Gender-specific differences and the impact of family integration on time trends in age-stratified Swiss suicide rates

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Summary. Suicide has become one of the leading causes of death of Swiss males aged between 15 and 44 years, whose age-standardised rates are about three times higher than those for females. We compared age-stratified suicide rates of Swiss men and women aged 15–79 and analysed gender-specific differences from 1950–2007. Furthermore, we explored whether changes in measures of family integration can explain changes in suicide trends. The use of multivariate age-period-cohort models avoids age aggregation and allows the exploration of heterogeneous time trends across age, period and birth cohort. In addition, explanatory variables can be included. We found strong gender-specific differences in suicide mortality. While the same risk factors may act on age and overdispersion, there was no significant correlation between gender-specific cohort effects. Family integration had an impact on Swiss suicide risk, but only partially explained the underlying trends over time.

Keywords: Age-Period-Cohort model; Bayesian analysis; Family integration; Suicide; Switzerland

1. Background and objectives

Age and gender are well established risk factors of suicide. In many countries especially elderly have a higher risk to commit suicide (Granizo et al., 1996; Shah and De, 1998). Suicide rates of males are generally higher than those of women. Besides age- and gender-specific factors, environmental factors occurring at a specific date in time may influence suicide risk. For example, Lester (1990) examined suicide rates in Switzerland during the period when domestic gas was detoxified. This study did not only indicate a decline of

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suicide by means of domestic gas, but also a decline of the overall suicide rate, indicating that people did not switch to alternative methods. Thus, if one method of suicide is made less available, such as detoxification of domestic gas or strict gun control rules, a reduction in the overall suicide risk might be observed. Experiences common to a particular birth cohort, e.g. war, might also influence the suicide risk. Hence a better understanding of age, period and cohort effects might help to target effective preventive strategies. Over the last years a number of age-period-cohort (APC) analyses of suicide rates have been published, see for example Granizo et al. (1996); Etzersdorfer et al. (1996); Snowdon and Hunt (2002); Stockard and O'Brien (2002a); Gunnell et al. (2003); Ajdacic-Gross et al. (2006); O'Brien et al. (2008).

In Switzerland, suicide rates are quite high compared to other affluent countries (Levi et al., 2003). Especially suicides by firearms are frequent compared to other European nations (see Ajdacic-Gross et al., 2008), which is probably related to the gun politics in Switzerland, which state that army-issue weapons can be kept at home. To gain more information on gender-specific differences in Switzerland, Ajdacic-Gross et al. (2006) performed univariate APC analyses on suicide data over the last century. They found similar age and period effects, but stronger cohort effects for males than for females. However, since males and females might be subject to similar risk factors it seems justified to model them jointly suggesting the possibility of common time (age, period, cohort) effects.

In this paper we will apply multivariate APC models to capture trends in the sex ratio. Such models borrow strength from both genders for estimating common sets of time effects, for example the period effects, while the remaining parameter sets can be different across gender. The well-known identifiability problem of APC models is avoided since differences of gender-specific time effects are identifiable and can be interpreted as log relative risk (Riebler and Held, 2010). Additionally, we will include correlation to capture the dependence that is likely to exist between gender-specific effects.

Since social aspects are strongly associated with suicide risk, we will further investigate whether changes in variables related to family integration can explain changes in age-stratified suicide rates over time. Following the theory of Durkheim (Durkheim, 1897) numerous papers were published investigating the relationship between marital status and suicide. So far mainly time-series analyses have been used, see for example Breault and Barkey (1982); Lester (1986); Stack (1987, 1990a,b, 1992); Surault (1992); Rossow (1993); Lester (1994). Populations with high divorce rates, for instance, were found to have high suicide rates even when controlling for confounding variables such as socio-economic status (Stack, 1990a). However, Stack (1990b) assumed that the association between being divorced and committing suicide has changed over the years. For example, divorce and unmarried couples are more common and more accepted. Barstad (2008) used, among others, separations as an indicator of family integration when trying to explain changing suicide rates in Norway. In this analysis, a stronger effect was estimated for separations than for divorces.

Stockard and O'Brien (2002a,b) ask if social integration can account for cohort variations. They used so called age-period-cohort-characteristic (APCC) models, in which the cohort effects are replaced by specific cohort characteristics, such as percentage of nonmarital births in the cohort or the relative cohort size. Replacing one set of effects by an explanatory variable is also a valid solution to the non-identifiability problem of APC models (Brown and Kessler, 1988). However, this is only the case if the covariate-effect does not depend on the time scale for which it is used. Otherwise a linear dependence between the three time scales remains, see the introduction of Riebler (2010, page 4) for a discussion of this topic.

For solving the non-identifiability problem in classical APC models, O'Brien et al. (2008) proposed to use a log-linear mixed model. In this approach the age and period effects are treated as fixed effects, while the cohort effects are treated as random effects. Thus the variance between the cohorts can be estimated. Model inference is based on restricted maximum likelihood. Comparing this mixed model with a model including, additionally, appropriate cohort characteristics, the amount of variance accounted for by the introduction of these proxy variables can be quantified.

In this paper, we are interested in the impact of family integration on period effects. In contrast to standard time-series models we also avoid age aggregation and apply Bayesian univariate APC models separately to males and females. We use thereby a log-linear Poisson model, which seems to be more appropriate, especially in the presence of low counts, than assuming that the rates are log-normally distributed. The period effects are replaced by an explanatory variable on family integration assuming either a parametric or non-parametric effect. Using the deviance information criterion and the logarithmic score the different model formulations will be compared with the ordinary APC model. Further, we apply a multivariate age-cohort (AC) model replacing the period effects by a correlated non-parametric covariate effect of family integration. In this model, not only the relative age and cohort estimates of males to females are identifiable, but also the separate gender-specific age and cohort effects. The non-parametric effect of the F-index can be compared between males and females as well. To account for confounding, the rate of unemployment is included in the model formulation. However, since the Swiss unemployment rate is so low (always less than five percent), variation may be quite small to affect the overall suicide trends (Stack, 1989).

In this paper we focus on two topics:

- Analysis of gender-specific differences in age-stratified Swiss suicide rates using correlated multivariate age-period-cohort models.
- Analysis of the impact of family integration on time trends of age-stratified Swiss suicide rates.

In Section 2 we will present our data and introduce the methodology used. Section 3 presents the results. We will close with a discussion in Section 4

2. Data and Methods

Annual age- and gender-specific suicide mortality counts and mid-year population data (calculated as the arithmetic mean between two subsequent end-year population counts), 1950–2007, were obtained from the Swiss Federal Statistical Office (SFSO) (2010a, 2008a,b, 2010b,c). Age groups are stratified by five-year intervals: 15–19, . . . , 75–79, resulting in 13 age groups and 58 one-year periods. We omitted data for children under the age of 15, when suicide is rare, and for adults over the age of 79 because for elderly assisted suicides have become frequent in Switzerland. Figure 1 shows age-specific crude rates and both crude and age-standardised rates per 100000 persons of all periods for males and females. Age-standardisation was performed using the WHO world standard population (Ahmad et al., 2001).

First, the data were analysed using Bayesian APC models for multiple outcomes (Riebler and Held, 2010). We assume that the number of suicides y_{ijg} of age group $i = 1, \ldots, 13$,

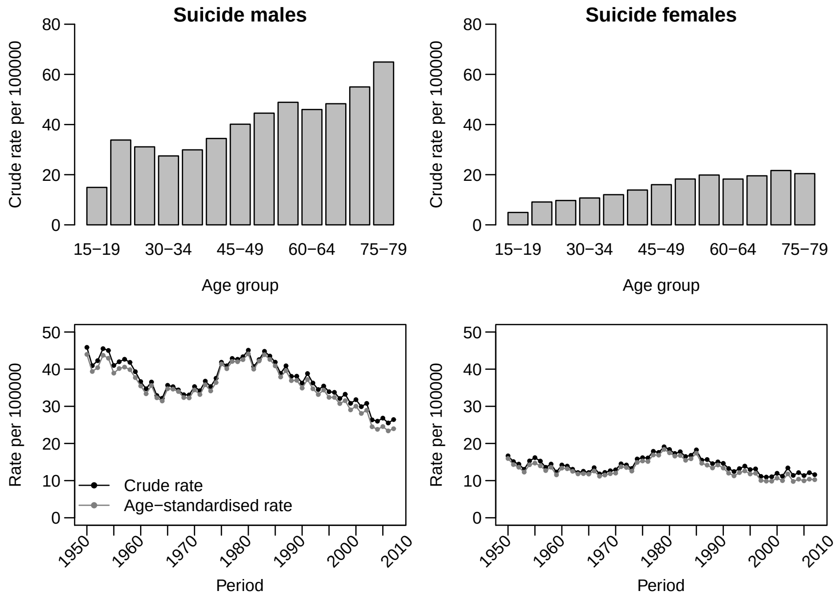

Fig. 1. Suicide rates from 1950–2007. Top: Age-specific crude rates for males and females. Bottom: Crude and age-standardised rates of all periods for males and females.

period $j = 1, \ldots, 58$ and sex g is Poisson distributed with rate $n_{ijg} \times \lambda_{ijg}$. Here n_{ijg} is the number of persons at risk and $\log(\lambda_{ijg})$ denotes the linear predictor. Under the assumption of joint period effects, for example, differences of gender-specific age and birth cohort estimates are identifiable. The linear predictor is

$$\log(\lambda_{ijg}) = \mu_g + \theta_{ig} + \varphi_j + \psi_{kg} \tag{1}$$

where μ_g represents the gender-specific mean (intercept), θ_{ig} the effect of age group i for sex g, φ_j the common period effect of period j and ψ_{kg} the effect of the kth cohort for sex g. Note that the cohort index $k = 1, \ldots, K$ depends on the age index i and period index j, but also on the width of age group and period intervals. We use the definition of Heuer (1997) which results in $K = 118$ birth cohorts. For identifiability of the gender-specific intercepts, we constrain all sets of time effects to sum to zero, i.e. here $\sum_{i=1}^{I} \theta_{ig} = 0$, $\sum_{j=1}^{J} \varphi_j = 0$ and $\sum_{k=1}^{K} \psi_{kg} = 0$ for both males ($g = 1$) and females ($g = 2$). If suitable, the linear predictor (1) can be modified to allow for separate age but common cohort effects or vice versa. Similarly, period and cohort effects may vary across gender but the age effects may be common, for example. However, keep in mind that differences are not identifiable if all sets of effects are allowed to vary (Riebler and Held, 2010).

Since we are in a Bayesian setting we treat all parameters as random and assign prior distributions. We follow Riebler and Held (2010) and use independent flat priors for the gender-specific intercepts. For the age, period and cohort effects we expect similarities between effects adjacent in time. Thus, we choose a Gaussian prior distribution based on independent second differences for all time effects, also known as random walk of second order (Besag et al., 1995). This is a natural choice since second differences of time effects are identifiable (Clayton and Schifflers, 1987). Note that variance parameters are not gender-specific. Thus, there is one variance parameter for each time scale resulting in three variance parameters in total. The variances are treated as random and suitable prior distributions are assigned.

As is well-known when working with registry data there are often inconsistencies in reporting systems or changes in reporting behaviour (Brillinger, 1986). For example the coding of causes of death might change over time. To adjust for such overdispersion, i.e. unobserved heterogeneity, we introduce further gender-specific variables z_{ijg} with mean zero and unknown variance into the linear predictor (1) (Besag et al., 1995).

To validate and compare the "joint period effects" model (1) with other models we use the well-known deviance information criterion (DIC) (Spiegelhalter et al., 2002). However, this criterion has recently been criticised for models with many random effects, e.g. (1), because complex models tend to be under-penalised (Plummer, 2008). For this reason we additionally calculate cross-validated proper scoring rules (Gneiting and Raftery, 2007), such as the mean Dawid-Sebastiani score (mean DSS), the mean ranked probability score (mean RPS) and the log score. Both DIC and proper scoring rules are negatively oriented such that smaller values are better.

Having found the best model the question arises whether it is necessary to allow for correlation between gender-specific time effects and/or gender-specific overdispersion parameters. A model with correlated overdispersion parameters is similar in spirit to a seemingly unrelated regression models (Zellner, 1962). In this class of models, there are several regression equations which are assumed to be correlated via their error terms. Regarding the time effects (age, period and cohort effects) the inclusion of a correlation would actually represent a balance between separate and joint effects. More precise relative risk estimates may be obtained. For comparing models with and without correlation structure we additionally use the log marginal likelihood. Although improper priors are used, the use of the marginal likelihood is valid because the candidate models only differ by the inclusion of correlation between the priors, for more details see Riebler et al. (2010).

All models are estimated using both Markov chain Monte Carlo (MCMC) techniques as described in Riebler and Held (2010) and Riebler et al. (2010), and integrated nested Laplace approximations (INLA) (Rue et al., 2009). INLA represents a deterministic alternative to MCMC. It computes directly very accurate approximations to the posterior marginal distributions and thus avoids time-consuming sampling. The INLA-program is freely available under `www.r-inla.org` and is easy to use under Windows, Mac and Linux via an R-interface (R Development Core Team, 2010). Here we use the INLA version built on 16.02.2011. DIC can be calculated within both settings. The log score and marginal likelihood are calculated using INLA, in contrast mean DSS and the mean RPS are calculated with MCMC. For comparing correlated multivariate APC models the multivariate analogues of the mean RPS and DSS score are used to capture the potential correlation present between the male and female suicide rates (Riebler et al., 2010).

For the MCMC analyses without inclusion of correlation we use a run of 120000 iterations, discarding the first 20000 iterations and storing every 20th sample thereafter, leading to a total of 5000 samples. When including correlation we use a run of 520000 iterations omitting the first 20000 iterations and storing every 200th sample thereafter, resulting in 2500 samples. This is necessary because of the high autocorrelations when accounting for correlations between time-effects and/or overdispersion parameters.

Explanatory variables on family integration are available for all observation years (1950–2007) and obtained for the 1970 to 2007 period from Swiss Federal Statistical Office (SFSO) (2009) and for the period before 1970 from Calot (1998). Since social integration is difficult to measure, there are several proposals and it is debatable which one to choose as an indicator. Furthermore, the choice of indicators is strongly limited by its availability for a long period of time. Breault and Barkey (1982) proposed to measure family integration by the marriage rates minus divorce rates divided by marriage rates plus divorce rates, since married people are supposed to be better integrated than single persons. A high value is related to a better integration. We will call this indicator F-index throughout the paper. The F-index is preferable to a crude measure, such as divorce rates alone as there is a high correlation between divorce rates and marriage rates. Alternatively the number of divorces per 100 marriages could be used.

To calculate the F-index we first adjusted the divorce rate for the introduction of a new divorce law in 2000 in Switzerland. The new law resulted in an extreme increase of divorces in 1999 and a strong decrease in 2000. First there were more divorce proceedings terminated in 1999 to have more time to adjust to the new legal situation in 2000. Then the introduction of the new divorce law in 2000 caused a prolongation of proceedings and thus less decisions. Thus, we substituted the divorce rates in the years 1999 and 2000 by the average of this two years. Alternatively a moving average of first or second order could be applied to the whole time-series to smooth random variations over the whole period.

As an alternative measure for family integration we consider the total marriage rate. This index represents the mean percentage of unmarried persons aged below fifty who would marry in the course of time, if they showed the same age-specific marriage behaviour as in the observation year.

The unemployment rate is calculated by dividing the number of unemployed persons by the sum of unemployed and employed persons. The number of employees is obtained from the Swiss Federal Statistical Office (SFSO) (2010d), the number of unemployed from the Swiss Federal Statistical Office (SFSO) (2010e).

For analysing the association of changes in family integration and changes in suicide trends we start with the calculation of pairwise correlations and perform standard time-series analyses, as proposed in Stack (1989, 1990a). Then, we use INLA to estimate separate univariate APC models for males and females substituting the period effect block by a time-constant regression variable related to the unemployment rate (%) and an explanatory variable on family integration assuming either a parametric or non-parametric effect. Finally, we use the multivariate APC model classified as the best model without covariates and replace the period effects by a non-parametric covariate effect of the F-index assuming a correlation between the effect on males and females. Figure 2 shows the F-index, the total marriage rates for males and females, and the unemployment rate from 1950–2007. Both the F-index and also the total marriage rates strongly decrease from 1950 to 2007. Especially around the middle of the 1970s there is a big drop. Around the early 1990s a local maximum is visible while afterwards all markers are decreasing again. The unemployment rates show the typical economical patterns indicated within the figure. However, note that the rates are always below five per cent.

3. Results

We will first present the results of the multivariate APC analysis for detecting trends in the sex ratio in suicide mortality of males and females. Then we will explore the impact of explanatory variables related to family integration on time trends of suicide rates.

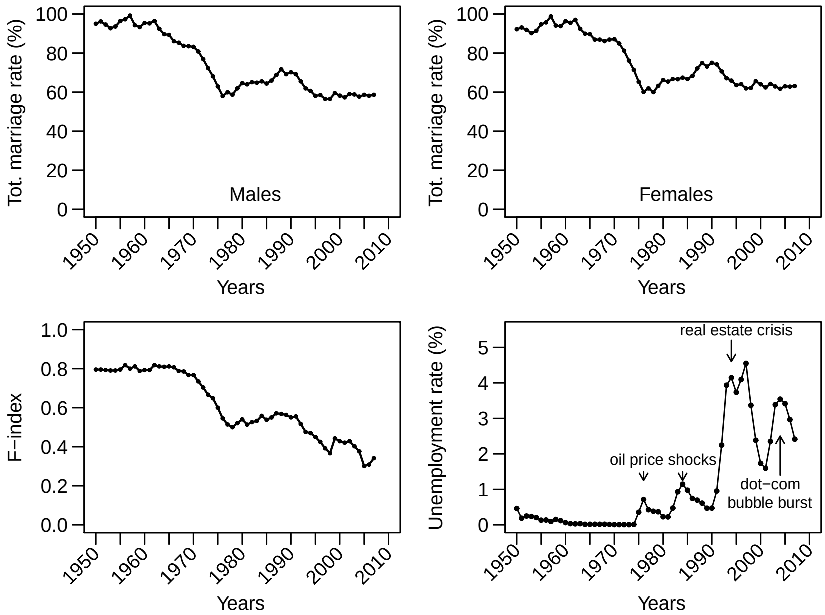

Fig. 2. Covariate information from 1950–2007. Top (left to right): Total marriage rate for males and females given in per cent. Bottom (left to right): F-index measured as (marriage rate - divorce rate)/(marriage + divorce) and unemployment rate measured as unemployed/(unemployed + employee).

3.1. *Analysis of gender-specific differences*

The model diagnostics for all models obtained by MCMC and INLA are shown in Table 1. The "joint period effects" model is classified by all model choice criteria as the best model, so that we assume gender-specific age and cohort effects. Table 2 shows that the inclusion of correlation for the overdispersion is clearly preferred to the model without correlation. The model with correlated overdispersion and the model with both correlated gender-specific effects and correlated overdispersion are almost equally classified. Although the additional inclusion of correlation between the gender-specific age- and cohort effects does not improve the model choice criteria, we gain additional information regarding the interpretation of the gender-specific differences through the estimated correlation coefficients. In this model, the correlation between overdispersion parameters was estimated to 0.56 with 95% credible interval $(0.17, 0.85)$. For the gender-specific age-effects the correlation was estimated to 0.82 $(0.50, 0.95)$ and for the cohort effects to 0.20 $(-0.61, 0.80)$. Thus, except for the cohort effects, the posterior distributions of all correlation estimates are clearly greater than zero, indicating that partly the same risk factors act on age and overdispersion for males and females. Accounting for a potential correlation more selectively, for example only between gender-specific age effects and overdispersion but not between gender-specific cohort effects, might lead to improved model choice criteria, however, the basic interpretation would

Figure 3 shows the relative risks of suicide for males compared to females for the "joint period effects" model with both correlated age and cohort effects, and correlated overdispersion. Men have an about three times higher risk to commit suicide than women. Especially men between 16 and 25 have a high risk compared to the corresponding age group of fe-

Table 1. Model choice criteria obtained from MCMC and INLA. For both approaches DIC estimates are given. In addition the mean Dawid-Sebastiani score $\overline{\text{DSS}}$ and the mean ranked probability score $\overline{\text{RPS}}$ are shown for MCMC and the log score for INLA. The column names indicate which effects (**A**ge, **P**eriod, **C**ohort) are assumed to be the same for males and females. The remaining effects are assumed to be gender-specific. The best value for each criterion is indicated in bold.

	Joint effects used for						
	A,P,C	P,C	A,C	A,P	C	P	A
MCMC model diagnostics							
Mean DSS	5.10	4.99	5.06	4.96	4.95	**4.88**	4.92
Mean RPS	4.62	4.37	4.53	4.34	4.28	**4.15**	4.21
DIC	2064.87	1971.86	2037.82	1942.87	1936.84	**1864.43**	1899.70
INLA model diagnostics							
Log Score	3.48	3.44	3.47	3.43	3.42	**3.39**	3.40
DIC	2064.16	1971.38	2037.46	1942.88	1936.73	**1864.16**	1899.27

Table 2. Model choice criteria obtained from MCMC and INLA for the "joint period effects" model without correlation, correlation between overdispersion parameters, between gender-specific age and cohort effects, between both overdispersion and gender-specific age and cohort effects. The best value for each criterion is indicated in bold.

	Correlation included for			
	-	overdispersion	time effects	both
MCMC model diagnostics				
Mean multivariate DSS	9.758	**9.752**	9.763	9.756
Mean multivariate RPS	6.653	**6.636**	6.647	6.640
DIC	1864.37	1854.80	1864.27	**1854.79**
INLA model diagnostics				
Log marginal likelihood	-5215.16	$-$**5213.80**	-5213.89	-5213.85
Log Score	3.390	**3.386**	3.390	3.386
DIC	1864.16	**1854.57**	1864.04	1854.65

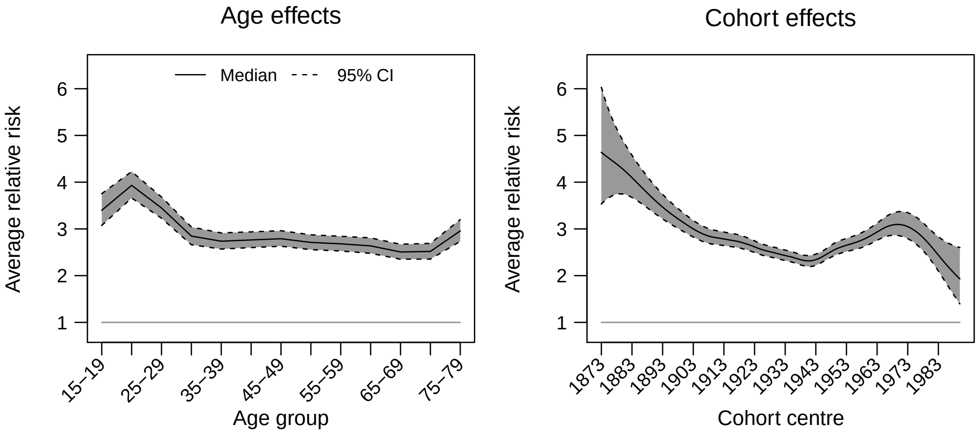

Fig. 3. Relative risk of suicide for males compared to females for the "joint period effects" model assuming a correlation between males and females for the age and cohort effects, and also the overdispersion parameters.

males. While the risk for males between 30 and 74 is almost three times as high as in women it is increasing again for elderly men.

For cohorts born around 1870 the risk for males is about four times as high compared to females. However, with successive cohorts the average relative risk falls to being about twice as high for cohorts born around 1940. Then it increases again reaching a local maximum for cohorts born around 1970. For the youngest cohorts a decreasing trend is visible.

We compared the posterior marginal distributions obtained by MCMC with those obtained by INLA for all models. The distributions coincide perfectly.

3.2. Analysis of the impact of family integration

Following the Durkheim tradition, one may ask whether explanatory variables on social integration can explain changes in suicide rates. The usual approach to study this is to look at the age-standardised male and female suicide rates. The matrix of pairwise Pearson correlations is shown in Table 3. Note, that neither the male suicide rates nor the female suicide rates in Switzerland are negatively correlated to the F-index. The total gender-specific marriage rates are positively correlated to both rates. Also the correlation between the unemployment rate and suicide mortality has the contrary sign of what we expected and indicates an inverse effect. However, since correlations alone might not be meaningful we continue with more sophisticated analyses.

3.2.1. Standard time-series analysis

We used separate linear models, fitted using ordinary least squares, for male and female mortality rates including three regressors, namely an intercept, the rate of unemployment and one covariate on family integration. To detect autocorrelation of first order between two successive residuals we used the Durbin-Watson test (Harvey, 1990). For each analysis the Durbin-Watson statistic was smaller than 0.6. The lower bound for 58 observations and

Table 3. Pair-wise Pearson correlations.

	Y1	Y2	X1	X2	X3
Male suicide rate (Y1)					
Female suicide rate (Y2)	0.84				
F-index (X1)	0.45	0.20			
Total male marriage rate (X2)	0.33	0.06	0.95		
Total female marriage rate (X3)	0.26	-0.02	0.94	0.99	
Unemployment rate (%) (X4)	-0.59	-0.51	-0.79	-0.66	-0.64

Table 4. The effect of family integration on suicide for men and women in Switzerland from 1950 to 2007. Standard errors are given in parentheses.

	Suicide			
	Males	Females	Males	Females
Suicide rate lag	$0.880_{(0.061)}$	$0.769_{(0.078)}$	$0.875_{(0.061)}$	$0.719_{(0.079)}$
F-index	$-2.280_{(2.744)}$	$-2.518_{(1.502)}$	-	-
Tot. marriage rate (males)	-	-	$-0.037_{(0.025)}$	-
Tot. marriage rate (females)	-	-	-	$-0.041_{(0.015)}$
Unemployment rate	$-0.665_{(0.351)}$	$-0.461_{(0.199)}$	$-0.728_{(0.301)}$	$-0.505_{(0.164)}$
Constant	$6.065_{(3.080)}$	$4.972_{(1.787)}$	$7.659_{(3.192)}$	$7.231_{(2.048)}$
Adjusted R-squared	0.858	0.771	0.862	0.786
Durbin's h statistic	-1.49	-1.74	-1.73	-1.94

three regressors at a 5% significance level is, however, 1.50. Thus, positive autocorrelation is indicated. Hence, we included a one-year lagged dependent variable as a regressor to eliminate autocorrelation. In autoregressive models the Durbin-Watson test statistics tends to underestimate autocorrelation, so that we used Durbin's h statistic (Harvey, 1990). Durbin's h is a normally distributed variable, so that the h-statistics should be within -1.96 and 1.96, which was the case for all models.

Table 4 shows the regression estimates for all models. The first two columns show the results for the models including the F-index as marker for family integration. In contrast the second two columns show the results when including total gender-specific marriage rates. The lagged suicide rate is positively related to the dependent variable for both gender in all regressions. Inspecting the results of the models including the F-index we see that neither the male nor the female suicide rate is related to the F-index. Unemployment is significantly negatively related to the female suicide rate.

Turning to the regressions that include the total gender-specific marriage rate the unemployment rate is again significantly negatively related to male and female suicide rates. For males the coefficient of the total male marriage rate is -1.48 $(-0.037/0.025)$ times its standard error. For females the coefficient of the corresponding female rate is -2.73 $(-0.041/0.015)$ times its standard error. Hence for higher values of the total marriage rate the female suicide mortality decreases.

3.2.2. Age-period-cohort analysis

So far age-aggregated data have been considered. To be able to keep the age-specific structure of the data, so that all information can be used, we integrate the explanatory variables into the APC model. Model estimation is performed using INLA. In the following we assume a time-constant effect of the rate of unemployment. Thus, we replace the period

Table 5. Log score and DIC of univariate APC models including either no covariate, or a time-constant effect of unemployment rate and either a time-constant (linear), quadratic or non-parametric effect of an explanatory variable on family integration instead of the period effects.

	Females		Males	
	Log score	DIC	Log score	DIC
No covariate	**3.090**	**849.27**	**3.677**	**1001.24**
Time-constant linear effect				
F-index	3.158	930.06	3.848	1135.33
Tot. marriage rate	3.151	922.41	3.814	1113.58
Time-constant quadratic effect				
F-index	3.116	881.51	3.721	1042.04
Tot. marriage rate	3.152	923.72	3.811	1112.98
Random walk of second order on covariate				
F-index	3.107	870.05	3.697	1021.05
Tot. marriage rate	3.119	885.46	3.730	1049.71

parameters with one linear effect of the unemployment rate and either a linear, quadratic or non-parametric effect of either the F-index or the total gender-specific marriage rates. Modelling the covariate in a non-parametric fashion we assume a random walk of second order as non-parametric prior for the covariate effect. This is a natural prior as it models deviations from a linear trend but reduces to the linear model if its variance goes to zero (Natario and Knorr-Held, 2003). In Natario and Knorr-Held (2003) an inverse gamma distribution with shape equal to 1 and scale equal to 0.00005 is proposed as prior for non-equally spaced covariates with an average distance equal to one. We used this prior and scaled each covariate on family integration appropriately. In addition, a sum-to-zero constraint is applied on the covariate effects to ensure identifiability of the intercept.

Table 5 shows the model choice criteria for all models in comparison to the ordinary APC model, in which, however, age, period and cohort effects are unidentifiable. For both sexes the ordinary APC model is clearly classified as the best model, which indicates that the covariates we proposed cannot fully replace the period effects. However, note that assuming a non-parametric effect of the F-index is much better than the corresponding parametric formulations assuming a linear or quadratic effect. In addition, this model is also not so far away from the standard APC model for both sexes. Table 6 shows the parameter estimates of all models with parametric covariate effects. The unemployment rate has a slight negative effect on the log female suicide rate in all models and on the log male suicide rate in models with a linear effect of F-index or total marriage rate. The F-index has a negative linear effect for both males and females. Thus, increasing the F-index by 0.1 units reduces the female suicide risk by 15% ($= 100 \cdot (1 - \exp(-0.165))$). Modelling the F-index in a quadratic way $\beta_0 \cdot$F-index $+\beta_1 \cdot$F-index^2, the estimate of β_0 is positive while the estimate of β_1 is negative for both males and females. Figure 4 shows the parametric and non-parametric estimates for the F-index and the total male and female marriage rate. Assuming a quadratic and non-parametric effect for the F-index results in very similar estimates. In contrast for the total marriage rate the quadratic and linear effect are very similar. Regarding the model choice criteria presented in Table 5 the inclusion of the F-index is preferred compared to the inclusion of the total marriage rate.

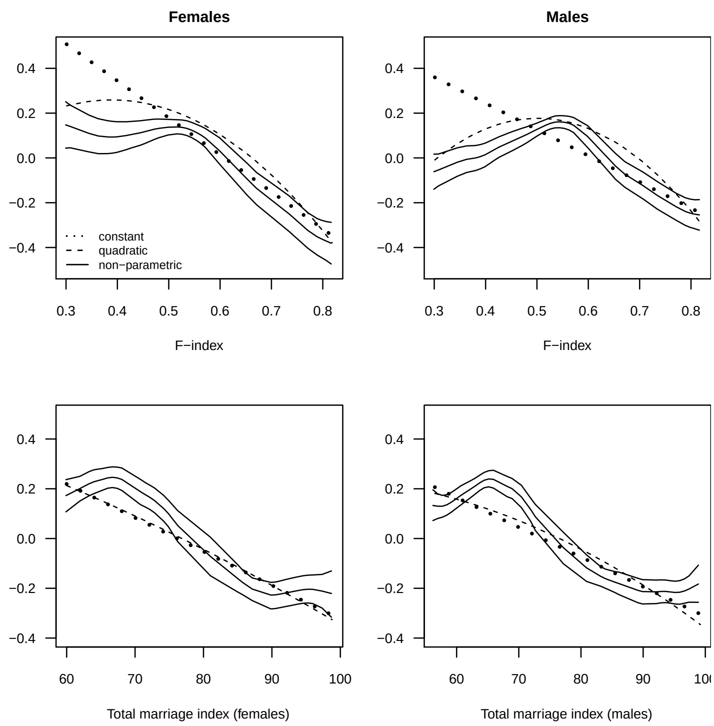

Fig. 4. Estimated parametric (linear and quadratic) and non-parametric effects of covariates related to family integration. For the non-parametric trend 95% pointwise credible bands are shown.

Table 6. Parameter estimates (posterior median, 2.5% and 97.5% quantile) for models with parametric covariate effects.

	Females			Males		
	2.5% qu.	Median	97.5% qu.	2.5% qu.	Median	97.5% qu.
Time-constant F-index						
(Intercept)	-8.05	-7.85	-7.66	-7.27	-7.11	-6.95
F-index	-1.96	-1.65	-1.34	-1.42	-1.17	-0.92
Unemployment rate	-0.09	-0.07	-0.06	-0.07	-0.05	-0.04
Time-constant total marriage rate						
(Intercept)	-8.03	-7.85	-7.66	-7.10	-6.95	-6.80
Tot. marriage rate	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01
Unemployment rate	-0.06	-0.04	-0.02	-0.04	-0.03	-0.02
Time-constant quadratic F-index						
(Intercept)	-9.52	-9.15	-8.78	-9.11	-8.84	-8.57
F-index	1.58	2.69	3.79	3.83	4.65	5.47
F-index^2	-4.31	-3.46	-2.61	-5.27	-4.64	-4.01
Unemployment rate	-0.06	-0.04	-0.02	-0.02	-0.01	0.01
Time-constant quadratic total marriage rate						
(Intercept)	-9.23	-8.18	-7.13	-8.46	-7.78	-7.10
Tot. marriage rate	-0.03	-0.00	0.02	-0.01	0.01	0.03
Tot. marriage rate^2	-0.00	-0.00	0.00	-0.00	-0.00	-0.00
Unemployment rate	-0.06	-0.04	-0.02	-0.03	-0.02	-0.00

Figure 4 shows that the effect of the F-index is very similar for males and females which suggests a joint analysis with correlated non-parametric F-index effects. We use the best-classified correlated multivariate APC model of Section 3.1, namely the "joint period effects" model with correlated age and cohort effects and correlated overdispersion parameters, and replace the period effects by a non-parametric effect of the F-index which is assumed to be correlated between males and females. In this model not only the relative risk estimates but also the direct gender-specific effects are identifiable. Figure 5 shows the resulting age effects, cohort effects and covariate effects. The estimated time variables exhibit a similar pattern for males and females. Table 7 shows that the correlation estimates are, except for the cohort effects, very high and significantly different from zero. Thus, similar risk factors may act on age and overdispersion. In addition, the F-index has a similar effect on males and females indicated by the estimated high correlation. Figure 5 shows that the age effects strongly increase from the youngest ages to the 20–24 years old persons. Then, for females, the effects slightly increase until the age of around 60 when they start to decrease again. For males the age effects clearly drop from the 20–24 age group to the 25–29 years old. Similar to the females the effects slightly increase until the age of 60, then start decreasing. For the oldest ones the age effects increase again. The cohort effects show a negative slope for both sexes from the oldest to the youngest cohorts. In contrast to males, the cohort effects in women stop decreasing for those born at the early 1970s. Finally, the effect of the F-index on females stays almost constant for values between 0.3 and 0.55. For larger values, representing a higher degree of social integration, the effect decreases. The effect on males increases slightly from a value of 0.3 to a maximum of about 0.55 and decreases for higher values as well. The joint time-constant effect of the unemployment rate is estimated as

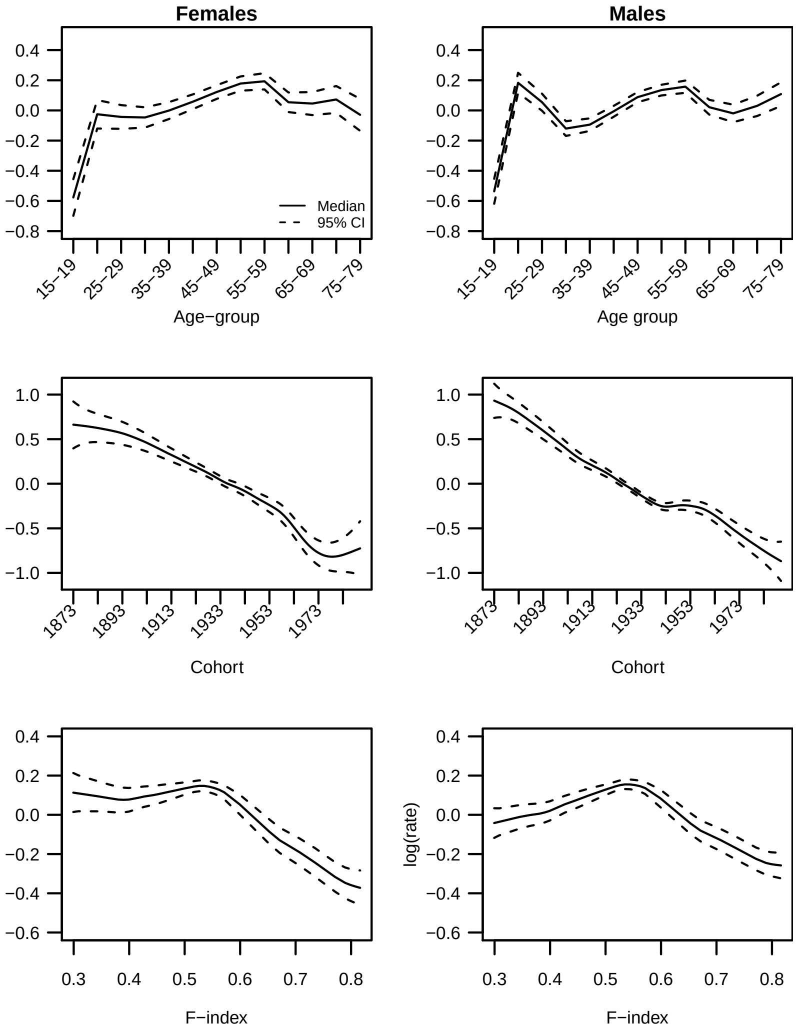

Fig. 5. Estimated age effects, cohort effects and non-parametric effects of the F-index obtained from a multivariate AC model assuming correlation between each pair of gender-specific effects: age effects, covariate effects, cohort effects and overdispersion.

Table 7. Model choice criteria and correlation estimates obtained from INLA for the AC model with correlated **A**ge and **C**ohort effects, correlated **O**verdispersion and a correlated non-parametric effect of the F-index (third column). For comparison the corresponding model without correlation (second column) and the correlated model without covariate but joint period effects (first column) is given. The triple notation ${}_LP_U$ for the correlation parameters denotes the posterior median P with 2.5 per cent quantile L and 97.5 per cent quantile U.

		Period effects replaced by F-index	
	A,C,O	no correlation	A,F-index,C,O
Model choice			
Log Score	**3.386**	3.402	3.393
DIC	**1854.65**	1890.07	1870.45
Correlation coefficients			
Correlation age	${}_{0.50}0.82_{0.95}$	-	${}_{0.50}0.82_{0.95}$
Correlation F-index	-	-	${}_{0.33}0.93_{1.00}$
Correlation cohort	${}_{-0.61}{+0.20}_{+0.80}$	-	${}_{-0.60}{+0.23}_{+0.82}$
Correlation overdispersion	${}_{0.17}0.56_{0.85}$	-	${}_{0.30}0.66_{0.89}$

-0.00 (95% CI: $-0.02, 0.01$). Thus the effect of the unemployment rate is not significantly different from zero.

Figure 6 shows the estimated relative risks of suicide of males compared to females. The estimates are very similar to those obtained in Figure 3, but slightly lower and with larger credible bands.

In Table 7 the log score and DIC estimate compared to the corresponding model without assuming correlation for any of the effects and compared to the model regarded best in Section 3.1 are given. The correlated version is clearly preferred. However, the standard correlated multivariate "joint period effects" model is classified as the best model.

4. Discussion

The results of the present multivariate age-period-cohort analysis confirm previous findings of strong gender-specific differences in suicide rates. Nevertheless the correlation estimates between gender-specific effects were, except for the cohort effects, very high. So it seems that similar risk factors act especially on age and overdispersion, which results in similar effect curves but on different overall levels. For all years and all age groups men have, compared to women, a three-fold risk to commit suicide. Elderly men and those between 16 and 25 show a especially high relative risk compared to their female peers in the same age group. While it might be surprising that men have a suicide rate higher than women, since women attempt suicide to a greater extent than men, this has been found in many previous studies in many different nations and is also known as "the gender paradox" (Canetto and Sakinofsky, 1998). An explanation might be that males use more lethal methods like hanging or firearms, while the most frequent method of females is poisoning (Ajdacic-Gross et al., 2008).

We further found a pronounced elevation for males born around 1970. Ajdacic-Gross et al. (2006) found in univariate APC models an inflexion point in cohort effects around 1970 for males as well, but not for females. Explaining this observed pattern is difficult. There should be risk factors related to cohorts born around 1970, but not to those born before or after 1970. Since the effect seems to be present especially in males and not females, also

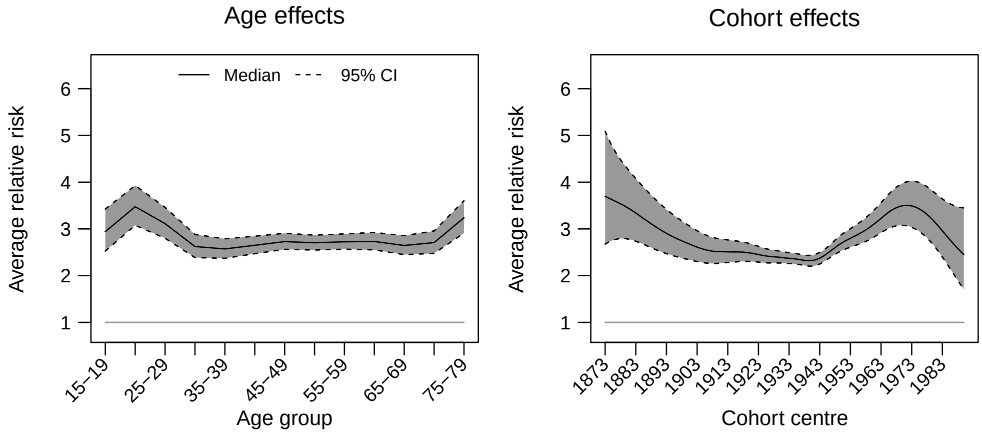

Fig. 6. Estimated relative risk of suicide for males compared to females obtained from a multivariate model assuming correlation between each pair of gender-specific effects: age effects, covariate effects, cohort effects and overdispersion.

reflected in an insignificant correlation estimate, we suppose that the causal factor must occur in later life. This is plausible in the context of suicide. Relevant risk factors for suicide are complex, so a better understanding is necessary to explain the observed pattern. Stockard and O'Brien (2002a) suggested that cohorts experiencing less social integration and having a large relative cohort size have higher suicide rates. We have the information that in Switzerland the persons around 1964 are the largest cohort. However, since this measure is not specific for males and females it does not provide further information explaining the gender-specific cohort differences.

We further explored whether changes in family integration could explain changes in suicide rates. We started with standard time-series analysis based on age-standardised rates. A significant influence was only found for the total female marriage rate on female suicide rate, indicating that with a higher total female marriage rate suicide rates of women decrease. To be able to exploit the age-specific structure of the data we further applied univariate age-period cohort models and replaced the period effects by parametric and non-parametric effects of variables related to family integration. To adjust for confounding induced by the rate of unemployment we additionally included a linear effect of the unemployment rate. The inclusion of the so-called F-index measured as (marriage rate - divorce rate)/ (marriage rate + divorce rate) was preferred compared to the gender-specific total marriage rate. Higher values, corresponding to better integration, have a decreasing effect on suicide risk. Of note, the effect of the F-index on males and females is very similar. Thus, we used a multivariate APC model and replaced the period effects by a correlated non-parametric effect of the F-index. The estimated correlation was very high. A difference we found for women and men was, that median values of the F-index, interpretable as normally integrated, have a higher effect on male suicide than being worse integrated. As the computation of the F-index is only based on marriage and divorce rates, this marker might be not suitable to measure bad integration. Many males might be not married, but nevertheless well integrated and happy.

By means of model choice criteria the standard APC model without covariates was preferred. This indicates that the measures of social integration we used cannot fully replace the period effects. If we had analysed only data from 1950 to 1980, we probably would have found a strong linear dependence between the F-index and the suicide rates, because from 1950 to 1970 the F-index value was almost constantly at 0.8. This indicates a high degree of social integration. In the same time-period suicide rates were strongly decreasing for both sexes. From 1970 to 1980 the F-index dropped and almost inversely the suicide rates increased. However after 1980 this linear relationship between the F-index and suicide has vanished. The reason may be possibly related to a change in the nature of intimate personal relationships. Although the trend to marry is still quite high in Switzerland compared to other nations, cohabitation rates have increased considerably during the last decades. Furthermore, in past generations marriage was more strongly correlated with having children, and more of them, which might have acted as a protective factor against suicide.

Thus, it might be that we need new measures. However, it is very difficult to decide how to measure social or family integration. There are several proposals and all of them are controversially discussed. Furthermore, the choice of a measure strongly depends on its availability for a long period of time. Thus, we have, for example, no appropriate information on separations over time. There are efforts outside the suicide literature, see for example Inglehart and Baker (2000), that have measured cultural shifts away from traditional value systems towards more individualism over the last 30 years in many nations. While these cultural measures, e.g. importance of god or GDP (gross domestic product) per capita, are likely to be relevant for future suicide research, they are not practical to employ in the present analysis, since they are not yet available on an annual basis.

A problem of this analysis is that it is not completely clear how to properly include information on explanatory variables in the APC model (Knorr-Held and Rainer, 2001). Since social integration might not be the main risk factor for committing suicide, it could be necessary to adjust for further confounding variables, for example mental disease or religiousness. Unfortunately, there exist no data, especially not on a yearly basis, to measure mental illness or relgiosity in Switzerland. However, we suppose that trends in religiousness and divorce rates are closely related, so that the omission of a control variable for religiousness is suspected to be not serious. Note that it would be also possible to include several covariates in a non-parametric fashion. In our analysis the two markers on social integration are strongly correlated, so that in this cases it is not meaningful to include both. Alternatively, the period effects could be kept in the model, but then the identifiability problem well known for APC models remains.

It could also be that the covariates on social integration exert a lagged influence on suicide mortality. For example, Wasserman (1984) determined a lag of nine months of the influence of divorce on suicide reported in the United States. Including a lagged covariate into a Bayesian APC model is particularly attractive, because then projections of suicide rates can be generated for future periods without any parametric assumptions. More research would be necessary to explore whether such a lagged effect is also present for Swiss suicide data. However, it is difficult to determine an exact time-lag because the separation of couples starts much earlier than the divorce proceeding is completed. Hence, the exact time-point which is relevant for suicide behaviour is difficult to determine.

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