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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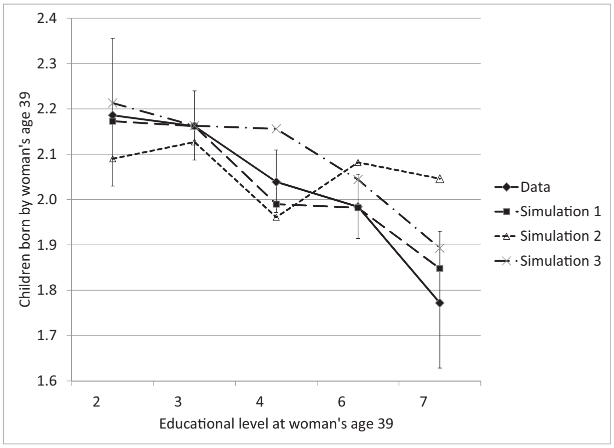

Fig. 1. Children born by woman's age 39 as a function of educational level at woman's age 39, according to data (filled diamond and solid line), simulation 1 (filled square and long dashed line), simulation 2 (open triangle and short dashed line), and simulation 3 (× and dashed line). Error bars around 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.

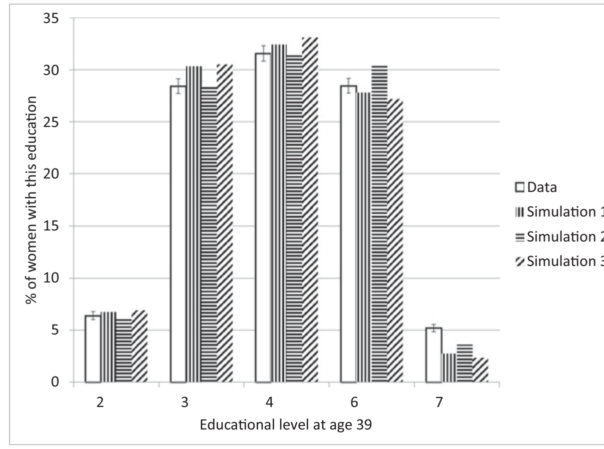

Fig. 2. Percentages of women with each educational level at age 39, according to data (white bars), simulation 1 (vertical lines), simulation 2 (horizontal lines), and simulation 3 (diagonal lines). Error bars around the data show 99% confidence intervals (*Methods*). Simulations are defined in the text 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 $t^{(f')}$

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

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

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

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

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:

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

$\boldsymbol{A}(a)$ 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 $n \leq q_2$, to 3 if $q_2 < n \leq q_2 + q_3$, to 4 if $q_2 + q_3 < n \leq q_2 + q_3 + q_4$, and to 6 if $q_2 + q_3 + q_4 < n \leq 1$.

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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1. Castro Martín T (1995) Women's education and fertility: Results from 26 demographic and health surveys. *Stud Fam Plann* 26:187–202.
2. Kravdal Ø, Rindfuss RR (2008) Changing relationships between education and fertility: A study of women and men born 1940 to 1964. *Am Sociol Rev* 73:854–873.
3. Breierova L, Duflo E (2004) The impact of education on fertility and child mortality: Do fathers really matter less than mothers? (National Bureau of Economic Research, Cambridge, MA), Working Paper No W10513.
4. Monstad K, Propper C, Salvanes KG (2008) Education and fertility: Evidence from a natural experiment. *Scand J Econ* 110:827–852.
5. Skirbekk V, Kohler HP, Prskawetz A (2004) Birth month, school graduation, and the timing of births and marriages. *Demography* 41:547–568.
6. Silles MA (2011) The effect of schooling on teenage childbearing: Evidence using changes in compulsory education laws. *J Popul Econ* 24:761–777.
7. Webbink D, Martin NG, Visscher PM (2011) Does teenage childbearing reduce investment in human capital? *J Popul Econ* 24:701–730.
8. Geronimus AT, Korenman S (1993) The socioeconomic costs of teenage childbearing: Evidence and interpretation. *Demography* 30:281–290, discussion 291–296.
9. Hoffman SD, Foster EM, Furstenberg FF, Jr. (1993) Reevaluating the costs of teenage childbearing. *Demography* 30:1–13.
10. Hofferth SL, Reid L, Mott FL (2001) The effects of early childbearing on schooling over time. *Fam Plann Perspect* 33:259–267.
11. Eloundou-Enyegue PM (2004) Pregnancy-related dropouts and gender inequality in education: A life-table approach and application to Cameroon. *Demography* 41: 509–528.
12. Hoem JM, Kreyenfeld M (2006) Anticipatory analysis and its alternatives in life-course research. Part 1: The role of education in the study of first childbearing. *Demogr Res* 15:461–484.
13. Kravdal Ø (2007) Effects of current education on second- and third-birth rates among Norwegian women and men born in 1964: Substantive interpretations and methodological issues. *Demogr Res* 17:211–246.
14. Zabel C (2009) Do imputed educational histories provide satisfactory results in fertility analysis in the West German context? *Demogr Res* 21:135–176.
15. Upchurch DM, Lillard LA, Panis CWA (2002) Nonmarital childbearing: Influences of education, marriage, and fertility. *Demography* 39:311–329.
16. Lutz W (2009) Editorial: Towards a world of 2–6 billion well-educated and therefore healthy and wealthy people. *Journal of the Royal Statistical Society A* 172:701–705.
17. Vaupel JW, Yashin AI (1985) Heterogeneity's ruses: Some surprising effects of selection on population dynamics. *Am Stat* 39:176–185.
18. SAS Inst Inc (2008) *SAS/STAT 9.2 User's Guide* (SAS Inst, Cary, NC).
19. Price RM, Bonett DG (2000) Estimating the ratio of two Poisson rates. *Comput Stat Data Anal* 34:345–356.