Modelling Time-Varying Contextual Effects in Family and Fertility Research

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Abstract

There is increased interest in examining the impact of contextual characteristics on partnership and fertility behaviour of individuals. The conventional multilevel approach provides guidance on how to measure time-constant contextual effects; the proper way of modelling time-varying contextual effects, however, remains unclear. This paper proposes a framework that allows us to distinguish between time-constant and time-varying contextual effects in multilevel event history analysis and to properly control for clustering in multilevel models with time-varying contextual factors. We use retrospective survey data from Austria to show how regional time-constant and time-varying characteristics influence fertility behaviour of individuals who live in these regions. The framework can be applied to also examine how country-level factors influence demographic behaviour of individuals.

1. Introduction

The life course approach and event history analysis have become standard methodology in demographic studies on the family and on fertility (Courgeau and Lelièvre 1989; Yamaguchi 1991; Hoem 1992; Blossfeld and Rowher 1995). While the focus on dynamics of and interplay between the family and other life domains of individuals has significantly improved our understanding of the causes of family and fertility behaviour, the limited attention to the social context of the individual activity remains a shortcoming of the predominant research (Hoem 2007). Multilevel modelling has been developed as an analytical tool to measure simultaneously the effects of individual and of contextual characteristics on the behaviour of individuals, and to overcome the traditional micro-macro dilemma in the social sciences (Goldstein 1995). However, the conventional multilevel approach mostly provides guidance for researchers working on cross-sectional data; the dynamic nature of human and social life remains poorly measured and understood in these applications. Recently, multilevel event history analysis has been proposed as a way to integrate the strengths of the temporal and contextual approaches in the social sciences (Courgeau and Baccaïni 1997; Barber *et al.* 2000). Most studies applying multilevel event history analysis properly identify and control for time-constant contextual effects; the way of measuring the impact of time-varying contextual effects, however, is less convincing.

In this paper, we propose a framework, which allows to distinguish between time-constant and time-varying contextual effects in multilevel event history analysis and to properly control for clustering in multilevel models with time-varying contextual effects. A similar extension of the conventional multilevel event history model has already been proposed elsewhere (see Windzio 2006).

2. Previous research on family dynamics applying multilevel models with contextual effects

Multilevel models have been developed for analysing hierarchical or clustered data. For clustered data observations within the same cluster are not independent (in statistical terms) and conventional regression analysis, which assumes independence of observations, underestimates standard errors of parameter estimates. Standard errors for the parameter estimates of higher-level covariates are the most affected by ignoring clustering. Multilevel modelling corrects for the biases in standard errors, which results from clustering, and provides correct confidence intervals and significance tests. Another important virtue of multilevel modelling is that it also enables researchers to decompose the total variance into portions associated with each level, and to study the sources of variation at each level in detail (Goldstein 1995; Guo and Zhao 2000).

While most applications of multilevel modelling in social sciences use cross-sectional data, recently, there has been increased use of multilevel models also among researchers working with longitudinal data including event history data (Barber et al. 2000; Singer and Willett 2003). An ingredient feature of time-to-event data is that not only characteristics of lower-level units (e.g. individuals) vary over time, but also characteristics of higher level units (e.g. regions) may change. Individuals live in regions, and both individuals and regions change over time. This raises a question of how to control for time-varying contextual effects in multilevel models, which, in their conventional form assume that contextual effects are time-constant (cf. Goldstein 1995). A search in the recent demographic literature shows that there are three ways of how the effect of higher-level characteristics is modelled in studies on contextual determinants of family and fertility behaviour.

The standard way is to set up a two-level model where individuals are nested within regions (or other spatial units). Such models include a regional-level random residual (or random effect) to control for the time-constant contextual effects on individual behaviour. Some studies identify the magnitude of regional variation in individual behaviour first and then proceed to explore the sources of this variation, i.e. how much compositional differences account for the regional variation, how much the variation reveals a 'true' contextual effect. Thereafter contextual characteristics, both time-constant and time-varying are included in the analysis to explain the contextual effect, when controlling for remaining / unobserved (time-constant) regional characteristics, i.e. the effect of clustering. Other studies begin with a two-level model where individual characteristics are already included. The major interest is in exploring how contextual characteristics shape individual demographic behaviour, again when controlling for the effect of remaining / unobserved characteristics. The two-level model described above has widely been used in family and fertility studies, e.g. recently in studies on determinants of marriage and family formation (Axinn and Yabiku 2001; Hank 2002; Hank and Kreyenfeld 2003) or factors influencing divorce (Härkönen and Dronkers 2006).

The fixed-effects approach is another way of modelling contextual effects in family and fertility research (Kravdal 2007). As opposed to random-effects (or multilevel) approach described above, a single-level model is estimated with time-varying characteristics of regions (or other spatial units) and with a set of dummy-variables for regions to control for the time-constant contextual factors. The effect of time-varying contextual characteristics on individual behaviour (when controlling for time-constant contextual effects) is thus of the main focus for the fixed-effects approach. The essence of time-constant effects is left for other studies to clarify. The idea of applying the fixed-effects approach has come from researchers working with large data-sets (e.g. Nordic register data) for which an estimation of a multilevel model may turn out to be too time-consuming or impossible for technical reasons. Yet, the large data-set ensures that a single-level model with many parameters could be estimated without much effort. In the recent demographic literature, the fixed-effect approach has been applied to study time-varying contextual effects on fertility (Derose and Kravdal 2007; Rindfuss et al. 2007), divorce (Lyngstad 2006) or mortality (Kravdal 2007).

Both above-described approaches share the same shortcomings. First, while random and fixed-effects models control for clustering of individuals within regions, they ignore further clustering which occurs across space-time (usually region-year) units. If time-constant and time-varying contextual effects (or variation) both exist, then not only are individual outcomes within the same region similar, but they are also similar in the same region in the same time period. According to multilevel theory ignoring this fact would lead to biased standard errors of parameter estimates, particularly for time-varying contextual factors. Second, neither approach allows to measure total variation associated with higher level and to decompose the variance into time-constant and time-varying parts. Conventional two-level model identifies the magnitude of regional-level time-constant variation, while the fixed-effects approach disregards the whole issue.

Recently, some researchers have proposed an extended version of two-level model. A model is estimated, with a random residual for region-years instead of regions (see Houle 2004; cf. Frank and Wildsmith 2005). This approach allows to measure total variation associated with the contextual level and to easily include in the analysis time-constant and time-varying contextual characteristics to account for the contextual variation. While the solution seems to have clear advantages over conventional approach at first glance, it similarly suffers from shortcomings. Most importantly, the two-level model assumes that time units (years) within the same spatial unit (region) are independent from each other, which is usually not the case. Again, ignoring the clustering results in biased standard errors of parameter estimates, this time for time-constant contextual characteristics.

Next, we propose a simple extension to conventional two-level model to distinguish between time-constant and time-varying contextual effects and to properly control for clustering in multilevel-models with time-varying contextual effects. We extend two-level model to a three-level model by including residual both for spatial units and space-time units.

3. Method

Assume that we have a homogeneous population spread across the country. The log-hazard of event for individual i in area k is then calculated as follows:

$$\ln h_{ik}(t) = \ln h_0(t) + \varepsilon_k$$

where $h_{ik}(t)$ is the hazard of event for individual i in area k at time t, ε_k represents area-level residual (unobserved characteristics of area k). We thus assume that the hazard of event varies between areas (between-area variance).

Assume that the hazard of event for individuals varies not only between areas, but also within areas over years. We can then extend our two-level event history model to a three-level model:

$$\ln h_{ijk}(t) = \ln h_0(t) + \varepsilon_k + u_{jk}$$

where u_{jk} represents area-year-level residual (unobserved characteristics of area k in year j). The log-hazard of event for individual i in year j in area k then equals to the baseline log-hazard plus area-level residual and area-year-level residual. The following example might help to clarify the point: the log-hazard of first birth for an individual in Vienna in 1985 equals to baseline-log-hazard (average for Austria) plus the deviance of Vienna from the average for Austria and the deviance of the year 1985 from the Vienna's average for the observation period, which is 1956–1996, for example. We thus assume that the hazard of event varies between areas and also within areas over years.

In reality, we have a heterogeneous population and we thus need to adjust our model to individual-level covariates. The inclusion of covariates may also reduce the error of our model as some variation between areas and within areas over years may result from the fact that individuals with different socio-economic characteristics live in different regions and in different years (i.e. we observe compositional effects instead of contextual effects).

$$\ln h_{ijk}(t) = \ln h_0(t) + \sum_l \alpha_l x_{ijkl}(t) + \varepsilon_k + u_{jk}$$

where $x_{ijkl}(t)$ are the values for individual i in year j in area k of a set of covariates which may be time-varying, α_l are the parameters describing the effects of covariates.

The variation in hazard between areas and within areas over years may further decrease after the inclusion of contextual-level characteristics in our model. These may be time-constant or time-varying characteristics of the areas.

$$\ln h_{ijk}(t) = \ln h_0(t) + \sum_l \alpha_l x_{ijkl}(t) + \sum_m \beta_m w_{km} + \sum_n \gamma_n v_{jkn} + \varepsilon_k + u_{jk}$$

where w_{km} are the values for area k of a set of covariates, β_m are the parameters describing the effects of covariates, v_{jkn} are the values for area k in year j of a set of covariates γ_n are the parameters describing the effect of covariates.

To sum up, the proposed framework allows, first, to disaggregate area-level residual into time-varying and time-constant parts; and, second, to properly control for clustering when investigating the effect of time-constant and time-varying area-level characteristics on the behavior of individuals.

4. Data

The data come from the Austrian Family and Fertility Survey (FFS). The Austrian FFS was carried out in 1995 and 1996 among 4,581 women and 1,539 men between the ages of 20 and 54 (Prinz et al. 1998). As a part of the Europe-wide FFS program, the survey was based on the collection of event-histories. All major demographic events that took place in the life of respondent were identified (to the accuracy of a month), including births, partnership and residential changes since age 15. In the FFS program, the collection of residential histories was optional. Austria was one country among the few that implemented this module, making the Austrian dataset valuable for exploring whether and how residential context influences childbearing behaviour.

Our sample consists of 3,928 Austrian women born 1941–1976. We examined the impact of residential context on the hazard of first, second and third birth. We modelled the time to conception (which subsequently led to a birth) in order to measure the effect of residential context on childbearing behaviour as precisely as possible. There were 2,970 first births, 1,853 second births and 630 third births in our data-set. We distinguished 98 districts or counties in Austria: each district or county was considered as a separate labour market area.

In our modelling strategy, we first estimated a three-level model where we identified and controlled for district-level time-varying and time-constant unobserved characteristics. We then included in the model individual and contextual characteristics to explain contextual-level variation and to uncover the essence of contextual effects. Finally, we compared the results of our three-level event history model with two- and single-level models to show the advantages of the three-level event history model.

5. Results

5.1. First Birth

Table 1 presents the models for first birth. In Model 1, we included random residuals at county level and county-year level and controlled for the age of the women (baseline). We see that the estimates for standard deviation and variance of residuals were significantly different from zero (we estimated standard deviation and then calculated variance). The likelihood ratio test supported that the model with random residuals was significantly better than the (single-level) model without residuals (not shown): the value of the test statistic (LR) was 4159.4 with 2 degrees of freedom, with p-value < 0.001. The hazard of first birth thus varied between counties and within counties over years. Our calculations showed that time-constant factors accounted for 44% of the total contextual variation, whereas time-varying contextual factors explained 56%. We also calculated the magnitude of the contextual variation. The residuals were expected to follow normal distribution in our multilevel hazard model, specified in the log-hazard form. The log-hazard differed 0.452 between the highest and the lowest values of about 68% of observations / counties and 0.904 between the highest and the lowest values of about 95% of cases[1]. (For the sake of simplicity, we disregarded the confidence intervals.) This meant the difference in hazard 57% and 2.47 times, correspondingly.

In Model 2, we controlled for the partnership status (in union or not) and union duration, and in Model 3, additionally marital status (married in union or not). The variance of county-level residuals decreased with partnership status by 14% and with marital status by further 23 percent points. The partnership / marital status thus accounted 37% of initial variation in the first birth risk across counties (we disregard the potential endogeneity of partnership status in our paper). In Model 4, we also included a set of socio-economic characteristics of women: their educational enrolment and level, employment status, number of siblings and their religiosity (at the moment of the survey). We see that the variance of county-level residuals further decreased, and that personal characteristics accounted for 58% of initial variation in the first birth risk between counties.

In Model 5, we also included a county-level time-constant covariate – the size of the largest settlement in county. The variance of county-level residuals decreased by further 24 percent points and we accounted for 82% of initial variation in the first birth risk across counties. However, there was still a significant variation left in the levels of first birth risk –

[1] As we know about 68% of observations lie within the range of $\pm 1\sigma$ from the mean for normal distribution and about 95% of observation lie within the range of $\pm 2\sigma$.

the hazard differed 21% between the two extremes of (about) 68% of observations. Demographic and socio-economic characteristics of women and the size of county thus explained a significant portion of time-constant contextual variation. Interestingly, however, the inclusion of personal characteristics in the model did not reduce the variance of county-year-level residuals – there were thus time-varying contextual effects, which need to be explained by an inclusion of county-level time-varying covariates in the model. (The data-set on time-varying contextual characteristics was still in preparation on the time of writing the first draft of the paper.) How should we interpret the effect of the size of county? The hazard of first birth decreased as the size of the county increased. More precisely, the log-hazard was shifted by -0.098 with an increase in log-population by one unit and hazard was thus multiplied by 0.91. The results are displayed in Figure 1 in order to better grasp the pattern. We see that the first birth risk was significantly lower in cities than in small towns and rural areas, but the levels did not differ much between the capital of Vienna and other cities.

Finally, we compared the results of our three-level event history model with those of two- and single-level models. In Model 5, we controlled for clustering of individuals within county-years and clustering of county-years within counties. In Model 6, we only controlled for clustering of individuals within county-years, but assumed independence of time-units for the same area. In Model 7, we did not control for any clustering, assuming independence of individuals and county-years, respectively. We see that the coefficient for the size of county is significantly different from zero for all three models and does not change much across the models. However, t-statistic reveals that the three-level model gives us the most conservative results – in other models we thus underestimate the values of standard errors.

5.2 Second birth

In Model 1, we controlled for the age of the first child, the women's age and union duration (we excluded episodes outside the union as there were very few second conceptions or births outside the union) (Table 2). The estimates for standard deviation and variance of county-level residuals were significantly different from zero – thus the hazard of second birth also varied across counties. However, we did not find much variation in the county-year-level residuals – the estimate for standard deviation was not significantly different from zero (the results are not shown). In Model 2, we additionally controlled for marital status. The variance of county-level residuals decreased by 22%. In Model 3, we also controlled for a set of socio-economic characteristics of women. The model fit improved significantly (LR=148.9, 9 df, $p<0.001$), but, interestingly, the variance of county-level residuals decreased only little compared to the previous step (by further 7 percent points). In Model 4, we also included a county-level (time-constant) covariate – the size of the largest settlement in county. The sign of the coefficient was as expected, but the model fit did not improve significantly (LR=1.46, 1 df, $p>0.10$). A significant contextual variation remained, which need to be explained by other contextual covariates.

Again, we carried out a comparison of models for pedagogical purposes. Model 5 is a single-level model, which includes a contextual covariate – the size of the largest settlement in county. We see that the value of t-statistic for the coefficient of the contextual covariate is much larger (and that of standard error smaller) for single-level model than for two-level model. The results of single-level model thus lead us to wrong conclusions – we would conclude that the effect of the county's size was significant when we should not draw such a conclusion.

5.3. Third birth

In Model 1, we controlled for the age of the second child, the women's age and cohabitation or marriage duration (almost all women with two children and in union were married). The estimates for standard deviation and variance of county-level residuals were significantly different from zero – the hazard of third birth thus also varied across counties. The estimates for standard deviation and variance of county-year level residual were not significantly different from zero. However, as the values of parameter estimates were relatively large and our sample was small, we decided to display the figures. In Model 2, we controlled for socio-economic characteristics of women. Interestingly, a significant variation of county-level residuals did not only persist, but did also increase by 10%. (Some cautious is needed with interpretation of the results, however, because of the small sample size for third births.) In the next model, we included the size of the largest settlement in county to explain time-constant contextual variation. Although the sign of the coefficient was as expected (the larger the settlement the lower the third birth risk), the model fit did not improve significantly (LR=0.65, 1 df, p>0.10).

As the last step, we compared the results of our three-level event history model with those of two- and single-level models (Table 3, Models 3 to 5). Again, we see that the three-level model provides us with the most conservative results, and that the single-level model leads us to wrong conclusions.

6. Conclusions and discussion

In this paper, we have proposed a simple extension to conventional two-level model in order to distinguish between time-constant and time-varying contextual effects in multilevel event history analysis and to properly control for clustering in multilevel models with time-varying contextual effects. We used data from the Austrian Family and Fertility Survey to examine regional contextual effects on childbearing behaviour. The analysis showed a significant variation in the fertility levels between counties and within counties over years in Austria. Demographic and socioeconomic characteristics of women explained much of the variation between counties for first birth, some for second, but little variation for third birth. Personal characteristics did not account for fertility variation within counties over years.

Our next step will be to also include in the models time-varying contextual characteristics. We have collected information on two contextual characteristics that vary over time: the share of children aged 3 to 6 in childcare; and the share of unemployed women in ages 15 to 49. It will be interesting to explore how much the two characteristics explain time-varying contextual effects, which we observed for first and possibly also for third birth. An inclusion in the analysis of the two time-varying contextual characteristics would also allow us to explicitly test and demonstrate the advantage of three-level model over conventional two-level models when measuring the effect of time-varying contextual characteristics. This is an important step that we were not able to do with the data available on the time of writing this paper. Nevertheless, our analysis showed how time-constant and time-varying contextual effects can be distinguished and controlled for in multilevel event history models.

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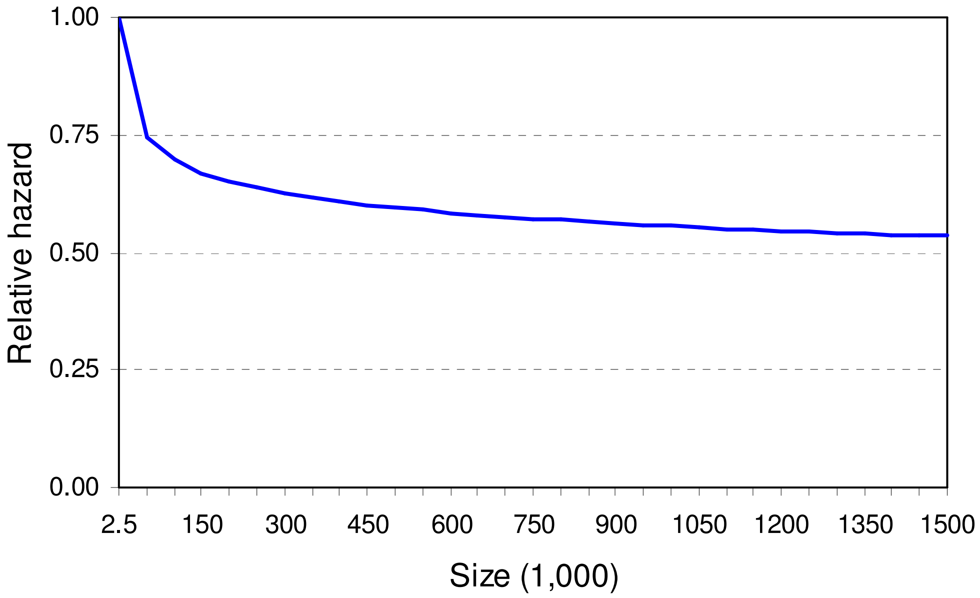

Figure 1. Relative hazard of first birth by the size of the largest settlement in county.

Table 1. Log-hazard of conception leading to first birth (parameter estimates).

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
Constant (baseline)	-4.330	***	-4.223	***	-4.176	***	-3.822	***	-3.574	***	-3.505	***	-3.484	***
Age of woman (baseline)														
15–19 years (slope)[1]	0.447	***	0.336	***	0.331	***	0.303	***	0.303	***	0.278	***	0.276	***
20–24 years (slope)	0.090	***	0.014		-0.005		-0.006		-0.005		-0.005		-0.006	
25–29 years (slope)	-0.016		0.001		0.006		0.002		0.004		-0.003		-0.003	
30+ years (slope)	-0.206	***	-0.165	***	-0.156	***	-0.165	***	-0.165	***	-0.154	***	-0.153	***
Cohabitation (ref=single)														
Enter cohabitation (constant)			1.823	***	1.465	***	1.430	***	1.438	***	1.409	***	1.404	***
0–1 years (slope)			-0.598	***	-0.597	***	-0.589	***	-0.589	***	-0.554	***	-0.555	***
1–3 years (slope)			0.006		-0.040		-0.030		-0.030		-0.027		-0.026	
3+ years (slope)			-0.077	***	-0.106	***	-0.101	***	-0.102	***	-0.111	***	-0.110	***
Marriage (ref=cohabitant)					0.769	***	0.712	***	0.707	***	0.776	***	0.775	***
Enrolled in education							-0.920	***	-0.903	***	-0.882	***	-0.883	***
Educational level (ref=basic)														
Secondary							-0.431	***	-0.402	***	-0.402	***	-0.399	***
Higher							-0.063		-0.051		0.000		0.002	
Employed							-0.328	***	-0.322	***	-0.291	***	-0.292	***
Number of siblings (ref=0–1)														
2							0.140	**	0.142	**	0.142	***	0.142	***
3+							0.250	***	0.249	***	0.256	***	0.253	***
Religiousness (ref=no)														
Very							0.048		0.042		-0.005		-0.004	
Somewhat							0.078		0.070		0.033		0.034	

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
Size of county (ln)									-0.098	***	-0.084	***	-0.082	***
T-statistic									(4.158)		(7.412)		(8.422)	
σ_{ε}	0.226	***	0.210	***	0.179	***	0.146	***	0.095	**				
σ_{ε}^2	0.051	***	0.044	***	0.032	***	0.021	***	0.009	**				
Relative to the variance in Model 1	1.00		0.86		0.63		0.42		0.18					
σ_u	0.253	***	0.292	***	0.274	***	0.259	***	0.259	***	0.214	***		
σ_u^2	0.064	***	0.085	***	0.075	***	0.067	***	0.067	***				
Relative to the variance in Model 1	1.00		1.33		1.17		1.05		1.05					
Log-likelihood	-14973.2		-14520.1		-14433.9		-14322.7		-14315.3		-16165.3		-16168.0	

Significance: '*'=10%; '**'=5%; '***'=1%.

N of counties: 98; N of county-years: 3,639; N of individuals: 3,928; N of events: 2,970.

[1] – We used a piecewise linear spline specification, instead of the widely used piecewise constant approach, to pick up the baseline log-hazard and the effect of (other) time-varying variables that change continuously. Parameter estimates are thus slopes for linear splines over user-defined time periods. With sufficient nodes (bend points) a piecewise linear-specification can efficiently capture any log-hazard pattern in the data. The value of the linear spline function between the points (t_n, y_n) and (t_{n+1}, y_{n+1}) is computed as follows: $y(t) = y_n + s_{n+1}(t - t_n)$ for n = 0, 1, 2 ..., where s_{n+1} is the slope of the linear spline over the interval [t_n, t_{n+1}]. To compute the linear spline function we thus need to define nodes and estimate from the data constant y_0 and slope parameters s_1, s_2, ...

Table 2. Log-hazard of conception leading to second birth (parameter estimates).

	Model 1		Model 2		Model 3		Model 4		Model 5	
Constant (baseline)	-2.539	***	-3.096	***	-2.973	***	-2.865	***	-2.714	***
Age of first child (baseline)										
0–1 years (slope)	1.229	***	1.271	***	1.279	***	1.280	***	1.308	***
1–3 years (slope)	-0.069		-0.059		-0.026		-0.026		-0.050	
3–5 years (slope)	-0.261	***	-0.245	***	-0.224	***	-0.224	***	-0.197	***
5+ years (slope)	-0.075	***	-0.067	**	-0.062	**	-0.062	**	-0.083	***
Age of woman										
–19 years (slope)	0.131		0.146		0.109		0.107		0.047	
20–24 years (slope)	0.026		0.019		0.016		0.017		0.039	*
25–29 years (slope)	0.032		0.036	*	0.035	*	0.036	*	0.033	*
30+ years (slope)	-0.124	***	-0.12	***	-0.124	***	-0.123	***	-0.120	***
Union duration										
0–1 years (slope)	-0.401	**	-0.545	***	-0.542	***	-0.545	***	-0.459	***
1–3 years (slope)	-0.027		-0.059		-0.061		-0.061		-0.082	*
3+ years (slope)	-0.091	***	-0.107	***	-0.108	***	-0.108	***	-0.107	***
Marriage (ref=cohabitant)			0.765	***	0.731	***	0.729	***	0.674	***
Enrolled in education					-0.815	**	-0.799	**	-0.479	**
Educational level (ref=basic)										
Secondary					0.034		0.039		0.060	
Higher					0.163		0.164		0.247	**
Employed					-0.292	***	-0.293	***	-0.296	***
Number of siblings (ref=0–1)										
2					-0.004		-0.005		0.029	
3+					0.153	**	0.150	**	0.153	***
Religiousness (ref=no)										
Very					0.209	**	0.207	**	0.279	***
Somewhat					0.106	*	0.104	*	0.148	***

	Model 1		Model 2		Model 3		Model 4		Model 5	
Size of county (ln)							-0.038		-0.035	***
T-statistic							(1.200)		(2.858)	
σ_{ε}	0.190	***	0.168	***	0.160	***	0.154	***		
σ_{ε}^{2}	0.036	***	0.028	***	0.026	***	0.024	***		
Relative to the variance in Model 1	1.00		0.78		0.71		0.66			
Log-likelihood	-8560.2		-8511.8		-8485.8		-8485.0		-9180.8	

Significance: '*'=10%; '**'=5%; '***'=1%.

N of counties: 96; N of county-years: 2,553; N of individuals: 2,913; N of events: 1,853.

Table 3. Log-hazard of conception leading to third birth (parameter estimates).

	Model 1		Model 2		Model 3		Model 4		Model 5	
Constant (baseline)	-2.082	***	-2.245	***	-2.174	***	-2.182	***	-2.102	***
Age of second child (baseline)										
0–1 years (slope)	1.114	***	1.149	***	1.141	***	1.142	***	1.111	***
1–3 years (slope)	-0.136		-0.128		-0.128		-0.143	*	-0.141	*
3–5 years (slope)	0.084		0.096		0.097		0.093		0.091	
5+ years (slope)	-0.050		-0.045		-0.045		-0.050		-0.050	
Age of woman										
–24 years (slope)	-0.112	*	-0.122	**	-0.121	**	-0.109	*	-0.104	*
25–29 years (slope)	-0.013		-0.027		-0.025		-0.024		-0.024	
30–34 years (slope)	-0.031		-0.039		-0.039		-0.037		-0.036	
35+ years (slope)	-0.151	***	-0.153	***	-0.154	***	-0.148	***	-0.148	***
Union duration										
0–1 years (slope)	0.111		0.113		0.124		0.096		0.092	
1–3 years (slope)	-0.202	*	-0.228	*	-0.226	*	-0.231	*	-0.222	*
3+ years (slope)	-0.109	***	-0.103	***	-0.103	***	-0.107	***	-0.108	***
Enrolled in education			-0.776		-0.760		-0.707		-0.695	
Educational level (ref=basic)										
Secondary			-0.134		-0.138		-0.152		-0.154	
Higher			0.458	**	0.465	**	0.474	**	0.474	**
Employed			-0.073		-0.067		-0.092		-0.089	
Number of siblings (ref=0–1)										
2			0.077		0.076		0.087		0.093	
3+			0.207	**	0.203	**	0.245	**	0.252	***
Religiousness (ref=no)										
Very			0.580	***	0.572	***	0.548	***	0.532	***
Somewhat			0.031		0.024		0.030		0.021	

	Model 1		Model 2		Model 3		Model 4		Model 5	
Size of county (ln)					-0.030		-0.044		-0.055	**
T-statistic					(0.931)		(1.594)		(2.271)	
σ_{ε}	0.361	***	0.379	***	0.396	***				
σ_{ε}^{2}	0.130	***	0.144	***	0.157	***				
Relative to the variance in Model 1	1.00		1.10		1.20					
σ_{u}	0.227		0.268		0.232		0.401	***		
σ_{u}^{2}	0.052		0.072		0.054					
Relative to the variance in Model 1	1.00		1.39		1.04					
Log-likelihood	-3930.2		-3910.7		-3910.4		-3920.8		-3922.4	

Significance: '*'=10%; '**'=5%; '***'=1%.

N of counties: 93; N of county-years: 2,332; N of individuals: 1,986; N of events: 630.