Multilevel generalized linear models for modelling age-related gender difference in violent behaviour and associated factors in the general household population

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Abstract

It is preferable to use longitudinal data when studying patterns of violence and antisocial behaviour over the lifespan together with the associated risk factors in the general population. From the statistical modelling perspective, random samples of cross-sectional data, representative of the population, can be a reliable alternative. Sampling, weighting, and possible geographical clustering of the behaviour must be considered in the analysis together with correct choice of model as a function of age, although cohort effects and age effects are not separated from the analysis. This paper demonstrates the use of multilevel generalized linear models in the British National Survey of Psychiatric Morbidity in 2000. A multilevel logistic model as a special case of a generalized linear model with individual weightings was adapted for a dichotomous measure of violence and extended to Poisson and negative binomial outcomes. Three types of age function, discrete age effects, continuous age effects, and piecewise polynomial function of age intervals were evaluated for goodness of fit, and for their practical advantages and disadvantages. Models were developed for possible risk factors in relation to specific age groups of interest. Copyright © 2005 John Wiley & Sons, Ltd.

Key words: multilevel modelling, weighted logistic models, functions of age trend, cross-sectional survey data, violent behaviour

Introduction

A longitudinal design with repeated measurements is recognized as the method of choice when studying the causal relationship between risk factors and disease in epidemiology, trends in the development of children in anthropometrics (Hitchcock et al., 1986), and the etiology of criminal careers (Farrington and West, 1990). Advanced multilevel models, also termed random effects and mixed models, have been developed to address problems of missing measurements, lost subjects, or irregular time intervals (Longford, 1993; Diggle et al., 1994; Bryk and Raudenbush, 2002; Goldstein 2003). Longitudinal study is expensive, however, and time consuming. Furthermore, early measures may not directly result in later outcomes

when impact of risk factors and changing patterns over time are mixed with other events or are time dependent. Cross-sectional surveys can provide alternative data representative of the targeted population, cover a wider age span, and provide rapid delivery of important information on socio-economic, environmental, and health measures. Cross-sectional data can also provide acceptable information on changes with age, but the population sample during the relevant time span should be random, error variance constant over time, and trajectories of individual subjects should be parallel (Kraemer et al., 2000). Although cohort, period and age effects cannot be separated using a single set of cross-sectional data, information on population differences between age groups, possible change

in patterns over the lifespan, and possible risk factors associated with differences among certain age groups can still be investigated using cross-sectional data.

When carrying out such analyses, several important methodological issues must be considered.

Firstly, for many outcomes in the study of behaviour, important interactions are present between the individual's behaviour and the social context. For example, certain behaviours are concentrated in areas where contextual factors may mediate variability in outcome. However, these variables may be widely distributed in other areas due to a different social environment. Significant geographical or neighbourhood variation in outcome is therefore observed in cross-sectional survey data, with violent behaviour, antisocial lifestyle and drinking problems being notable examples (Sampson et al., 1997; Wallace and Wallace, 1998; Shaw et al., 2004). Lack of independence in outcome for individuals from the same geographic area must therefore be addressed adequately using multilevel models or random effect models (Longford, 1993; Bryk and Raudenbush, 2002; Goldstein, 2003) to obtain robust estimates and correct standard errors for statistical inference. Epidemiologists in behavioural and psychiatric studies have underutilized this relatively new statistical method.

A second issue to be considered is that cross-sectional samples from large-scale surveys are often drawn following specific sampling procedures such as clustering, proportional, stratified or multiple-phased methods, with structured and unequal probability in the selection of different subgroups of individuals. The traditional approach is to adjust the standard error of an ordinary least-squared (OLS) estimator by a weighting procedure when analysing the data to increase precision (Kish and Frankel, 1974). From a modelling perspective, this may be of secondary importance if the aim is to uncover relationships between the outcome and covariates. However, when the outcome variable has clustering effects, or is dependent on geographical boundaries in addition to the structured sampling procedure, a more complex weighting procedure is required (Pfeffermann et al., 1997; Goldstein, 2003). Adequate weighting procedures for hierarchical data are not currently available in major statistical packages, such as SPSS and SAS (software review, www.multilevel.ioe.ac.uk), and are therefore seldom applied. A third issue is that discrete measures in

binary form, which indicate the status of an individual, for example having a drinking problem or not, or alternatively to indicate number of episodes of a behaviour (such as the number of violent incidents) are frequently made as continuous variables in psychiatric and behavioural research. For a continuous or normal outcome with clustering effects in a cross-sectional survey, multilevel growth models, such as grafted polynomials that join and smooth functions over different age groups, have been developed (Pan et al., 1992) but have not been extended to non-normal outcomes such as variables with binomial or Poisson errors. Although generalized linear models (GLM) with random effects can be fitted by statistical packages such as SAS, HLM, Stata, EGRET, aML, SPlus and MLwiN, only HLM and MLwiN can readily handle weightings at all levels of the data.

In the present study, we explore GLM under the iterative generalized least-squared (IGLS) estimation (Goldstein, 2003) in MLwiN (Rasbash et al., 2000) for a binary outcome on self-reported violence, and extend this to a Poisson outcome using number of violent incidents. Individual and area weightings are included, using data from the National Survey of Psychiatric Morbidity (NSPM) in Britain (Singleton et al., 2001). We also demonstrate how different functions over age, discrete or dose-response age effects, and piecewise polynomials of age intervals can be constructed on the same binary outcome to capture age patterns and gender difference. We examine the goodness of fit of each model and discuss the merits and drawbacks of these models in practice. Having obtained a satisfactory model, we then demonstrate how the model can be elaborated to include individual covariates of sociodemographics, mental health, substance misuse, and lifestyle to explain sex-differentiated change within certain age spans, together with possible risk factors associated with the difference observed between the sexes.

The data

The NSPM, carried out by the Office for National Statistics (ONS) in 2000, provided representative data on psychiatric morbidity, personality disorders (PD), substance use, health service use, and demography of 8,580 individuals aged 16–74 years in private households from 438 postal areas in UK. The weighted prevalence of self-reported violent behaviour among the British population will be published separately

from this paper. A measurement of violent behaviour, as the outcome of interest, was obtained using questions similar to those used in previous surveys in New York (Swanson et al., 1990) and Israel (Stueve and Link, 1997). Subjects were asked

- Have you been in a physical fight, assaulted or deliberately hit anyone in the past five years?
- and
- How many times in the past five years?

Modelling the first outcome will be the main focus of this paper but with consideration of an extension of the model to the second.

The weighted raw age-sex specific prevalence of violent behaviour is shown in Table 1 and indicates that the peak age for female violence was not captured. Women aged 20–24 years reported less violence compared to those aged 16–19 years. For men, the relevance of reported violence was the same at ages 20–24 years as at 16–19 years. Thereafter, from age 25 years onwards, both males and females demonstrated a progressive reduction. Weighted and unweighted prevalences at each age by sex in Figure 1 demonstrate falling violence for women at age 20 years and a rise in that of men. This phenomenon poses an important research question regarding the change in pattern of violent behaviour and age-related gender difference in

the general population, together with the possible factors associated with this gender differentiated change during transition from teenage years to early adulthood. A number of research questions will be addressed further:

1. How does the pattern of violent behaviour and age among the general population compare with a high-risk criminal population?
2. Does the pattern differ between men and women?
3. How could mental illness, substance misuse, lifestyle, and sociodemographic factors be associated with different patterns between men and women?

To answer those questions, we first established a model that took account of four important features in the data: the cross-sectional sample, two-stage random sampling with individual weightings, binary outcome for prevalence of violent behaviour, and geographical variation of violent behaviour. An assumption was also made that cohort effects do not overcome true age effects, since that the cohort effects are much greater than the age effects in countries like the UK, with a stable political system for decades and any changes in social norms and cultural value that could affect behaviour of people will take a long period to be observed. Possible bias in the outcome of self reported violence is therefore not dealt with in this study.

Table 1. Self-reported violence behaviour by age by gender in population of Britain

Age group	Respondents (weighted)		Prevalence of violence in percentage N = 8,367 (95% CI)	
	Male	Female	Male	Female
16–19	330	262	51.6 (43.9–59.2)	24.1 (17.6–32.0)
20–24	315	355	50.3 (42.2–58.1)	14.5 (10.5–19.6)
25–29	435	358	32.0 (26.8–37.7)	8.0 (5.7–10.0)
30–34	447	486	18.2 (14.5–22.5)	7.0 (5.2–9.4)
35–39	468	453	16.8 (13.3–21.0)	5.2 (3.6–7.5)
40–44	418	409	11.8 (8.7–15.9)	3.9 (2.4–6.3)
45–49	358	371	10.8 (7.6–15.1)	2.6 (1.3–5.0)
50–54	391	406	3.2 (1.8–5.8)	0.6 (0.2–1.6)
55–59	291	308	3.8 (2.2–6.7)	0.5 (0.1–2.4)
60–64	283	299	2.4 (1.2–5.0)	0.3 (0.0–1.9)
65–69	250	287	1.2 (0.5–3.3)	0.5 (0.1–2.1)
70–74	183	212	0.3 (0.0–1.9)	0.0 (–)
Total	4170	4206	18.0 (16.6–19.5)	5.5 (4.8–6.4)

Figure 1. Weighted and unweighted raw prevalence of self-reported violence by age by sex.

Models

Statistical models for discrete or count outcomes are referred to as generalized linear models (McCullagh and Nelder, 1989). They are extended to fit data with a hierarchical structure (Longford, 1993; Bryk and Raudenbush, 2002; Goldstein 2003). We start the model with the logit link for the binary measure of violence.

A simple two-level weighted logistic model for binary outcome

For the i^{th} individual from the j^{th} postal area, the probability of reporting any violence π_{ij} as a function of other explanatory variables $\mathbf{X}$ such as age and sex can be defined by equation (1), following the notation of MLwiN:

$$y_{ij} \sim \text{Bin}(1, \pi_{ij}) \quad (1)$$

$$y_{ij} = \pi_{ij} + e_{ij}Z_{1ij}, Z_{1ij} = \{\pi_{ij}(1 - \pi_{ij})/1\}^{1/2}, \sigma^2_e = 1$$

$$\log\{\pi_{ij}/(1 - \pi_{ij})\} = X_{ij}\boldsymbol{\beta} + Z_{2j}u_j, u_j \sim N(0, \sigma^2_u)$$

In (1) Z_1 and Z_2 are the sets of explanatory variables in relation to the level 1 and level 2 random coefficients respectively, and Z_2 is reduced to a vector of unit I_2 in the random-intercepts-only model. Here u_j is a

random effect of the intercept for the j^{th} postal area with the variance component or residual variance σ^2_u that captures the variation in prevalence of violent behaviour among geographic areas. The conventional intra-area correlation for this model can be calculated as $\sigma^2_u/(\sigma^2_u + \pi^2/3)$, here $\pi = 3.1416$ (the gradient parameter), which quantifies the degree of clustering with its value ranged between 0 and 1 indicating the degree of dependency or clustering in the outcome variable from weak to strong. The fixed effects of any explanatory variables are estimated by $\boldsymbol{\beta}$ s. Given parameter estimates of $\boldsymbol{\beta}$ s and σ^2_u , u_j can be estimated and termed a posterior mean or shrunken estimate (Bryk and Raudenbush, 2002; Goldstein 2003). The detailed estimation procedure of improved restrictive quasi-likelihood approximations for discrete response data under iterative generalized least-square estimation (IGLS) can be found elsewhere (Breslow and Clayton, 1993; Goldstein and Rasbash, 1996) and integrated in MLwiN.

Given the sampling weights for individuals w_{1ij} in our case, the weights of level 2 units, area in our case w_{2j} can be computed by $J \times \sum_i w_{1ij} / [\ln \sum_j (\sum_i w_{1ij} / n_j)]$, where J is the total number of areas, and n_j is the number of individuals in the j^{th} area. The weighted estimates of fixed effects in GLM may be written as

$$\hat{\boldsymbol{\beta}}w = (X^T V^{-1} w X)^{-1} X^T V^{-1} w Y \quad (2)$$

and an analogous result for the random parameter estimates can be derived.

The sub-explanatory variables for level 1 and level 2 units, conditional on $\hat{\beta}_w$ and random effects estimators at level 2, could be constructed as $Z_{w1ij} = \{\pi_{ij}(1 - \pi_{ij})/w_{1ij}\}^{1/2}$ and $Z_{w2j} = w_{2j}I_{2j}$ respectively.

The detailed estimations of weighted residuals at level 2, covariance of the residuals, $\text{cov}(\hat{\beta}_w)$, random parameters and their covariance for normal outcomes are given elsewhere (Goldstein, 2003) with general extension to binary cases as the penalized quasi-likelihood (PQL) estimation procedure is available. In the case where the level-2 variance can be ignored, this model reduces to a conventional single-level weighted logistic model that can also be estimated by other software such as SPSS, SAS and Stata.

In the binomial case where the outcome variable is a proportion, the unit denominator in (1) becomes n_{ij} .

For a count variable such as number of fight events, on which the majority of respondents scored 0 and a small proportion scored over 100 – a long-tailed distribution to a large number, model (1) can be extended to Poisson distribution with a link function of log

$$y_{ij} \sim \text{Poisson}(\pi_{ij})$$

$$y_{ij} = \pi_{ij} + e_{ij}Z_{1ij}, Z_{1ij} = (\pi_{ij})^{1/2}, \sigma_e^2 = 1$$

$$\log(\pi_{ij}) = X_{ij}\beta + Z_{2j}u_j, u_j \sim N(0, \sigma_u^2)$$

where π_{ij} = observed count / offset in its general form. In the extreme binomial event the term ‘offset’ could be the population number for some rare diseases or expected deaths of the SMR in the epidemiological research. In the case of number of fights, ‘offset’ is simply unit i.e., the value 1. Under the log link function, the same estimation and weighting procedures apply.

For negative binomial data, the model is defined as with an additional error term at level 1, σ_{e2}^2 , that takes up the excess variance in addition to the Poisson variance σ_{e1}^2 .

$$y_{ij} = \pi_{ij} + e_{1ij}Z_{1ij} + e_{2ij}Z_{2ij}, Z_{1ij} = (\pi_{ij})^{1/2}, Z_{2ij} = \pi_{ij}, \sigma_{e1}^2 = 1, \text{var}(e_{2ij}) = \sigma_{e2}^2$$

To focus our analysis on the main difference of age groups and the difference between gender we consider

three forms of fixed effects that have been applied widely as functions of time. For simplicity, the subscripts of weighting in the following models are dropped.

Model 1 – discrete age function with gender difference

In this model, individuals are grouped into 12 age bands of 5-year intervals, from 16–19 years to 70–74 years. For the i^{th} individual from the j^{th} postal area, the probability of reporting any violence π_{ij} as a function of sex denoted by x_1 (0 for women and 1 for men) and the age bands, denoted by 11 indicators x_h ($h = 2, 3, \dots, 12$), can be modelled as (3).

$$\text{logit}(\pi_{ij}) = \beta_{0j} + \beta_1 x_{1ij} + \sum_h \beta_h x_{hij} + \sum_s \alpha_s x_{1ij} x_{(s+1)ij} \quad (3)$$

$$\beta_{0j} = \beta_0 + u_{0j}, u_{0j} \sim N(0, \sigma_{u0}^2), s \leq 11$$

These discrete age bands fall in the traditional age cutoffs for adolescence, young adulthood, and so on, which is more convenient for interpreting the estimates of age and sex affects as odds ratios. They are convenient for capturing the irregular patterns of different age groups’ involvement in violent behaviour. The parameter β_1 estimates the overall gender difference to give the odds ratio of men over women. The discontinued step function of age by gender is predicted by estimates of β_s for the age intervals 5, 10, $(h-1) \times 5, \dots$ years. The parameter α_s in (3) quantifies the interactive effect between sex and age band, for example, α_2 estimates the gender difference between men and women in the 20–24 age band in contrast with the 16–19 age band, α_3 estimates the difference between men and women in 25–29 age band in contrasting with the 16–19 age band. A general Wald test of $\chi^2_{df=1}$ distribution or an asymptotic normal score test is generally valid for inference on the fixed parameters. A significant finding on α_s indicates a different pattern of age-related gender difference for further investigation.

For the random effects of sex as well as the random intercepts among areas in (3), we extend (3) by allowing β_1 to vary by the random residuals u_{1j} among areas to give an area distribution of sex effects, i.e., $\beta_{1j} = \beta_1 + u_{1j}$. For the random affects of age, we model the level-two variance as a function of the continuous age, denoted by t , with its fixed effect constrained to be zero, and other discrete age effects are still modelled as fixed parameters. This gives the following model:

$$\begin{aligned} \text{logit}(\pi_{ij}) &= (\beta_0 + u_{0j} + u_{tj}) + (\beta_1 + u_{1j})x_{1ij} + \sum_h \beta_h x_{hij} \\ &\quad + \sum_s \alpha_s x_{1ij} x_{(s+1)ij} \\ (u_{0j} \ u_{1j} \ u_{tj})' &\sim \text{MVN}(0, \Omega), \end{aligned}$$

$$\Omega = \begin{pmatrix} \sigma^2_0 & & \\ \sigma_{01} & \sigma^2_1 & \\ \sigma_{0t} & \sigma_{1t} & \sigma^2_t \end{pmatrix} \quad (4)$$

where σ^2_1 and σ^2_t are the variance of the random effects for sex and age respectively, with covariance σ_{1t} . The presence of random age effects in this setting can be interpreted as heterogeneity in age reporting of violent behaviour across areas. The presence of random sex effects suggests different effects of sex on violence among areas.

Any significant random effects of sex and age in (4) should improve the model fit over (3).

Model 2 – continuous age function with gender difference

In this model, exact age in years is fitted as a continuous polynomial function. Quadratic and cubic age terms can be added to reflect curvature of the age pattern, and interactions between sex and age function could reflect sex differentiation in the overall patterns. However, in the monotonous declining pattern over age demonstrated in both men and women (except for the large sex difference at age 20 observed in Figure 1) a conventional polynomial function may not capture such a difference, merely smoothing the curve through the age points. For our particular interest in the first two/three age bands, we break off the continuous polynomial function at those age points by adding dummy age-band variables and interacting them with sex to test the model. The modified polynomial model is shown in (5), where only the linear term of age effect is fitted with the same random intercepts as in (3), and $s = 1, 2$ for the first two age groups.

$$\text{logit}(\pi_{ij}) = \beta_{0j} + \beta_{1x1ij} + \beta_{t1ij} + \sum_h \beta_h x_{hij} + \sum_s \alpha_s x_{1ij} x_{(s+1)ij} \quad (5)$$

The term β_{t1ij} in (5) gives a smooth and continuous function of age overall. The fourth term isolates the difference of age groups 20–24 and 25–29 years, and the fifth term enables us to test the sex differentiation at the first two age bands in addition to the overall age

pattern and sex effects. Higher order polynomial powers in association with t_{ij} can be built in (5) straightforwardly, which enables us to calculate the peak age of violence or velocity function by means of the first derivative of the polynomial function (Yang and Leung, 1994).

Extending (5) to include random effects of sex and age among areas, as in (6), is more straightforward than that in (4) with the same multivariate normal distribution assumption made as in (4) on the three sets of random effects with the full variance-covariance matrix Ω .

$$\begin{aligned} \text{logit}(\pi_{ij}) &= (\beta_0 + u_{0j}) + (\beta_1 + u_{1j})x_{1ij} + (\beta_1 + u_{tj})t_{ij} + \\ &\quad \sum_h \beta_h x_{hij} + \sum_s \alpha_s x_{1ij} x_{(s+1)ij} \end{aligned} \quad (6)$$

Model 3 – piecewise polynomial age function with gender difference

It is arguable that the discrete age function model may be less interesting if the sex differentiation of age pattern was observed in older age groups, for example 40–44 years compared with 16–19 years. The estimated difference would be based on an approximate 25-year age span of the cross-sectional sample, where period or cohort effects are most likely confounded by the true age difference. It may be argued that the continuous age function model would be difficult to fit when the age patterns are more dramatic or fractural. These alternative possibilities require examination of piecewise polynomial age function models, where the whole age span of the cross-sectional population is divided into several segments to suit the needs of study on different age groups with a mono-pattern within each group and to fit the model better by allowing different polynomial age functions for different age ranges.

Observing the raw prevalence pattern by age in Figure 1, we considered dividing the age span of 16–74 years into three segments: 16–24 years (the most prevalent and changeable period), 25–34 years (the mono-declining period), and 35–74 year (the violence-ceasing change or flattening change period). The basic model has a quadratic polynomial function for the first interval, and simple linear functions for each of the second and third intervals. The gender effect and interaction between gender and age effects are fitted separately in each of the three age segments. The model may be expressed as below:

$$\begin{aligned}
& \{ \beta_{0j,t1} + \beta_{1,t1} x_{1ij} + \sum s \gamma_{s,t1} t_{sij} + \sum s \alpha_{s,t1} x_{1ij} t_{sij} \\
& \text{for } t \in [16, 24] \\
\text{Logit}(\pi_{ij}) = & \{ \beta_{0j,t2} + \beta_{1,t2} x_{1ij} + \gamma_{1,t2} t_{ij} + \alpha_{1,t2} x_{1ij} t_{ij} \\
& \text{for } t \in [25, 34] \\
& \{ \beta_{0j,t3} + \beta_{1,t3} x_{1ij} + \gamma_{1,t3} t_{ij} + \alpha_{1,t3} x_{1ij} t_{ij} \\
& \text{for } t \in [35, 74] \\
\beta_{0j} = & \beta_0 + u_{0j}, u_{0j} \sim N(0, \sigma^2_{u0}) \text{ for } t \in [16, 74]
\end{aligned} \tag{7}$$

There are 14 fixed parameters to be estimated in (7), and the random intercepts are collected by the single vector of one over the entire age span of 16–74 years. The three pieces of polynomial function, broken at the two joining ages 24 and 34 years, can be smoothly jointed by constraining two pieces of the adjunct functions equal at the joint age $t = 24$ and $t = 34$.

The fitting of a piecewise polynomial function on cross-sectional growth data with fixed parameter constraints was described elsewhere (Goldstein and Pan, 1992). The same technique is used straightforwardly for our model.

Extension (7) to allow random effects of sex and age overall is the same as in models (4) and (6).

Goodness of fit

The classic method to test goodness of fit of a model is to use the likelihood ratio statistic. However, for the weighted quasi-likelihood estimation procedure under IGLS for non-linear multilevel model, the parameter estimates are not evaluated at its likelihood value. This means that the likelihood value may not be reliable for testing the goodness of fit. The Gauss quadrature integration method generates a likelihood value to a certain degree of approximation, but the weighting procedure to residuals at all levels in multi-level framework is rarely articulated.

For our purpose in finding a suitable model to describe the pattern of violence behaviour over age in cross-sectional population data, we use an asymptotic χ^2 statistic with continuity correction,

$$\chi^2_{df=k} = \sum k (|N_k - \hat{N}_k| - 0.5)^2 / \hat{N}_k, \tag{8}$$

where k is the number of age groups in year ($k = 1, 2, \dots, 59$) covering the age range of 16–74 years, $\hat{N}_k$ the predicted number of individuals in the k^{th} age group and calculated as $\sum_j \hat{\pi}_{ij}$ within the age group. This non-parametric statistic only tests whether a fitted model is acceptable statistically with rough guidance on which model is better than the other among either nested or non-nested models.

Elaboration of the model for covariates

When considering the sharp rise in violence among men aged 20–24 years compared with the fall in violence among young women, we quantified gender difference in the age pattern by the parameter of sex and age interaction α_1 in all three types of models. All models have captured this difference in answering our research questions 1 and 2. To answer our research question 3, a satisfactory model needs to investigate explicitly variables that might be associated with gender difference in this age group. Variables of interest for violent behaviours include mental health, personality disorders, substance abuse, conduct disorder (CD) before 15 years, and current life style. Most variables reflect certain conditions of individuals as cumulated over the years of their life. Demographic and socio-economic backgrounds of the individual are to be adjusted for in this investigation. This can be done in two steps. Firstly, we add variables under investigation in the fixed part of the model to test their independent effects on violence. For the significant variables, we then differentiate the estimated α_1 for subjects with and without these variables by adding a three-way interaction term, for example, $\text{sex} \times \text{age}_{20-24} \times (\text{drug})$ in the discrete age-effect model (4) for drug dependent young men. This can be expressed in the discrete age-effect model (3) as

$$\begin{aligned}
\text{logit}(\pi_{ij}) = & \beta_{0j} + \beta_{1j} x_{1ij} + \sum_h \beta_h x_{hij} + \sum_s \alpha_s x_{1ij} x_{(s+1)ij} + \\
& \sum_l \gamma_l t_{lij} + \alpha'_1 x_{1ij} x_{2ij} t_{lij}
\end{aligned} \tag{9}$$

If drug dependence contributes to the rise of reported violence in young men, the parameter estimate, $\hat{\alpha}'_1$ in (9) would be statistically significant, and the estimate $\hat{\alpha}_1$ in association with the term $\text{sex} \times \text{age}_{20-24}$ should be ignored. The overall estimate on drug impact $\hat{\gamma}_1$ could still be significant. As the model elaboration occurs only in the fixed part of the model, the procedure of adding variables in any model is simple and straightforward.

Results

Weighted versus unweighted estimation

Weighted and unweighted procedures were compared on the discrete age-effect model (3) only. Marked differences between procedures were observed in the effects of younger age groups and sex, which were followed by a large difference in the interaction between the age group 20–24 and sex, due to its weighting score being considerably away from unit. Where the weighting score is close to unit, the difference made by weighting is small. The variance of level 2 random effects was also significant in each of the weighted model but not so obvious in the un-weighted model. The difference in parameter estimates between the two weighted procedures, weighting both level 1 and level 2 units and weighting only level 1 units, was generally small in this case owing to the moderate weighting factors for each age group at level 2. However, there is evidence that weighting at both levels in fitting multilevel models is necessary.

Random intercepts model

Estimates of discrete age-effect model (3), linear continuous age-effect model (5) and piecewise polynomial model (7) are presented in Tables 3 and 4.

All three models estimated considerable clustering effects of violent behaviour among areas with intra-area correlation coefficient in the range of 0.10 ~ 0.12, with the 95% distribution of self-reported violence prevalence among areas ranged as (7% to 10%) ~ (51% to 59%). Both discrete and continuous age-effect models showed higher prevalence in men than women, with a steadily declining trend of violence over age, and a significant interaction between age difference and gender difference in the age group 20–24 years. In the discrete age-effect model, the decline parameter at age 20–24 years was estimated as –0.706 for women and –0.106 for men. In the linear continuous age-effect model, the average decline in violent behaviour was around –2.047 in logit scale for women, and around –1.623 for men. In the piecewise polynomial model, higher prevalence in men was shown in

Table 2. Estimates of age and gender effects for weighted and unweighted discrete age effect models, S.E. in brackets

Variable, parameter	Weighted for both level 1 and level 2 units	Weighted for level 1 units only	Un-weighted	Average weighting scores (level 1: level 2)
Intercept, β_0	–1.265 (0.121)	–1.197 (0.120)	–1.072 (0.135)	
Women: ref	1.347 (0.111)	1.320 (0.110)	1.161 (0.106)	0.91 : 0.99
Men, β_1				1.12 : 1.00
Age of ref: 16–19				1.17 : 1.03
20–24, β_2	–0.706 (0.199)	–0.734 (0.199)	–0.472 (0.213)	1.49 : 1.04
25–29, β_3	–1.349 (0.237)	–1.350 (0.232)	–1.180 (0.219)	1.10 : 1.01
30–34, β_4	–1.678 (0.144)	–1.683 (0.143)	–1.477 (0.156)	0.99 : 1.00
35–39, β_5	–1.828 (0.148)	–1.844 (0.148)	–1.731 (0.159)	0.93 : 1.00
40–44, β_6	–2.214 (0.169)	–2.239 (0.168)	–2.131 (0.180)	1.00 : 1.00
45–49, β_7	–2.398 (0.187)	–2.455 (0.188)	–2.317 (0.196)	1.04 : 1.01
50–54, β_8	–3.734 (0.296)	–3.738 (0.291)	–3.506 (0.278)	0.99 : 0.99
55–59, β_9	–3.623 (0.317)	–3.650 (0.315)	–3.384 (0.285)	0.87 : 0.99
60–64, β_{10}	–4.099 (0.396)	–4.127 (0.392)	–4.008 (0.364)	0.82 : 0.99
65–69, β_{11}	–4.534 (0.515)	–4.504 (0.494)	–4.309 (0.437)	0.84 : 0.98
70–74, β_{12}	–6.435 (1.516)	–6.528 (1.538)	–5.948 (1.032)	0.70 : 0.98
Interaction				
Men*20–24, α_1	0.600 (0.230)	0.586 (0.231)	0.238 (0.243)	
Men*25–29, α_2	0.435 (0.257)	0.421 (0.253)	0.342 (0.235)	
Area level variation				
Var(int.), σ^2_{u0}	0.439 (0.076)	0.400 (0.073)	0.113 (0.056)	

Table 3. Estimates of age and gender effects – discrete and continuous age effects models, S.E. in brackets

Variable, parameter	Discrete age effect		Linear continuous age effect	
	Random intercepts	Random effects of age and sex	Random intercepts	Random effects of age and sex
Intercept, β_0	–1.265 (0.121)	–1.183 (0.133)	–1.058 (0.067)	–1.044 (0.127)
Men, β_1	1.347 (0.111)	1.283 (0.118)	1.294 (0.106)	1.278 (0.117)
Age (centred at 16)			–0.089 (0.004)	–0.089 (0.004)
Age of ref: 16–19				
20–24, β_2	–0.706 (0.199)	–0.679 (0.204)	–0.178 (0.182)	–0.175 (0.190)
25–29, β_3	–1.349 (0.237)	–1.294 (0.234)	–0.349 (0.216)	–0.345 (0.218)
30–34, β_4	–1.678 (0.144)	–1.613 (0.152)		
35–39, β_5	–1.828 (0.148)	–1.761 (0.157)		
40–44, β_6	–2.214 (0.169)	–2.132 (0.177)		
45–49, β_7	–2.398 (0.187)	–2.296 (0.195)		
50–54, β_8	–3.734 (0.296)	–3.605 (0.293)		
55–59, β_9	–3.623 (0.317)	–3.509 (0.317)		
60–64, β_{10}	–4.099 (0.396)	–3.991 (0.390)		
65–69, β_{11}	–4.534 (0.515)	–4.456 (0.502)		
70–74, β_{12}	–6.435 (1.516)	–6.373 (1.459)		
Interaction				
Men*20–24, α_1	0.600 (0.230)	0.537 (0.236)	0.513 (0.223)	0.504 (0.235)
Men*25–29, α_2	0.435 (0.257)	0.370 (0.252)	0.405 (0.247)	0.368 (0.252)
Area level variation				
Var(int.), σ^2_{u0}	0.439 (0.076)	1.239 (0.302)	0.352 (0.067)	1.171 (0.294)
Var(sex), σ^2_{u1}		0.814 (0.276)		0.806 (0.274)
Var(age), σ^2_{u2}		0.0015 (0.0005)		0.0014 (0.0005)
Cov(int, sex), σ_{u01}		–0.270 (0.227)		–0.311 (0.225)
Cov(int, age), σ_{u02}		–0.038 (0.010)		–0.035 (0.010)
Cov(sex, age), σ_{u12}		–0.003 (0.008)		–0.001 (0.008)

all three time intervals. The strongest effect was in the age range 24–34 years. The age-declining pattern was significant in the age range 34–74 years for both men and women. In the age range 16–24, a significant interactive effect between gender and age decline pattern was captured, with the estimated age function as $-0.273t_{16-24} + 0.019t_{16-24}^2$ for women and $0.483t_{16-24} - 0.033t_{16-24}^2$ for men. The first derivative of the estimated quadratic polynomial function suggested a peak age of self-reporting violence in men at 18.3 years, and a fall among women at 22.6 years. The direction of interaction in this age period was consistent among all three types of models. In the age range 24–34, a considerable interaction between age and gender effects

suggested a faster decline of violence in men than in women. This change was not captured by the discrete or the linear continuous age-effect models.

The overall goodness of fit of the three models in Table 5 was acceptable, but when the measure was separated for men and women, only the continuous age-effect model for women was satisfactory.

Models with random effects of age and sex

Not only are we interested in the sex differentiated age pattern in young adults captured by the interaction terms in models (3), (5) and (7) but we are also interested in knowing whether both effects of sex and age were constant across areas. For instance men's violence

Table 4. Estimates of age and gender effects – piecewise polynomial model, S.E. in brackets

Variable	No constraints		With constraints
	Random intercepts	Random effects of age and sex	Random effects of age and sex
t ∈ [16, 24]			
Intercept	−0.913 (0.389)	−0.800 (0.415)	−0.800 (0.414)
Men	0.509 (0.236)	0.686 (0.530)	0.731 (0.515)
Age	−0.273 (0.189)	−0.271 (0.196)	−0.271 (0.195)
Age squared	0.019 (0.019)	0.019 (0.019)	0.019 (0.019)
Men * age	0.759 (0.484)	0.484 (0.251)	0.450 (0.235)
Men * age squared	−0.052 (0.024)	−0.048 (0.025)	−0.044 (0.022)
t ∈ [25, 34]			
Intercept	−1.934 (0.741)	−1.836 (0.711)	−1.831 (0.711)
Men	3.048 (0.855)	2.784 (0.835)	2.027 (0.774)
Age	−0.052 (0.049)	−0.049 (0.047)	−0.049 (0.048)
Men * age	−0.112 (0.058)	−0.099 (0.056)	−0.041 (0.051)
t ∈ [35, 74]			
Intercept	−0.530 (0.568)	−0.373 (0.535)	−0.383 (0.536)
Men	0.853 (0.639)	0.728 (0.605)	0.376 (0.586)
Age	−0.112 (0.020)	−0.112 (0.019)	−0.112 (0.019)
Men * age	0.019 (0.022)	0.022 (0.021)	0.032 (0.020)
Area level variation			
Var(int.), σ^2_{u0}	0.430 (0.076)	2.464 (0.622)	2.327 (0.606)
Var(sex), σ^2_{u1}		0.816 (0.277)	0.844 (0.278)
Var(age), σ^2_{u2}		0.0015 (0.0005)	0.0013 (0.0005)
Cov(int, sex), σ_{u01}		−0.120 (0.298)	−0.142 (0.296)
Cov(int, age), σ_{u02}		−0.056 (0.016)	−0.052 (0.015)
Cov(sex, age), σ_{u12}		−0.0068 (0.0082)	−0.0064 (0.0080)

Table 5. Goodness of fit, Chi-squared value and probability in brackets

Model	Random intercepts model			Random effects of age and sex		
	Men	Women	All	Men	Women	All
Discrete age	47.04(0.87)	90.57(0.01)	42.27(0.86)	41.22(0.96)	63.44(0.32)	37.27(0.99)
Continuous age	41.92(0.95)	61.07(0.40)	44.92(0.91)	36.71(0.99)	37.33(0.99)	36.07(0.99)
Piecewise polyno.	42.22(0.95)	73.54(0.10)	36.47(0.99)	39.29(0.98)	51.60(0.74)	31.28(0.99)

could be no different from women's violence in some areas but with a higher risk than the overall OR 4.12 in other areas. Failing to capture random effects of sex and age could cause underestimation of standard error of their parameters and associated effects such as sex and age interaction parameters, resulting in an artefact

due to inadequate method. Modelling random effects of sex and age are substantively interesting in their right, leading to future research on context or geographical variation and community interventions for violence (Sampson et al., 1997; Wallace and Wallace, 1998).

Fitting random effects models (4), (6) and the piecewise polynomial model yielded satisfactory goodness of fit both to the overall data and for men and women separately (Table 5). The estimated variances of the sex and age effects across areas were comparable among the three models with statistical significance. Both models (4) and (6) estimated the 95% distribution of the gender odds-ratio among areas as 0.6 to 21, whereas the piecewise polynomial provided the odds-ratio distribution for each of the three age intervals, 0.4–13, 1.3–46 and 0.2–8.8 respectively. The 95% distribution of age effect among areas was about ± 1.96 (0.038) from all three random slope models. The fixed effects of age and sex remained the same as those estimated in the random intercepts models with greater standard error estimates as expected.

Most importantly, the significant interaction

between sex and age of 20–24 years was still presented in all three models with random effects of age and sex. The age and sex interaction in the time interval of 24–34 years in the piecewise polynomial model then became redundant.

Elaborated random effects model

Given the fact that all three models fitted our data almost equally, with similar parameter estimates in the fixed effects of age, sex and their interaction, as well as their random effects, we elaborated model (4) (the discrete age-effect model) with random effects for further investigation of covariates possibly associated with age-related gender difference. We followed the analytical strategy previously explained in this paper.

Table 6 shows independent fixed effects of all variables on violence. The effects of individual

Table 6. Odds-ratio estimates of fixed effects of all factors (demographics, mental health, lifestyle) on self-reported violence, expansion of Model (6)

Factors	OR (95% CI)	P	Factors (demographic)	OR (95% CI)	P
Sex: Female					
Male	4.04 (3.11–5.26)	<0.001			
Age: 16–19			Socio class I		
20–24	0.60 (0.37–0.98)	<0.001	II	1.83 (1.05–3.18)	<0.01
25–29	0.36 (0.20–0.65)	<0.05	III	2.76 (1.58–4.82)	<0.001
30–34	0.27 (0.17–0.41)	<0.001	IV	2.22 (1.12–4.42)	<0.05
35–39	0.23 (0.14–0.36)	<0.001	V	8.41 (1.96–36.2)	<0.01
40–44	0.16 (0.09–0.26)	<0.001	Married/cohabiting		
45–49	0.12 (0.07–0.22)	<0.001	Single	0.96 (0.73–1.26)	NS
50–54	0.03 (0.02–0.07)	<0.001	Divorced/separated	2.12 (1.53–2.95)	<0.001
55–59	0.04 (0.02–0.09)	<0.001	Widowed	0.28 (0.03–2.32)	NS
60–64	0.03 (0.01–0.07)	<0.001	Degree qualification		
65–69	0.02 (0.007–0.06)	<0.001	Teaching / HND / nursing	1.76 (1.15–2.69)	<0.05
70–74	0.004 (0.000–0.08)	<0.001	A level	1.15 (0.79–1.69)	NS
Any PD excluding AS PD	1.41 (1.15–1.74)	<0.01	GCSE A-C	1.43 (0.99–2.07)	NS
Conduct PD	1.56 (1.18–2.07)	<0.01	GCSE D-F	1.11 (0.70–1.74)	NS
Neurotic	1.72 (1.35–2.19)	<0.01	No qualification	1.21 (0.79–1.84)	NS
Hazardous drinking	2.37 (1.95–2.88)	<0.001	Part-time work	1.34 (1.04–1.74)	<0.05
Drug dependent	1.75 (1.21–2.55)	<0.01	Urban		
Always a drinker			Semi-rural	0.94 (0.73–1.20)	NS
Non drinker	0.39 (0.19–0.83)	<0.05	Rural	0.68 (0.44–1.04)	NS
Used to drink but stopped last yr	1.17 (0.67–2.05)	NS	Owned home		
Never on drug			Owned through mortgage	0.77 (0.56–1.07)	NS
Always on drug	2.03 (1.53–2.70)	<0.001	Rented from local authority or HA	1.32 (0.91–1.90)	NS
Used to drug but not last year	1.56 (1.23–1.97)	<0.01	Rented from other resources	0.77 (0.52–1.15)	NS
Live without parents			Interaction		
Live with 1 parent	1.04 (0.76–1.45)	NS	Male 20–24 vs female 20–24	1.73 (1.02–2.95)	<0.05
Live with 2 parents	1.71 (1.08–2.70)	<0.05	Male 25–29 vs female 25–29	1.21 (0.69–2.13)	NS

Table 7. Estimates of risk effects on violence for males in age 20–24 year

Factor	Men × (20–24) yr OR: e^{α_1} (95% CI)	Factor × men × (20–24) yr Excess OR: e^{α_1} (95% CI)
Single factor examined separately		
Any PD* excluding AS PD** (current diagnosis)	2.03 (1.34–3.10) ‡	0.26 (0.12–0.58) ‡
Any neurotic (current diagnosis)	1.59 (1.08–2.36) †	0.49 (0.17–1.47)
Drug dependent (current diagnosis)	1.55 (1.03–2.33) †	0.80 (0.34–1.90)
Conduct PD (misbehaviour before 15 year old)	1.36 (0.92–2.02)	2.32 (0.81–6.64)
Hazardous drinking (current diagnosis)	1.22 (0.66–2.22)	1.36 (0.68–2.74)
Live with parent(s) (current living arrangement)	1.03 (0.54–1.95)	2.50 (1.24–5.04) ‡
Two conditions examined pairwise		
Conduct PD	1.06 (0.56–2.00)	2.45 (0.84–7.18)
Hazardous drinking		1.44 (0.70–2.93)
	0.86 (0.50–1.48)	
Conduct PD		2.10 (0.74–6.00)
Live with parent(s)		2.41 (1.19–4.90) †
	0.67 (0.32–1.45)	
Hazardous drinking		1.49 (0.73–3.03)
Live with parent(s)		2.61 (1.28–5.35) ‡
Three factors examined simultaneously		
	0.66 (0.28–1.53)	
Conduct PD		2.23 (0.76–6.56)
Hazardous drinking		1.56 (0.75–3.21)
Live with parent(s)		2.53 (1.23–5.20) ‡
Outstanding interaction from previous models: men × (20–24) years		
Model (5)	1.82 (1.16–2.86) ‡	————
Model (6)	1.71 (1.08–2.72) †	————

† $P < 0.05$; ‡ $P < 0.01$

*PD = personality disorder; **ASPD = antisocial personality disorder

sociodemographic variables are discussed elsewhere (Coid et al., 2004), and were retained in the model as adjustments. Variables that increase risk of violence behaviour in the population include any PD, CD, neurotic disorder, hazardous drinking, drug dependence and living with parent(s). Their significant effects in this model did not change the conclusion that the sex and age interaction previously presented fitted.

Fitting the three-way interaction model (9), we finally examined how each of these factors might contribute, singly and jointly, to the persistence of violence in young adult men in contrast to the decline

among women of the same age. Table 7 demonstrates that CD, hazardous drinking, and living with parent(s) showed a positive effect of three-way interaction and reduced the original two-way interaction between men and age 20–24. Among three variables, living with parent(s) had the most consistent and significant impact on young adult men persisting in violent behaviour.

Discussion

We have demonstrated statistical models that identify different patterns with age between genders and have

investigated possible risk factors associated with these gender differences in a random, cross-sectional survey. The high prevalence of violence among young adult men in all models and peak age of 18.2 years in men, with a trough of 22.6 years among women from the piecewise polynomial model, suggested a peak age of violent behaviour around 16–24 years in males, with the peak occurring earlier in females. These gender differences are comparable with a previous study in the UK which reported a peak age of 18 for males and 15 years for females (Mirrlees-Black, 1999), but with an earlier peak age than in north American follow-up studies (Robins et al., 1984; Bland et al., 1988) for anti-social personality disorder. As possible period and cohort effects on violence cannot be separated from true age difference in cross-sectional data, the peak age of violence could be different in a longitudinal study, partly due to cohort effects and partly due to age patterns. Cultural differences in different countries could also play a part.

Having established this modelling technique, we can build in adequate interactive terms between age groups and sex in each of our models to capture a significant gender difference in the early adult age group, regardless of whether it is a true age effect or a cohort effect. The further elaborated model with covariates of interest identified three factors: hazardous drinking, CD, and living with parents, which explained over 61% of the gender difference in early adulthood. The effects of drinking problems and childhood behavioural problems on violence in adulthood are well established, but little attention has been paid to lifestyle factors. Prolonged dependence on parents over subsequent generations of young adult men have been observed in the longitudinal study of youth transition, which examined 1958 and 1970 birth cohorts in the UK (Bynner and Pan, 2002). Young men remaining in the parental home demonstrated delay in independence compared to young women, with a larger proportion in the later birth cohort (corresponding to 28–29 year olds in our cross-sectional sample). Despite confirmation of the same lifestyle factor in both cohort and cross-sectional studies, further research is needed to distinguish between cohort effect and true age-change patterns during transition from teens to early adulthood, together with exactly why it is that young men living with parents report more violence. This could be done using repeated surveys and the multilevel models developed in this paper.

Multilevel models take into account geographic and neighbourhood variations when estimating effects of covariates on individuals, together with context factors (Sampson et al., 1997; Wallace and Wallace, 1998). The clustering effects absorbed by random parameters as variance and covariance at area level provide additional statistics for further interpretation, providing information for community intervention policies. Improved estimation procedure PQL applied throughout this study gives better results on all parameter estimates (Breslow and Clayton, 1993; Goldstein and Rasbash, 1996). By fitting a weighted multilevel logistic model we have found notable clustering effects among areas in violent behaviour with an intra-class correlation (ICC) between 0.10 – 0.13, even after adjusting for all individual factors. Sex difference and age effect varied considerably across areas after adjustment, which suggests further study of associations between socioeconomic deprivation, socio-demography, mental health, and individual violence at area level.

These models can be extended to fit Poisson distribution, negative binomial distribution, and binomial outcome data with random effects. But there are other possibilities using our models. Firstly, data with more than two hierarchical levels, such as households nested within areas and individuals nested within households, could be included. Secondly, a multilevel multivariate model could be applied when several outcomes are taken at the same time and these outcomes are inter-correlated (Yang et al., 2000; Ribaudo and Thompson, 2002). This could be important in psychological and psychiatric research where comorbidity between diagnostic measures is a major concern.

A discrete age-effect model is particularly convenient where change in pattern within a specific age group is of special interest. Within a short age gap of 5 years (from 16–19 years to 20–24 years in our case) the period or cohort effects are likely to either be similar between the two cohorts or small enough to be ignored. The model could cope with a non-linear change pattern as long as the age grouping reflects the different patterns in different age groups. However, if the gender difference was found over a large age span, for example, from 16–19 years to 40–44 years, cohort effects occur in the age effect estimated by the model. The discrete age-effect model does not provide a smoothed curve over age but a step function, shown in Figure 2.

Figure 2. (a) Raw and predicted prevalence of violence by three types of age function (female); (b) raw and predicted prevalence of violence by three types of age function (male).

Gender differentiated age differences in patterns can easily be modelled by interactions of sex and the overall age function. But it would not be a good choice if the change in patterns over age is fractural or multiple peaked over the entire age span. In our case, the overall linear polynomial function was not sensitive enough to pick up the sex difference of the behav-

ioural change. We therefore developed a model in which the peak of violence in early adulthood in men was treated as an outlier in addition to the continuous age function by fitting an indicator variable of the group in the model. This model worked as well as a discrete age-effect model and with a better fit over the female population.

A piecewise polynomial model could naturally handle irregular age patterns by fitting different forms of function for each time interval. It smoothes the curve as effectively as the continuous age-effect model through constraints of the function pieces between neighbouring intervals. The smoothed model appears equivalent to the spline function (Goldstein and Pan, 1992). We could leave each piece unconstrained and elaborate risk factors only for the age range of interest, or constrain a particular effect of a risk factor the same for all age ranges if they are known to have a common relationship to the outcome. This model could be particularly useful in linking several cross-sectional data of different age spans to form a smoothed overall function to cover all age groups. However, we observed large standard errors of parameter estimates of this model in age and sex effects due to reduced individual numbers in each time interval. This could result in reduced effectiveness if the model was elaborated in each time interval. Imposing more constraints on parameter estimates between the pieces could improve the model efficiency, but further study is required in this area.

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