Childbearing impeded education more than education impeded childbearing among Norwegian women

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In most societies, women at age 39 with higher levels of education have fewer children. To understand this association, we investigated the effects of childbearing on educational attainment and the effects of education on fertility in the 1964 birth cohort of Norwegian women. Using detailed annual data from ages 17 to 39, we estimated the probabilities of an additional birth, a change in educational level, and enrollment in the coming year, conditional on fertility history, educational level, and enrollment history at the beginning of each year. A simple model reproduced a declining gradient of children ever born with increasing educational level at age 39. When a counterfactual simulation assumed no effects of childbearing on educational progression or enrollment (without changing the estimated effects of education on childbearing), the simulated number of children ever born decreased very little with increasing completed educational level, contrary to data. However, when another counterfactual simulation assumed no effects of current educational level and enrollment on childbearing (without changing the estimated effects of childbearing on education), the simulated number of children ever born decreased with increasing completed educational level nearly as much as the decrease in the data. In summary, in these Norwegian data, childbearing impeded education much more than education impeded childbearing. These results suggest that women with advanced degrees have lower completed fertility on the average principally because women who have one or more children early are more likely to leave or not enter long educational tracks and never attain a high educational level.

Norway | birth rate | parity | hazard regression | reverse causality

It has been known for a long time that women who by, for example, age 40 have attained a high educational level have, on the average, had fewer children than women who have less education within the same society (1, 2). The causal mechanisms underlying this relationship are very complex. To illustrate, consider a woman who has reached a certain age a in the relatively early part of her reproductive period, when taking further education is still a highly relevant option. Her educational level and enrollment status at that time (E_a) and her number of children (F_a) probably affect her fertility within the next year (ΔF_a), for reasons not spelled out here. Conversely, her number of children (F_a) and her education (E_a) are likely to affect her enrollment and her chance of attaining a higher educational level within the year (ΔE_a).

In addition to causal effects of education and fertility on each other, common determinants of education and fertility may be partly responsible for any apparent effects of E_a on ΔF_a and for any apparent effects of F_a on ΔE_a that might be estimated from observations of E_a and F_a over the life course. For example, E_a is to a large extent a result of the individual's long-term educational goals, which in turn reflect factors such as parental resources, individual endowments, values, and whether the person has grown up in an urban environment with many schools and norms supporting long education. Her educational goals, in combination with her expectations about how a young child might inhibit her subsequent educational career (i.e., her ideas about effects of childbearing on education), probably also affect the woman's childbearing intentions. Furthermore, the resources and other factors behind her educational goals may influence fertility desires and actual fertility through a variety of channels, such as, for example, her partnership status.

A better understanding of the association between education and childbearing would have broad social importance. Better quantitation of the effects of education on fertility would make possible better projections of the level of human resources in the next generation and of the demographic consequences of the increases in education expected in coming decades. It would also inform arguments that intensified efforts to expand education in poor countries are one way to achieve lower fertility levels. Conversely, better knowledge of the effects of fertility on education would illuminate a potential determinant of education.

Some researchers have tried to identify causal effects of education on childbearing by using exogenous interventions in education (3–6). Others have tried to estimate a causal effect of childbearing (e.g., births to teenagers) on subsequent education (7–11). Our intention is not to add to that literature.

Instead, we will estimate effects of education on fertility and the reverse effects of fertility on education—ignoring the sociocultural determinants—and estimate through a simulation experiment how much each of them contributes to the relationship between a woman's achieved educational level at age 39 and the number of children she has had by that age. It is widely acknowledged that childbearing may affect subsequent education and that one should therefore be careful to draw conclusions about the importance of education for fertility on the basis of measurement of education at a high age (12–14). However, very little is known about the strength of this influence.

Results

When each woman's number of children was measured at the end of the year when the woman was 39 and the woman's education was measured October 1 of that year (i.e., 3 mo earlier), the average number of children per woman decreased with an increase in the woman's educational level (Fig. 1, filled diamonds, solid line).

Using detailed annual data (*Methods*), three dynamic year-to-year models were estimated for parity-specific birth hazards, educational attainment-specific educational progression hazards, and the probability of enrollment in the coming year. Three simulations were then based on these models (*Methods*) and the parameter values estimated for them (Table S1).

In the "realistic" simulation 1, which incorporated all estimated effects of childbearing on education and of education on childbearing, the average number of children at age 39 varied

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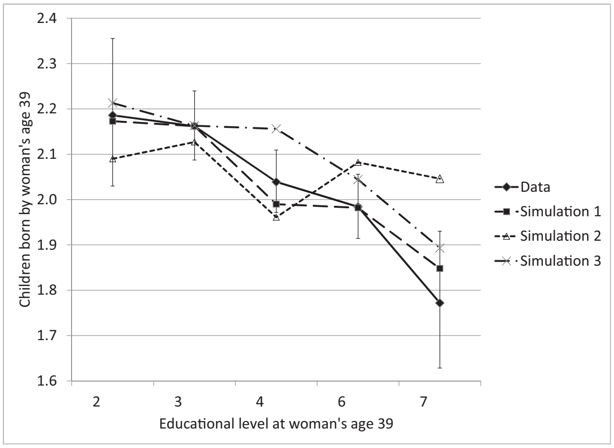

Fig. 1. Children born by woman's age 39 as a function of educational level at woman's age 39, according to data (filled diamond and solid line), simulation 1 (filled square and long dashed line), simulation 2 (open triangle and short dashed line), and simulation 3 (× and dashed line). Error bars around the data show 99% confidence intervals (*Methods*). Simulation 1: all parameters were estimated from the data. Estimated total fertility corresponded well with observation. Simulation 2: effects of fertility on education were set to zero; remaining parameters were estimated from the data. The declining trend of total fertility with increasing educational attainment largely disappeared from these predictions. Simulation 3: effects of education on fertility were set to zero; remaining parameters were estimated from the data. Estimated total fertility corresponded to observed total fertility much better than in simulation 2.

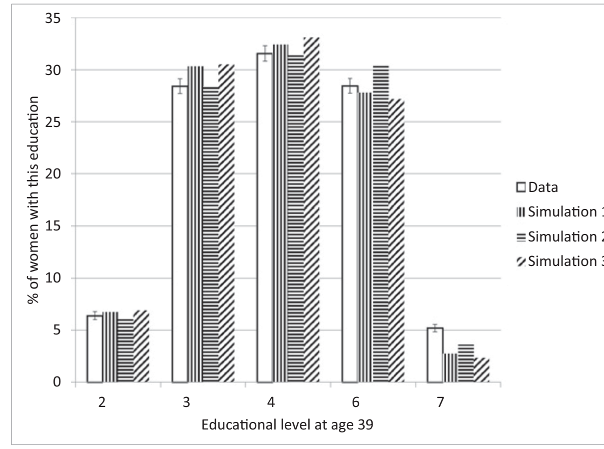

Fig. 2. Percentages of women with each educational level at age 39, according to data (white bars), simulation 1 (vertical lines), simulation 2 (horizontal lines), and simulation 3 (diagonal lines). Error bars around the data show 99% confidence intervals (*Methods*). Simulations are defined in the text and the legend of Fig. 1.

between 2.123 for women who had only compulsory schooling at that age (coded as level 2) and 1.798 among those with an advanced university degree (coded as level 7; see *Methods* for definitions of codes for all educational levels; Fig. 1, solid squares and long dashed lines). Numerical values in Figs. 1 and 2 are in Table S2. Thus, there was only slightly less variation in completed fertility across educational levels at age 39 in simulation 1 than in the data, where the corresponding numbers were 2.136 and 1.722.

For every educational level in Fig. 1, the average number of children per woman in simulation 1 fell within the confidence interval (CI) computed by each of the two methods of computing CIs. These calculations suggested that our models were able to reproduce reasonably well the observed data on the average number of children per woman at each educational level. Simulation 1 reproduced less well, but not badly, the observed percentages of women at each educational level at age 39 (Fig. 2).

The simulated percentage enrolled at some selected ages fell within the CIs for those ages (Table 1), suggesting a reasonable agreement between simulation 1 and this feature in the data. (Other features suggested the same for simulation 1.)

Simulation 2 assumed no effect of childbearing on educational attainment ($\beta_3^{(f,f')} = 0$ in Eq. **2** in *Methods*) and no effect on enrollment ($\gamma_3^{(f')} = 0$ in Eq. **3** in *Methods*). Simulation 2 produced no clear educational gradient in fertility (Fig. 1, open triangles and dotted line): the average number of children was lowest for the women who ended up in category 4 and highest for those who ended up in category 3. The simulated average number of children per woman fell within the CIs for educational levels 2 and 3, and very slightly below the CI for educational level 4, but fell notably above the CIs for educational levels 6 and 7. In other words, the gradient of smaller completed fertility with higher educational level in data and in simulation 1 reflected primarily the effect of births on education, rather than the opposite. Experiencing from age 17 through 39 the combinations of educational level and enrollment that typically led to an advanced degree did not produce low fertility, but one that was rather high. Simulation 2 reproduced accurately the fractions of women at age 39 with the lower educational levels 2, 3, and 4, but not the fractions of women at age 39 with the higher educational levels 6 and 7 (Fig. 2).

Simulation 3 kept the effects of childbearing on educational progress (β_3) and on enrollment (γ_3) as estimated from the data, but assumed no effects of educational level on fertility ($\alpha_3 = 0$ in Eq. **1**) and no effects of enrollment on fertility ($\alpha_4 = 0$ in Eq. **1**). In this hypothetical situation (Fig. 1, × marks with dashed line), the educational gradient in fertility was comparable in direction and magnitude to the observed educational gradient in fertility. Simulation 3 gave a distribution of women at age 39 by educational level that fell outside the CIs of the data at every educational level (Fig. 2).

To test further the conclusion that educational attainment and enrollment had less impact on fertility than the stronger reverse effect, we simulated the number of children from Eq. **1** using three preset educational histories. If we assumed no enrollment after age 16 and thus 10 y of compulsory schooling only (educational level coded as 2), throughout all ages, the average number of children at age 39 was 2.08. If we instead assumed completion of upper secondary education at age 19 and no subsequent enrollment and no change in the educational level (i.e., code 4 throughout the woman's remaining years), the number was 2.00. Finally, when we assumed continuous enrollment through age 27, followed by a master's degree (code 7, and secondary school was assumed to be completed at 19 and a bachelor's degree obtained at age 25), the number was 2.03. The

Table 1. Comparison of the observed percentage (data) of women enrolled at some selected ages with the percentage in the realistic simulation 1, which is defined in text

		99% confidence interval		
Age, y	Data, %	Low	High	Simulation 1, %
17	74.9	74.2	75.6	74.6
20	30.2	29.5	30.9	29.7
25	16.4	15.8	17.0	15.7
30	8.5	8.1	9.0	8.2
35	6.8	6.4	7.2	7.8
39	8.0	7.6	8.4	8

latter educational career included 12 y of enrollment, which according to the data for the 1964 cohort was the average for those with a master's degree by age 39. The effect on fertility of these three educational trajectories was small and not monotonic.

However, if we instead assumed a quick progress, with a master's degree earned at age 26, the average number of births was 2.26, whereas it was 1.70 if the degree was taken at age 31. In other words, education mattered little for fertility in the sense that the typical combinations of enrollment and educational level over the years that led to the final levels 2–6 gave similar completed fertility, whereas additional years of enrollment to attain those levels depressed fertility. These patterns reflect the negative effects of enrollment and, as discussed by Kravdal (13), partly positive effects of high educational levels (see estimates in Table S1). To summarize, these calculations show that the impact of educational attainment on fertility is sensitive to the time course of enrollment. Our finding that fertility impedes education more than education impedes fertility is conditional on the time patterns of enrollment and attainment observed in the Norwegian data.

Discussion

Our simulation models assumed that a woman's fertility was directly caused by her educational attainment and enrollment together with a few demographic variables that reflected her age and past childbearing, and that her educational progress was directly caused by the number and ages of her children and by her educational attainment and enrollment. Given these simple models, the main finding was that, in Norway in the last two decades of the 20th century, the observed inverse relationship between a woman's education and her parity at age 39 arose from the estimated effects of childbearing on education and a much smaller reverse effect of education on fertility (in the sense that the typical combinations of enrollment and educational level over the years that led to the various final levels gave highly similar completed fertility). Stated differently, in Norway in this period, the explanation for the observed low fertility among women with advanced degrees was principally that women who had one or more children relatively early were more likely to leave or not enter a long educational track and never attain such a high educational level.

We do not claim that the simulated effect of childbearing on education is a true, or the sole, causal effect. The causal mechanisms were certainly more complicated than assumed in our simple models. Individual and community characteristics probably affected education and childbearing simultaneously. If we had taken such factors and mechanisms better into account, the effect of education on fertility might have been more (or less) important. In an analysis of US data, Upchurch et al. (15) estimated simultaneously equations for nonmarital fertility, educational attainment, marriage, marital dissolution, and marital fertility, with exogenous and potentially endogenous variables. An unobserved factor included in each equation was allowed to be correlated with each other unobserved factor. One cannot know at the outset how the use of such models with potentially correlated unobserved factors would affect key results. In our case, some factors that promote education, such as health, may also promote fertility. Other factors, such as having parents with career ambitions for their children, may influence education positively and fertility negatively. If the latter factors dominate and are included in models, one would see less-sharp negative effects of fertility on education than in simpler models that omit such factors.

Notwithstanding these open questions related to uncontrolled factors, our findings justify the concern about the possible effects of fertility on education, among researchers who assess the importance of education for fertility (16). An obvious implication is that we should hesitate to draw firm conclusions about the effects of education on fertility from data in which education is measured only at a high age, and that we should collect more data that include richer information about education, especially in the form of education histories.

Another lesson is that, when estimating effects of education on fertility, it might be valuable to simulate the implications for completed fertility. Perhaps there are quite small differences across various realistic preset educational careers. In any such estimation, one should incorporate relevant control variables, observed and unobserved. Unobserved variables should be included to control for constant factors that are randomly distributed at the start of the reproductive process but that become linked to education as the process evolves. Kravdal (13) showed that controlling for such constant unobserved factors may make the effects of educational level less positive or more negative.

Limitations of These Models and Some Alternatives. These conclusions presuppose that our simulation models approximated reality. Why was our realistic simulation 1 not always very close to the data? One reasonable possibility is that our models were not sufficiently flexible in the variables considered. To illustrate this possibility, we give a simple artificial example.

Suppose we followed 1,000 initially childless women from age 20. Ten had their first child at 21, 50 at 22, 200 at 23, and 100 at 24. If we calculated 1-y birth probabilities from these data and simulated 1 million women's fertility histories from those probabilities, we would find results very close to 10, 50, 200, and 100 per 1,000 of the starting population at the corresponding ages. If we instead had supposed that the fertility rate was constant over age and had simulated from that assumed constant rate, we would have simulated too many births at age 21 and too few at age 24 compared with observations. That discrepancy should prompt us to look for alternative model specifications, even though on average we might still be quite close to the true fertility.

In response to such concerns, we experimented with a number of models. For example, we left out of model Eq. **2** the number of years of enrollment at the relevant level and its interaction with age, and also left out of model Eq. **3** the enrollment in the preceding years and its interaction with age. With this specification, the proportion of women with the highest education was similar to that in the data, whereas the differences between data and simulation 1 in the enrollment age profile across educational levels were larger. However, it was just as clear that the effect of fertility on education, rather than the reverse effect, was primarily responsible for the education-fertility negative relationship at age 39.

We also experimented with interactions between age and enrollment, age and level, and enrollment and level in model Eq. **1**. We included number of years of previous enrollment as a grouped variable in model Eq. **2** to allow nonlinear effects. We included such a variable also in model Eq. **3** instead of the enrollment status in the preceding year. And we experimented with various alternative specifications of the fertility variable in models Eqs. **2** and **3**. All these alternatives gave slightly poorer fits to the data.

Our models did not include an independent variable that represented duration since the woman's last educational transition. We do not know if duration had any effect once number of years of enrollment (at the relevant level) and age were included, or whether we would get other results if we included duration since the woman's last educational transition instead of or in addition to years of enrollment. We suspect such modifications would have small effects.

Another possible cause of the discrepancies between the data and the simulation results is that the models omit influential determinants that contribute significant heterogeneity (17) to hazards of childbearing and hazards of educational progression or probabilities of enrollment, such as parents' social class, urban/rural location, or cultural/religious values. In the example above, it would not matter whether fertility was, say, 50% higher in one subgroup of the population than in another, and whether this were taken into account. We would reconstruct the 10, 50, 200, and 100 births per 1,000 with our simulation anyway. However, the situation might be different when more complexity is involved.

The models estimated the transitions in each variable (children born, educational level, and enrollment) without regard to whether the other two variables changed in the same year. The effects of this assumption are probably small, but remain untested. Testing this assumption would require a much larger set of models than the set used here.

Our conclusion that the apparent effects of childbearing on education outweighed the reverse effects would be strengthened if it could be supported by other simulation studies, especially if these gave a closer fit to the data. It is important to carry out such studies in a variety of countries at varying stages of development. Our data come from a specific setting in Norway, where generous policies make it relatively easy to continue schooling in the presence of young children and where there are good opportunities to return to school after a period of work or homemaking. Also, better-educated women have relatively easy access to child care arrangements that allow them to continue earning relatively high incomes. Further empirical studies with more sophisticated models are needed to come closer to a conclusion about causal effects of education on fertility and of fertility on education. We hope the importance of such a conclusion will motivate further empirical studies along the lines illustrated here. This study illustrates the kind of data and analyses that make it possible to test elsewhere the generality of our conclusion.

Possible Policy Implications. Our main finding was that fertility impeded education much more strongly than education impeded fertility among Norwegian women born in 1964, ignoring other factors that may have influenced both fertility and education. We do not know whether similar findings would result from parallel analyses of similar data in other countries at similar and different stages of economic development. We also do not know whether taking account of other factors that may have influenced both fertility and education among Norwegian women born in 1964 would leave our main finding intact.

We set aside the possible policy implications of the weak effect of education on fertility, which means that Norway will continue to have fairly high fertility by European standards, even if more women get higher education.

Whether there are policy implications of the negative effect of relatively early fertility on education depends on additional facts, assumptions, and values. Here are some examples.

One could argue that, as long as women know that having a child makes it more difficult to complete their education and take that into account in their decision making, there is no reason for concern. Some women may prefer not to have a child at a relatively early age because of the consequences for their educational careers, whereas others may want to have a child despite this disadvantage because they consider it outweighed by rewards of childbearing. Thus, early childbearing may be a result of decisions made by well-informed individuals, and should not be generally discouraged. This argument assumes that there are no externalities for other people of women's foregone education, or the value judgment that individual choices about childbearing and education take precedence over societal interests. If, however, there is a large societal value of education that is inadequately taken into account through individuals' decision making, one could adopt policies that weaken people's desires for having children early. If women underestimate how much childbearing interferes with further education (with potentially adverse consequences for their long-term quality of life), then a case could be made that it would be a good idea to create more awareness about the educational consequences of early childbearing. Though poor contraception is a key issue in some countries, in others, women may want a child based on inadequate understanding of the consequences (and the consequences always depend on the context, such as attitudes toward pregnant women in the classroom). In such cases, the unmet need is not only for contraception but for education about the lifelong impacts of a woman's fertility and education on herself.

Further, if a woman has unwanted children, with adverse consequences for the woman's education (and therefore also other people), then one could argue that efforts should be made to help people who wish to regulate their fertility.

Finally, one might consider mitigating the effect of childbearing on education by, for example, lowering the cost of child care for students who are mothers. Such a policy would in principle make more women interested in having a child early; it would increase the educational levels for those who would have a child while they are still young, with potentially beneficial effects also on others' well-being; and it would make early unwanted childbearing less of a disadvantage for the mothers and society more generally.

We cannot affirm unconditionally any of these possible policy implications of our results. The suggested possible policy implications are conditional on context and on a causal interpretation of our modest empirical conclusions.

This discussion of possible policy implications has been phrased entirely in terms of women and their choices. In fact, choices about fertility and women's education are influenced by women's partners and families, so policies should address men as well as women.

Methods

Data and Summary Statistics. The data used for estimation included all women who were born in Norway in 1964 and who lived in Norway continuously from January 1, 1980, to the end of 2003. Information about the timing of their births was taken from the Central Population Register, and educational histories were taken from the Educational Database operated by Statistics Norway. The latter included the highest educational level achieved as of October 1 every year from 1980, as well as whether the women were enrolled in school at those dates. We used five categories for the educational level, denoted by the first digit of the codes in the standard classification used by Statistics Norway: 2 (compulsory school, which currently takes 10 y), 3 (lower secondary, typically 11 y), 4 (upper secondary, 12–13 y), 6 (lower university education, 14–17 y, plus a small group with other postsecondary education that is coded as 5 in the standard classification), and 7 (master's degree or the equivalent, 18 or more years). Compulsory school starts in August of the year when the child attains age 6 and ends in June of the year the child is 16 (so in principle everyone is enrolled in school during that period). For simplicity, the 99 women who had more than five children by the end of the year when they were 39 (2003) were excluded. This exclusion reduced the average number of children by less than 0.01 child. We also excluded the 87 women who already had a child in January of the year they were 17, and the 1,811 who for some reason were registered with unknown education, or more than or less than compulsory education in October the year before that (code 1 was for people with less than compulsory schooling, hence we did not use code 1). This left us with a sample of 26,349 women.

Model Estimation. Three sets of models were estimated for various 1-y probabilities, starting in January of the year when the women attained age 17 (at which time all were childless and had no more or less than compulsory education). One set of models was for the probability $r^{(p)}$ that a woman who had p children at the beginning of the year had another child (who could be a twin or a triplet) during the year (parity-specific discrete-time birth hazard models). A second set of models was for the probability $u^{(f,f')}$ that a woman who had educational level f at the beginning of the year (measured October 1 the preceding year) was registered with level f' on October 1 later that year (educational attainment-specific discrete-time educational progression hazard models; because multiple values of f' were possible, these were competing-risk models). A third set of models was for the probability $t^{(f')}$

SOCIAL SCIENCES

that a woman with educational level f' on October 1 of a certain year (typically attained in the prior June or earlier) was enrolled on October 1.

More specifically, the following logistic model was estimated for the childless ($p = 0$):

$$\log\left(r^{(p)}/\left(1-r^{(p)}\right)\right) = \alpha_1^{(p)} + \alpha_2^{(p)}\boldsymbol{A}(a) + \alpha_3^{(p)}\boldsymbol{F}(f) + \alpha_4^{(p)}s,$$

where $\boldsymbol{A}(a)$ is a vector of 1-y age dummies for each age a between 17 and 39, except 19, which was chosen as a reference category. $\boldsymbol{F}(f)$ is a vector of dummies for each of the educational levels 3, 4, 6, and 7 (2 being the reference category), with education measured October 1 the preceding year. s is a dummy for enrollment, also measured on October 1 of the preceding year ($s = 0$ if the woman was not enrolled, $s = 1$ if she was enrolled). The αs are the corresponding coefficients and, like the βs and γs in the following models, are all vectors (Table S1).

For women who already had at least one child, models were estimated separately for parities $p = 1$, 2, 3, and 4, and duration since last previous birth (age of youngest child) was included. This model was

$$\log\left(r^{(p)}/\left(1-r^{(p)}\right)\right) = \alpha_1^{(p)} + \alpha_2^{(p)}\boldsymbol{A}(a) + \alpha_3^{(p)}\boldsymbol{F}(f) + \alpha_4^{(p)}s + \alpha_5^{(p)}\boldsymbol{D}(d),$$

where $\boldsymbol{D}$ was a vector of dummies corresponding to the duration d, which was measured in completed years. There was one dummy for each d between 0 and 9, except 2 (reference category), and an 11th category corresponded to 10 or more years. The definition of $\boldsymbol{A}$ varied slightly with parity. For $p = 1$ and $p = 2$, there were no observations below age 18, so we started at age 18 and used age 20 as the reference category; for $p = 3$, there were no observations below age 20, so we started at age 20 and used age 23 as the reference category; for $p = 4$, there were no observations below age 23, so we started at age 23 and used age 26 as the reference category.

These models can also be referred to as parity-specific discrete-time birth hazard models. We can alternatively write the models as

$$r^{(p)} = e^V/(1+e^V) \text{ where } V = \alpha_1^{(p)} + \alpha_2^{(p)}\boldsymbol{A}(a) + \alpha_3^{(p)}\boldsymbol{F}(f) + \alpha_4^{(p)}s + \alpha_5^{(p)}\boldsymbol{D}(d), \quad \textbf{[1]}$$

with the last term left out if $p = 0$.

A second set of models specified the probability $u^{(f,f')}$ that a woman who had educational level f at the beginning of the year (measured on October 1 of the preceding year) was registered with level f' on October 1 later that year. The level f' was not necessarily the same as f or one step above. For example, students in medical school or other professional educational programs were registered with upper secondary education throughout their studies, until they graduated with an advanced degree, without passing through the lower university level (bachelor's degree). Similarly, it was common to be registered as going directly from compulsory education to upper secondary education. In addition, some educational transitions that in principle should be registered were left out. To allow for more than two values of f', multinomial models were estimated, and the estimation was done separately for $f = 2$, 3, 4, and 6. The models were of the form

$$u^{(f,f')} = e^Z/\left(1+\sum\nolimits_{\phi\neq f} e^{Z(f,\phi)}\right), \quad \textbf{[2]}$$

where $Z = Z(f,f') = \beta_1^{(f,f')} + \beta_2^{(f,f')}\boldsymbol{A}(a) + \beta_3^{(f,f')}\boldsymbol{R}(r) + \beta_4^{(f,f')}s + \beta_5^{(f,f')}m + \beta_6^{(f,f')}m\times a$ (with variables defined below) and the summation was over all f' not equal to f. The probability of remaining at the same educational level was $u^{(f,f')} = 1-\sum_{f'\neq f} u^{(f,f')} = 1/\left(1+\sum_{\phi\neq f} e^{Z(f,\phi)}\right)$.

$\boldsymbol{A}(a)$ were 1-y dummies for ages 17–39, except for the reference age 19, with the following exceptions: for $f = 3$, we started at age 18 and used age 20 as the reference category; for $f = 4$, we started at age 18 and used age 22 as the reference category; for $f = 6$, we started at age 19 and used age 24 as the reference category. r reflects a combination of number of children and their age at the beginning of the year. It had nine categories: childless women were in category 1 (chosen as the reference), and those with one or more children were in category 2 if their youngest child was 0 (measured in completed years), 3 if the child was 1, 4 if the child was 2, 5 if the child was 3, 6 if the child was 4–5, 7 if the child was 6–7, 8 if the child was 8–9, and 9 if the child was 10 or older. The $\boldsymbol{R}$ vector included dummies corresponding to those categories. s was the enrollment the preceding October 1, as above. m was the number of years of enrollment while having level f. The β's were the corresponding coefficients.

When $f = 2$, the possible values of f' were 2, 3, 4, and 6, and when $f = 3$, the possible values of f' were 3, 4, and 6. Only 10 women in the entire population moved directly from 2 or 3 to 7, and they were simply ignored. These 10 women were included in the total count of 26,349 women analyzed here. Similarly, when $f = 4$, the possible values of f' were 4, 6, and 7, and when $f = 6$, the possible values of f' were 6 and 7 (the latter was thus equivalent to a logistic model).

The third set of models was for the probability $t^{(f')}$ that a woman with educational level f' on October 1 of a certain year (typically attained in June) was enrolled on October 1. The following logistic models were estimated separately for $f' = 2$, 3, 4, 6, and 7:

$$t^{(f')} = e^W/\left(1+e^W\right), \text{ where } W = \gamma_1^{(f')} + \gamma_2^{(f')}\boldsymbol{A}(a) + \gamma_3^{(f')}\boldsymbol{R}(r) + \gamma_4^{(f')}s + \gamma_5^{(f')}s\times a. \quad \textbf{[3]}$$

$\boldsymbol{A}(a)$ were again 1-y dummies for ages 17–39, except for the reference age 19, with the following exceptions: for $f' = 6$, we started at age 18 and used age 21 as the reference category, and for $f' = 7$, we started at age 22 and used age 24 as the reference category. $\boldsymbol{R}(r)$ was as defined above. s was the enrollment the preceding October 1, as above. The γ's were the corresponding coefficients.

SAS (18) software was used for the estimation: Proc Catmod for the multinomial models and Proc Logistic for the logistic models. The estimated coefficients are in Table S1.

Simulation Procedure. Each simulation used three models in consecutive time steps from January 1 of one year to the following January 1: first the education model Eq. **2**, next the enrollment model Eq. **3**, and finally the childbearing model Eq. **1**. The three models were applied to each successive year with covariate values for each model as predicted from all three models for earlier years.

We performed three simulations. Simulation 1 used all of the parameters estimated from the data and was intended to mimic the data realistically. Simulation 2 set to zero the parameters that represented the influence of childbearing on educational enrollment and level, while keeping unchanged the remaining parameter values estimated from the data. Simulation 3 set to zero the parameters that represented the influence of educational enrollment and level, while keeping unchanged the remaining parameter values estimated from the data. We now describe in detail the procedure of simulation 1.

Simulation 1 started with 1 million childless women January 1, all of whom were assumed to become 17 y old during the following year and to have only compulsory education. A total of 85% of them were selected as enrolled in October the preceding year, as observed in the data. For each woman and each of the years from age 17 through 39, we predicted from model Eq. **2** the probabilities of attaining various educational levels in October following the

Table 2. Percentage of women who were enrolled in school at various current ages, by completed educational levels 2, 4, and 7 at age 39, in data and the realistic simulation 1

	Level 2 at age 39		Level 4 at age 39		Level 7 at age 39	
Age, y	Data	Simulated	Data	Simulated	Data	Simulated
17	14	35.0	84	83.5	96	93.3
20	1	3.0	25	26.7	79	78.2
25	1	1.7	7	10.4	72	55.6
30	1	1.4	5	5.6	29	22.6
35	1	1.0	5	5.2	11	11.0
39	3.4	3.3	7.8	7.7	7.4	8.2
No. of women	1,682		8,315		1,371	

	99% confidence intervals					
Age, y	Lower	Upper	Lower	Upper	Lower	Upper
17	11.9	16.3	82.9	85.0	94.4	97.2
20	0.5	1.8	23.8	26.2	76.0	81.8
25	0.5	1.8	6.3	7.8	68.8	75.1
30	0.5	1.8	4.4	5.6	25.9	32.3
35	0.5	1.8	4.4	5.6	8.9	13.4
39	2.4	4.7	7.1	8.6	5.7	9.4

Educational levels are defined in text. For example, 14% of women who had educational level 2 at age 39 were enrolled at age 17. In simulation 1, 35% were enrolled, far above the upper limit 16.3% of the 99% confidence interval.

initial January. Assume that the predicted probabilities of having educational level 2, 3, 4, or 6 were q_2, q_3, q_4, and q_6 respectively (the q's adding up to 1). We drew a number n between 0 and 1 from a uniform distribution. The educational level in October was set to 2 if $n \le q_2$, to 3 if $q_2 < n \le q_2 + q_3$, to 4 if $q_2 + q_3 < n \le q_2 + q_3 + q_4$, and to 6 if $q_2 + q_3 + q_4 < n \le 1$.

Similarly, the probability of enrollment in October (following the initial January) was predicted from model Eq. **3**, using the educational level in that same October (assigned by the previous step of the simulation) and the age and fertility status at the beginning of the year. The enrollment status was then assigned based on another number drawn from the uniform distribution. Finally, the probability of having a birth within the year was predicted from model Eq. **1**, using the educational level and enrollment in the preceding year. Based on yet another independent draw of a uniformly distributed random number, the woman was assigned zero or one additional child. To allow for twin births, 1% of the women who had been assigned one additional child were assigned yet another child.

Summary measures were computed from the simulation sample and compared with the corresponding figures in the data.

Uncertainty Analysis. To assess quantitatively the agreement between the simulation results and the data, we analyzed uncertainty for each tabulated comparison. The simulations were based on such a large number of realizations that the numerical results were essentially free of sampling variability, for the number of digits of precision quoted here. The results did not change if the simulations were done with 10 million women instead of 1 million women. The underlying concept of these uncertainty analyses is a hypothetical ensemble of Norways from which the observed Norway was one random sample. We investigated the variability expected in the data in a hypothetical sample of Norways that had the probability parameters estimated from the observed Norway.

Table S2 compares the observed and simulated average number of children among women of age 39, for women of each educational level at age 39, using a CI for the observed average number of children per woman. We arbitrarily chose a confidence level of 99%; such a choice is one of a number of conventional choices and is widely used. For each educational level, we supposed that the number of women at that level was Poisson distributed with mean equal to the observed number of such women, that the aggregate number of all of the children of all those women was also Poisson distributed with mean equal to the observed number of all such children, and that the average number of children per woman was distributed as the ratio of these two Poisson variables. For example, there were 1,682 women of educational level 2, and they had in aggregate 3,592 children. So we assumed the average number of children per woman was distributed as the ratio of a Poisson variable with mean 3,592 to a Poisson variable with mean 1,682. Many approximate methods of estimating a CI for a ratio of Poisson variables are available (19). Table S2 gives 99% CIs according to two of these methods: the square-root transformation (Eq. **2.4**) and the Wald method (Eq. **2.5**) in Price and Bonett (19). The CIs produced by these methods were very similar. CIs for the percentage of women with each level of education at age 39 were calculated using Matlab function binofit. This procedure ignored the multinomial dependence among the CIs but correctly estimated the binomial CIs for each level of education considered individually.

Table 1 compares the observed percentages of women enrolled with the simulated percentages at selected ages. For example, at age 30, 8.5% of 26,349 women were enrolled. We supposed that (in an ensemble of statistically identical Norways) the number of enrolled women (at age 30) was binomially distributed with n = 26,349 and P = 0.085. We used Matlab function binofit to obtain the 99% CI for the percentage enrolled (8.1%, 9.0%). In Table 1, the simulated percentage enrolled at age 30 was 8.2%, so there was no strong evidence of disagreement between observed and simulated percentages at this age. The same was true at most of the other ages in Table 1, although the simulated percentage enrolled was slightly low at age 25 and too high at age 35. The deviations between data and simulation 1 were not systematic.

Table 2 gives the percentage of women who were enrolled in school, for completed educational levels 2, 4, and 7 at age 39, at selected current ages, in data and simulation 1. The 99% CIs were calculated using the Matlab function binofit.

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Supporting Information

Cohen et al. 10.1073/pnas.1107993108

Table S1. Parameter values estimated for model Eqs. 1–3 (*Methods*)

Table S1 (DOC)

Xa17–xa39 are dummy variables (dummies) for woman's age. Xchage1–xchage8 are dummies for number of **and** age of children. Xenrprev is enrollment preceding year. Xedu3–xedu7 are educational-level dummies. Xy0–xy10 are dummies for years since last previous birth. Xc0 is number of years of enrollment at the educational level under consideration. Xc2 is Xc0 multiplied by woman's age. Xcy0 is enrollment preceding year, same as Xenrprev. Xcy2 is xcy0 multiplied by woman's age. Parameters marked with # are regarded as infinite. Educational levels 2, 3, 4, 6, **and** 7 are defined in the text. In the "Model for educational level, starting from educational level 2," the column headed "Function Number" has entries 1, 2, 3 for parameters of transitions to levels 3, 4, 6, respectively. In the "Model for educational level, starting from educational level 3," the column headed "Function Number" has entries 1, 2 for parameters of transitions to levels 4, 6, respectively. The column headed "Function Number" is absent from "Model for educational level, starting from educational level 6," because a transition to educational level 7 is the only possible change.

Table S2. Educational level attained by woman's age 39, average number of children of women at age 39 who attained each educational level, and percentage of women who attained each educational level by age 39: Data (*Upper* half table), 99% confidence intervals around the data (*Lower* half table) and corresponding results of three simulations

Table S2 (DOCX)

Educational levels: 2, 10 y, compulsory; 3, 11 y, lower secondary; 4, 12–13 y, upper secondary; 6, 14–17 y, lower university; 7, 18+ years, Master's degree or equivalent. **For example,** women at educational level 2 at age 39 had on average 2.136 children at age 39, with 99% CI (1.98, 2.31) by either method. All three simulations gave average numbers of children per woman within this CI. However, the percentage of women with educational level 2 at age 39 fell within the CI (6.00, 6.78) in simulations 1 and 2, but above the CI in simulation 3. Simulation 1: all parameters were estimated from the data. Simulation 2: effects of fertility on education were set to **zero**; remaining parameters were estimated from the data. Simulation 3: effects of education on fertility were set to **zero**; remaining parameters were estimated from the data.

"Childbearing impeded education more than education impeded childbearing in a cohort of Norwegian women"

Joel E. Cohen, Øystein Kravdal, Nico Keilman

PNAS Supplementary Information

Table S1. Parameter values estimated for model equations (1), (2), and (3) (see Methods). Xa17-xa39 are dummy variables ("dummies") for woman’s age. Xchage1-xchage8 are dummies for number of & age of children. Xenrprev is enrollment preceding year. Xedu3-xedu7 are educational-level dummies. Xy0-xy10 are dummies for years since last previous birth. Xc0 is number of years of enrollment at the educational level under consideration. Xc2 is Xc0 multiplied by woman’s age. Xcy0 is enrollment preceding year, same as Xenrprev. Xcy2 is xcy0 multiplied by woman’s age. Parameters marked with '#' are regarded as infinite. Educational levels 2, 3, 4, 6, 7 are defined in text.

Model for educational level, starting from educational level 2

Parameter	Function Number	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	-3.4649	0.0709	2387.92	<.0001
	2	-6.1672	0.1573	1537.56	<.0001
	3	-12.6962	1.0638	142.44	<.0001
xa17	1	-0.6957	0.0628	122.70	<.0001
	2	-6.9632	0.4566	232.57	<.0001
	3	-8.8994#	.	.	.
xa18	1	-0.6538	0.0551	140.91	<.0001
	2	-4.1415	0.0748	3065.25	<.0001
	3	-1.4522	1.4174	1.05	0.3056
xa20	1	0.7623	0.0844	81.51	<.0001
	2	-1.6445	0.0858	367.54	<.0001
	3	2.6349	1.1201	5.53	0.0187
xa21	1	0.5403	0.1009	28.67	<.0001
	2	-3.8157	0.1829	435.23	<.0001
	3	4.2732	1.0343	17.07	<.0001
xa22	1	0.1450	0.1168	1.54	0.2144
	2	-3.8909	0.2312	283.16	<.0001
	3	4.3298	1.0382	17.39	<.0001
xa23	1	-0.3208	0.1396	5.28	0.0215
	2	-4.3388	0.3245	178.77	<.0001
	3	4.0830	1.0536	15.02	0.0001
xa24	1	-0.7618	0.1715	19.74	<.0001
	2	-3.9089	0.3969	96.99	<.0001
	3	5.1263	1.0441	24.10	<.0001
xa25	1	-0.4097	0.1580	6.73	0.0095
	2	-3.9419	0.4785	67.86	<.0001
	3	3.8506	1.0990	12.28	0.0005
xa26	1	-0.4010	0.1556	6.64	0.0099
	2	-3.0632	0.4302	50.70	<.0001
	3	3.8927	1.1042	12.43	0.0004
xa27	1	-0.7391	0.1685	19.24	<.0001
	2	-1.1936	0.3110	14.73	0.0001
	3	4.8413	1.0886	19.78	<.0001
xa28	1	-1.0263	0.1822	31.72	<.0001
	2	-1.3763	0.3692	13.89	0.0002
	3	4.9659	1.0943	20.59	<.0001
xa29	1	-0.7841	0.1738	20.35	<.0001
	2	-2.0585	0.5478	14.12	0.0002
	3	3.4333	1.2149	7.99	0.0047
xa30	1	-1.0626	0.1959	29.43	<.0001
	2	-0.4863	0.3623	1.80	0.1795
	3	4.4974	1.1482	15.34	<.0001
xa31	1	-1.1168	0.1973	32.03	<.0001
	2	-0.4402	0.3896	1.28	0.2585
	3	3.9650	1.2047	10.83	0.0010
xa32	1	-1.3549	0.2111	41.21	<.0001
	2	0.0436	0.3653	0.01	0.9049
xa32	3	3.9100	1.2215	10.25	0.0014

xa33	1	-2.0402	0.2590	62.05	<.0001
	2	0.7576	0.3197	5.62	0.0178
	3	3.8831	1.2274	10.01	0.0016
xa34	1	-1.3558	0.2287	35.15	<.0001
	2	1.6395	0.2853	33.03	<.0001
	3	3.9414	1.2810	9.47	0.0021
xa35	1	-1.6344	0.2376	47.33	<.0001
	2	1.2783	0.3100	17.00	<.0001
	3	3.8456	1.3188	8.50	0.0035
xa36	1	-2.4064	0.2972	65.55	<.0001
	2	0.8060	0.3591	5.04	0.0248
	3	2.5435	1.5669	2.64	0.1045
xa37	1	-1.8275	0.2489	53.92	<.0001
	2	1.5235	0.3075	24.55	<.0001
	3	3.1647	1.4305	4.89	0.0269
xa38	1	-2.7376	0.3361	66.34	<.0001
	2	1.5622	0.3182	24.10	<.0001
	3	3.4110	1.4055	5.89	0.0152
xa39	1	-2.6322	0.3095	72.32	<.0001
	2	0.7808	0.3904	4.00	0.0455
	3	4.3319	1.3557	10.21	0.0014
xc0	1	-1.9524	0.0770	642.89	<.0001
	2	3.7531	0.1342	782.00	<.0001
	3	0.5942	0.3004	3.91	0.0479
xc2	1	0.0594	0.00296	403.13	<.0001
	2	-0.1095	0.00495	489.50	<.0001
	3	0.00858	0.00998	0.74	0.3897
xenrprev	1	4.6834	0.0671	4867.73	<.0001
	2	3.3343	0.1157	829.81	<.0001
	3	3.4562	0.2525	187.37	<.0001
xchage1	1	-1.4558	0.1938	56.40	<.0001
xchage1	2	-0.7357	0.3101	5.63	0.0177
	3	-10.4726#	.	.	.
xchage2	1	-0.5073	0.1242	16.68	<.0001
	2	-0.6443	0.2756	5.47	0.0194
	3	-0.8089	0.4641	3.04	0.0814
xchage3	1	-0.1827	0.1216	2.26	0.1329
	2	0.1693	0.2676	0.40	0.5269
	3	-0.8917	0.4924	3.28	0.0701
xchage4	1	-0.1617	0.1367	1.40	0.2369
	2	0.6248	0.2569	5.92	0.0150
	3	-0.9391	0.5184	3.28	0.0701
xchage5	1	0.0723	0.1216	0.35	0.5520
	2	0.2073	0.2447	0.72	0.3970
	3	-0.8440	0.4622	3.33	0.0678
xchage6	1	-0.0167	0.1496	0.01	0.9109
	2	0.3598	0.2411	2.23	0.1355
	3	-0.2048	0.4252	0.23	0.6301
xchage7	1	-0.0247	0.1851	0.02	0.8940
	2	0.2451	0.2676	0.84	0.3597
	3	-0.2078	0.4931	0.18	0.6735
xchage8	1	0.3011	0.1842	2.67	0.1021
	2	0.6815	0.2295	8.82	0.0030
	3	0.4420	0.4623	0.91	0.3390

Model for educational level, starting from educational level 3

Parameter	Function Number	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	-5.0743	0.0611	6901.54	<.0001
	2	-10.9812	0.3680	890.61	<.0001
xa18	1	-4.8507	0.3046	253.62	<.0001
	2	-10.3000#	.	.	.
xa19	1	-0.0253	0.0463	0.30	0.5840
	2	-10.7426#	.	.	.
xa21	1	-0.5763	0.0619	86.61	<.0001
	2	0.4005	0.4386	0.83	0.3612
xa22	1	-0.6060	0.0703	74.34	<.0001
	2	1.6154	0.3712	18.94	<.0001
xa23	1	-0.6543	0.0776	71.10	<.0001
	2	1.5390	0.3826	16.18	<.0001
xa24	1	-0.8770	0.0927	89.46	<.0001
	2	2.3123	0.3576	41.82	<.0001
xa25	1	-1.1175	0.1072	108.71	<.0001
	2	2.5551	0.3532	52.34	<.0001

xa26	1	-1.1238	0.1104	103.66	<.0001
	2	2.5083	0.3548	49.98	<.0001
xa27	1	-0.7019	0.1049	44.78	<.0001
	2	2.6958	0.3586	56.53	<.0001
xa28	1	-0.7852	0.1165	45.41	<.0001
	2	2.4218	0.3743	41.86	<.0001
xa29	1	-0.5991	0.1158	26.76	<.0001
	2	2.5599	0.3782	45.81	<.0001
xa30	1	-0.6814	0.1263	29.11	<.0001
	2	2.6562	0.3829	48.12	<.0001
xa31	1	-0.2934	0.1209	5.89	0.0153
	2	2.9036	0.3904	55.32	<.0001
xa32	1	0.0193	0.1207	0.03	0.8729
	2	2.8653	0.4077	49.38	<.0001
xa33	1	0.4069	0.1144	12.66	0.0004
	2	2.6693	0.4273	39.03	<.0001
xa34	1	0.8931	0.1078	68.62	<.0001
	2	2.9277	0.4335	45.62	<.0001
xa35	1	0.7579	0.1154	43.11	<.0001
	2	1.7832	0.5112	12.17	0.0005
xa36	1	0.4626	0.1273	13.21	0.0003
	2	2.3045	0.4873	22.36	<.0001
xa37	1	0.7580	0.1226	38.20	<.0001
	2	2.5239	0.4921	26.31	<.0001
xa38	1	0.7186	0.1273	31.89	<.0001
	2	2.6374	0.4978	28.07	<.0001
xa39	1	0.7969	0.1294	37.91	<.0001
	2	2.3557	0.5227	20.31	<.0001
xc0	1	1.7720	0.0574	953.40	<.0001
	2	0.9380	0.1675	31.36	<.0001
xc2	1	-0.0484	0.00191	643.18	<.0001
xc2	2	-0.00846	0.00541	2.45	0.1177
xenrprev	1	2.7607	0.0419	4341.81	<.0001
	2	3.9012	0.1396	781.32	<.0001
xchage1	1	-0.9589	0.1268	57.17	<.0001
	2	-0.6976	0.2631	7.03	0.0080
xchage2	1	-0.4381	0.0984	19.84	<.0001
	2	-0.7996	0.2364	11.44	0.0007
xchage3	1	-0.2770	0.0919	9.08	0.0026
	2	-1.3532	0.2748	24.24	<.0001
xchage4	1	-0.0287	0.0866	0.11	0.7405
	2	-0.8978	0.2163	17.23	<.0001
xchage5	1	0.0337	0.0728	0.21	0.6431
	2	-0.7435	0.1599	21.62	<.0001
xchage6	1	0.0240	0.0804	0.09	0.7653
	2	-0.6510	0.1699	14.69	0.0001
xchage7	1	0.1661	0.0890	3.48	0.0621
	2	-0.2032	0.1838	1.22	0.2690
xchage8	1	0.1832	0.0865	4.48	0.0342
	2	-0.1745	0.1900	0.84	0.3584

Model for educational level, starting from educational level 4

Parameter	Function Number	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	-5.5945	0.0630	7878.60	<.0001
	2	-13.3660	0.6747	392.44	<.0001
xa18	1	1.3632	1.2110	1.27	0.2603
	2	-5.3596#	.	.	.
xa19	1	1.5767	0.1624	94.29	<.0001
	2	-5.0862#	.	.	.
xa20	1	0.7240	0.0569	161.74	<.0001
	2	-6.4223#	.	.	.
xa21	1	0.4671	0.0558	69.98	<.0001
	2	-7.5082#	.	.	.
xa23	1	0.2406	0.0573	17.62	<.0001
	2	0.4212	0.5614	0.56	0.4532
xa24	1	0.3496	0.0597	34.25	<.0001
	2	1.2317	0.5331	5.34	0.0209
xa25	1	0.3802	0.0649	34.32	<.0001
	2	0.8363	0.5686	2.16	0.1413
xa26	1	0.2996	0.0715	17.57	<.0001
	2	0.1278	0.6443	0.04	0.8428
xa27	1	-0.0353	0.0837	0.18	0.6734
	2	-0.7390	0.7656	0.93	0.3344

xa28	1	-0.1542	0.0919	2.82	0.0932
	2	-0.6068	0.8930	0.46	0.4968
xa29	1	-0.3608	0.1023	12.44	0.0004
	2	-0.8512	1.0498	0.66	0.4174
xa30	1	-0.4306	0.1098	15.38	<.0001
	2	-1.1361	1.2303	0.85	0.3558
xa31	1	-0.4837	0.1185	16.65	<.0001
	2	-1.1213	1.4095	0.63	0.4263
xa32	1	-0.4445	0.1210	13.50	0.0002
	2	-1.5557	1.6485	0.89	0.3453
xa33	1	-0.4216	0.1237	11.62	0.0007
	2	-0.4397	1.7134	0.07	0.7975
xa34	1	-0.7677	0.1376	31.14	<.0001
	2	-10.1586#	.	.	.
xa35	1	-1.1537	0.1506	58.67	<.0001
	2	-10.0406#	.	.	.
xa36	1	-0.8285	0.1435	33.33	<.0001
	2	-1.0552	2.3515	0.20	0.6536
xa37	1	-0.9293	0.1499	38.45	<.0001
	2	-9.2617#	.	.	.
xa38	1	-0.9336	0.1525	37.49	<.0001
	2	-0.7494	2.6788	0.08	0.7797
xa39	1	-1.0920	0.1612	45.91	<.0001
	2	-0.3955	2.7991	0.02	0.8876
xc0	1	0.3842	0.0572	45.08	<.0001
	2	2.8550	0.7142	15.98	<.0001
xc2	1	0.00129	0.00193	0.45	0.5029
xc2	2	-0.0427	0.0271	2.48	0.1153
xenrprev	1	3.0930	0.0459	4545.35	<.0001
	2	1.9154	0.2792	47.07	<.0001
xchage1	1	-0.3026	0.0919	10.85	0.0010
	2	-0.6970	0.3814	3.34	0.0677
xchage2	1	-0.3377	0.0930	13.17	0.0003
	2	-0.6692	0.4157	2.59	0.1074
xchage3	1	-0.5006	0.1049	22.76	<.0001
	2	-0.3407	0.4907	0.48	0.4876
xchage4	1	-0.1176	0.0957	1.51	0.2189
	2	-1.4081	1.0211	1.90	0.1679
xchage5	1	0.0429	0.0788	0.30	0.5864
	2	-0.5990	0.6149	0.95	0.3300
xchage6	1	0.3802	0.0886	18.40	<.0001
	2	-0.8391	1.0413	0.65	0.4204
xchage7	1	0.4640	0.1042	19.84	<.0001
	2	-7.6411#	.	.	.
xchage8	1	0.5195	0.1045	24.70	<.0001
	2	-0.1467	1.1447	0.02	0.8980

Model for educational level, starting from educational level 6

Parameter	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	-10.9901	0.3777	846.53	<.0001
xa19	-5.3785#	.	.	.
xa20	-5.9653#	.	.	.
xa21	-7.0497#	.	.	.
xa22	-9.3762#	.	.	.
xa23	-0.6641	0.6532	1.03	0.3093
xa25	1.6855	0.3225	27.32	<.0001
xa26	1.5010	0.3223	21.69	<.0001
xa27	1.5758	0.3227	23.84	<.0001
xa28	1.5318	0.3281	21.80	<.0001
xa29	1.3900	0.3398	16.73	<.0001
xa30	1.4281	0.3543	16.24	<.0001
xa31	1.5253	0.3737	16.66	<.0001
xa32	1.5039	0.3969	14.36	0.0002
xa33	1.6846	0.4214	15.98	<.0001
xa34	1.7746	0.4494	15.59	<.0001
xa35	1.4870	0.4874	9.31	0.0023
xa36	1.3591	0.5181	6.88	0.0087
xa37	1.5757	0.5357	8.65	0.0033
xa38	1.7703	0.5569	10.10	0.0015
xa39	1.1585	0.6115	3.59	0.0582
xc0	1.3387	0.1933	47.99	<.0001
xc2	-0.0202	0.00623	10.55	0.0012

xenrprev	3.0831	0.1597	372.69	<.0001
xchage1	-0.9012	0.1832	24.20	<.0001
xchage2	-0.1684	0.1391	1.46	0.2262
xchage3	-0.1923	0.1610	1.43	0.2322
xchage4	-0.7706	0.2327	10.96	0.0009
xchage5	-0.2447	0.1693	2.09	0.1484
xchage6	-0.4253	0.2387	3.18	0.0748
xchage7	0.3026	0.2341	1.67	0.1961
xchage8	0.3071	0.2769	1.23	0.2674

Model for enrollment, starting from educational level 2

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-2.5036	0.0499	2512.7985	<.0001
xa17	1	1.8688	0.0532	1235.4493	<.0001
xa18	1	1.6775	0.0538	971.9081	<.0001
xa20	1	-0.0890	0.0819	1.1832	0.2767
xa21	1	-0.1083	0.0884	1.5010	0.2205
xa22	1	-0.4388	0.0999	19.3013	<.0001
xa23	1	-0.8198	0.1147	51.0819	<.0001
xa24	1	-0.9286	0.1234	56.6718	<.0001
xa25	1	-0.6119	0.1157	27.9512	<.0001
xa26	1	-0.5953	0.1158	26.4365	<.0001
xa27	1	-0.7466	0.1239	36.3131	<.0001
xa28	1	-0.7701	0.1266	36.9981	<.0001
xa29	1	-0.9999	0.1387	51.9492	<.0001
xa30	1	-0.9442	0.1383	46.5968	<.0001
xa31	1	-1.0182	0.1429	50.7739	<.0001
xa32	1	-1.1845	0.1530	59.9300	<.0001
xa33	1	-1.4511	0.1690	73.7142	<.0001
xa34	1	-1.1483	0.1590	52.1421	<.0001
xa35	1	-1.4349	0.1781	64.8794	<.0001
xa36	1	-1.1575	0.1617	51.2411	<.0001
xa37	1	-1.6911	0.1938	76.1038	<.0001
xa38	1	-1.3004	0.1758	54.6979	<.0001
xa39	1	-1.2624	0.1752	51.9072	<.0001
xcy0	1	2.6166	0.1374	362.6956	<.0001
xcy2	1	0.0358	0.00694	26.6878	<.0001
xchage1	1	-0.8336	0.0935	79.4411	<.0001
xchage2	1	-0.4044	0.0927	19.0226	<.0001
xchage3	1	-0.1655	0.0959	2.9798	0.0843
xchage4	1	-0.2248	0.1103	4.1584	0.0414
xchage5	1	0.1360	0.0911	2.2256	0.1357
xchage6	1	0.1074	0.1111	0.9334	0.3340
xchage7	1	0.1883	0.1315	2.0493	0.1523
xchage8	1	0.0849	0.1323	0.4117	0.5211

Model for enrollment, starting from educational level 3

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-1.4738	0.0248	3535.0413	<.0001
xa17	1	0.8744	0.0340	662.5046	<.0001
xa18	1	0.3047	0.0294	107.0897	<.0001
xa20	1	-0.5667	0.0345	269.8084	<.0001
xa21	1	-0.8258	0.0382	466.2681	<.0001
xa22	1	-1.0022	0.0417	578.0117	<.0001
xa23	1	-1.2869	0.0466	763.3480	<.0001
xa24	1	-1.2641	0.0485	678.0376	<.0001
xa25	1	-1.1691	0.0482	587.6548	<.0001
xa26	1	-1.2688	0.0500	643.4851	<.0001
xa27	1	-1.4453	0.0535	728.4416	<.0001
xa28	1	-1.3993	0.0540	672.1044	<.0001
xa29	1	-1.5819	0.0569	773.4682	<.0001
xa30	1	-1.6947	0.0595	812.2016	<.0001
xa31	1	-2.0052	0.0657	930.5407	<.0001
xa32	1	-1.9158	0.0660	841.9168	<.0001
xa33	1	-1.9885	0.0681	852.2555	<.0001
xa34	1	-2.1427	0.0722	880.5705	<.0001
xa35	1	-2.1751	0.0738	869.1258	<.0001
xa36	1	-2.1295	0.0741	825.2925	<.0001
xa37	1	-2.0886	0.0739	798.9656	<.0001

xa38	1	-2.0944	0.0750	780.6101	<.0001
xa39	1	-2.1213	0.0768	762.8505	<.0001
xcy0	1	-1.2348	0.0741	278.0725	<.0001
xcy2	1	0.1432	0.00305	2200.8434	<.0001
xchage1	1	-0.8817	0.0496	316.3704	<.0001
xchage2	1	-0.4783	0.0442	117.0883	<.0001
xchage3	1	-0.1663	0.0433	14.7740	0.0001
xchage4	1	-0.0315	0.0461	0.4673	0.4943
xchage5	1	0.0243	0.0410	0.3495	0.5544
xchage6	1	0.1489	0.0481	9.5784	0.0020
xchage7	1	0.0700	0.0598	1.3673	0.2423
xchage8	1	-0.0593	0.0613	0.9376	0.3329

Model for enrollment, starting from educational level 4

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-1.5033	0.0313	2308.7125	<.0001
xa17	1	0.8530	0.9131	0.8728	0.3502
xa18	1	0.2659	0.1120	5.6396	0.0176
xa20	1	0.3368	0.0305	121.6593	<.0001
xa21	1	0.1840	0.0327	31.6670	<.0001
xa22	1	0.1130	0.0343	10.8441	0.0010
xa23	1	-0.1632	0.0364	20.1085	<.0001
xa24	1	-0.4425	0.0397	124.4708	<.0001
xa25	1	-0.5813	0.0431	182.3518	<.0001
xa26	1	-0.9195	0.0474	376.7207	<.0001
xa27	1	-1.0618	0.0506	440.7230	<.0001
xa28	1	-1.1615	0.0536	470.2395	<.0001
xa29	1	-1.3658	0.0569	576.9371	<.0001
xa30	1	-1.6100	0.0613	690.9591	<.0001
xa31	1	-1.6430	0.0632	676.0864	<.0001
xa32	1	-1.6909	0.0648	681.0202	<.0001
xa33	1	-1.8628	0.0678	754.7148	<.0001
xa34	1	-1.8091	0.0674	720.0339	<.0001
xa35	1	-2.0235	0.0705	823.8257	<.0001
xa36	1	-1.9996	0.0713	785.8939	<.0001
xa37	1	-1.9460	0.0714	743.5276	<.0001
xa38	1	-2.0850	0.0742	790.2593	<.0001
xa39	1	-2.1410	0.0761	790.8868	<.0001
xcy0	1	-1.8184	0.0782	540.0886	<.0001
xcy2	1	0.1691	0.00304	3092.9403	<.0001
xchage1	1	-0.7056	0.0437	261.2187	<.0001
xchage2	1	-0.5373	0.0436	152.1785	<.0001
xchage3	1	-0.2261	0.0442	26.1366	<.0001
xchage4	1	-0.1424	0.0487	8.5662	0.0034
xchage5	1	-0.00054	0.0425	0.0002	0.9898
xchage6	1	0.0746	0.0506	2.1792	0.1399
xchage7	1	0.0723	0.0608	1.4147	0.2343
xchage8	1	0.0761	0.0617	1.5204	0.2176

Model for enrollment, starting from educational level 6

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-0.7035	0.0611	132.4667	<.0001
xa18	1	-1.2118	1.4153	0.7331	0.3919
xa19	1	0.3744	0.3223	1.3494	0.2454
xa20	1	0.6421	0.0990	42.0951	<.0001
xa22	1	0.0355	0.0695	0.2602	0.6100
xa23	1	-0.6744	0.0639	111.5105	<.0001
xa24	1	-1.0566	0.0627	284.3849	<.0001
xa25	1	-1.1780	0.0635	343.6529	<.0001
xa26	1	-1.2560	0.0648	375.3708	<.0001
xa27	1	-1.3749	0.0666	426.2655	<.0001
xa28	1	-1.4211	0.0683	432.3761	<.0001
xa29	1	-1.5235	0.0700	473.5818	<.0001
xa30	1	-1.7603	0.0722	594.0760	<.0001
xa31	1	-1.7280	0.0736	551.5843	<.0001
xa32	1	-1.8636	0.0754	611.1662	<.0001

xa33	1	-2.0162	0.0774	677.7878	<.0001
xa34	1	-1.9555	0.0780	628.0515	<.0001
xa35	1	-1.8101	0.0775	545.2732	<.0001
xa36	1	-1.8336	0.0781	550.9646	<.0001
xa37	1	-1.8302	0.0786	541.6010	<.0001
xa38	1	-1.9043	0.0800	567.0823	<.0001
xa39	1	-1.9761	0.0813	590.2071	<.0001
xcy0	1	1.1123	0.1108	100.8600	<.0001
xcy2	1	0.0446	0.00365	149.4981	<.0001
xchage1	1	-0.4621	0.0386	143.6218	<.0001
xchage2	1	-0.3579	0.0391	83.7073	<.0001
xchage3	1	-0.2725	0.0426	40.8300	<.0001
xchage4	1	-0.1490	0.0460	10.4907	0.0012
xchage5	1	-0.1550	0.0403	14.7904	0.0001
xchage6	1	-0.0670	0.0472	2.0138	0.1559
xchage7	1	-0.1703	0.0587	8.4045	0.0037
xchage8	1	-0.0587	0.0574	1.0474	0.3061

Model for enrollment, starting from educational level 7

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-3.2213	0.2988	116.2109	<.0001
xa22	1	-9.8755	177.2	0.0031	0.9556
xa23	1	0.4396	0.5739	0.5868	0.4436
xa25	1	0.6919	0.3065	5.0968	0.0240
xa26	1	0.8190	0.2964	7.6327	0.0057
xa27	1	0.7187	0.2945	5.9547	0.0147
xa28	1	0.5237	0.2965	3.1197	0.0774
xa29	1	0.4947	0.3014	2.6935	0.1008
xa30	1	0.2744	0.3072	0.7982	0.3716
xa31	1	0.2585	0.3123	0.6848	0.4079
xa32	1	0.1941	0.3164	0.3762	0.5397
xa33	1	0.00217	0.3220	0.0000	0.9946
xa34	1	0.0212	0.3267	0.0042	0.9484
xa35	1	-0.1427	0.3332	0.1835	0.6684
xa36	1	0.3838	0.3264	1.3826	0.2397
xa37	1	0.3542	0.3295	1.1557	0.2824
xa38	1	0.0106	0.3388	0.0010	0.9751
xa39	1	0.1680	0.3388	0.2457	0.6201
xcy0	1	-0.6661	0.5015	1.7641	0.1841
xcy2	1	0.0987	0.0154	40.9214	<.0001
xchage1	1	-0.2351	0.1148	4.1931	0.0406
xchage2	1	-0.3121	0.1162	7.2153	0.0072
xchage3	1	-0.3495	0.1323	6.9814	0.0082
xchage4	1	-0.0768	0.1463	0.2754	0.5997
xchage5	1	-0.4086	0.1415	8.3392	0.0039
xchage6	1	0.00483	0.1684	0.0008	0.9771
xchage7	1	-0.5386	0.2566	4.4044	0.0358
xchage8	1	-0.2948	0.2581	1.3050	0.2533

Model for 1st birth

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-2.6618	0.0374	5051.9764	<.0001
xa17	1	-0.9798	0.0703	193.9862	<.0001
xa18	1	-0.3025	0.0528	32.8003	<.0001
xa20	1	0.1970	0.0449	19.2801	<.0001
xa21	1	0.3560	0.0442	64.9430	<.0001
xa22	1	0.5480	0.0435	158.7248	<.0001
xa23	1	0.6600	0.0436	229.4767	<.0001
xa24	1	0.8273	0.0433	365.9031	<.0001
xa25	1	0.9616	0.0433	493.4061	<.0001
xa26	1	1.1124	0.0435	655.2361	<.0001
xa27	1	1.1478	0.0443	670.5672	<.0001
xa28	1	1.0310	0.0462	497.2007	<.0001
xa29	1	0.9525	0.0481	392.7620	<.0001
xa30	1	0.9433	0.0495	362.9844	<.0001
xa31	1	0.9141	0.0512	318.3488	<.0001
xa32	1	0.7528	0.0546	190.1228	<.0001
xa33	1	0.6596	0.0576	131.2291	<.0001

xa34	1	0.4769	0.0621	58.9645	<.0001
xa35	1	0.4116	0.0650	40.1071	<.0001
xa36	1	0.2959	0.0693	18.2339	<.0001
xa37	1	0.0664	0.0769	0.7454	0.3879
xa38	1	-0.1236	0.0842	2.1531	0.1423
xa39	1	-0.5717	0.1022	31.3147	<.0001
xenrprev	1	-1.1657	0.0221	2784.7986	<.0001
xedu3	1	0.0111	0.0252	0.1948	0.6590
xedu4	1	-0.2780	0.0266	109.5331	<.0001
xedu6	1	-0.0692	0.0290	5.6736	0.0172
xedu7	1	0.0973	0.0471	4.2675	0.0388

Model for 2nd birth

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-1.2738	0.0845	227.0285	<.0001
xa18	1	0.2799	0.3074	0.8290	0.3626
xa19	1	-0.00881	0.1588	0.0031	0.9558
xa21	1	0.0293	0.1004	0.0850	0.7707
xa22	1	0.1016	0.0939	1.1716	0.2791
xa23	1	0.1538	0.0910	2.8532	0.0912
xa24	1	0.2781	0.0893	9.7035	0.0018
xa25	1	0.2723	0.0887	9.4111	0.0022
xa26	1	0.3363	0.0882	14.5348	0.0001
xa27	1	0.3111	0.0880	12.4868	0.0004
xa28	1	0.2567	0.0881	8.4862	0.0036
xa29	1	0.2764	0.0883	9.8002	0.0017
xa30	1	0.2561	0.0889	8.3069	0.0039
xa31	1	0.2339	0.0897	6.8058	0.0091
xa32	1	0.2742	0.0903	9.2180	0.0024
xa33	1	0.1219	0.0918	1.7625	0.1843
xa34	1	0.0322	0.0934	0.1187	0.7305
xa35	1	-0.0570	0.0951	0.3594	0.5488
xa36	1	-0.2741	0.0982	7.7941	0.0052
xa37	1	-0.3115	0.1000	9.6922	0.0019
xa38	1	-0.6265	0.1055	35.2984	<.0001
xa39	1	-0.9637	0.1130	72.7317	<.0001
xy0	1	-2.1341	0.0352	3683.7911	<.0001
xy1	1	-0.4258	0.0241	312.5726	<.0001
xy3	1	-0.1015	0.0278	13.3588	0.0003
xy4	1	-0.4236	0.0332	162.8349	<.0001
xy5	1	-0.6884	0.0394	305.0359	<.0001
xy6	1	-0.8271	0.0453	332.8818	<.0001
xy7	1	-1.1637	0.0559	433.4761	<.0001
xy8	1	-1.2910	0.0641	406.0736	<.0001
xy9	1	-1.4496	0.0743	380.1838	<.0001
xy10	1	-1.6913	0.0504	1124.3686	<.0001
xenrprev	1	-0.9263	0.0380	594.2249	<.0001
xedu3	1	0.1701	0.0303	31.5981	<.0001
xedu4	1	0.3138	0.0322	94.8109	<.0001
xedu6	1	0.7111	0.0352	407.2172	<.0001
xedu7	1	0.9546	0.0564	286.4687	<.0001

Model for 3rd birth

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-1.9388	0.5199	13.9049	0.0002
xa18	1	-8.2791	257.3	0.0010	0.9743
xa19	1	-8.5033	82.5714	0.0106	0.9180
xa21	1	0.0788	0.5809	0.0184	0.8921
xa22	1	-0.0976	0.5465	0.0319	0.8583
xa23	1	-0.2322	0.5335	0.1894	0.6634
xa24	1	-0.1072	0.5264	0.0415	0.8386
xa25	1	-0.0342	0.5235	0.0043	0.9479
xa26	1	-0.0854	0.5225	0.0267	0.8702
xa27	1	-0.0514	0.5218	0.0097	0.9216
xa28	1	-0.1844	0.5216	0.1250	0.7236
xa29	1	-0.2248	0.5214	0.1860	0.6663

xa30	1	-0.3302	0.5214	0.4011	0.5265
xa31	1	-0.3655	0.5214	0.4914	0.4833
xa32	1	-0.4413	0.5214	0.7163	0.3974
xa33	1	-0.5902	0.5216	1.2803	0.2579
xa34	1	-0.7595	0.5219	2.1176	0.1456
xa35	1	-0.8522	0.5221	2.6640	0.1026
xa36	1	-1.0519	0.5226	4.0514	0.0441
xa37	1	-1.2585	0.5232	5.7853	0.0162
xa38	1	-1.7267	0.5248	10.8250	0.0010
xa39	1	-1.9518	0.5260	13.7670	0.0002
xy0	1	-1.5758	0.0543	843.7524	<.0001
xy1	1	-0.1806	0.0378	22.8557	<.0001
xy3	1	0.0834	0.0396	4.4460	0.0350
xy4	1	0.0148	0.0433	0.1176	0.7317
xy5	1	-0.0551	0.0479	1.3209	0.2504
xy6	1	-0.1633	0.0544	8.9999	0.0027
xy7	1	-0.4534	0.0667	46.1678	<.0001
xy8	1	-0.5223	0.0769	46.1362	<.0001
xy9	1	-0.4673	0.0857	29.7450	<.0001
xy10	1	-0.6396	0.0707	81.9399	<.0001
xenrprev	1	-0.4849	0.0565	73.7300	<.0001
xedu3	1	0.0750	0.0420	3.1820	0.0745
xedu4	1	0.1382	0.0450	9.4393	0.0021
xedu6	1	0.6221	0.0480	168.1531	<.0001
xedu7	1	0.7602	0.0770	97.4445	<.0001

Model for 4th birth

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-2.4937	0.5992	17.3176	<.0001
xa20	1	-7.8831	304.7	0.0007	0.9794
xa21	1	-8.0932	127.7	0.0040	0.9495
xa22	1	0.8350	0.9540	0.7660	0.3814
xa24	1	0.2819	0.6892	0.1673	0.6825
xa25	1	-0.2289	0.6708	0.1164	0.7330
xa26	1	0.0953	0.6258	0.0232	0.8790
xa27	1	0.1041	0.6136	0.0288	0.8653
xa28	1	0.0801	0.6079	0.0174	0.8952
xa29	1	0.0258	0.6052	0.0018	0.9660
xa30	1	-0.0306	0.6038	0.0026	0.9596
xa31	1	-0.1917	0.6034	0.1009	0.7507
xa32	1	-0.2602	0.6029	0.1863	0.6660
xa33	1	-0.3477	0.6027	0.3329	0.5640
xa34	1	-0.6398	0.6037	1.1232	0.2892
xa35	1	-0.5738	0.6033	0.9046	0.3416
xa36	1	-0.8376	0.6046	1.9190	0.1660
xa37	1	-0.9530	0.6054	2.4782	0.1154
xa38	1	-1.3149	0.6080	4.6770	0.0306
xa39	1	-1.5692	0.6107	6.6026	0.0102
xy0	1	-1.0619	0.1001	112.6110	<.0001
xy1	1	0.0747	0.0771	0.9377	0.3329
xy3	1	-0.00502	0.0864	0.0034	0.9536
xy4	1	-0.1947	0.0980	3.9452	0.0470
xy5	1	-0.2082	0.1073	3.7628	0.0524
xy6	1	-0.3648	0.1260	8.3789	0.0038
xy7	1	-0.2573	0.1368	3.5377	0.0600
xy8	1	-0.2203	0.1548	2.0260	0.1546
xy9	1	-0.7363	0.2261	10.6044	0.0011
xy10	1	-0.3229	0.1612	4.0114	0.0452
xenrprev	1	-0.2104	0.1115	3.5593	0.0592
xedu3	1	-0.0923	0.0788	1.3729	0.2413
xedu4	1	-0.1900	0.0879	4.6734	0.0306
xedu6	1	0.1660	0.0942	3.1037	0.0781
xedu7	1	0.4384	0.1701	6.6419	0.0100

Model for 5th birth

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-3.4255	1.0318	11.0226	0.0009
xa23	1	-11.8533	1716.7	0.0000	0.9945
xa24	1	-11.9756	952.1	0.0002	0.9900

xa25	1	-11.9460	569.0	0.0004	0.9832
xa27	1	-0.6108	1.4319	0.1820	0.6697
xa28	1	0.6430	1.1000	0.3417	0.5588
xa29	1	0.4944	1.0726	0.2125	0.6448
xa30	1	0.0572	1.0719	0.0028	0.9575
xa31	1	-0.0591	1.0625	0.0031	0.9556
xa32	1	0.0719	1.0493	0.0047	0.9454
xa33	1	0.3458	1.0382	0.1109	0.7391
xa34	1	0.3056	1.0363	0.0869	0.7681
xa35	1	0.2776	1.0355	0.0719	0.7887
xa36	1	0.2593	1.0350	0.0628	0.8022
xa37	1	0.2847	1.0345	0.0758	0.7831
xa38	1	-0.3662	1.0454	0.1227	0.7261
xa39	1	0.0866	1.0388	0.0069	0.9336
xy0	1	-0.3681	0.2156	2.9154	0.0877
xy1	1	0.3143	0.1890	2.7644	0.0964
xy3	1	-0.5236	0.2505	4.3681	0.0366
xy4	1	-0.4622	0.2624	3.1026	0.0782
xy5	1	-0.1616	0.2570	0.3953	0.5295
xy6	1	-0.5304	0.3205	2.7386	0.0980
xy7	1	-0.5933	0.3722	2.5403	0.1110
xy8	1	-0.5337	0.4156	1.6489	0.1991
xy9	1	-0.9795	0.6052	2.6191	0.1056
xy10	1	-0.7763	0.4853	2.5592	0.1097
xenrprev	1	0.1567	0.2519	0.3872	0.5338
xedu3	1	-0.0448	0.1798	0.0621	0.8031
xedu4	1	-0.2179	0.2084	1.0929	0.2958
xedu6	1	-0.0418	0.2269	0.0340	0.8538
xedu7	1	0.1711	0.4549	0.1415	0.7068

Supplementary Information Table S2. Educational level attained by woman's age 39, average number of children of women at age 39 who attained each educational level, and percentage of women who attained each educational level by age 39: data (in upper half table), 99% confidence intervals around the data (in lower half table), and corresponding results of 3 simulations. Educational levels: 2, 10 years, compulsory; 3, 11 years, lower secondary; 4, 12-13 years, upper secondary; 6, 14-17 years, lower university; 7, 18+ years, Master's degree or equivalent. E.g., women at educational level 2 at age 39 had on average 2.136 children at age 39, with 99% confidence interval (1.98, 2.31) by either method. All three simulations gave average numbers of children per woman within this confidence interval. However, the percentage of women with educational level 2 at age 39 fell within the confidence interval (6.00, 6.78) in simulations 1 and 2, but above the confidence interval in simulation 3. Simulation 1: all parameters were estimated from the data. Simulation 2: effects of fertility on education were set to 0; remaining parameters were estimated from the data. Simulation 3: effects of education on fertility were set to 0; remaining parameters were estimated from the data.

Educational level at age 39	Average number of children at woman's age 39				% of women with this education			
	Data	Simulation 1	Simulation 2	Simulation 3	Data	Simulation 1	Simulation 2	Simulation 3
2	2.136	2.123	2.040	2.163	6.38	6.75	6.04	6.90
3	2.112	2.112	2.077	2.113	28.41	30.31	28.42	30.5
4	1.989	1.940	1.911	2.106	31.56	32.41	31.38	33.09
6	1.934	1.932	2.032	1.994	28.45	27.78	30.54	27.18
7	1.722	1.798	1.996	1.843	5.2	2.75	3.61	2.32
Total	2.004	1.998	1.997	2.076	100	100	100	99.99

(Table continues on next page)

	number of women	number of children of all such women	Average number of children at woman's age 39				% of women with this education	
			Confidence interval by square-root transformation		Confidence interval by Wald method		Confidence interval by binofit	
	Data	Data	lower	upper	lower	upper	lower	upper
2	1682	3592	1.980	2.305	1.979	2.304	6.00	6.78
3	7485	15808	2.037	2.190	2.037	2.190	27.70	29.13
4	8315	16539	1.921	2.059	1.921	2.059	30.82	32.30
6	7496	14495	1.864	2.006	1.864	2.006	27.74	29.17
7	1371	2361	1.578	1.880	1.578	1.879	4.85	5.56
Total	26349	52795	1.965	2.043	1.965	2.043	NA	NA