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Socio-economic Differences in Postponement and Recuperation of fertility in Italy: Results from a Multi-Spell Random Effect Model.

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ABSTRACT

One of the major explanations brought forward for the emergence if low fertility in Italy (and other Mediterranean countries) has been increased education and labour force participation among women. The argument relies on the fact that higher education and earnings increase women's opportunity cost, which in turn delay the onset of childbearing and therefore reduce completed fertility. In this paper we consider the role of women's socio-economic status on delaying motherhood and fertility. Using two different data sets, one to infer socio-economic status, the other to estimate models of first, second and third births, we show that women's socio-economic status indeed delays the onset of motherhood, but also that there are strong recuperation effects which works through first and second births. Socio-economic status has little effect on third births however. The paper demonstrates how such delay and recuperation effects can be estimated through a multi-spell hazard rate model. We also perform extensive sensitivity analysis, and show that controlling for unobserved heterogeneity is important but that the assumption imposed on its distribution function is of minor importance.

Keywords: lowest-low fertility, recuperation and postponement effect, random effect model.

JEL Classification: J13, J18, C41

NON-TECHNICAL SUMMARY

The positive association between postponement in fertility and a general decline in total fertility rate has been accepted as an empirical regularity across cohorts and countries. One of the major findings from this literature is that women with higher education or higher earnings potential tend to postpone first birth. But the postponement of the first birth does not necessarily imply a lower completed fertility because it could be associated with recuperation in terms of the second and third birth. Unfortunately it is not straightforward to separately identify the postponement and the recuperation effect: they depend both on observed and unobserved characteristics.

Combining two different data sets (from the ISTAT Labor Force Survey and the Survey of Households' Wage and Wealth led by the Bank of Italy in 2002), we investigate socio-economic differences in delay and recuperation of childbearing in Italy, a country that is suffering from what is termed the lowest low-fertility. The approach is based on a multi-spell random effect hazard model, whereby estimation of first, second and third birth is done jointly. The model allows for unobserved heterogeneity and we test to what extent the assumption about its functional form has any impact on the overall parameter estimates.

An expected result is that women with high wages tend to delay the first birth: we expected this result because education is the best predictor for potential earnings. Thus for a woman with high wage it could be optimal to complete her education, establish herself in the labour market and then start their childbearing career. We also find a strong recuperation effect of a high earning woman in terms of the progression to the second birth. As a consequence, by the age of 40 high earning women have caught up with low earning women almost completely. However, socio-economic status has little effect on third birth. To overcome the estimation problems caused by women specific unobserved characteristics we control for sample heterogeneity. In particular we show that the introduction of the unobserved heterogeneity is important, but the assumption of its functional form is not. The case of a non parametric specification of the random effect identifies two different groups: the “movers”, i.e. women who make the transition faster than the “stayers” and that are more family oriented.

In order to asses which is the wage level that captures the largest part of the variance of the unobserved heterogeneity, we interact the random effect with different socio-economic groups. Women with relatively low and high wages are the typology of women for which it is more difficult to explain their attitude towards fertility decisions without considering other unobserved characteristics.

1 Introduction

It is a widely held view that postponement in fertility leads to a general decline in the total fertility rate. In other words, the longer a woman delays the onset of her child bearing career the lower is her completed fertility. This has been documented in various studies and the pattern has been accepted as an empirical regularity across cohorts and countries (see for instance Billari and Kohler 2000; Bumpass and Mburugu 1977; Bumpass et al. 1978; Marini and Hodson 1981). This regularity has sparked considerable research into the determinants behind the timing of first births, arguing that a greater understanding of the driving forces behind the onset of the child bearing career, also informs us about the determinants of completed fertility. One of the important findings from this literature is that women with higher education or higher earnings potential tend to postpone first birth. However, the fact that women with higher education tend to delay first birth does not necessarily imply that they have lower completed fertility, or at least it is difficult to predict its exact extent. It is not unreasonable to think that the very same women who delayed the onset of childbearing, will also have an incentive to accelerate the second and third birth events in order to achieve their desired fertility level. This is commonly referred to as the recuperation effect on fertility. Unfortunately the identification of postponement and recuperation effects on total fertility is not trivial. Whereas both will depend on observed characteristics, they will also depend on unobserved characteristics. Thus considerable caution is needed if one wants to establish the determinants and extent of the postponement and recuperation effects respectively. In light of these difficulties, the aim of this paper is twofold. First we are interested in estimating the impact of womens social and economic characteristics on the decision to postpone fertility. Second, given differences in postponement, an interest lies in estimating the extent to which women with different characteristics are able to recuperate fertility within the first, second and third parities. The analysis enables us to assess to what extent socio-economic status might be driving the underlying low fertility in Italy. Our analysis is based on data from Italy, which was one of the first countries to experience lowest low fertility levels (i.e. TFR less than 1.3). In 1995 Italian TFR fell to an all time low of 1.19, a development that has been followed by a general increase in the mean age at first birth. In order to estimate postponement and recuperation effects we specify a multi-spell random effect hazard model of the first, second and the third births. The model allows for unobserved heterogeneity, and we test to what extent the assumption about its functional form has any impact on the overall parameter estimates. Socio-economic status of women is inferred from the Survey of Italian Households Income and Wealth, whereas the model of fertility is based on the Italian Labour Force Survey.

The paper is organized as follows. In Section 2 we review the literature on the postponement effect focussing on the Italian context. Sections 3 and 4 describe methodological issues, including the surveys and the statistical model. In section 5 we discuss the empirical evidence concerning determinants of first, second and third births. Section 6 concludes.

2 Postponement and recuperation of fertility in Italy

Over the last two decades, the mean age at first birth increased substantially in many countries, a rise that has been linked to a significant decline in the observed total fertility rate. In Italy, mean age at the first birth (MAFB) was 25 years in 1980, 26.9 in 1990, 28.0 in 1995, 28.4 in 1996 and 28.7 in 1997 (Council of Europe 2004). During the same period the Total Fertility Rate (TFR) declined from 2.2 in 1980 to 1.19 in 1995 (see table 1) which is below the threshold of 1.3 children per woman that Kohler et al. (2002) define as 'lowest-low fertility'. It seems therefore clear that the increase in mean age at first birth is associated with a substantial decline in the observed total fertility rate.

There are many explanations for why such a postponement has taken place. A prominent theory is that increased returns to female education and labour market participation makes childbearing more costly. Moreover, as women increase their participation in higher education, a delay of the onset of childbearing seems inevitable (Brewster and Rindfuss 2000; Cigno 1994). Gustafsson (2001) suggests that the delay is a likely consequence of the increasing presence of women in the labour force and of their level of human capital accumulation. This is particularly true of Italy. As table 1 shows, the female employment rate increased during the 1990s, starting from a value of 35.4 percent in 1994 and reached 39.6 percent in 2000. During the same period, the percentage of women (aged from 20 to 24) having completed at least secondary school increased sharply from 58.1 in 1993 to a 73.8 in 2000. A related issue concerns increased difficulties in re-conciliating labour force participation and childbearing. Certainly, as women increase their commitment to work and educational attainment, child bearing becomes more strenuous if there is no follow-up in terms of availability of external child care. A further factor concerns lack of available and affordable housing. An interesting feature of Italian family dynamics is that young individuals are increasingly late in leaving the parental home, possibly due to lack of financial resources or affordable housing as Duce

Table 1: Education, Total Fertility Rate and women participation in labor market in Italy (1994-2004).

	1993	*1994*	*1995*	*1996*	*1997*	*1998*	*1999*	*2000*
Education	58.1	59.9	62.7	64.8	66.7	70	70.4	73.8
Employment Rate	35.8	35.4	35.4	36	36.4	37.3	38.3	39.6
TFR	1.25	1.21	1.18	1.2	1.22	1.19	1.22	1.24

Source: Eurostat. Fertility rates: 1998 and 1999 are provisional values and 2000 is an estimated value. Education is the percentage of the female population aged 20 to 24 having completed at least upper secondary education. The female employment rate is calculated by dividing the number of women aged 15 to 64 in employment by the total female population of the same age group.

Tello (1995) suggests. The process of setting up ones dwelling can take several years after entering in the labor market. Additionally, Aassve et al. (2002) argue that the inherent uncertainty of the labor market perpetuates the pattern of staying at home with parents until a relatively high age, again having an effect on timing of marriage and the onset of child bearing.

It has been demonstrated that the youth labour market in Mediterranean Countries are considerably worse than many other European countries. Low wage and a high prevalence of fixed term job contracts dominates, discouraging many young individuals from entering the labour market. Instead, entering higher education has become more popular and attractive. Certainly higher education has become an important way in which individuals can increase their chance of finding a stable job with a sufficient wage.

The empirical evidence on postponement and recuperation effects in Mediterranean countries based on micro level data are still limited. Using a simple regression framework on individual data, Kohler et al. (2002) find that in Italy the postponement effect is relatively high and it implies a relative reduction of completed fertility between 2.9 and 5.1 percent for each one-year delay in the onset of motherhood. For cohorts 1952-1958 they estimate a postponement effect equal to 2.9 percent, a level which is substantially above the levels found for Denmark and Sweden, two countries where there is evidence of strong recuperation. Applying an Heckman type sample selection model (Heckman 1979), Billari and Borgoni (2004) showed that the postponement effect is stronger in Italy than all other 'Southern European' lowest-low fertility countries. Overall they suggest that heavy postponement of the first birth and relatively low progression to higher level births is a common feature of these countries. Kohler et al. (2002) suggest that the lowest-low fertility in

Italy is associated with a low progression probability to parities higher than the first, and that any recuperation effects are weak, and certainly incomplete.

One issue that complicates the analysis of postponement and recuperation is that it might be driven by unobserved factors. Marini and Hodson (1981) underline that only a part of the observed negative association between postponement and completed fertility is due to a causal mechanism; another part of the effect may be spurious. There might for instance be systematic differences in individuals preferences for family size. If such preferences are not controlled for then estimates will be inconsistent and biased (Kohler et al., 2002). A strong preference for larger family size will naturally accelerate the first birth. But if such preferences are unobserved, then the impact of age at first birth on total fertility becomes overestimated. An additional source of unobserved heterogeneity may be differences in fecundity. Couples who have their first birth earlier may do so simply as a result of higher fecundity, whereas women with lower fecundity may conceive later. Importantly, these sources of heterogeneity might carry an effect onto subsequent births, leading to incorrect estimates of completed fertility. Yet another source of unobserved heterogeneity might be differences in ability which affects the incentives to invest in education and labour market skills. This in turn may affect age-related costs of postponing first birth (Kohler et al. 2000). As will be clear from the next section, our data lack information about marriage and therefore information about husbands, which is another source of unobserved heterogeneity.

To overcome the estimation problems caused by unobserved factors, Kohler et al. (2002) use Danish data on female monozygotic twins to estimate the postponement effect in a linear model for the logarithm of the total number of children. Nevertheless, there are two problems with this approach. First, a technical problem: the analysis on the logarithm of the total number of children is possible only when women are past or very close to the end of childbearing ages. Second, data on twins exist only in very few countries, and the postponement effect might depend on societal factors that vary across nations (Kohler et al., 2002; Billari and Borgoni, 2005).

An alternative way to overcome these issues is to specify a parametric hazard regression model that explicitly controls for the influence of observed and unobserved heterogeneity. It is well known that when analyzing the timing of life-course events, failure to control for sample heterogeneity may produce severe biases in structural estimates of duration models (see for instance Vaupel et al. 1979; Heckman and Singer 1984; Lancaster 1992). The choice of the heterogeneity distribution might also matter. Heckman and Singer (1984) argue for instance that an incorrect assumption on the distribution of the unobserved heterogeneity may cause serious parameter bias, and suggest as a result the use of a flexible non-parametric distribution of unobserved heterogeneity. In this paper, we specify a hazard regression model of first, second and third births, estimated in a joint framework. The model is estimated with different assumptions concerning the heterogeneity component, and we assess to what extent different assumptions impacts the parameter estimates of interest.

3 Data

The socio-economic status is measured by a womans predicted earnings potential. Unfortunately, none of the Italian data sets currently available contains information on both fertility histories and measures of their opportunity cost (i.e. their wage and income). The approach we take is similar to that of Rondinelli et al. (2006) in which information from the The Bank of Italy's SHIW (Survey of Italian Households' Income and Wealth, 2002), is merged with information from the labour force survey. The benefit of the SHIW is that it contains detailed information on earnings and income. A serious disadvantage is that the sample size is small, a drawback that becomes particularly critical for the estimation of third birth events. Consequently we use the SHIW survey to estimate wage and earnings equations, where predicted wages are matched with individuals in the ISTAT (Labor Force Survey, 2003) data set. A detailed description on how income is estimated is given in Rondinelli et al. (2006). In brief, a Tobit augmented log-wage equation is estimated as follows:

$$\hat{\omega}_{it} = \hat{\beta}_0 + \hat{\beta}_1 \text{age}_{it} + \hat{\beta}_2 (\text{age})^2_{it} + \hat{\beta}_3 \sum_{j=1}^{8} \text{education}_{itj} + \hat{\beta}_4 \sum_{j=1}^{20} \text{region}_{itj} \tag{1}$$

where $\hat{\omega}_{it}$ denotes the log hourly predicted wage for the i-th woman at time t, $t = 1983, ..., 2003$, age_{it} is the age of the i-th woman at time t, $(\text{education})_{itj}$, for $j = 1, ..., 8$, are eight dummy variables for different levels of education attained from the i-th woman at time t and $(\text{region})_{itj}$, for $j = 1, ..., 20$, are twenty dummy variables, one for each of the Italian regions. In line with the economics literature, wage increases with age but at decreasing rate. Education is an important driver of wage levels; the higher the education level, the higher the wage. The hourly wage does not exhibit very large variability across different regions of Italy, but there is a clear North/South divide. This difference is caused by prevalence of public jobs and the percentage of women not working.

The woman is taken as the unit of analysis and linked with her co-resident children at the moment of the interview. In order to ensure that the recorded children are the only ones of the

Table 2: Sample size of women at risk of first, second and third birth.

	Women at Risk of having a child of parity j	Women having a Child of parity j
First Birth $j = 1$	34224	25281 (73.86%)
Second Birth $j = 2$	25275	14334 (56.71%)
Third Birth $j = 3$	14508	2506 (17.27%)

Notes: Our calculations from Labor Force Survey (ISTAT, 2003). Women having twins as first births are not in the risk set of second birth, but they are directly at risk of a third birth.

mother, we limit the analysis to only include women who are 40 or less in 2003 and we reconstruct retrospectively their fertility histories going back to 1983. We also drop all households where we were unable to link children with mothers (i.e. male head of the household with no wife and all single men). Note that we are unable to use information of husbands since we only know the womens marital status in 2003. Thus, marital histories cannot be reconstructed.

Following this approach we end up with a sample of 34,914 women, for which we have information about their childbearing career. Every woman is right censored in 2003 or if she experience all the three births at time, say t, we observe her until that time t. If she gives a birth of parity j in time T she is at risk for a new birth since $T + 1$ and until she experience a new birth $j + 1$ or, if she does not, until 2003. All women are followed from age 15, which we assume is the start of her childbearing career. In table 2 we report basic descriptions of the sample across different parities.

4 The Model

We present two versions of the model. The first assumes that unobserved heterogeneity can be captured by a normally distributed error term. The second assumes a non-parametric specification for the unobserved women-specific characteristics. The second version is the similar to Heckman and Singer (1984), but differently from that approach we specify the baseline hazard to follow a piecewise linear spline specification.

We model the decision to have the first, second and third birth as a multiple spell duration model:

$$H^*_{ijt} \quad = \quad \gamma_j \left(T_j(t) W_{ijt}\right) + \beta_j^{'} X_{ijt} + \mu_i + \epsilon_{ijt} \tag{2}$$

where H^*_{ijt} indicates the propensity of the $i-th$ woman to give $j-th$ birth ($j = 1$, 2, 3 for first, second and third birth) at time t, $T_j(t)$ is a duration spline for parity j, W_{ijt} indicates the wage while X_{ijt} captures observed characteristics other than wage for the i-th woman at time t for parity j, μ_i represents the random effect specific for each woman and ϵ_{ijt} is a residual error term distributed as a logistic with zero mean and variance $\frac{\pi^2}{3}$. The most aggregated level is the woman, and therefore the unit of analysis. Since each woman might have more than one child, we can consider parities. $j = 1$ if the woman is at the risk of having the first child, $j = 2$ if birth has taken place and she is at risk of having the second, and $j = 3$ if the second birth has taken place and she is at risk of having the third, and so on. The most disaggregated level is time periods $t = 1, ..., T$, and all time varying variables are given at this level. From (1) it is clear that if $H^*_{ijt} < 0$, then the woman does not give the jth birth and $H_{ijt} = 0$. If $H^*_{ijt} \geq 0$ she experiences the $j-th$ birth as $H_{ijt} = 1$.

Duration dependence for first, second and third births are modeled separately. Importantly, womens wage levels (W_{ijt}) are interacted with the duration splines ($T_j(t)$). This means that the resulting parameter estimates gives us direct measures of the extent to which women with different wage levels may postpone the first birth, and possibly recuperate through second and third births. Within each parity order we stratify the wage variable into low, medium, high and very high wage. The stratification was chosen according to the 25th, 50th and 75th percentile of the wage distribution. Other observed characteristics at the woman and child level (across time) are captured by X_{ijt}, and this includes region, age at the first birth, age at the second birth. The subscript of β_j signifies that women living in the same region, having a first birth at the same age may behave differently depending on the parity considered.

Unmeasured characteristics (μ_i) are assumed to be woman-specific and constant across time and parity orders. An important question in this analysis concerns the amount of heterogeneity captured by the error term μ_i. Given our data source, there are certainly many reasons why we could expect it to be important. For instance, the lack of data on marriage histories prevents us from reconstructing retrospective marriage histories, which in effect leaves out any relevant information about husbands role in fertility outcomes.

We study the sensitivity of the model to parametric and non parametric specification for the distribution of the unobserved heterogeneity. We start by assuming a normal specification for the random effect, $\mu_i \sim N(0, \sigma_\mu^2)$, and compare this model to one without random effect. We then extend this parametric setting with a non-parametric one specifying two and three mass point. There is no closed form solution of the likelihood function for hazard models with random effects. The residual or the random effect is therefore integrated out using a numerical integration algorithm based on Gauss Hermite Quadrature (Abramowitz and Stegun, 1972). This algorithm selects a number of support points and weights such that the weighed points approximate a normal distribution:

$$\int_{-\infty}^{\infty} \phi(\epsilon) L(\epsilon) dx \approx \sum_{l=1}^{k} w_l x_l$$

where w_l and x_l are Gauss-Hermite weights and support point, respectively. The higher the number of support points the more accurate the approximation, but the slower the computation [1]. The Non Parametric Maximum Likelihood (NPML) is highly sensitive to starting values and estimation is difficult when the location of the mass points were specified arbitrary. Estimation is considerably easier when the unobserved heterogeneity is specified by the normal distribution. It is therefore convenient to estimate the model with normally distributed errors, and take these estimates as starting values for the non-parametric version. In the case of the non-parametric specification we can think to μ_i in terms of a "mover-stayer" structure [2]. The "movers" reflect individuals who, for some unobserved reason, make the transition faster than the "stayers". Because unobserved heterogeneity may arise from a number of sources, any specific interpretation is difficult, though in the next section we provide a tentative interpretation of the estimated masspoints.

Having estimated these models we offer an extension (2) in which the regressors are interacted with the unobserved heterogeneity term. For reasons will become clear in next section, the analysis is conducted when the unobserved heterogeneity term is specified parametrically (i.e. normal). In particular we estimate four models, one for each interaction of the normal random effect with a different wage level:

$$H^*_{ijt} \quad = \quad \gamma_j \left(T_j(t) W_{ijt} \right) + \beta_j^{'} X_{ijt} + \mu_i W_l + \epsilon_{ijt} \tag{3}$$

where W_l indicates wage levels, say $l = 1$ low, $l = 2$ medium, $l = 3$ high, $l = 4$ very high wage. With a variance decomposition we assess which socio-economic group that captures the largest amount of the unobserved heterogeneity. If we denote $\mu_i W_l$ a normal random effect u_{il} we get:

[1]In the case of the finite mixture Unobserved Heterogeneity we chose 10 integration points.

[2]This argument applies to the non-parametric specification of the random effect.

$$\mathbb{V}ar(u_{il}) = \mathbb{V}ar(\mathbb{E}((u_{il}|l)) + \mathbb{E}(\mathbb{V}ar(u_{il}|l)) \tag{4}$$

and because the random effect is assumed to be normally distributed with zero mean and variance to be estimated, the right hand side of (4) reduces to $\mathbb{E}(\mathbb{V}ar(u_{il}|l))$. More precisely:

$$\begin{aligned} \mathbb{E}(\mathbb{V}ar(u_{il}|l)) &= E_l(\sigma_l^2) \\ &= \sum_{s=1}^{4} \sigma_s^2 \, Pr(l = s) \end{aligned} \tag{5}$$

where $Pr(l = s)$ if $s = 1$ is the proportion of poor women in the sample. As a consequence, the part of variance captured by a low wage woman is going to be:

$$\frac{\sigma_1^2 \, Pr(l = 1)}{\sum_{s=1}^{4} \sigma_s^2 \, Pr(l = s)} \tag{6}$$

Next section presents the main results concerning the models introduced in (2) and (3) and we offer an explanation of the main income and recuperation effect together with the role played by the age at the first birth.

5 Results

We start by discussing the parameter estimates for first, second and third births respectively. We then assess the estimates when heterogeneity is included compared to when it is not. The model without unobserved heterogeneity is presented in column (1) of table (4), the estimates where unobserved heterogeneity is included and assumed normal is presented in column (2) in the same table, whereas the model with non parametric unobserved heterogeneity are presented in columns (3) and (4). Finally we summarise the results when wages are interacted with the heterogeneity term.

5.1 First Birth

From age 15 to 18 women of different wage groups are quite similar in terms of their likelihood of entering motherhood. It is from the age 18 and onwards the rate of first birth starts to diverge, and the pattern is clear: those with low wages have a considerably higher rate of entering motherhood compared to those with high wages. The difference reflects a clear postponement effect, in that those staying on in higher education (i.e. those with high predicted wages) tend to delay the

Figure 1: Estimated Duration Spline for First birth across different wage levels

onset of childbearing. The differences between wage groups are significant until age 32 where the hazard rates cross. From this age onwards, those with low wage have the lowest rate of entering motherhood.

Postponement and recuperation effects can be better viewed through the predicted survival curves. These are plotted in figure 2. The postponement effects are clear, as those with lower wages have a considerably steeper survival curve (i.e. they have the first birth earlier). However, the most remarkable feature of figure 2 is the very strong recuperation effect. By age 40 the proportion of women with high wages having had the first birth is almost the same as for women with low wages. It is worth bearing in mind that these are the predicted survival curves based on our parametric model. Also note that in our sample we have omitted women aged 40 and over, thereby leaving out many who are recorded as childless, which in turn explains why the predicted survival curve is close to zero at age 40.

5.2 Second Birth

Figure 3 plots the log-hazard for second birth. Here we see that women with very high predicted wages show a higher log-hazard from the beginning. However, the risk is only higher until 4 years after the first birth takes place, and after five years they have the lowest, whereas after 12 years

Figure 2: Estimated Spline-Survival Curves for First Birth across different wage levels

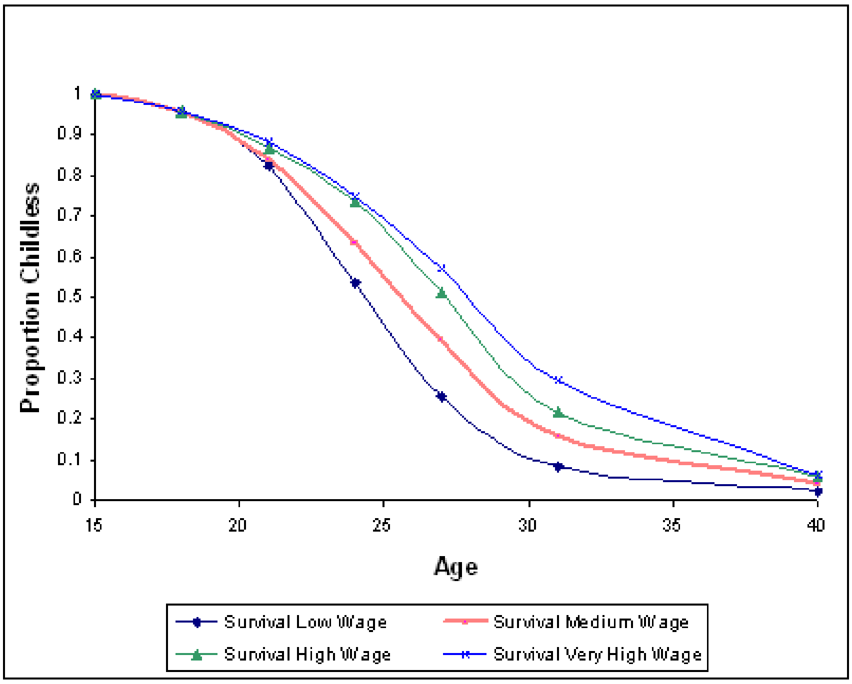
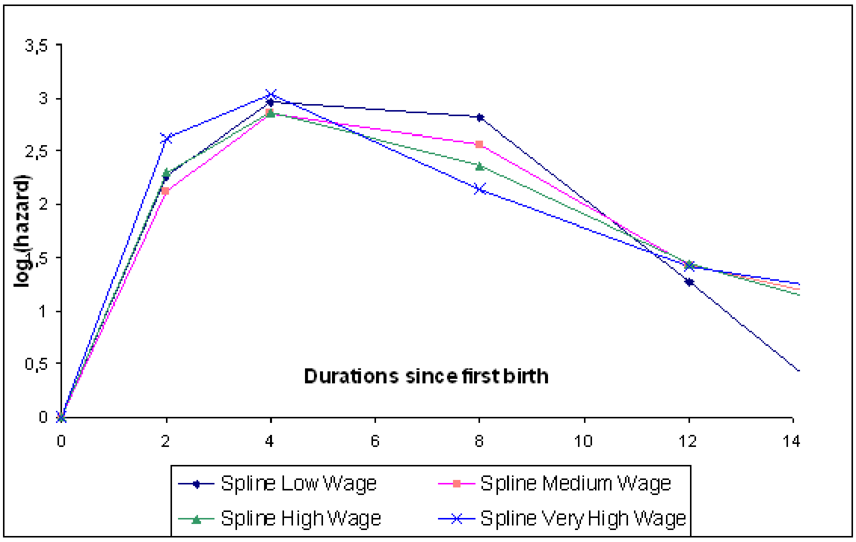


Figure 3: Estimated Duration Spline for Second birth across different wage levels



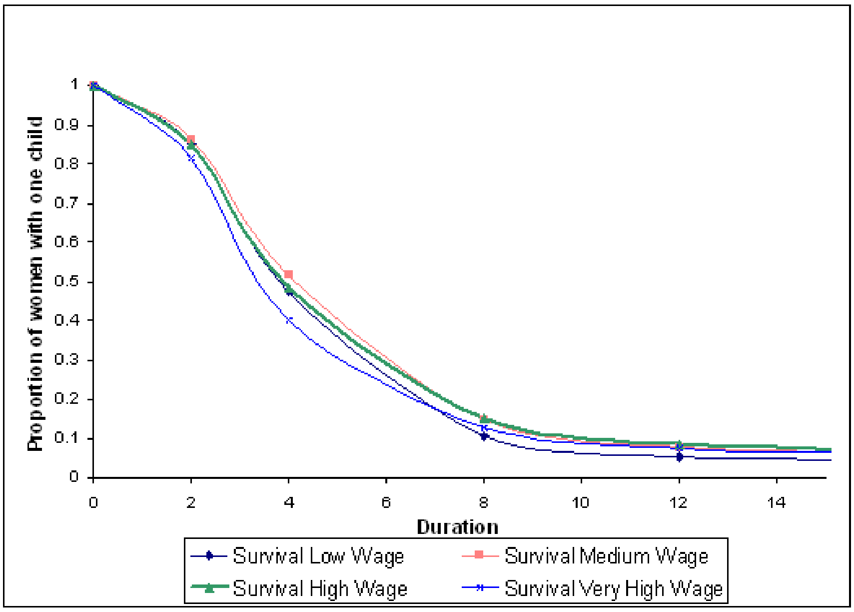
women with the lowest wage have the lowest risk of second births. Thus, the effect of wage is mixed in that the relative rank between in the groups (in terms of wage level) varies by duration. The fact that women with high wages have the highest log hazard in the beginning is consistent with the argument of Heckman [3] et al. (1990) who suggest that women with high wages tend to concentrate their fertility history in a shorter period of their life. In this sense, we observe here a recuperation effect among women with the highest wages. The pattern is clearly confirmed in figure 4 where the predicted survival curve for women with high wages lies below the other groups. After two years the proportion of those with highest wages not having another child is 0.81, whereas this proportion falls sharply to 0.39 three to four years after they entered motherhood. In summary, our results show that whereas those with high predicted wages tend to postpone the onset of childbearing, they also recuperate, not only through first birth, but also through the second. As was clear, the recuperation was not complete during parity one, but recuperation is close to complete once considering second birth. In other words, figure 4 underlines that the recuperation is delayed and only completed through the second parity.

Of course, the explanation is quite clear. For women to reach a higher economic status they need to invest longer in education, and therefore postpone the first birth. Once education is completed, they gradually recuperate compared to the other women. In order to recuperate completely they also need to accelerate second birth compared to the others. In this way they may also exploit the scale economies: having two children of similar age concentrates and possibly shortens the time needed away from work for the purpose of childrearing. Obviously, one can make the opposite argument: births occurring within shorter amount of time may result in an increase in physical and psychological costs in infant care (Bumpass et al. 1978).

In figure 5 we have plotted the predicted probability of having a second birth conditioning on the age of the first one. Age at the first birth has a negative effect on the pace of subsequent fertility: this effect is particularly strong during the second year following the first birth and persists (with lower probability) even after four years the first birth happened. The experience of early motherhood tend to be associated with an increase in the probability of a second birth, so that early fertility is associated with a rapid and subsequent fertility. For a woman with low predicted wage the probability of having a second birth two years after she gave the first birth and conditioned on the fact she had the first one when she was 25, approaches 0.54. However if another low wage woman had the first child when she was 35, the probability of giving a second birth in

[3] They apply this argument to third birth in Sweden

Figure 4: Estimated Spline-Survival Curves for Second Birth across different wage levels



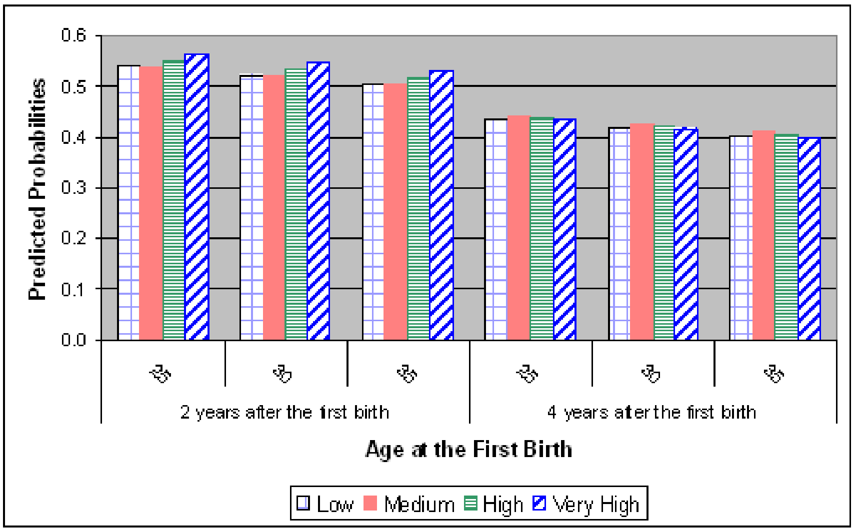
the two following years is lower (around 0.49). The probability of giving a second birth four years after a woman had the first one are 0.44, 0.41 and 0.39 if she gave the first birth at the age of 25, 30 and 35 respectively. In particular, for women having a second birth four years after she experienced the first one, there is a clear homogenous pattern of these probabilities across different wage levels. However a formal likelihood ratio test reject the null of no differences, suggesting there is an improvement in the model if we divide the two categories and estimate them separately [4].

5.3 Third Birth

The spline log hazard plotted in figure 6 suggests that for short durations, i.e. within the forth year since the second birth, a third birth is less dependent on wage level. The only exception is women with very high income and who conceived in the interval immediately following the second birth. However, for very long durations the scenario changes and women with low wages remain at

[4]More formally, we find that when collapsing women with low and medium wages into one category and comparing the model with the one reported in column (2) of table (4), the difference in the deviance statistics (2*134.6) exceeds the 0.1 percent critical value of a χ^2 distribution with 15 degrees of freedom (37.69). A similar argument applies if we collapse women of high and medium wage: the deviance statistics assumes the value of 2*151.75 that again exceeds the mentioned percentile of a χ^2 distribution with 15 degrees of freedom. When considering into one category women with high and very high wages the deviance is equal to 2*87.27 and the rejection of the null applies again.

Figure 5: Probability of a Second Birth across different wage levels and conditioning on age at the Firth Birth



higher risk of experiencing a third birth given they have already had the second one. The survival curves in figure 7 show that there is little difference between the different wage groups, apart from an evident distinct pattern after four years the woman conceive the second birth. At that time there is a high proportion of women with medium wage remaining with two children, while the proportion of those with very high income and two children is smaller. It seems clear therefore that socio-economic factors do not play any important role in explaining why women choose to have third child.

We have so far considered the role of socio-economic factors, measured through their predicted wages. When considering the other variables, we find that women living in the South have a higher rate of childbearing in all parities. The Center and North are very similar and the estimated coefficients with the interaction region and wages for the Center is very close to zero. Among women living in the North, those with high wages have a higher risk of second and third births. This is in line with the argument of Ermish (1989) who suggest that women with very high income are more able to afford external childcare, and thereby generating higher rates of childbearing. This argument applies mostly to second and third birth, while for first birth the introduction of the random effect captures parts of the effect.

Figure 6: Estimated Duration Spline for Third Birth across different wage levels

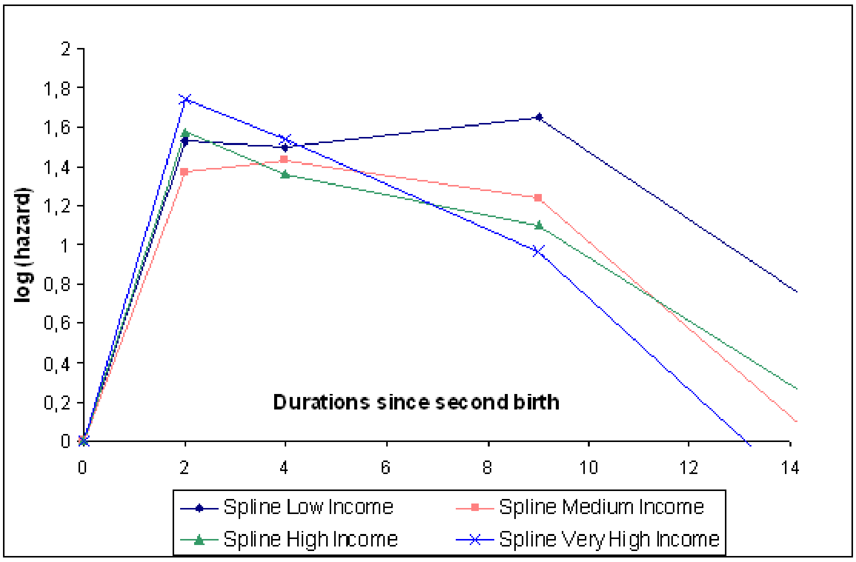
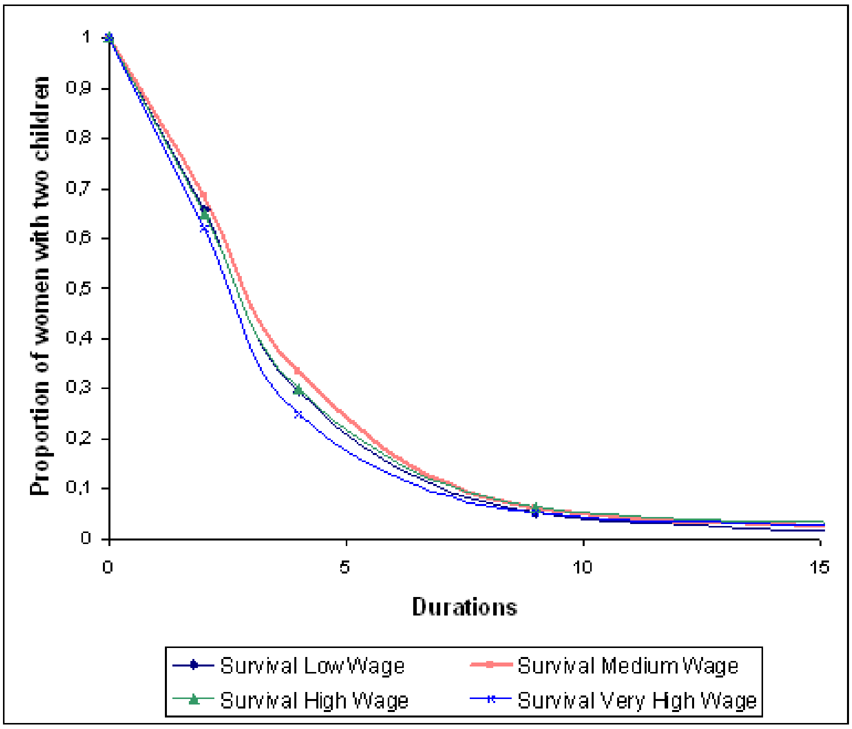


Figure 7: Estimated Spline-Survival Curves for Third Birth across different wage levels



5.4 Unobserved Heterogeneity

The main consequence from introducing a random effect on first birth is to increase the estimated parameters for women in the low and medium wage groups who make the transition after age 24. For those entering motherhood after 27 we see an impact for those having high and very high wages. For the transition to second birth the effect of the random effect is to increase the estimated parameters four to eight years after the first child is born. This is the case for low, medium and high wage women. Women with very high income, instead, experience this effect after two to four years they enter into motherhood. This is a consequence of the fact that women with very high income tend to have the second birth rapidly after they had the first. The random effect also captures the effect of postponed marriage, since after marriage they tend to concentrate their childbearing in a shorter time span. The main consequence of introducing the random effect for third births is in the intercept of the process as column (2) of table (4) shows.

The random effect may explain the relative inconvenience for a woman to take time away from work when the previous birth happened in the past. For women with very high income, instead, unobserved factors could be linked to the higher likelihood of having another birth as soon as you had the first one. Without particularly focussing on socio-economic features, Marini et al. (1981) shows that the spacing of the first birth have a causal effect on the spacing of the second.

As pointed out at the beginning of the section, the functional form of the unobserved heterogeneity does not impact on the estimated coefficients even when a three mass point specification is assumed. Despite this, the model is sensitive to the introduction of the random effect. The variance of the unobserved heterogeneity is 0.53 when it is modeled as a normal distribution. When we estimate the NPML with two mass points we find that the two groups are almost identical (0.52 and 0.48). The variance, however, do not differ much from the normal case (0.57 for two mass points). The algorithm also converges with three mass points, finding one large group (65 percent), one medium group (32 percent) and one very small group (3 percent). The variance explained by a three mass point non parametric finite mixture is the same as the one with two mass points.

The interpretation of the mass points, of course, is difficult and any explanation is merely tentative. In applications of fertility behaviour they are often taken to reflect differences in family orientation. Thus women with a strong family orientation (more likely to marry and have children) would be associated with a positive masspoint ("movers"). The group with a negative masspoint (the "stayers") can be thought of women with a higher career orientation, as it is natural to assume

Table 3: Estimated Variance of the Random Effect when interacted with different wages levels.

Coefficient	Normal Random Effect		$Pr(l = s)$
	(1)		(2)
Without Interaction	0.5323***		
	(0.034)		
Low Wage	0.343***	$s = 1$	0.25
	(0.047)		
Medium Wage	0.186**	$s = 2$	0.25
	(0.084)		
High Wage	0.384***	$s = 3$	0.25
	(0.050)		
Very High Wage	0.222**	$s = 4$	0.25
	(0.096)		

Notes: Estimates of the other covariates included in model (3) are omitted but are not significantly different from the one showed in table 4. We estimate four separated models ($s = 1, ..., 4$). Coefficient indicate the level of wage interacted with the random effect. Column (1) report the estimates of the standard errors of the random effect for the related model. $Pr(l = s)$ for $s = 1, ..., 4$ is the proportion of women with low, medium, high and very high wage respectively. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

that have a lower rate of marriage and childbearing as a result. Of course, it is also possible that the masspoints somehow reflect our omission of the husband's wages as covariates in the fertility process.

5.5 Variance Decomposition

We now extend this model as suggested by (3). In particular we would like to asses which wage level captures the largest part of the variance of the random effect. To this extent we estimate four separated models which differ by the interaction of the random effect with a particular wage level (i.e. socio-economic group) (see table 3). More precisely the amount of explained variance is 0.302, 0.163, 0.33 and 0.195 for the groups of women with low, medium, high and very high income, respectively. This implies that women with relatively low and high wages are the typology of women for which it is more difficult to explain their attitude towards fertility decisions without considering other unobserved characteristics.

A tentative interpretation of this result can be the role of a childcare availabilities as suggested by Ermisch (1989). To this extent women with high wages are more likely to have children because they can afford external childcare. Women with low wages, instead, have more children because of their low opportunity cost and they are more family oriented. In this scenario only those with medium and very high wages have less children. The former because they cannot afford external childcare, the latter because they are highly career oriented. As a consequence, the interacted wage random effect could capture the remaining effect of the socio-economic environment not entirely explained by wage.

6 Conclusions

The focus of this paper has been to investigate socio-economic differences in delay and recuperation of childbearing in Italy, a country that is suffering from what is termed the lowest-low fertility. In order to do so we have combined information from the Survey of Italian Households Income and Wealth and the Italian Labour Force Survey. The former is used to collect information about womens socio-economic status, measured in terms of their predicted wages, whereas the latter has provided us with sample sizes ensuring safe estimation of birth parities. The approach is based on a hazard regression, whereby estimation of first, second and third births is done jointly. As a result we have been able to control for individual specific unobserved heterogeneity for which we have experimented with alternative assumed distribution functions.

Our main finding is that there are strong differences in the onset of childbearing or the timing of first birth. Women with high wages delay this transition considerably compared to women with low predicted wages. This is not unexpected as the strongest predictor behind earnings is educational attainment. Thus women with high earnings spend longer time in education, and possibly in the labour market, before they start their childbearing career. However, we also observe a strong recuperation effect, and by the age of 40 high earning women have caught up with low earning women almost completely. The recuperation of high earning women continues into the progression of second birth. Interestingly there are no strong socio-economic differences in terms of progression to third births. The result is highly interesting, since it suggest that any delay in child bearing due to higher predicted earnings, cannot explain the underlying low fertility levels in Italy. Other forces are at play.

Our analysis has also provided a detailed sensitivity analysis of the possible roles played by the assumptions imposed on the statistical model. We show that, though the introduction of unobserved heterogeneity is important, the assumption of its functional form is not. This is most likely a result of the fact that the baseline hazard is given a flexible functional form, and that predicted wages are interacted with the unobserved heterogeneity term.

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Table 4: Estimated Coefficients for First, Second and Third Birth without Random Effect, with Normal Random Effect and a non parametric specification of the Unobserved Heterogeneity with two and three Mass Points.

	No Random Effect	Normal Random Effect	Two Mass Points	Three Mass Points
First Birth	(1)	(2)	(3)	(4)
Constant	-4.5360 ***	-4.6611 ***	-4.3643 ***	-4.7240 ***
	(0.0754)	(0.0774)	(0.1272)	(0.2390)
Spline1* Low Wage	0.2570 ***	0.2636 ***	0.2615 ***	0.2644 ***
	(0.0318)	(0.0319)	(0.0319)	(0.0320)
Spline2* Low Wage	0.5069 ***	0.5177 ***	0.5142 ***	0.5205 ***
	(0.0197)	(0.0201)	(0.0200)	(0.0201)
Spline3* Low Wage	0.2039 ***	0.2412 ***	0.2389 ***	0.2442 ***
	(0.0194)	(0.0204)	(0.0204)	(0.0205)
Spline4* Low Wage	0.0734 ***	0.1210 ***	0.1248 ***	0.1330 ***
	(0.0255)	(0.0267)	(0.0273)	(0.0277)
Spline5* Low Wage	-0.0491	-0.0090	-0.0105	0.0139
	(0.0353)	(0.0368)	(0.0378)	(0.0410)
Spline6* Low Wage	-0.2208 **	-0.1980 *	-0.2055 *	-0.1831
	(0.1071)	(0.1101)	(0.1090)	(0.1126)
Spline1*Medium Wage	0.3272 ***	0.3351 ***	0.3344 ***	0.3379 ***
	(0.0321)	(0.0322)	(0.0322)	(0.0323)
Spline2*Medium Wage	0.3007 ***	0.3145 ***	0.3111 ***	0.3173 ***
	(0.0214)	(0.0217)	(0.0216)	(0.0217)
Spline3*Medium Wage	0.1864 ***	0.2090 ***	0.2056 ***	0.2107 ***
	(0.0171)	(0.0177)	(0.0176)	(0.0177)
Spline4*Medium Wage	0.1267 ***	0.1602 ***	0.1613 ***	0.1640 ***
	(0.0186)	(0.0194)	(0.0197)	(0.0197)
Spline5*Medium Wage	0.0235	0.0676 ***	0.0704 ***	0.0856 ***
	(0.0216)	(0.0228)	(0.0238)	(0.0254)
Spline6*Medium Wage	-0.1973 ***	-0.1659 ***	-0.1736 ***	-0.1454 ***
	(0.0437)	(0.0447)	(0.0453)	(0.0496)
Spline1*High Wage	0.3410 ***	0.3507 ***	0.3506 ***	0.3574 ***
	(0.0374)	(0.0376)	(0.0376)	(0.0378)
Spline2*High Wage	0.0590 *	0.0781 **	0.0747 **	0.0791 **
	(0.0315)	(0.0317)	(0.0316)	(0.0317)
Spline3*High Wage	0.2849 ***	0.2963 ***	0.2943 ***	0.2980 ***
	(0.0198)	(0.0202)	(0.0201)	(0.0202)
Spline4*High Wage	0.2121 ***	0.2409 ***	0.2392 ***	0.2428 ***
	(0.0163)	(0.0170)	(0.0170)	(0.0171)
Spline5*High Wage	0.0696 ***	0.1083 ***	0.1107 ***	0.1181 ***
	(0.0136)	(0.0145)	(0.0153)	(0.0157)
Spline6*High Wage	-0.1886 ***	-0.1642 ***	-0.1644 ***	-0.1489 ***
	(0.0228)	(0.0234)	(0.0242)	(0.0258)
Spline1*Very High Wage	0.2026 **	0.2140 ***	0.2172 ***	0.2217 ***
	(0.0807)	(0.0809)	(0.0809)	(0.0811)
Spline2*Very High Wage	0.2724 ***	0.2868 ***	0.2821 ***	0.2901 ***
	(0.0848)	(0.0849)	(0.0849)	(0.0850)
Spline3*Very High Wage	0.1386 ***	0.1576 ***	0.1548 ***	0.1596 ***
	(0.0306)	(0.0309)	(0.0308)	(0.0309)
Spline4*Very High Wage	0.1639 ***	0.1854 ***	0.1830 ***	0.1869 ***
	(0.0174)	(0.0178)	(0.0177)	(0.0178)
Spline5*Very High Wage	0.1285 ***	0.1591 ***	0.1604 ***	0.1635 ***
	(0.0103)	(0.0111)	(0.0115)	(0.0116)
Spline6*Very High Wage	-0.1091 ***	-0.0823 ***	-0.0800 ***	-0.0717 ***
	(0.0119)	(0.0124)	(0.0132)	(0.0139)

(continued)

	No Random Effect	Normal Random Effect	Two Mass Points	Three Mass Points
First Birth	(1)	(2)	(3)	(4)
Center	-0.3596 ***	-0.4114 ***	-0.4103 ***	-0.4255 ***
	(0.0221)	(0.0253)	(0.0257)	(0.0270)
North	-0.4159 ***	-0.4764 ***	-0.4754 ***	-0.4914 ***
	(0.0202)	(0.0231)	(0.0234)	(0.0245)
Center*Wage	0.0481 ***	0.0272	0.0253	0.0186
	(0.0186)	(0.0204)	(0.0206)	(0.0214)
North*Wage	0.0536 ***	0.0328 *	0.0310 *	0.0235
	(0.0153)	(0.0168)	(0.0172)	(0.0181)
Second Birth				
Constant	-3.1991 ***	-3.8636 ***	-3.5397 ***	-3.9627 ***
	(0.0956)	(0.1343)	(0.1654)	(0.2522)
Spline1* Low Wage	1.1045 ***	1.1333 ***	1.1254 ***	1.1388 ***
	(0.0399)	(0.0407)	(0.0405)	(0.0408)
Spline2* Low Wage	0.2916 ***	0.3486 ***	0.3381 ***	0.3490 ***
	(0.0243)	(0.0258)	(0.0259)	(0.0261)
Spline3* Low Wage	-0.0864 ***	-0.0365 *	-0.0317	-0.0362 *
	(0.0192)	(0.0204)	(0.0209)	(0.0211)
Spline4* Low Wage	-0.3955 ***	-0.3870 ***	-0.3818 ***	-0.3817 ***
	(0.0514)	(0.0525)	(0.0529)	(0.0529)
Spline5* Low Wage	-0.4091 ***	-0.4008 ***	-0.4033 ***	-0.4025 ***
	(0.1444)	(0.1453)	(0.1455)	(0.1456)
Spline1*Medium Wage	1.0271 ***	1.0617 ***	1.0520 ***	1.0660 ***
	(0.0409)	(0.0417)	(0.0415)	(0.0418)
Spline2*Medium Wage	0.3271 ***	0.3646 ***	0.3562 ***	0.3658 ***
	(0.0285)	(0.0294)	(0.0294)	(0.0295)
Spline3*Medium Wage	-0.1098 ***	-0.0727 ***	-0.0725 ***	-0.0738 ***
	(0.0182)	(0.0192)	(0.0194)	(0.0194)
Spline4*Medium Wage	-0.3033 ***	-0.2838 ***	-0.2802 ***	-0.2825 ***
	(0.0383)	(0.0391)	(0.0393)	(0.0392)
Spline5*Medium Wage	-0.1302 *	-0.1102	-0.1088	-0.1063
	(0.0779)	(0.0792)	(0.0794)	(0.0796)
Spline1*High Wage	1.1214 ***	1.1519 ***	1.1405 ***	1.1576 ***
	(0.0412)	(0.0420)	(0.0418)	(0.0422)
Spline2*High Wage	0.2449 ***	0.2795 ***	0.2734 ***	0.2784 ***
	(0.0303)	(0.0313)	(0.0312)	(0.0313)
Spline3*High Wage	-0.1562 ***	-0.1268 ***	-0.1286 ***	-0.1294 ***
	(0.0193)	(0.0200)	(0.0201)	(0.0200)
Spline4*High Wage	-0.2416 ***	-0.2289 ***	-0.2288 ***	-0.2292 ***
	(0.0346)	(0.0352)	(0.0352)	(0.0351)
Spline5*High Wage	-0.1627 ***	-0.1419 **	-0.1411 **	-0.1388 **
	(0.0629)	(0.0637)	(0.0638)	(0.0637)
Spline1*Very High Wage	1.2816 ***	1.3097 ***	1.2997 ***	1.3160 ***
	(0.0429)	(0.0439)	(0.0439)	(0.0441)
Spline2*Very High Wage	0.1714 ***	0.2089 ***	0.2046 ***	0.2055 ***
	(0.0285)	(0.0294)	(0.0295)	(0.0295)
Spline3*Very High Wage	-0.2485 ***	-0.2227 ***	-0.2236 ***	-0.2250 ***
	(0.0202)	(0.0209)	(0.0209)	(0.0209)
Spline4*Very High Wage	-0.1953 ***	-0.1822 ***	-0.1826 ***	-0.1831 ***
	(0.0386)	(0.0392)	(0.0392)	(0.0391)
Spline5*Very High Wage	-0.1017 *	-0.0784	-0.0775	-0.0741
	(0.0594)	(0.0605)	(0.0606)	(0.0605)

(continued)

Second Birth	No Random Effect (1)	Normal Random Effect (2)	Two Mass Points (3)	Three Mass Points (4)
Age at the First Birth	-0.0315 ***	-0.0133 ***	-0.0140 ***	-0.0126 ***
	(0.0027)	(0.0040)	(0.0041)	(0.0042)
Center	-0.4483 ***	-0.5407 ***	-0.5393 ***	-0.5405 ***
	(0.0298)	(0.0349)	(0.0354)	(0.0358)
North	-0.4764 ***	-0.5824 ***	-0.5772 ***	-0.5802 ***
	(0.0268)	(0.0320)	(0.0325)	(0.0328)
Center* Wage	-0.0666 **	-0.0824 **	-0.0900 ***	-0.0811 **
	(0.0297)	(0.0324)	(0.0324)	(0.0325)
North* Wage	0.1194 ***	0.1260 ***	0.1160 ***	0.1237 ***
	(0.0254)	(0.0272)	(0.0275)	(0.0276)
Third Birth				
Constant	-1.5592 ***	-2.4236 ***	-1.8454 ***	-2.6245 ***
	(0.2223)	(0.2547)	(0.2432)	(0.3525)
Spline1* Low Wage	0.7486 ***	0.7665 ***	0.7592 ***	0.7695 ***
	(0.0893)	(0.0898)	(0.0896)	(0.0901)
Spline2* Low Wage	-0.0298	-0.0174	-0.0257	-0.0097
	(0.0557)	(0.0562)	(0.0559)	(0.0566)
Spline3* Low Wage	0.0213	0.0302	0.0240	0.0355
	(0.0262)	(0.0264)	(0.0263)	(0.0267)
Spline4* Low Wage	-0.1876 ***	-0.1732 ***	-0.1775 ***	-0.1711 ***
	(0.0449)	(0.0451)	(0.0450)	(0.0452)
Spline1*Medium Wage	0.6737 ***	0.6862 ***	0.6785 ***	0.6941 ***
	(0.0916)	(0.0921)	(0.0918)	(0.0923)
Spline2*Medium Wage	0.0243	0.0284	0.0249	0.0308
	(0.0652)	(0.0657)	(0.0655)	(0.0663)
Spline3*Medium Wage	-0.0442	-0.0378	-0.0419	-0.0330
	(0.0323)	(0.0326)	(0.0324)	(0.0328)
Spline4*Medium Wage	-0.2346 ***	-0.2230 ***	-0.2268 ***	-0.2213 ***
	(0.0600)	(0.0604)	(0.0602)	(0.0605)
Spline1*High Wage	0.7891 ***	0.7879 ***	0.7843 ***	0.7968 ***
	(0.0917)	(0.0923)	(0.0920)	(0.0927)
Spline2*High Wage	-0.1133	-0.1078	-0.1110	-0.1044
	(0.0711)	(0.0716)	(0.0713)	(0.0719)
Spline3*High Wage	-0.0587 *	-0.0524	-0.0557	-0.0492
	(0.0345)	(0.0349)	(0.0347)	(0.0352)
Spline4*High Wage	-0.1767 ***	-0.1628 ***	-0.1677 ***	-0.1622 ***
	(0.0479)	(0.0485)	(0.0482)	(0.0488)
Spline1*Very High Wage	0.8739 ***	0.8707 ***	0.8690 ***	0.8779 ***
	(0.0919)	(0.0924)	(0.0922)	(0.0927)
Spline2*Very High Wage	-0.1049	-0.1019	-0.1037	-0.1003
	(0.0667)	(0.0671)	(0.0669)	(0.0673)
Spline3*Very High Wage	-0.1188 ***	-0.1138 ***	-0.1168 ***	-0.1105 ***
	(0.0376)	(0.0379)	(0.0377)	(0.0381)
Spline4*Very High Wage	-0.2484 ***	-0.2353 ***	-0.2395 ***	-0.2340 ***
	(0.0799)	(0.0803)	(0.0801)	(0.0806)

(continued)

Third Birth	No Random Effect (1)	Normal Random Effect (2)	Two Mass Points (3)	Three Mass Points (4)
Age at the Second Birth	-0.1172 ***	-0.0984 ***	-0.1082 ***	-0.0942 ***
	(0.0063)	(0.0072)	(0.0070)	(0.0078)
Center	-0.2893 ***	-0.3847 ***	-0.3387 ***	-0.4066 ***
	(0.0745)	(0.0785)	(0.0766)	(0.0814)
North	-0.2157 ***	-0.3032 ***	-0.2576 ***	-0.3285 ***
	(0.0664)	(0.0703)	(0.0684)	(0.0733)
Center* Wage	0.0482	0.0479	0.0452	0.0575
	(0.0743)	(0.0765)	(0.0752)	(0.0779)
North* Wage	0.1850 ***	0.1897 ***	0.1807 ***	0.2065 ***
	(0.0592)	(0.0609)	(0.0599)	(0.0622)
Random Effect				
Normal Random Effect		0.5323 ***		
		(0.0341)		
Masspoint 1			-0.7600	-0.7794
Masspoint 2			0.2514 ***	0.3770 **
			(0.0715)	(0.1561)
Masspoint 3				1.7348 ***
				(0.2713)
Probability 1			0.52	0.32
Probability 2			0.48	0.65
Probability 3				0.03
Log-Likelihood	-141651.62	-141610.44	-141614.47	-141605.72

Notes: Standard errors are shown in parentheses. Spline First Birth: Spline1 (age 15-18), Spline2 (age 18-21), Spline3 (age 21-24), Spline4 (age 24-27), Spline5 (age 27-31), Spline6 (age 31-40). Spline Second Birth (Duration from the First Birth): Spline1 (duration 0-2), Spline2 (Duration 2-4), Spline3 (Duration 4-8), Spline4 (Duration 8-12), Spline5 (Duration 12-26), Spline4 (age 31-40). Spline Third Birth (Duration from the Second Birth): Spline1 (duration 0-2), Spline2 (Duration 2-4), Spline3 (Duration 4-9), Spline4 (Duration 9-26). Reference Group for Region is South. Because we inserted an intercept in the model, when estimating a non parametric maximum likelihood with aML you need to fix one masspoint (we fixed the first one). Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.