a good approximation, except for the oldest age groups. In the oldest age groups for the Flemish region there is some overestimation and for the Walloon region and Brussels there is some underestimation of the observed rates. This may indicate that in the oldest age

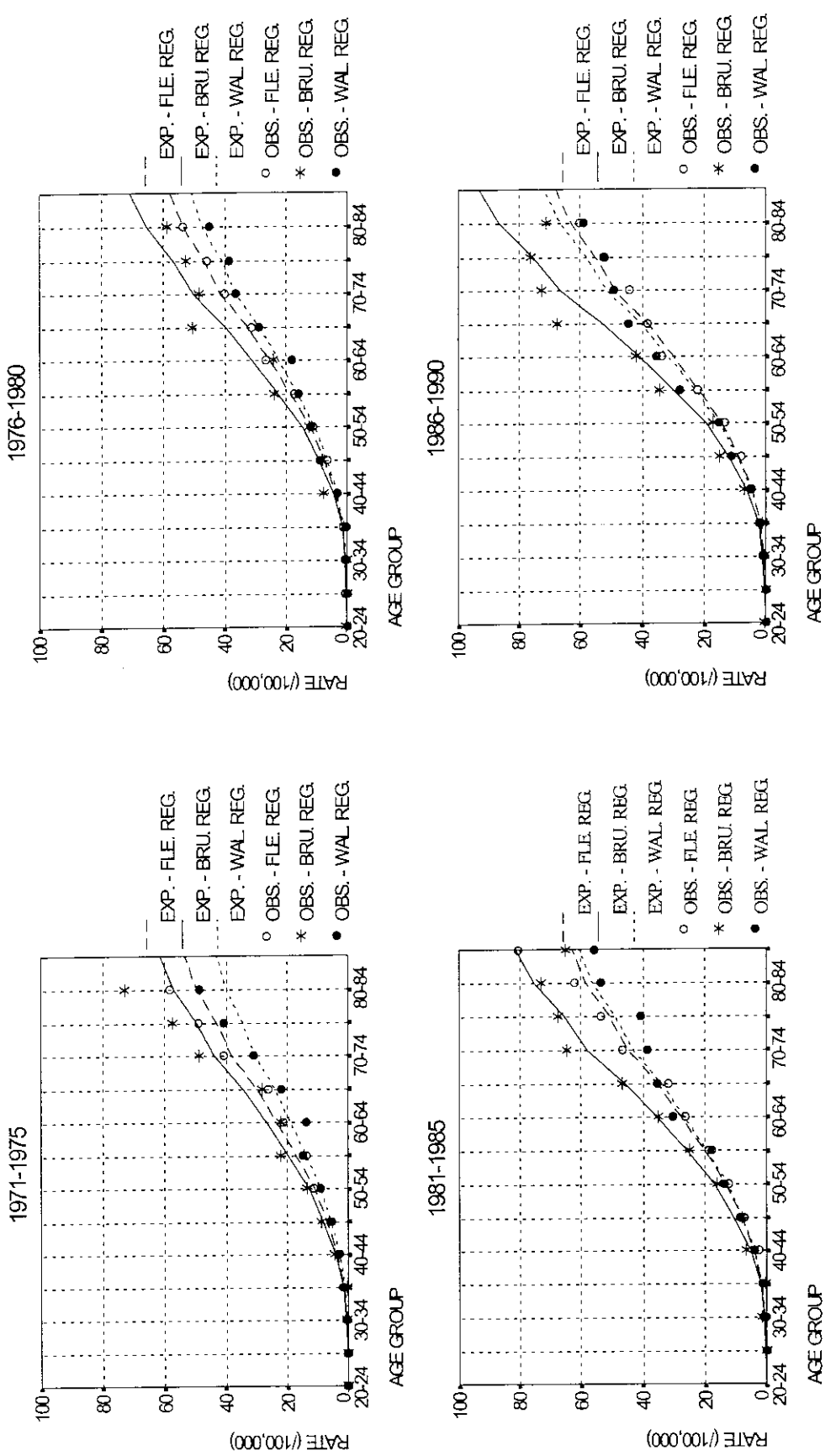

Fig. 7: Observed and expected mortality rates by period and region.

group for the Flemish region the mortality is still increasing, while for the other regions it is decreasing. This difference may be due to problems related to a cause specific mortality in the oldest age group which may not be equal for the different regions.

4. Conclusion

The fit of the model was appropriate. Only in the Flemish Region we observe some fluctuations, mainly in the residuals of the youngest age group. Often the dominant reason for fluctuation of observed rates is the natural fluctuation of numerators, which vary according to the well-know Poisson law. It is then appropriate to give less weight to poor prediction of observed rates based on small numbers of cases. With this Poisson criterion, good fit of the rates based on larger numerators is more important (7).

Overall there is a linear increasing trend for the mortality of lung cancer among women in Belgium for the period 1971 to 1990. But there is an interaction between "drift" and region. This means that the evolution is different in the three region: in the first period (1971-1975) the mortality rate in the Flemish region was higher than the mortality rate in the Walloon region, but with the evolution in time the mortality in the Walloon region increases faster, so that at the end of the period the mortality rate in the Walloon region is higher than in the Flemish region.

The data provide no evidence that the increasing trend of lung cancer mortality in female will be slowing down or reversing in the near future.

5. Discussion

Most causes of cancer require prolonged exposure, determined by an aspect of life-style, such as occupation or smoking habits, which is fixed very early in adult life (7). There is a strong association between cigarette smoking and the mortality from lung cancer (1, 16, 17).

Trends among younger adult women are highly sensitive to recent changes in smoking behaviour during adolescence. Death rates among younger women in the U.S.A., Belgium, Denmark, Finland, Australia and New Zealand begin to decline, at least at younger age (1). If these trends continue, overall lung cancer mortality rates will

start to decline after the year 2000 among women below 45 years (16). But recent studies (18) have demonstrated that there is an increment of adolescent girls (15-16 years) who experiment with smoking for the years 1990 to 1994, namely from 45% to 52%. Eighteen percent of the 17-18 year old girls in 1994 smoked daily. The risk of daily smoking rose with a factor of 1.5 in comparison with 1990. Also these studies show that the smoking behaviour of the parents have a strong influence on their children. The prevalence of daily smoking is the three fold when both parents smoke. In the period 1982-1993, the percentage of daily smokers was decreasing from 40% to 25%, but has a tendency to increase again since 1994. According to Peto et al. (19), the percentage of all deaths attributed to smoking has been increasing from 0.1% in 1955 to 7% in 1995 for females of the age group 35-69 years.

The lung cancer mortality in Belgian women is still 10 times lower compared to men. In both men and women, there has been an increase in the lung cancer mortality between 1971-1990. However, the increase among male is less steep and between 1986-1990 there was no further increase. The main difference in evolution of lung cancer mortality between the sexes is the age specific mortality for the consecutive cohorts. In women, the lung cancer mortality keeps on increasing in each consecutive generation. We can therefore not yet expect a bending. Among men, the expectations may be more positive, because the risk of dying in the younger cohorts is decreasing.

The difference in the trend between women and men is a result of the decline in smoking uptake and smoking prevalence in adolescent and young adult males contrary to the increasing prevalence of young smoking women. According to a consumers organisation (OIVO), the percentage of daily female smokers in Belgium is increasing from 26% in 1994 to 28% in 1995. Divided by region, there were in 1995 in the Flemish Region 27%, in the Brussels Region 28% and in the Walloon Region 29% daily smokers. Therefore, if Belgium wants to reach the objective of the world health organisation of 20% smokers in the year 2000, then this can not be done without additional arrangements. An efficient policy concerning the prevention of tobacco requires a continue effort. Otherwise, the consumption menaces to stagnate or even increase.

In order to reverse the current lung cancer mortality trend it is very important to encourage smoking prevention programs. These pro-

grams should reach larger segments of the population, especially children, adolescents and minorities. Targeting young people for prevention programs has the potential to result in major reductions in mortality from lung cancer (16). A complete ban on publicity of tobacco, an increment of the price of tobacco products, a ban on the sale of tobacco products via a vending machine, reducing the legal permitted maximum nicotine content of tobacco products, a better protection of the non-smokers and more prevention campaigns can lead again to a decreasing of smoking habits in Belgium. The effect of rises the price of tobacco doesn't only lead to a lower consumption, but also to a decrease of the number of smokers (20-23). Several studies demonstrate that a real increment of the price of tobacco leads to a lower consumption: both the size of the smokers population and the daily consumption by smokers are reducing. An increment of the taxes on tobacco products doesn't lead only to a decrease of the consumption, but also to a lower smoking related mortality. On short term, an increment of the taxes will therefore lead to a higher income for the government. This extra income could be used to lead anti-smoking campaigns. Furthermore, not only cigarettes, but also all the smoking products have to be taxed so substitution can be fought. Therefore, a rational criterion is taxation on the content of nicotine or tar by article (24).

Résumé

La mortalité par cancer du poumon est entrain de devenir une cause de mortalité importante chez les femmes. On observe en effet une augmentation en Belgique des taux de mortalité ajusté pour l'âge. Dans le cadre de la présente étude, nous avons examiné l'impact de l'âge, de l'année de naissance et de décès sur la mortalité entre 1971 et 1990.

Des modèles de Poisson (GLIM) ont été utilisés. La variance des modèles emboités a été étudiée, de sorte que le modèle le plus simple était toujours compatible avec les données. L'opportunité des modèles a été controlée par l'étude des résudus.

Le modèle « drift» a été consideré après celui sans variation temporelle (le modèle âge). Ce modèle envisage une tendance régulière, laquelle ne peut pas être attribuée aux influences des périodes (année des décès) ou des cohortes (année de naissance). En dernier lieu, l'effet spécique des cohortes or/et des périodes a été évalué à côté du modèle « drift ».

Dans le cas spécifique de la mortalité par cancer du poumon chez les femmes, des effets de période or de cohorte ne peuvent pas été identifiés à côté de la tendance régulière dans le temps. Il y a une indication que la tendance est différente entre les régions.

En Région Wallon, la mortalité a augmenté plus que deux fois plus vite dans le temps (R.R. (risque relatif) = 1,19 par période de 5 années (I.C. (interval de confiance 95%): 1,16-1,22)) qu'en Région Flamande (R.R. = 1,08 (I.C.: 1,06-1,10)). En 1971, la mortalité était plus élevée en Région Flamande tandis qu'en 1990, la mortalité dans cette région était la plus basse qu'en Wallonie. La mortalité à Bruxelles a augmenté avec un facteur de 1,16 (I.C.: 1,11-1,20)) par période 5 années.

Samenvatting

Sterfte aan longkanker is een belangrijke doodsoorzaak geworden bij vrouwen. In België, is er een toename in het voor leeftijd gestandaardiseerd sterftecijfer. We hebben onderzocht welke impact leeftijd, perioden en cohorten hadden op de sterfte tussen 1971 en 1990.

Poisson modellen (GLIM) werden gebruikt. De deviantie van de geneste modellen werd vergeleken, zodat het simpelste model nog altijd compatibel was met de gegevens. De geschiktheid van de modellen werd gecontroleerd d.m.v. residu-plots.

Het „drift" model werd beschouwd na het model zonder tijdelijke variatie (het leeftijdsmodel). Het „drift" model is een regelmatige trend, welke noch kan worden toegeschreven aan periode- noch aan cohortinvloeden. Als laatste werd het specifiek effect van cohort en/of periode naast de „drift" geëvalueerd.

In het specifiek geval van longkankersterfte bij vrouwen konden geen specifieke periode- of cohorteffecten naast de regelmatige evolutie in de tijd worden geïdentificeerd. Wel is er een aanduiding dat de trend verschillend was tussen de gewesten.

In het Waals Gewest, steeg de sterfte meer dan twee keer zo snel in de tijd (R.R. (relatief risico) = 1,19 elke 5 jaar (B.I. (betrouwbaarheidsinterval 95%): 1,16-1,22)) dan in het Vlaams Gewest (R.R. = 1,08 (B.I.: 1,06-1,10)). In 1971 was de sterfte hoger in het Vlaams Gewest en in 1990 was de sterfte in dit gewest het laagst. De sterfte in het Brussels Gewest steeg met een faktor 1,16 (B.I.: 1,11-1,20)) elke 5 jaar.

References

1. LOPEZ A D, CASELLI G, VALKONEN T. The lung cancer epidemic in developed countries. In: Adult mortality in developed countries: from description to explanation. Anonymous Oxford: Clarendon Press, 1995, 111-134.
2. VAN OYEN H, TAFFOREAU J, DRIESKENS S, AELVOET W. Overlijden en oorzaakspecifiek overlijden in de Vlaamse Gemeenschap 1989-1991. 3rd Ed. Brussel. Ministerie van de Vlaamse Gemeenschap, 1997 (in press).
3. POLLAN M, LOPEZABENTE G, PLAMESTRE R. Time trends in mortality for multiple myeloma in Spain, 1957-1986. Int J Epidemiol 1993; 22: 45-50.
4. SVERRE J M. Trends in suicide mortality among the elderly in Norway, 1966-1986. Epidemiology 1991; 2: 252-256.
5. AVILA M H, WALKER A M. Age dependence of cohort phenomena in breast cancer mortality in the United States. Am J Epidemiol 1987; 126: 377-384.

6. KUPPER L L, JANIS J M, KARMOUS A. Statistical age-period-cohort analysis: a review and critique. J Chronic Dis 1985; 38: 811-830.
7. CLAYTON D G, SCHIFFLERS E. Models for temporal variation in cancer rates. I: Age-period and age-cohort models. Statistics in Medicine 1987; 6: 449-467.
8. LEE W C, LIN R S. Analysis of cancer rates using excess risk age-period-cohort models. Int J Epidemiol 1995; 24: 671-677.
9. VAN DER HOFF N M. Cohort analysis of lung cancer in the Netherlands. Int J Epidemiol 1979; 8: 41-47.
10. CLAYTON D, SCHIFFLERS E. Models for temporal variation in cancer rates. II: Age-period-cohort models. Statistics in Medicine 1987; 6: 469-481.
11. ARMITAGE P, BERY G. Statistical methods in medical research. Oxford: Blackwell Scientific Publications 1987; 399-405.
12. NORUSIS M J. SPSS/PC + Base system user's guide, version 5.0. Chicago, Illinois. SPSS Inc. 1992; 1-910.
13. SMITH P. Comparison between registries: age-standardized rates. In: Muir C, Waterhouse J, Mack T, Powell J, Whelan S (eds.), Cancer incidence in five continents, Volume V. Lyon: IARC, 1987, 790-795.
14. McCULLAGH P, NELDER J A. Log-linear models. In: Generalized linear models. 2nd Ed. Anonymous London: Chapman & Hall, 1989, 193-236.
15. AITKIN M, ANDERSON D, FRANCIS B, HINDE J. Multinomial and Poisson response data. In: Statistical modeling in GLIM. Anonymous Oxford: Oxford University Press, 1989, 217-255.
16. DEVESA S S, BLOT W J, FRAUMENI Jr J F. Declining lung cancer rates among young men and women in the United States: a cohort analysis. J Natl Cancer Inst 1989; 81: 1568-1571.
17. TVERDAL A, THELLE D, STENSVOLD I, LEREN P, BJARTVEIT K. Mortality in relation to smoking history: 13 years' follow-up of 68,000 Norwegian men and women 35-49 years. J Clin Epidemiol 1993; 46: 475-487.
18. VAN DE MIEROOP E, MAES L. Jongeren en Gezondheid in Vlaanderen. Gent, U.I.A.-U.G. 1996; 1-27.
19. PETO R, ALAN D, LOPEZ A D, BOREHAM J, THUN M, HEATH Jr C. Mortality from smoking in developed countries 1950-2000. Oxford. Oxford University 1994; 1-553.
20. WARNER K E. Smoking and health implication of a change in the Federal Cigarette Excise Tax. JAMA 1986; 255: 1028-1032.
21. LEWIT E M, COATE D. The potential for using excise taxes to reduce smoking. Journal of Health Economics 1982; 1: 121-145.
22. LEWIT E M, COATE D, GROSSMAN M. The effects of government regulation on teenage smoking. Journal of Law and Economics 1981; 24: 545-569.
23. WARNER K E. Statistics: A guide to the unknown. 3th Ed. Belmont. Wadsworth & Brooks/Cole Advanced Books & Software 1989.
24. PANDELAERE M, VAN DEN BROUCKE S, VAN DEN BERGH O. Het effect van omgevingsinterventies op gezondheidsgerelateerd gedrag. 1996 (unpubl.).