Published in final edited form as:

Ann Epidemiol. 2014 August ; 24(8): 570–574. doi:10.1016/j.annepidem.2014.06.002.

Mortality cohort effects from mid-19th to mid-20th century Britain: did they exist?

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Abstract

Purpose—Identification is a central problem with age–period–cohort analysis. Because age + cohort = period, there is no unique solution to the linear effect using generalized linear modeling, but cohort effects have caused greater controversy than age and period effects. To illustrate the magnitude of cohort effects given the presence of collinearity, we reanalyze data from the seminal study by Kermack et al, with an update.

Methods—Relative mortality data in England and Wales between year 1845 and 1995 were analyzed using partial least squares regression. There were seven age groups ranging from 5 to 74 years old and 16 periods with 22 cohorts.

Results—Our reanalysis seemed to support the existence of cohort effects in the mortality trends. Period and cohort effects were generally consistent with changes in the social, economic, and environmental factors taking place in the last two centuries. Our analysis also showed a declining trend in period effects up to 1950s.

Conclusions—Partial least squares and related methods provide intuitive pointers toward the separation of linear age, period, and cohort effects. Because statistical algorithms cannot distinguish between relative and actual mortality rates, cohort effects may be underestimated because of contamination by negative age effects.

Keywords

Age–period–cohort analysis; Mortality; Partial least squares; Cohort effects

How to separate the distinct linear effects of age, period, and birth cohort on the changes in, for example, attitudes, behaviors, and health outcomes in the population has a long and controversial history in epidemiology and social sciences [1–9]. Age effects typically reflect changes in the distribution of an outcome across the life course, reflecting changes in the distributions of biological, developmental, and sociological risk factors independent of

period, and generational experience [10]. Most approaches to assessing age, period, and cohort effects consider age effects as nearly universally present for most outcomes [1–4]. Period effects are usually considered to reflect environmental experiences common to a given period, which affects the whole population living at that time. People of different ages at a given period share the same experience. Birth cohort effects are collective environmental effects uniquely experienced by groups of individuals born around the same time [10]. They are generally considered to be the consequence of events occurring during particular sensitive periods of the life course, often early life, including the in-utero and early postnatal period. Although age, period, and birth cohort effects seem to be conceptually unique, they are nevertheless mathematically related because $\text{age} + \text{cohort} = \text{period}$. Consequently, when traditional regression models attempt to simultaneously consider age, period, and cohort effects as linear constructs, there is no unique solution, giving rise to the identification problem. Recently, several approaches have been proposed to deal with this collinearity; whereas some approaches make implicit constraints about the relations among the three effects to allow them to become estimable [11–14], others use smoothing functions to obtain age, period, and cohort effect patterns [15–17].

Despite having some resonance within epidemiology, particularly with regard to the fetal/developmental origins of health and disease hypothesis, cohort effects have probably caused greater controversy than age and period effects in the past [18–20]. Data used for most age–period–cohort analyses are aggregated data crosstabulated by age and period, in which cohort is represented by the diagonals. Early and recent cohorts therefore have fewer observations than those in the middle and are often more elusive to detect.

Changes in generations' mortality in England and Wales

The pioneering study by Kermack et al. [21] was an important early work that apparently demonstrated cohort effects in mortality in England and Wales. Using the mortality at year 1845 as a reference, their study showed a clear decline in mortality for groups for age more than 5 years beginning around the year 1845 and seen in later periods for the same cohort. This finding has been interpreted in terms of the impact of social and environmental factors from the mid-19th century onward on population health. Although the study by Kermack et al. has been influential, cohort effects shown by their analysis are still being questioned [20]. In this article, we revisit the cohort effects in Kermack et al. using partial least squares regression to address the identification problem [22]. We will also discuss issues related to the use of relative mortality in identifying cohort effects.

Materials and methods

We used the relative mortality data in England and Wales between year 1845 and 1995, which was first presented by Kuh and Davey Smith [23,24] with updates obtained from the web site for Office for National Statistics, London [22,25]. There were seven age groups ranging from 5 to 74 years old and 16 periods with 22 cohorts. Following a similar approach by Roberson and Boyle [26], we first used a three-dimensional perspective plot to show the trends in the relative mortality rates with the use of the earliest period as the reference (Fig. 1). In Figure 1, as each diagonal from one of the age groups in different periods represents a

cohort, a trend from the bottom left to the upper right across diagonals would suggest cohort effects; there seemed to be a decreasing trend in mortality after 1845 from the earliest cohort at the upper left corner to the most recent cohort at the lower right corner, which seems to suggest a cohort effect. However, as age, period, and cohort effects are not independent, a visual examination alone could be misleading.

We then used partial least squares regression, to estimate the age, period, and cohort effects [27–30]. As details of partial least squares regression have been described elsewhere, we only gave a brief explanation here. For the analysis of crosstabulated data with seven age groups and 16 periods, the linear model for the natural log transformation of relative mortality rate (MR) with all the dummy variables for age, period, and cohort groups is written as follows:

$$\log(\text{MR}) = a_0 + \sum_{i=1}^7 \alpha_i \text{age}_i + \sum_{j=1}^{16} \beta_j \text{period}_j + \sum_{k=1}^{22} \gamma_k \text{cohort}_k + \varepsilon \quad (1)$$

where a_0 is the intercept, ε the residual error term, and α_i , β_j , and γ_k are the regression coefficients for the dummy variables. As first shown by Kupper et al. [31], after all the variables are centered, there are four identification problems in Equation 1.

$$\sum_{i=1}^7 \text{age}_i = \sum_{j=1}^{16} \text{period}_j = \sum_{k=1}^{22} \text{cohort}_k = 0 \quad (2)$$

$$\sum_{i=1}^a \left(i - \frac{(a+1)}{2} \right) \text{age}_i - \sum_{j=1}^p \left(i - \frac{(p+1)}{2} \right) \text{period}_j + \sum_{k=1}^{a+p-1} \left(i - \frac{(a+p)}{2} \right) \text{cohort}_k = 0 \quad (3)$$

where a and p are the number of groups of age and period, that is, seven and 16, respectively. As shown in our previous study [30], partial least squares regression implicitly applied the following constraints on the parameters to make Equation 1 estimable.

$$\sum_{i=1}^7 \alpha_i = \sum_{j=1}^{16} \beta_j = \sum_{k=1}^{22} \gamma_k = 0 \quad (4)$$

and

$$\sum_{i=1}^a \left(i - \frac{(a+1)}{2} \right) \alpha_i - \sum_{j=1}^p \left(i - \frac{(p+1)}{2} \right) \beta_j + \sum_{k=1}^{a+p-1} \left(i - \frac{(a+p)}{2} \right) \gamma_k = 0 \quad (5)$$

Fu [16] and later Yang et al. [11,12] proposed the use of the Equations 4 and 5 as a solution to the identification problem, and their proposed solution is widely known as the intrinsic estimator. From a mathematical viewpoint, imposing Equations 4 and 5 in the estimation is equivalent to using the Moore–Penrose generalized inverse method to obtain a unique

inverse matrix for the perfectly collinear design matrix that consist of all the age, period, and cohort variables [7,11,30].

Partial least squares analysis is a data-reduction technique and successively extracts orthogonal components, which are weighted combinations of explanatory variables [30]. The first component has the largest covariance with the outcome variable and the second component has the second largest covariance, etc. Usually, the first few components can explain most of covariance with the outcome. For seven age groups, 16 period groups, and 22 cohort groups, the total number of dummy variables is 45, but the rank of the design matrix is only 41 owing to four collinearity constraints (Equations 2 and 3). The maximum number of components can be extracted is therefore 41. As shown in our previous studies [29,30], the weights in any partial least squares component always satisfy the constraints in Equations (4) and (5), and consequently, the partial least squares regression coefficients will satisfy these constraints irrespective of the number of components. We have shown elsewhere that when the maximum number of components is extracted, results from partial least squares regression is equivalent to that from the Moore–Penrose generalized inverse method. Consequently, when the maximum number of partial least squares components is extracted, the intrinsic estimator and partial least squares regression will yield the same results [30]. In most analyses, one group from each of age_{*i*}, period_{*j*}, and cohort_{*k*} is removed from Equation 1, but the identification remains a problem because of Equation 3. Although the constraint in Equation 5 may look complex, it has been shown that results from partial least squares regression and the intrinsic estimator have an intuitive interpretation, that is, the sum of the age and cohort effects is equal to the sum of period effects, which is exactly the mathematical relation among the three groups of variables [7,30]. In other words, the constraints imposed by partial least squares on the estimation of regression coefficients are exactly the collinearity constraints within the data. To further understand the constraints made by partial least squares regression, let us suppose we collect mortality data for a population between age 1 and 80 years at the year 2000, and we would like to estimate age and cohort effects. This age–cohort model is unidentifiable using traditional linear confounding assumptions, because age + cohort = 2000. When both variables are centered (i.e., by subtracting the mean of a variable from the individual values), the mathematical relation becomes age + cohort = 0. Consequently, partial least squares regression imposes the following constraint: $b_{\text{age}} + b_{\text{cohort}} = 0$, where b_{age} and b_{cohort} are the regression coefficients for age and cohort, respectively. In other words, the effects of age and cohort are the same but in opposite directions. As age and cohort also have the same variance, the overall effects are split equally between them. Without additional information, this seems to be a reasonable constraint, because people who were born 1 year earlier were also 1 year older in 2000. It may be argued that age generally has a greater biological or physiological effect on mortality than cohort, so the overall effects should not be equally split. Although this may be true for many diseases, how much greater weight should be given to age effects cannot be determined by the observed mortality data alone. Auxiliary information about the disease mechanisms within different age groups is required to assign the weights. This information is usually unavailable, and consequently, equally split would be reasonable for exploratory analyses, since age and cohort has unity correlation and equal variances.

We used the package *pls* for free *R* software (version 2.15.1, R Development Core Team, Vienna, Austria) for partial least squares analysis. Cross-validation was used for the selection of parsimonious models [30]. As discussed in a previous publication [30], the estimation process for confidence intervals for partial least squares regression coefficients obtained by resampling methods, such as jackknifing, became unstable, when the extracted partial least components was close to the rank of the design matrix (which was 41 in our data). Therefore, we used the command *cnsreg* in Stata (version 12.1, College Station, TX) for constrained regression to obtain the results for the model with 41 components with the four constraints shown in Equations 4 and 5.

Results

Figure 2 showed the partial least squares regression coefficients for age, period, and cohort effects and their confidence intervals. For the one- and two-component models, the confidence intervals were obtained using jackknifing methods. For the saturated model, results were obtained using constrained regression analysis with Equations (4) and (5). Table 1 showed the regression coefficients from the partial least squares analysis, and the coefficients from each of the three models satisfied the constraints in Equations 4 and 5. Cross-validation suggested two-component model was parsimonious, so we showed the point estimates and confidence intervals for one-component, two-component, and the saturated 41-component models in Figure 2. Figure 2A showed that mortality gradually increased with ages and then started to take off after the age of 40 years. Mortality in England and Wales continued to decrease after 1845, but this trend was twice interrupted by the two great wars (Fig. 2B). The decreasing trend leveled off after 1955. Figure 2C showed an interesting pattern for cohort effects: they increased from 1775 and reached the peak around 1835–1845; then they gradually declined and leveled off around 1935. There were some differences in cohort effects at the beginning and final years between the two-component and 41-component models, and this was probably due to their being the first and the last few cohorts with very few observations each.

Discussion

Results from our reanalysis by means of partial least squares regression seemed to support the existence of cohort effects in the mortality trends in England and Wales as shown in the original analysis by Kermack et al. Our analysis also showed a declining trend in period effects up to 1950s, which was consistent with the continued improvement in the nutrition and living standard in Britain in the first half of the 20th century [32,33]. However, the cohort effects still need to be interpreted with caution, because in this study and Kermack et al., mortality rates for each age groups at the earliest period, 1845, were used as the referents and their values were set at 100. Consequently, there were no observed age effects at 1845. As a result, mortality rates of the same age groups across different periods are made comparable, but mortality rates of different age groups within a specific period cannot be directly compared. As statistical software cannot distinguish between relative and actual mortality rates, this may result in underestimation of cohort effects. Nevertheless, it should be noted that although cohort effects shown by our partial least squares analysis are also

consistent with those from a visual examination of Figure 1, we still need a substantive theory to support those findings.

It is worth mentioning a few statistical issues regarding to regression approach to the age–period–cohort model. First, the identification problem occurs in the separation of linear effects of age, period, and cohort. Because of the perfect collinearities within the data, there is no unique solution to the estimation of those linear effects. Equations 4 and 5 provide one resolution of the identification problem with desirable statistical properties [11,16,17] and an intuitive interpretation [7,30,31]. However, whether a solution is justifiable depends on the imposed constraints, and ideally, the substantive theory should provide a guidance for the choice of constraints [30]. Although Equations 4 and 5 provide a statistical solution to estimating the linear effects, it is by no means the only one. Other methods that do not attempt to separate the linear effects directly can also provide estimates for age, period, and cohort effects [15,34]. Second, the number of observations for each age or period dummy variable is the same; consequently, the variances of dummy variables for age are equal and so are those for period. However, the number of observations for each cohort dummy variable is different: small for the first and the last few cohorts. As a result, their variances are smaller, and this also affects their covariances with the outcome. As component extraction in partial least squares regression is based on maximizing the covariances, this may explain the greater differences in early or late cohort effects among different models in Figure 2.

Conclusions

In this article, we demonstrate that analyses of relative mortality have to be interpreted with caution, because statistical software cannot distinguish between relative and actual mortality rates; external information would be useful for choosing the most appropriate analysis. Therefore, we feel relative mortality should not be used for age–period–cohort analysis. Our analysis also suggests that cohort effects in this study may have been underestimated because of the contamination of negative age effects. The identification problem has been cited as the barrier to making progress with age–period–cohort analysis, but a more fundamental issue is the lack of a well-articulated theory and research hypothesis about the effects of age, period, and cohort. Partial least squares regression separates the linear effects of age, period, and cohort by imposing implicitly the collinearity constraints that are intrinsic to the data. As is clear from our discussion in this article, the identification problem with the age–period–cohort analysis is how the overall effect should be split among the three groups of variables, and this should ideally be guided by a well-elaborated theory based on which the data can then be shown to be either compatible or incompatible with. The task of tackling the identification problem will not be accomplished without developing such a theory.

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Fig. 1.
Perspective plot for relative mortalities in England and Wales between 1845 and 1985.

Fig. 2. Estimated (A) age, (B) period, and (C) cohort effects using partial least squares regression (PLSR) with one, two, or 41 components.

Table 1

Regression coefficients from partial least squares regression analysis with one, two, and 41 components extracted

Variables	1 Component	2 Components	41 components
Age groups			
10	-21.25 (9.09)	-13.63 (2.90)	-12.86 (0.90)
20	-17.30 (8.79)	-11.84 (2.37)	-12.06 (0.90)
30	-12.59 (9.24)	-9.45 (2.25)	-10.20 (0.90)
40	-4.47 (9.21)	-4.01 (2.10)	-4.87 (0.90)
50	9.89 (8.36)	6.98 (1.69)	6.49 (0.90)
60	20.71 (7.52)	14.85 (1.91)	15.10 (0.90)
70	25.01 (6.85)	17.10 (2.15)	18.41 (0.90)
Period groups			
1845	21.03 (7.77)	27.19 (6.91)	36.16 (1.53)
1855	18.82 (6.89)	22.61 (5.94)	27.01 (1.50)
1865	18.91 (6.90)	22.32 (5.72)	23.90 (1.48)
1875	16.92 (6.47)	19.42 (4.95)	18.49 (1.48)
1885	12.99 (5.70)	14.06 (3.93)	11.23 (1.48)
1895	10.19 (5.51)	11.02 (3.76)	7.63 (1.49)
1905	4.22 (4.44)	3.42 (2.39)	-1.14 (1.50)
1915	2.83 (3.54)	3.49 (1.48)	0.17 (1.51)
1925	-3.80 (3.89)	-4.85 (1.85)	-8.83 (1.51)
1935	-6.25 (4.38)	-6.67 (2.44)	-9.51 (1.50)
1945	-10.49 (5.15)	-11.66 (3.38)	-14.03 (1.49)
1955	-14.67 (6.55)	-17.00 (4.97)	-18.88 (1.48)
1965	-15.57 (6.72)	-17.54 (5.06)	-17.45 (1.48)
1975	-16.56 (6.90)	-18.75 (5.27)	-16.70 (1.48)
1985	-18.40 (7.32)	-21.80 (5.77)	-18.17 (1.50)
1995	-20.17 (7.77)	-25.27 (6.22)	-19.88 (1.53)
Cohort groups			
1775	3.00 (3.01)	2.62 (2.72)	-8.94 (3.70)
1785	5.79 (4.03)	4.84 (3.33)	-4.27 (2.64)
1795	8.64 (4.83)	7.61 (4.03)	1.54 (2.18)
1805	12.04 (5.77)	12.19 (5.21)	10.54 (1.91)
1815	15.32 (6.54)	16.98 (6.03)	18.13 (1.73)
1825	18.28 (7.14)	21.31 (6.37)	23.35 (1.60)
1835	19.99 (7.35)	23.97 (6.32)	25.93 (1.50)
1845	16.45 (6.18)	19.75 (5.44)	23.96 (1.55)
1855	11.35 (4.50)	13.38 (4.09)	18.81 (1.59)
1865	5.32 (2.71)	5.74 (2.23)	11.45 (1.61)
1875	0.30 (1.97)	-0.12 (1.46)	6.00 (1.62)
1885	-2.90 (2.39)	-3.06 (1.91)	3.85 (1.62)

Variables	1 Component	2 Components	41 components
1895	−6.28 (3.23)	−6.43 (2.43)	0.64 (1.61)
1905	−9.07 (4.11)	−9.26 (3.11)	−2.76 (1.59)
1915	−12.25 (5.08)	−12.67 (3.71)	−6.54 (1.55)
1925	−15.15 (5.94)	−16.00 (4.38)	−10.78 (1.50)
1935	−17.30 (6.89)	−19.34 (5.68)	−16.70 (1.60)
1945	−16.74 (7.17)	−18.94 (6.52)	−18.92 (1.73)
1955	−14.26 (6.84)	−16.11 (6.70)	−18.84 (1.91)
1965	−11.04 (6.19)	−12.68 (6.54)	−18.56 (2.18)
1975	−7.55 (5.27)	−8.91 (6.02)	−18.35 (2.64)
1985	−3.95 (3.96)	−4.88 (4.96)	−19.54 (3.70)

The values within brackets are standard errors.