WORKING PAPER 2019:10

Skills, education and fertility

and the confounding impact of family background

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ISSN 1651-1166

Skills, education and fertility[a]

and the confounding impact of family background

by

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2019-05-12

Abstract

Skilled and educated women have on average fewer children and are more likely to remain childless than the less skilled and educated. Using rich Swedish register data, we show that these negative associations found in most previous studies largely disappear if we remove the impact of family background factors using twin (or sibling) fixed effects. For males, human capital measures are virtually unrelated to fertility, but this again masks the role of family background factors: more educated and skilled males tend to have more children than their less skilled peers once we use twin/sibling fixed effects to remove family background factors. Hence, for both men and women, human capital and fertility become more positively associated once the joint family components are removed, i.e. when studying the within-family associations. The one human capital measure which deviates from these patterns is non-cognitive ability, which has a very strong overall positive association with fertility, an association which instead is muted within families. We end by showing that these results can be reconciled in a stylized theoretical model where family-specific preferences for fertility shape the relative investments in different types of skills and traits when children are small as well as the choices, in terms of family formation and human capital investments, these children make when they enter into adulthood.

Keywords: Fertility, education, grades, cognitive ability, non-cognitive ability, twins
JEL-codes: I24, I26, J13, J24

[a] The authors thank Lena Hensvik, Anna Sandberg, Björn Öckert, Helena Holmlund and seminar participants at IFAU and Uppsala University for helpful comments.
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1 Introduction

The relationship between human capital measures such as skills and education on the one hand and fertility on the other is a widely studied topic within demography, sociology, economics and other social sciences. As Fort et al. (2016) point out; the bulk of this literature clearly supports the notion that more education reduces fertility rates at the aggregate level. Developed countries have higher levels of education and lower levels of completed fertility than developing countries (United Nations, 2015). The same negative association can be seen within countries over time. More recent cohorts with higher levels of education typically have lower levels of fertility than older cohorts (see e.g. Frejka and Calot, 2001). There are two main explanations for these observations. First, education improves the earnings capacity, making it more costly to bear and raise children. Second, education improves awareness of contraceptive technologies.

From the perspective of the individual it is, however, less clear what to expect *a priori*. If pursuing higher education makes it more costly to raise a family, then individuals may be forced to choose between accumulating more human capital and raising children, a fear that appears relevant for women in many countries. On the other hand, increased human capital may be complementary to family formation outcomes (such as fertility) if increased human capital increases the attractiveness on the marriage market in comparison with peers of the same cohorts. It is useful to imagine two persons who compete on the same side in the same marriage market and who are identical in all aspects other than their level of education. In this case, it is not clear that the more educated individual will have lower completed fertility since the theoretical effect of education on completed fertility is ambiguous because of the opposing forces discussed above.

The bulk of the existing literature (see e.g. Martin, 2000; Kravdal and Rindfuss 2008; Meisenberg 2008; Rodgers et al. 2008; Andersson et al., 2009; Nisén et al. 2013, Amin and Behrman 2014; Tropf and Mandemakers 2017; Jalovaara et al., 2018) has found negative associations between fertility and human capital measures at least for females.[1] However, it is far from clear which underlying forces drive these associations and, in particular, to what extent the observed associations reflect causal relationships or other background factors (such as, e.g., preferences or financial wealth) which may affect both human-capital accumulation and fertility. The answer to this question can of course differ between men and women and differ between different types of human capital. The aim of this paper is to contribute to the understanding of the joint determinants of fertility and human capital by netting out, and scrutinizing, the role of family background factors for men and women. We are interested in scrutinizing a broad set of human capital measures covering years of schooling, compulsory school grades, cognitive ability and non-cognitive ability measures. Grades and cognitive ability are highly correlated (as we show), which suggests that they may be capturing similar types of human capital (e.g. reflecting the stock of knowledge and the ability to process information). We also analyze direct measures of non-cognitive abilities capturing human capital in a more social dimension. These skills (cognitive and non-cognitive) are measured during teen years, and they jointly serve as (potential) inputs for the final choice of whether or not to pursue higher education.

A confounding factor affecting the often-documented raw empirical association between fertility and education (see e.g. Amin and Behrman 2014; Kravdal and Rindfuss 2008; Meisenberg 2008; Nisén et al. 2013) is that predetermined factors such as endowments of skills, as well as e.g. preferences and wealth, may affect both the possibilities of pursuing higher education and fertility outcomes. As noted above, this makes the raw association between education and fertility difficult to interpret. A set of recent studies have tried to remove the

[1] See Section 2 below for a more detailed discussion of individual studies.

confounding impact of background factors by controlling for family fixed effects (see e.g. Amin and Behrman 2014; Kohler et al. 2011; Nisén et al. 2013). These papers mainly focus on women and the evidence is mixed, perhaps partly because of small sample sizes, but the evidence tends to suggest that the inclusion of family fixed effects pushes the association between education and fertility in a positive direction.

A related set of studies have directed attention to the association between initial skill endowments (mainly intelligence) and fertility (see e.g. Chen et al. 2013; Kanazawa 2014; Meisenberg 2010; Wang et al. 2016), thus focusing on the impact on fertility of endowments that are predetermined at the time when schooling and fertility choices are made. Generally, the above studies have documented a negative association between human capital and fertility for women and a relationship close to zero for men.

In this paper, we combine these earlier approaches by analyzing the impact of both skills and education on fertility while accounting for family background factors using twin fixed effects. We thus remove the impact of all family background factors such as preferences or financial wealth that simultaneously affect accumulated human capital and fertility. An advantage relative to previous studies is that we use nationwide register data (from Sweden) on several different measures of human capital and fertility. Our fertility measures are: Age at first birth (AFB), a dummy for having children at all at age 45 and the number of children at age 45. In addition, we have data to study both men and women (for most of, but not all, of our human capital measures) in contrast to earlier papers that often focus on women. Thus, we are able to give a very comprehensive picture of the relations between human capital and fertility within and across families.

Our results highlight that family background factors are important determinants of the raw empirical associations between different human capital measures and fertility. For women, we find significantly negative raw associations between years of schooling, compulsory school grades and fertility, as in most previous studies. However, after accounting for twin (or sibling) fixed effects, the associations are instead close to zero. For men, the raw associations between human capital (years of schooling, compulsory school grades and cognitive skills) and fertility are instead close to zero, while the estimates from twin fixed effects models are firmly positive.

Overall, we thus conclude the raw associations may overemphasize the degree to which human capital accumulation crowds out childbearing for women and that the raw associations similarly underestimate the degree of complementarity between human capital and fertility for men. These patterns imply that there must exist some important family background factor (shared between twins and siblings) that is positively related to grades, cognitive abilities and acquired education but negatively related to our fertility measures (consequently pushing the raw associations in a negative direction) for both men and women.

With respect to non-cognitive ability, which we show to be very strongly related to fertility, we instead find the opposite pattern; the inclusion of twin fixed effects pushes the association with fertility in a more negative direction. We end the paper by showing that these results can be reconciled in a stylized theoretical model where shared preferences within a family affect both the types of skills children accumulate, and the choices these children make later in life.

2 Previous literature

The overall literature on the determinants of fertility outcomes is clearly much too vast to be summarized here. Instead, we give a broad overview of the most closely related studies, i.e. papers presenting findings concerning the associations between non-cognitive skills, cognitive skills and years of schooling on the one side, and individual fertility measures on the other side.[2]

We start with the raw association between years of schooling and fertility. For women, years of schooling is generally negatively associated with completed fertility (Amin and Behrman 2014; Kravdal and Rindfuss 2008; Meisenberg 2008; Nisén et al. 2013). However, at least in the Nordic countries, there have been substantial changes over time. Andersson et al. (2009) and Jalovaara et al. (2018) report that the educational gradient in completed fertility has decreased over time. The cross-sectional association between years of education and AFB for women is consistently positive (Amin and Behrman 2014; Kravdal and Rindfuss 2008; Martin 2000; Rodgers et al. 2008; Tropf and Mandemakers 2017).

The results for men are more mixed. In developed countries the association between years of schooling and completed fertility is suggested to be zero or slightly positive (Kravdal and Rindfuss 2008; Meisenberg 2008; Nisén et al. 2013). For the Nordic countries, Jalovaara et al. (2018) report a persistent positive educational gradient in completed fertility. In developing countries, however, the association is firmly negative (Meisenberg 2008). But, it appears quite clear that higher education is associated with higher AFB for men (Kravdal and Rindfuss 2008; Nisén et al. 2013).

Recently, a set of papers in the demographic literature has investigated within-twin associations between years of schooling and fertility, in an attempt to move closer to an estimating a causal effect of educational attainment on fertility.[3] Kohler et al. (2011) and Amin and Berhman (2014) investigate within-twin associations between years of schooling and fertility using data on identical female twins in the U.S. Both studies find that more education is associated with lower completed fertility in terms of number of children. Amin and Berhman (2014) further suggest that education delays childbearing. However, they find no association between education and childlessness. Nisén et al. (2013) study male and female twin pairs in Finland and find no effect of education for any of the genders on completed fertility in terms of having children at all. Nisén et al. (2013) further shows that the within-twin association between years of schooling and AFB for men is close to zero while it is slightly positive for women. Rodgers et al. (2008) and Tropf and Mandemakers (2017) have also investigated within-twin associations between years of schooling and AFB for women using data on Danish and British twins. Rodgers et al. (2008) suggest that the effect of education on AFB is zero but Tropf and Mandemakers (2017) report significant (albeit small) positive effects.[4]

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[2] A condense overview is presented in Table A1 in Appendix A.

[3] It is of course debatable whether within-twin pair estimates of the effect of education on fertility can be given a causal interpretation. But at the very least, family fixed effects models remove the confounding influence of environmental factors that simultaneously determine fertility and education. See Kohler et al. (2011) for a detailed description of the benefits of twin data in social science.

[4] There are also several papers that have used schooling reforms to study the causal effect of years of education on fertility outcomes. McCrary and Royer (2011) suggest that the causal effect of education on AFB for women is zero. Monstad et al. (2008), Grönqvist and Hall (2013), Black et al. (2008), Cygan-Rehm and Maeder (2013) and Silles (2011), on the other hand, report positive effects. For men, Grönqvist and Hall (2013) find zero effects of education on AFB and on fertility at age 32. The evidence on the causal effect of years of schooling on completed fertility for women is quite mixed. Fort et al. (2016) find negative effects for England but positive effects for continental Europe. Monstad et al. (2008) find zero effects. Grönqvist and Hall (2013) find zero effects (but measured at age 32). Cygan-Rehm and Maeder (2013) find negative effects.

The above twin studies use different techniques to study the relation between education and fertility. One approach is to use variation in education and fertility within identical twin pairs (e.g. Amin and Behrman 2014). The idea is that variation in schooling within identical twin pairs should be more random (exogenous) than variation in schooling across families since the twins should be more similar in terms of potentially confounding factors (e.g. genes and environment). Another approach is to study both fraternal and identical twins and use differences in the associations between education and fertility for the different twin-pair types to draw conclusions about what forces that are driving the covariance between education and fertility (e.g. Nisén et al. 2013). With this approach it is possible to draw conclusions about how shared genetic and environmental factors contribute to the covariance between the studied variables. It is also possible to estimate the relative importance of factors that are unique to the individual, i.e. that are not shared by twins. If anything, the first approach is more informative about causality while the second is better at providing a fuller picture of the sources of covariance. A notable recent contribution is Tropf and Mandemakers (2017) who combine the two approaches into one unified framework.

The previous research on the raw association between cognitive ability/intelligence and fertility has produced two robust findings for women. First, intelligence is negatively associated with completed fertility (Chen et al. 2013; Kanazawa 2014; Meisenberg 2010; Wang et al. 2016). Second, intelligence is positively correlated with AFB (Rodgers et al. 2008). For men, the picture is less clear. Several recent papers report small negative associations between intelligence and completed fertility (Chen et al. 2013; Meisenberg 2010; Wang et al. 2016). Kanazawa (2014), however, find no relation between intelligence and childlessness, and Woodley and Meisenberg (2013) even find a positive association. To the best of our knowledge, the relation between intelligence and AFB for men remains uninvestigated.

Research on the within-family association between intelligence and fertility outcomes is very scarce. We are only aware of the paper by Rodgers et al. (2008) that investigates the within-twin association between intelligence and AFB for women. They find a zero effect.

Finally, the only study we found on the association between non-cognitive ability and fertility is ongoing work by Öckert et al. (2017) who use similar data to ours to estimate raw associations between fertility and draft test scores (scores for females are imputed from male family members), but they do not present any within-family estimates.

In our paper, we estimate associations between years of education, compulsory school grades, cognitive and non-cognitive abilities and the three most commonly used fertility outcomes in the literature reviewed above, i.e. an indicator for positive completed fertility (having children at all at age 45), a continuous measure of completed fertility (number of children at age 45) and AFB.[5] We do this separately for men and women. We provide raw associations and within twin-pairs estimates for all of these variables except within twin-pair associations for female ability scores.[6] This means that we, in contrast to earlier studies, can give a more comprehensive picture of the relations between grades, years of schooling, non-cognitive and cognitive skills on the one side and standard fertility measures on the other side.

[5] To keep the presentation concise, and in concordance with the reviewed studies, we abstain from analyzing alternative measures such as parity progression ratios or parity at different ages.
[6] We use the term "raw" even though year of birth fixed effects are included in our models.

3 Data

Our main data source is a multigenerational register covering all individuals in Sweden born in the period 1932–2017. This dataset contains year and month of birth, gender and a personal identifier that can be linked to other registers. It also contains personal identifiers for the father and the mother. We approximate completed fertility by fertility outcomes at age 45. Consequently, we do not include individuals who are born after 1972. The included cohorts vary depending on the independent variables used; our largest (smallest) sample contains cohorts born between 1935–1972 (1969–1972 Through the multigenerational register, we can measure the reproductive results of these cohorts up until age 45. We summarize their fertility through three different measures: AFB, a dummy for having children at age 45 and a count of the total number of children at age 45.

This multigenerational register is also used to identify twins. Individuals that are born in the same month in the same year and that have the same mother and father are considered twins. We only study same-sex twins. We do not observe if the twins are monozygotic or dizygotic, but it is a well-known fact that about half of same-sex twin pairs are dizygotic (Haworth et al. 2008).

We measure skills and schooling using three different data sources. First, we have access to the final average grade from compulsory school for all individuals that graduated from 1985 onward.[7] Students typically graduate from compulsory school in the year when they turn 16. Consequently, we can only study individuals born in 1969–1972 when using this skill measure. Second, we can observe cognitive and non-cognitive ability test results *for men* from the military draft. The cognitive score, which is measured through a written test, is known to be a good measure of general intelligence (Carlstedt 2000).[8] Non-cognitive ability is evaluated in the following way (Mood et al. 2012). During the draft, the draftees have a 20-minute interview with a trained psychologist. The psychologist asks questions about how they feel and behave in different situations and on the basis of the answers and the psychologist's perception of the draftee, the draftee is scored along four different dimensions. These dimensions are: social maturity (e.g. extroversion and independence), psychological energy (e.g. focus and perseverance), intensity (e.g. activation without external pressure) and emotional stability (e.g. tolerance to stress). These subscores are summarized in an overall non-cognitive score reported using a normally distributed Stanine scale. The cognitive test results are also summarized in the same way. We use these overall scores and we standardize them by enlistment year (as in Grönqvist et al. 2017).[9] The draft typically occurs at age 18 which restricts our sample to individuals born in 1950–1972 (draft information is available from 1969). During this period military service was compulsory for men and hence almost all men participated in the draft. Only a very tiny fraction of the women participated in the draft and thus this analysis is (primarily) confined to men.[10] At the time of the draft, there is little variation in years of schooling in our population. Instead, almost all variation in years of schooling is beyond this point. The timing thus ensures that variation in years of schooling cannot have caused much of the variation in skills within our data, despite of the fact that participation in schooling is likely to add to the accumulation of ability in general (see e.g. Carlsson et al. 2015; Fredriksson et al. 2013).

[7] We primarily think of compulsory school grades as capturing cognitive ability. In Table 3, we show results supporting this notion. We standardize the grades by graduation year.

[8] See Carlsson et al. (2015) for a detailed description of the tests of cognitive ability.

[9] The measures of cognitive and non-cognitive ability used in this paper have previously been shown to be strong predictors of labor market outcomes (Fredriksson et al. 2018; Lindqvist and Vestman 2011).

[10] Grönqvist et al. (2017) have developed a method to impute cognitive and non-cognitive ability for women using the test results of their brothers. Using their method, we can thus estimate raw associations between skills and fertility also for women.

Third, we can link our main dataset to a register called LOUISE (Longitudinal database about education, income and employment). This register covers all individuals in Sweden aged 16–65 in a given year and contains data on the highest level of education. We use LOUISE data from 2000–2013. Individuals born before 1935 do not appear in these data and thus the included individuals in this analysis are born between 1935–1972. We require that the individuals are at least 35 years of age when we measure their educational attainment. The highest education level variable is transformed into a continuous years of schooling variable.[11] Table 1 gives an overview of the data we use.

Table 1 Overview of available data

Measure of human capital:	Available for persons born:	Available for:
Years of schooling	1935–1972	Women and men
Compulsory school grades	1969–1972	Women and men
Cognitive and non-cognitive ability (from the military draft)	1950–1972	Men

Notes: In order to observe fertility outcomes at age 45 we cannot study individuals born after 1972. For women with brothers who have participated in the military draft we can impute cognitive and non-cognitive skills (see Grönqvist et al. 2017).

Table 2 shows descriptive statistics for our main samples. The average number of children at age 45 lies between 1.6 and 2.0 depending on the sample, the probability of having a child at all at age 45 is between 0.75 and 0.87 and the average AFB is between 25 and 30. The differences are explained by known factors; women have higher fertility rates than men and later cohorts have children at older ages and are more likely to be childless (Andersson et al. 2009; Jalovaara et al. 2018). The overall impression is that twins are relatively similar to the average person in our key dimensions. Most notably, twins have only marginally fewer children on average. We also show that twins resemble each other in terms of skills and education, but that a non-trivial variation remains within twin pairs. The between twin pair standard deviation in years of schooling for men is 2.4 whereas the corresponding within twin pair number is 1.2, for women the numbers are 2.3 and 1.1. Turning to grades, we find a between twin standard deviation of 0.9 vs 0.3 within for both men and women. For both cognitive and non-cognitive abilities, the numbers are in the order of 0.9 between and 0.4 within twin pairs.

[11] See Appendix B for the construction of the years of schooling variable.

Table 2 Descriptive statistics

Column:	(1)	(2)	(3)	(4)
Gender:	Men		Women	
Sample:	All	Twins	All	Twins
A. Years of schooling sample (birth cohorts 1935–1972)				
Year of birth	1954.55	1954.87	1954.41	1954.46
Years of schooling	11.52	11.45	11.70	11.56
# of children at 45	1.83	1.74	2.01	1.92
1[children at 45>0]	0.80	0.77	0.87	0.85
Age at first birth	28.45	28.44	25.47	25.70
Between-pair (sd)	N/A	2.43 (schooling)	N/A	2.31 (schooling)
Within-pair (sd)	N/A	1.18 (schooling)	N/A	1.12 (schooling)
Observations	2,233,137	19,758	2,180,083	20,244
B. Compulsory school grade sample (birth cohorts 1969–1972)				
Year of birth	1970.53	1970.61	1970.53	1970.60
Grades (std)	-0.19	-0.14	0.19	0.20
# of children at 45	1.65	1.64	1.88	1.78
1[children at 45>0]	0.77	0.76	0.85	0.82
Age at first birth	30.55	30.35	28.03	28.42
Between-pair (sd)	N/A	0.95 (grade)	N/A	0.88 (grade)
Within-pair (sd)	N/A	0.31 (grade)	N/A	0.27 (grade)
Observations	207,679	2,070	201,634	2,110
C. Military draft score sample (birth cohorts 1950–1972)			(imputed skill values)	
Year of birth	1961.75	1961.59	1962.30	N/A
Cogn. ability (std)	0.00	-0.16	-0.02	N/A
Noncog. ability (std)	-0.00	0.01	-0.01	N/A
# of children at 45	1.73	1.69	1.97	N/A
1[children at 45>0]	0.77	0.75	0.85	N/A
Age at first birth	29.36	29.44	26.59	N/A
Between-pair (sd)	N/A	0.92 cog, 0.87 non	N/A	N/A
Within-pair (sd)	N/A	0.41 cog, 0.46 non	N/A	N/A
Observations	1,076,204	10,784	225,226	N/A

Notes: The grades are standardized (std) with mean 0 and standard deviation 1 for each examination year. The skill measures are standardized (std) with mean 0 and standard deviation 1 for each draft year. The between-pair (within-pair) standard deviation in number of children at age 45 for women is 0.95 (0.71) (sample is column 4 of panel A). The between-pair (within-pair) standard deviation in number of children at age 45 for men is 0.99 (0.79) (sample is column 2 of panel A).

As a final descriptive analysis, Table 3 shows the relationships between skills, grades and years of schooling for men. The purpose of this exercise is not to investigate the *effect* of the abilities on grades and years of schooling, instead we want to learn to what extent grades and years of schooling can be said to represent alternative measures of cognitive and non-cognitive ability. Two things should be noted from Table 3. First, cognitive skills are contributing more to the final average grade from compulsory school than non-cognitive skills (consistent with results in Grönqvist et al. 2017, and Almlund et al. 2011). This is true for the general population of men (column 1) as well as within male twin pairs (column 2). It also holds for women when we use imputed skills (see Table C1 in Appendix C). Therefore, we primarily view compulsory school grades as capturing cognitive ability. Second, cognitive ability is a stronger predictor of years of schooling than non-cognitive ability. Again, this is true both for men in general (column 3) and within male twin pairs (column 4). Results for women follow the same pattern (see Table C1 in Appendix C).

Table 3 Relations between the human capital measures

Column:	**(1)**	**(2)**	**(3)**	**(4)**
Outcome:	**Grade (std)**	**Grade (std)**	**Years of schooling**	**Years of schooling**
Men				
Cognitive	0.6156***	0.3346***	1.0727***	0.5787***
ability (std)	(0.0018)	(0.0286)	(0.0022)	(0.0381)
Non-cognitive	0.2276***	0.0938***	0.3167***	0.1253***
ability (std)	(0.0019)	(0.0269)	(0.0022)	(0.0347)
Observations	187,613	1,780	1,027,581	9,984
Mean of dep.	-0.1515	-0.1152	11.9671	11.9906
Variation	All	Within family	All	Within family

Notes: The grades are standardized (std) with mean 0 and standard deviation 1 for each examination year. The skill measures are standardized (std) with mean 0 and standard deviation 1 for each draft year. In columns (1) and (3) we include year of birth dummies. We implicitly control for year of birth also in columns (2) and (4) since twins obviously have the same year of birth. In parentheses we present robust standard errors. Asterisks indicate that the estimates are significantly different from zero at the ***1% level, **5% level, and *10% level.

4 Empirical analysis

We analyze our data using two straightforward regression models. Equation (1) is used to capture the raw association between fertility and skills/schooling:

$$Fertility_i = \beta_0 + \beta_1 Skills/Schooling_i + \theta_b + \varepsilon_i \qquad (1)$$

where fertility is measured in terms of AFB, a dummy for having children at age 45 and number of children at age 45. We include birth year fixed effects (θ_b) to ensure that the associations are estimated within birth cohorts. This model is estimated using the general population and the estimate of β_1 therefore relies mainly on across-family variation. If there are family background characteristics that jointly determine fertility and skills/schooling the estimate of β_1 will be biased. To control for potentially confounding family background characteristics and come closer to a causal estimate of β_1 we estimate Eq. (2) using the twin pairs (indexed by j) in our sample:

$$Fertility_{ij} = \beta_0^W + \beta_1^W Skills/Schooling_i + \delta_j + \varepsilon_{ij}^W \qquad (2)$$

where δ_j represents a twin-pair fixed effect. The inclusion of this twin-pair fixed effect ensures that β_1 is estimated using within-family variation in fertility and skills/schooling.

4.1 Fertility and years of schooling

We start by documenting the associations between years of schooling and fertility in Table 4. Results for females are presented in Panel A and for males in Panel B. The first column shows the (within birth cohort) raw associations between schooling and the number of children at age 45. Consistent with previous evidence, we find a significantly negative association for females; each additional year of schooling is associated with 0.04 fewer children. For males we find a small, but statistically significant, positive association. This is consistent with the result in Jalovaara et al. (2018) who also use Nordic data. When introducing twin fixed effects in the second column, the negative association for females almost disappears whereas the estimate for males becomes substantially more positive (0.033).

Columns (3) and (4) present corresponding results for models where the outcome instead is a dummy for having at least one child by age 45. The raw association for females suggests that one year of additional schooling is associated with 0.5 percentage points lower probability of having a child, whereas the estimate for males reveals a significantly positive association of approximately the same size. As in the case of the number of children, the introduction of twin fixed effects, moves the estimates in a positive direction for both men and women.

The last two columns repeat the exercise for AFB. The sample is here restricted to parents and is therefore somewhat smaller. We find that an additional year of schooling delays the first child birth by 0.66 years for females and by 0.45 years for males according to the raw association (column 5). Again, conditioning on twin fixed effects (column 6) moves the estimates in a direction that is consistent with a less negative association between fertility and education (interpreting earlier births as a positive indicator of fertility). Within twin pairs, one additional year of schooling is only associated with a quarter of a year's delay for females and one sixth of a year for males. The results in columns 5–6 (panel A) are very similar to what Tropf and Mandemakers (2017) found in their study on female twins in the UK.

Table 4 Fertility explained by years of schooling

Column:	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	# of children	# of children	1[children>0]	1[children>0]	AFB	AFB
A. Women						
Years of	-0.0412***	-0.0114	-0.0049***	-0.0004	0.6629***	0.2637***
schooling	(0.0003)	(0.0066)	(0.0001)	(0.0021)	(0.0014)	(0.0285)
Observations	2,180,083	20,244	2,180,083	20,244	1,898,864	15,228
Mean of dep.	2.0061	1.9239	0.8706	0.8487	25.4741	25.6951
Variation	All	Within family	All	Within family	All	Within family
B. Men						
Years of	0.0055***	0.0331***	0.0061***	0.0147***	0.4524***	0.1658***
schooling	(0.0003)	(0.0069)	(0.0001)	(0.0023)	(0.0015)	(0.0354)
Observations	2,233,137	19,758	2,233,137	19,758	1,801,464	12,724
Mean of dep.	1,8312	1,7444	0,7994	0,7697	28,4467	28,4442
Variation	All	Within family	All	Within family	All	Within family

Notes: AFB=Age at first birth. The outcomes in columns (1–4) are measured at age 45. In columns (1), (3) and (5) we include year of birth dummies. We implicitly control for year of birth also in columns (2), (4) and (6) since twins obviously have the same year of birth. In parentheses we present robust standard errors. Asterisks indicate that the estimates are significantly different from zero at the ***1% level, **5% level, and *10% level.

4.2 Fertility and grades

In Table 5, we turn to an analysis of grades. Based on the results in Table 3, we argue that grades can be viewed as primarily capturing cognitive ability. The raw association between grades and the number of children for females (panel A, column 1) is negative and statistically significant at -0.060 for each standard deviation. The association for males (panel B, column 1) is smaller, but positive and significant. When adding twin fixed effects (column 2), the results become less precise because of the relatively limited sample, but in both cases the estimates become more positive but insignificant. The results for the probability of having children follow the same pattern. The final two columns (5 and 6) repeat the exercise for AFB. Recall that we expect the opposite pattern with this outcome. Here, we find that both males and females have children later if compulsory school grades were higher, although more so for females. Adding twin fixed effects reduce the delaying effect of good grades for both men and women.

Overall, we conclude that the point estimates for grades have a similar relationship to fertility as years of schooling. Although we need to acknowledge that the statistical precision is quite poor due to the small sample, we are somewhat reassured by the fact that widening the sample to include all close siblings gives a similar picture, but with better statistical precision (see Table C7 in the Appendix C).

Table 5 Fertility explained by compulsory school grades

Column:	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	# of children	# of children	1[children>0]	1[children>0]	AFB	AFB
A. Women						
Grade (std)	-0.0579***	0.0031	-0.0058***	0.0059	2.0571***	1.1518**
	(0.0028)	(0.0803)	(0.0008)	(0.0315)	(0.0124)	(0.4495)
Observations	201,634	2,110	201,634	2,110	171,479	1,486
Mean of dep.	1.8760	1.7777	0.8500	0.8180	28.0331	28.4159
Variation	All	Within family	All	Within family	All	Within family
B. Men						
Grade (std)	0.0356***	0.1493*	0.0132***	0.0775***	1.3831***	-0.1869
	(0.0027)	(0.0838)	(0.0009)	(0.0284)	(0.0134)	(0.4722)
Observations	207,679	2,070	207,679	2,070	160,250	1,322
Mean of dep.	1.6507	1.6440	0.7684	0.7614	30.5544	30.3472
Variation	All	Within family	All	Within family	All	Within family

Notes: AFB=Age at first birth. The outcomes in columns (1–4) are measured at age 45. The grades are standardized (std) with mean 0 and standard deviation 1 for each examination year. In columns (1), (3) and (5) we include year of birth dummies. We implicitly control for year of birth also in columns (2), (4) and (6) since twins obviously have the same year of birth. In parentheses we present robust standard errors. Asterisks indicate that the estimates are significantly different from zero at the ***1% level, **5% level, and *10% level.

4.3 Fertility and draft skill measures

Next, we turn to an analysis of cognitive and non-cognitive skills. These measures are sourced from military draft registers and are only available for men. Following a procedure in Grönqvist et al. (2017) we have, however, imputed skill measures for women with brothers using the draft scores of their brothers. This enables us to estimate raw associations between the skill measures and fertility also for women, but the imputation cannot give us within twin-pair variation in the skills for women. As can be seen from Table C2 in Appendix C, cognitive ability is firmly negatively related to fertility for women. The raw relationship between non-cognitive ability and fertility is instead slightly positive. Both ability types correlate positively to AFB.

Results for cognitive and non-cognitive skills for men are reported in Table 6. Starting with the raw associations, we find significant negative associations for cognitive skills for both number of children at age 45 (column 1) and the probability of having a child before age 45 (column 3). The raw associations for non-cognitive skills are, however, positive and very large; the results imply 0.17 more children and the males are 7 percentage points more likely to have a child for each standard deviation in non-cognitive skills. When introducing family fixed effects, the results across the two skill types are substantially harmonized. For cognitive ability, the estimate goes from being significantly negative to significantly positive. For non-cognitive ability, the twin fixed effects are instead reducing the association. This suggests that non-cognitive skills have a different correlation structure to family-level unobservables than cognitive skills, grades and years of schooling.

Turning to AFB, the results suggest that cognitive skills delay child birth more than non-cognitive skills. By introducing twin fixed effects, we substantially reduce the delaying effect of cognitive skills, and also (but to a much lesser extent) of non-cognitive skills.

Table 6 Fertility explained by cognitive and non-cognitive skills

Column:	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	# of children	# of children	1[children>0]	1[children>0]	AFB	AFB
Men						
Cognitive	-0.0212***	0.0935***	-0.0072***	0.0240**	1.0491***	-0.0185
ability (std)	(0.0013)	(0.0272)	(0.0004)	(0.0096)	(0.0067)	(0.1662)
Noncognitive	0.1662***	0.1275***	0.0686***	0.0585***	0.1731***	0.0486
ability (std)	(0.0013)	(0.0252)	(0.0004)	(0.0085)	(0.0068)	(0.1418)
Observations	1,076,204	10,784	1,076,204	10,784	840,106	6,718
Mean of dep.	1.7340	1.6942	0.7732	0.7517	29.3557	29.4408
Variation	All	Within family	All	Within family	All	Within family

Notes: AFB=Age at first birth. The outcomes in columns (1–4) are measured at age 45. The skill measures are standardized (std) with mean 0 and standard deviation 1 for each draft year. In columns (1), (3) and (5) we include year of birth dummies. We implicitly control for year of birth also in columns (2), (4) and (6) since twins obviously have the same year of birth. In parentheses we present robust standard errors. Asterisks indicate that the estimates are significantly different from zero at the ***1% level, **5% level, and *10% level.

4.4 Discussion and robustness

Our results, which are summarized in Table D1 in Appendix D, show that the association between fertility and skills/education is consistently more positive if estimated within twin pairs. This pattern holds for all measures, except for the non-cognitive skills that (relative to cognitive skills) have a closer relationship to fertility than to education even within families.[12]

4.4.1 The skill measures

Initially, we noted that grades and cognitive scores are closely correlated, and we therefore discuss them as indicators of similar abilities. In contrast, non-cognitive scores appear to measure alternative types of traits. Consistent with this view, we noted that the link between cognitive scores/grades and education is stronger than the link between non-cognitive scores and education. If anything, the converse is true for fertility.

4.4.2 Measurement errors

A concern in most sibling fixed effects applications is that measurement errors may be attenuating within-family estimates more than raw associations. In this setting, however, we note that the twins often are scored during the same day by the same individuals (same teachers for grades,

[12] The estimate on non-cognitive ability in column 2 of Table 6, where number of children at age 45 is the outcome, is 0.1275. The estimate on non-cognitive ability in column 4 of Table 3, where years of education is the outcome, is 0.1253. The quotient between them is 1.018. The corresponding quotient for cognitive ability is 0.162. Thus, relative to cognitive ability, non-cognitive ability matters more for fertility than for education.

same psychologist for non-cognitive scores). Thus, it is likely that the scores only deviate between twins when there are real differences, and potential measurement errors may be at least as distorting across families as within. Consistent with this view, we note that results are consistently more positive, but not consistently closer to zero, within twin pairs. The estimate of the association between cognitive ability and number of children at age 45 for men is significant and *negative* without twin fixed effects, but significant and *positive* when estimated within twin pairs. This cannot be explained by classical measurement errors. Similarly, the estimate of the association between years of schooling and number of children at age 45 for men moves from a small positive estimate to a *larger* positive estimate when introducing twin fixed effects. The one result where we can be less sure, partly because we have fewer alternative metrics, is the estimate for non-cognitive abilities, an estimate which moved closer to zero when twin fixed effects were introduced.

4.4.3 External validity of the twin samples

A potential concern is that relations between variables in a sample of twins might not hold for the general population. We address this concern in two ways. *First*, we isolate the between family effects in the twin sample directly using only *across family* variation in the twin sample. As can be seen from Tables C3, C4 and C5 in Appendix C, estimates from models using between-family variation in the twin samples are generally similar to the overall raw associations found for the general population.[13] *Second*, we re-estimate all our family fixed effects models using *close siblings* instead of twins.[14] Since twin births generally are associated with more complications than single births one could worry that differences in ability and fertility within twin pairs are more likely to reflect underlying health differences. We argue that this concern is reduced when studying close siblings. In Tables C6, C7 and C8 in Appendix C we replicate the results in Tables 4, 5 and 6 using samples of close siblings instead of twins. Throughout, the sibling estimates are very similar to the twin estimates. Taken together, these results corroborate the notion that it is the family fixed effects rather than the twins per se that are driving our results.

[13] The one exception is the relation between compulsory school grades and completed fertility for women (panel A of Table C4 in Appendix C). Here, the between-family estimates in the twin sample are more positive than the overall raw associations. Thus, the difference between column 1 and 2 (and column 3 and 4) in panel A of Table 5 should be interpreted with some caution. We note, however, that the within-family estimates in the twin sample in Table 5 still are larger than the between-family estimates in the twin sample in Table C4 in Appendix C. We also note that when we reproduce Table 5 using close siblings instead of twins (thus relying on a much larger sample) we still find that the inclusion of family fixed effects pushes the associations between grades and fertility in a positive direction (see Table C7 in Appendix C).

[14] We include sibling pairs where the siblings are born within three years from each other.

5 Explaining the role of families: Family preferences and endogenous skills

Our results imply that the association between fertility and skills/education is consistently more positive if estimated within twin pairs. This pattern holds for all measures, except for non-cognitive skills that (relative to cognitive skills) have a closer relationship to fertility than to education. These patterns strongly suggest that unobserved within-family factors that are positively related to cognitive skills and education are negatively related to fertility, whereas the converse appears to be true for non-cognitive skills. In this section, we propose a hypothesis that can explain the patterns.

To this end, we set up a stylized model of the process. To minimize detours, we assume that families derive utility from the fertility (in the spirit of Becker, 1973) and education (as in, e.g., Chiappori et al. 2017) of their offspring. We further assume that skills can be useful to achieve success in the marriage market, and hence increase fertility as in Becker (1973). We treat educational attainment and fertility as individual-level outcomes, whereas skills are considered individual endowments as in, e.g., Chiappori et al. (2017) and Chiappori et al. (2018). We design our model with the aim of generating predictions that are consistent with our results based on a minimum of assumptions.[15] Thus, the model is exceptionally stylized and simple. Despite the simple nature of the model, we end up with a precise empirical prediction which we take to the data.

Our empirical patterns can arise because families with a stronger preference for education invest more in cognitive skills for their children. In contrast, families with a stronger preference for fertility may invest more in non-cognitive skills. These endowments may be useful in both the educational "production function" and for fertility, but we let the different types of skills differ in their relative usefulness for the two outcomes as was indicated by our data. Here, it should be noted that fertility, of course, is an outcome of a complicated process where the marriage market is one component, but other aspects may be relevant as well. We do not model those aspects in detail, but simply let the associations from the data result in a "production function" from skills and effort onto fertility. We return to extensions where effort towards fertility and education interact after having shown the basic model.

5.1 The basic model

Skills and outcomes: Each individual *i* is endowed (see below) with skills in two dimensions; C and N. The outcomes (education attainment, fertility) are denoted by *Y* with superscript τ=(E, F) and are produced as linear, additively separable, functions of the skill endowments:

$$Y_i^{\tau} = \theta_i^{C\tau} C_i + \theta_i^{N\tau} N_i + \mu_i^{\tau}. \qquad (3)$$

For simplicity, assume that $\theta_i^{CE} = \theta_i^{NF} = 1$ and $\theta_i^{NE} = \theta_i^{CF} = \theta < 1$ such that skill *C* is more productive for education (*E*) and skill *N* more productive for fertility (*F*).[16] The variable μ_i^{τ} is the individual choice of effort on each margin.

[15] For an updated discussion of more elaborate models, see Chiappori et al. (2018).

[16] This assumption is consistent with our empirical results (see Table 3 and 6).

Individuals are bestowed with skills and preferences by their families (indexed by j): Each family invests in specific skill levels of their children. Denote the investments by π_j^S where S = N,C.[17] Skills also have a random component which varies across siblings within families. The random component is partly skill-specific (u_i^S) and partly reflect that individuals may be better skilled in all dimensions, i.e. there is a joint (across skills) individual fixed effect (α_i). Thus:

$$S_{ij} = \pi_j^S + \alpha_i + u_i^S, \qquad (4)$$
$$E(u_i^S) = 0.$$

Families bestow their members with preferences over education (representing, e.g., consumption) and fertility (children). The family-specific utility function takes the form $e_j Y_i^E + (1 - e_j)Y_i^F$ where the preference weight ($e_j \in (0,1)$) is an inherited family-specific preference that represents the preference weight on education relative to fertility.

Optimization: There are two choices to be made: Families choose how to invest in skills for their children and individuals choose how to allocate their effort between education and fertility (below we present an extension that allows for complementarity between the effort margins).

Individuals choose effort on the two markets (μ_i^E, μ_i^F) so as to maximize their utility *U* according to $U(Y_j^E, Y_j^F)$ =$e_j Y_i^E + (1 - e_j)Y_i^F$ subject to $\mu_i^F + \mu_i^E \leq 1$ and $\mu_i^\tau \geq 0$ and Eq. (3).

Similarly, parents choose investments over the two skills (π_j^N, π_j^C) for their children so as to maximize their utility *V* according to $V(Y_i^E, Y_i^F)$ =$e_j Y_i^E + (1 - e_j)Y_i^F$ subject to $\pi_i^N + \pi_i^C \leq 1$ and $\pi_i^S \geq 0$ and Eq. (3) and (4).

Results: Since both choices depend on the joint preference parameter and all aspects of production are additively separable and linear the model derives an intuitive separation into two types of families:[18]

$$\begin{aligned} e_j < \tfrac{1}{2} &\leftrightarrow \mu_i^F = 1\,;\ \mu_i^E = 0;\ \pi_i^N = 1;\ \pi_i^C = 0 \\ e_j > \tfrac{1}{2} &\leftrightarrow \mu_i^F = 0\,;\ \mu_i^E = 1;\ \pi_i^N = 0;\ \pi_i^C = 1. \end{aligned} \qquad (5)$$

Thus, in families that prefer fertility over education $\left(e_j < \frac{1}{2}\right)$, all investments will be geared towards *N*-skills and all effort will be geared towards fertility. For families that prefer education over fertility $\left(e_j > \frac{1}{2}\right)$, the converse is true for both choices. It is, however, straightforward to introduce reasons for the agents not to fully specialize in one of the two dimensions and we present such an extension below. However, since predictions are intuitively visible in the simplified version presented in Eq. (5), and remain valid also in the extended version, we first derive the main conclusions here. Equation (5) implies that:

[17] As is evident from what we show below, families will not have incentives to vary skills across siblings.
[18] We ignore the possibility that families are indifferent, i.e. $e_j = \frac{1}{2}$, without loss of intuition.

1. *The within-family association between C and fertility* is more positive than the overall association. The reason is that the overall association also captures the impact of the family preference which is reflected in high C and a low fertility effort.

2. *The within-family association between N and fertility* is instead lower than the overall association. The reason is that the overall association also captures the impact of the family preference which is reflected in high *N* and a *high* fertility effort.

3. *The association between education and fertility* is affected by the correlations of skills and effort since both are outcomes. There are two counteracting effects, one from the fact that generally better-skilled individuals are more likely to succeed on both markets (from α_i), and one from the fact that individuals differ in skill sets and how they choose to allocate (specialize) their effort. When estimating the model within twin pairs, we remove the effort and skill choices (since they are shared within the family), and isolate the effect of the skills (α_i). Thus, the within-family association should be more positive than the overall association.

5.2 Extensions

The basic model provides a stylized first-order approximation of the relationships under study. The simple linear additively separable functional forms generate corner solutions with only two types that make all predictions very clear. If we let the return to effort be declining (by introducing $ln\mu_i^\tau$ instead of μ_i^τ in Eq. 3) such that:

$$Y_i^\tau = \theta_i^{C\tau} C_i + \theta_i^{N\tau} N_i + ln\mu_i^\tau. \qquad (6)$$

and similarly let the returns to skill investments be declining by introducing $ln\pi_i^\tau$ instead of π_i^τ in Eq. (4) such that:

$$S_{ij} = ln\pi_j^S + \alpha_i + u_i^S, \qquad (7)$$
$$E(u_i^S) = 0.$$

we get solutions where both effort and investments are directly proportional to *e*. We optimize to get the first order conditions (see Appendix E for the derivation):

$$\pi^C = \frac{\theta^{NE} + e(1-\theta^{NE})}{1+\theta^{NE}}, \pi^N = \frac{1-e(1-\theta^{NE})}{1+\theta^{NE}}. \qquad (8)$$
$$\mu_i^E = e_i, \mu_i^F = 1 - e_i.$$

Thus, families with high *e* invest more in C and less in N. And, the same families put more effort into education, and less effort into fertility. Thus, the qualitative results remain unchanged.

The setup is also simplified in assuming that effort spent on education has no impact on fertility. But it is not implausible that, e.g., males benefit from their effort on the education front also for fertility. We can easily extend the model to allow for such complementarities. Assume that (6) holds for education (i.e. $Y_i^E = \theta_i^{CE} C_i + \theta_i^{NE} N_i + ln\mu_i^E$) but that there are positive spillover effects from education onto fertility. We assume that the spillover effects have a lower effect on fertility than effort spent directly on fertility (otherwise everyone will trivially spend all effort on education). By defining a parameter $\rho < 1$ and assuming:

$$Y_i^F = \theta^{CF} C + \theta^{NF} N + ln\mu^F + \rho ln\mu^E. \qquad (9)$$

we get the following first order conditions for effort (see Appendix E for the derivation):

$$\mu^E = \frac{e+\rho(1-e)}{1+\rho(1-e)} \Rightarrow \frac{\partial\mu^E}{\partial e} > 0, \frac{\partial\mu^E}{\partial\rho} > 0 \qquad (10)$$

$$\mu^F = \frac{1-e}{1+\rho(1-e)} \Rightarrow \frac{\partial\mu^F}{\partial e} < 0, \frac{\partial\mu^F}{\partial\rho} < 0$$

This implies that the qualitative conclusions hold in the sense that a higher preference for education directs more effort into education and less effort towards fertility. However, an additional insight is that agents with more pronounced spillover effects (as defined by a higher ρ) invest more in education because this allows them to achieve both ends. It does not seem unlikely that this logic pertains more to men than to women and that the complementarity explains why the raw association between education and fertility is more positive for males.

A relevant concern is what happens if preferences are individually based, rather than family based. This is fine as long as individual preferences, and thus endogenous effort, is not correlated with skills. But if individuals have preferences that are correlated with their skills (within twin-pairs), we will capture that as part of the skills in our regressions. However, this is not unique to the twin identification strategy. In fact, we cannot think of any identification strategy that would circumvent this problem with certainty since any educational intervention that raises the skills of an individual simultaneously may affect the preferences, and hence the allocation of effort.

Finally, it can be noted that similar predictions could be generated by assuming that families differ in *exogenous* skill endowments and that the endowments are correlated with joint family preferences. Note, however, that the association needs to be at the family, not the individual, level.

5.3 An empirical test

The model highlights the association between parental preferences for fertility and the accumulation of non-cognitive skills relative to cognitive skills of their children. One way to test this assumption is to note that the residuals from regressions explaining education and fertility by cognitive and non-cognitive skills (i.e. $Y_i^\tau = \theta_i^{C\tau} C_i + \theta_i^{N\tau} N_i + \mu_i^\tau$) provide a theory-consistent measure of effort devoted on the two markets. Thus, the difference ($\mu_i^{Fertility} - \mu_i^{Education}$) provides a measure of the relative preference for children. According to our model, this preference should be related to the investment in non-cognitive relative to cognitive skills of children within the same family (i.e. to $N_{ij} - C_{ij} = \pi_j^N - \pi_j^C + \Delta u_i$).

In Table 7, we test this association using data on all father-son pairs where we have information on both types of skills for father and son.[19] In the first two columns, we show the regressions that

[19] To produce the results in columns 1 and 2 of Table 7 we construct a sample containing all men born between 1950–1972 who have non-missing information on skills, years of schooling and fertility. We do not require that these men have children. From the regressions in columns 1 and 2 we generate residuals for years of schooling and fertility. We then calculate the difference in residuals (fertility-education). To produce the results in columns 3 and 4 of Table 7 we

takes out the residuals, i.e. the $Y_i^\tau = \theta_i^{C\tau} C_i + \theta_i^{N\tau} N_i + \mu_i^\tau$ regressions. In column (3), we relate the difference in residuals to the difference in skills. The results show that fathers with a relatively high residual on fertility are more likely to have children with a higher relative endowment of non-cognitive skills as presumed by the model.

A potential concern is that the results are affected by a quantity-quality tradeoff that lets parents invest less in overall skills if they have more children. Reassuringly, our results are robust to accounting for the overall level of skills of the child as shown in column (4). For further robustness, we have ensured that the results are robust to first normalizing fertility and education to have standard deviations equal to one to ensure that scales of residuals are comparable (see Table C9 in Appendix C).

Table 7 Parental effort and investment in skills

Column:	**(1)**	**(2)**	**(3)**	**(4)**
Type of regression:	**Parent regressions (first stage)**		**Child regressions (second stage)**	
Outcome:	**Fertility (F)**	**Education (E)**	**N-C difference**	**N-C difference**
Cognitive (C) skill (std)	-0.0151***	1.0727***		
	(0.0013)	(0.0022)		
Non- cognitive (N) skill (std)	0.1674***	0.3167***		
	(0.0013)	(0.0022)		
Residual correlation (F, E)	*-0.0214*			
Parent residual difference (F-E)			0.0200***	0.0208***
			(0.0012)	(0.0012)
Child overall skills (N+C)				0.0095***
				(0.0014)
Observations	1,027,581	1,027,581	167,956	167,956

Notes: Fertility=number of children at 45. Education=years of schooling at 35. In columns (1) and (2) we include year of birth dummies. In parentheses we present robust standard errors. Asterisks indicate that the estimates are significantly different from zero at the ***1% level, **5% level, and *10% level.

start out from a sample of men with a known father. We then require these men to have non-missing information on skills and non-missing information on their father's difference in residuals (which comes from the exercise in columns 1 and 2). With these restrictions imposed we end up with a sample of sons born between 1966–1987. A father can be matched to several sons in this sample, so we do not restrict the analysis to first-born sons.

6 Conclusions

The relationship between education and fertility for men and women is a widely studied topic within demography and sociology. A set of recent studies have introduced the role of skills (typically intelligence) into the picture. A general conclusion is that skills and schooling are negatively associated with completed fertility for women. For men, the picture is less clear with estimates hovering around zero. However, we know little about the extent to which these associations are confounded by family background factors. Previous papers that have employed family fixed effects models to address this potentially confounding influence have produced mixed results regarding the role of family background factors. But if anything, it appears to be a tendency that the inclusion of family fixed effects pushes the association between years of schooling and completed fertility in a positive direction.

In this paper, we build on previous research and contribute by giving a comprehensive picture of the relations between human capital and fertility for women and men. We do this by estimating a large number of associations between fertility and skills/schooling, both between and within (using twin-pairs) families. In line with some of the previous studies using family fixed effects models, our results suggest that traditional estimates are confounded by differences across families which are pushing the estimates in a negative direction. A consistent finding across all our estimations is that within-family associations between fertility and skills/schooling are considerably more positive than overall associations (the one exception is non-cognitive ability). For men, the effects of skills/schooling on completed fertility are firmly and consistently on the positive side once family background characteristics are accounted for. For women, the association between years of schooling and completed fertility is very close to zero, and the corresponding estimates with respect to grades from compulsory school appear to be positive. This implies that the inclusion of twin fixed effects has a very similar impact for men and women in the sense that they push the associations in a more positive direction (from negative to zero for women, and from zero to positive for men). This holds for both of our two completed fertility outcomes (having children at all and number of children) whereas the impact on the age at first birth is more mixed.

The main conclusion from the paper is that raw associations between human capital measures and fertility provide a much bleaker picture regarding the association between human capital accumulation and fertility outcomes than the within family estimates. For women, the raw associations appear to overestimate the degree to which human capital accumulation crowds out fertility, and for men the raw associations instead underestimate the degree of complementarity between human capital and fertility outcomes. Our findings thus suggest that family background factors are the main explanation for the raw negative associations found for females and the small benefits found for males in the raw data.

The results imply that unobserved family-specific factors that have a positive impact on fertility are negatively correlated to education, grades and cognitive skill levels of the family. We propose that an important unobservable may be preferences. We further show that non-cognitive ability instead appears *positively* correlated with unobservable family specific factors that have a positive impact on fertility. This suggests that family preferences over education and fertility are related to the types of skills their children accumulate. A possible reason for our results is endogenous accumulation of skills. We present a stylized model that incorporates this feature into a world where families differ in the extent to which they value the fertility and the education of their offspring. The model predicts that families who put a high relative value on fertility raise their children to have comparative-skill advantages in the non-cognitive rather than the cognitive dimension if non-cognitive skills are more important as determinants of fertility. Consistent with this hypothesis, we find that children of fathers with higher-than-expected fertility have comparative advantages in non-cognitive skills.

References

Almlund, Mathilde, Angela Lee Duckworth, James Heckman, and Tim Kautz. 2011. "Personality Psychology and Economics." In Handbook of the Economics of Education. Volume 4, ed. Eric A. Hanushek, Steve Machin, and Ludiger Woessmann. Amsterdam: North Holland.

Andersson, G., Rønsen, M., Knudsen, L. B., Lappegård, T., Neyer, G., Skrede, K., Teschner, K., & Vikat, A. (2009). Cohort fertility patterns in the Nordic countries. *Demographic Research*, *20*, 313–352.

Amin, V., & Behrman, J. R. (2014). Do more-schooled women have fewer children and delay childbearing? Evidence from a sample of US twins. *Journal of Population Economics*, *27*(1), 1–31.

Becker, G. (1973). A theory of marriage: Part I. *Journal of Political Economy*, *81*(4), 813–846.

Black, S. E., Devereux, P. J., & Salvanes, K. G. (2008). Staying in the classroom and out of the maternity ward? The effect of compulsory schooling laws on teenage births. *The Economic Journal*, *118*(530), 1025–1054.

Carlsson, M., Dahl, G. B., Öckert, B., & Rooth, D. O. (2015). The effect of schooling on cognitive skills. *Review of Economics and Statistics*, *97*(3), 533–547.

Carlstedt, B. (2000). *Cognitive abilities - aspects of structure, process, and measurement* (Göteborg Studies in Educational Sciences 148). Göteborg: Acta Universitatis Gothoburgensis.

Chen, H. Y., Chen, Y. H., Liao, Y. K., & Chen, H. P. (2013). Relationship of fertility with intelligence and education in Taiwan: a brief report. *Journal of Biosocial Science*, 45(4), 567–571.

Chiappori, P. A., Salanié, B., & Weiss, Y. (2017). Partner choice, investment in children, and the marital college premium. *American Economic Review*, *107*(8), 2109–2167.

Chiappori, P-A., Costa Dias, M., & Meghir, C. (2018). The marriage market, labor supply and education choice. *Journal of Political Economy*, 126(S1), S26–S72.

Cygan-Rehm, K., & Maeder, M. (2013). The effect of education on fertility: Evidence from a compulsory schooling reform. *Labour Economics*, *25*, 35–48.

Fort, M., Schneeweis, N., & Winter-Ebmer, R. (2016). Is education always reducing fertility? Evidence from compulsory schooling reforms. *The Economic Journal*, *126*(595), 1823–1855.

Fredriksson, P., Öckert, B., & Oosterbeek, H. (2013). Long-term effects of class size. The *Quarterly Journal of Economics*, 128(1), 249–285.

Fredriksson, Peter., Hensvik, L., & Nordström Skans, O. (2018). Mismatch of talent: Evidence on match quality, entry wages, and job mobility. *American Economic Review*, 108(11), 3303–3338.

Grönqvist, E., Öckert, B., & Vlachos, J. (2017). The intergenerational transmission of cognitive and non-cognitive abilities. *Journal of Human Resources*, *52*(4), 887–918.

Grönqvist, H., and Hall, C. (2013). Education policy and early fertility: lessons from an expansion of upper secondary schooling. *Economics of Education Review*, *37*, 13–33.

Haworth, C. M., Dale, P., & Plomin, R. (2008). A twin study into the genetic and environmental influences on academic performance in science in nine-year-old boys and girls. *International Journal of Science Education*, *30*(8), 1003–1025.

Jalovaara, M., Neyer, G., Andersson, G., Dahlberg, J., Dommermuth, L., Fallesen, P., & Lappegård, T. (2018). Education, gender, and cohort fertility in the Nordic countries. *European Journal of Population*, 1-24.

Kanazawa, S. (2014). Intelligence and childlessness. *Social Science Research*, *48*, 157–170.

Kohler, H. P., Behrman, J. R., & Schnittker, J. (2011). Social science methods for twins data: Integrating causality, endowments, and heritability. *Biodemography and Social Biology*, *57*(1), 88–141.

Kravdal, Ø., & Rindfuss, R. R. (2008). Changing relationships between education and fertility: A study of women and men born 1940 to 1964. *American Sociological Review*, *73*(5), 854–873.

Lindqvist, E., & Vestman, R. (2011). The labor market returns to cognitive and noncognitive ability: Evidence from the Swedish enlistment. *American Economic Journal: Applied Economics*, *3*(1), 101–28.

Martin, S. P. (2000). Diverging fertility among US women who delay childbearing past age 30. *Demography*, *37*(4), 523–533.

McCrary, J., & Royer, H. (2011). The effect of female education on fertility and infant health: Evidence from school entry policies using exact date of birth. *American Economic Review*, *101*(1), 158–195.

Meisenberg, G. (2008). How universal is the negative correlation between education and fertility?. *The Journal of Social, Political, and Economic Studies*, *33*(2), 205–227.

Meisenberg, G. (2010). The reproduction of intelligence. *Intelligence*, *38*(2), 220–230.

Monstad, K., Propper, C., & Salvanes, K. G. (2008). Education and fertility: Evidence from a natural experiment. *The Scandinavian Journal of Economics*, *110*(4), 827–852.

Mood, Carina, Jan O. Jonsson, and Erik Bihagen. 2012. "Socioeconomic Persistence across Generations: Cognitive and Non-cognitive Processes." In From Parents to Children: The Intergenerational Transmission of Advantage, ed. John Ermisch, Markus Jäntti, and Timothy M. Smeeding, 53–83. New York: Russell Sage.

Nisén, J., Martikainen, P., Kaprio, J., and Silventoinen, K. (2013). Educational differences in completed fertility: a behavioral genetic study of Finnish male and female twins. *Demography*, *50*(4), 1399–1420.

Rodgers, J. L., Kohler, H. P., McGue, M., Behrman, J. R., Petersen, I., Bingley, P., & Christensen, K. (2008). Education and cognitive ability as direct, mediating, or spurious influences on female age at first birth: Behavior genetic models fit to danish twin data 1. *American Journal of Sociology*, *114*(S1), S202–S232.

Silles, M. A. (2011). The effect of schooling on teenage childbearing: evidence using changes in compulsory education laws. *Journal of Population Economics*, *24*(2), 761–777.

Statistics Sweden. 2000. https://www.scb.se/contentassets/32dca14e741e42f2b5542d0321c897b8/missun.pdf

Tropf, F. C., & Mandemakers, J. J. (2017). Is the association between education and fertility postponement causal? The role of family background factors. *Demography*, *54*(1), 71–91.

Wang, M., Fuerst, J., & Ren, J. (2016). Evidence of dysgenic fertility in China. *Intelligence*, 57, 15–24.

Woodley, M. A., & Meisenberg, G. (2013). A Jensen effect on dysgenic fertility: An analysis involving the National Longitudinal Survey of Youth. *Personality and Individual Differences*, 55(3), 279–282.

Öckert, B., Vlachos, J., & Grönqvist, E. (2017). Unpublished manuscript.

Appendix A Previous literature

Table A1 Associations between fertility and skills/schooling in the previous literature

Column:	(1)	(2)	(3)	(4)	(5)	(6)
Ind. variable:	Years of schooling		Cognitive ability		Non-cognitive ability	
Variation:	All	Within-family	All	Within-family	All	Within-family
Women						
AFB	(+)[a]	(0/+)[g]	(+)[l]	(0)[q]	N/A	N/A
# of children	(-)[b]	(-)[h]	(-)[m]	N/A	N/A	N/A
1[children>0]	(-)[c]	(0)[i]	(-)[n]	N/A	N/A	N/A
Men						
AFB	(+)[d]	(0)[j]	N/A	N/A	N/A	N/A
# of children	(Unclear)[e]	N/A	(unclear)[o]	N/A	N/A	N/A
1[children>0]	(Unclear)[f]	(0)[k]	(0)[p]	N/A	N/A	N/A

Notes: AFB=Age at first birth.
a=Amin and Behrman (2014), Kravdal and Rindfuss (2008), Rodgers et al. (2008), Tropf and Mandemakers (2017) and Martin (2000).
b=Amin and Behrman (2014), Kravdal and Rindfuss (2008), Kohler et al. (2011), Nisén et al. (2013) and Meisenberg (2008). Nisén et al. (2013) also find a negative association and they argue that family background factors only moderately contribute to the negative association.
c= Amin and Behrman (2014), Kravdal and Rindfuss (2008), Meisenberg (2008) and Nisén et al. (2013).
d=Kravdal and Rindfuss (2008) and Nisén et al. (2013).
e=In advanced countries the association is suggested to be zero or slightly positive (Kravdal and Rindfuss 2008, Meisenberg 2008, Nisén et al. 2013). In other countries, however, it is firmly negative (Meisenberg 2008).
f=In advanced countries the association is suggested to be zero or slightly positive (Kravdal and Rindfuss 2008, Meisenberg 2008, Nisén et al. 2013). In other countries, however, it is firmly negative (Meisenberg 2008).
g=Rodgers et al. (2008) suggest a zero effect. Nisén et al. (2013) and Tropf and Mandemakers (2017) report positive effects. Amin and Behrman (2014) also report positive effects, but smaller effects than when using across family variation.
h=Kohler et al. (2011) and Amin and Behrman (2014).
i=Nisén et al. (2013) report a zero effect. Amin and Behrman (2014) report a negative effect but smaller than when using across family variation.
j=Nisén et al. (2013).
k=Nisén et al. (2013).
l=Rodgers et al. (2008).
m=Meisenberg (2010). Wang et al. (2016). Chen et al. (2013).
n=Kanazawa (2014).
o= Chen et al. (2013), Meisenberg (2010) and Wang et al. (2016) report a negative association. Woodley and Meisenberg (2013) report a positive association.
p=Kanazawa (2014).
q=Rodgers et al. (2008).

Appendix B Coding of years of schooling

Table B1 Codes for educational attainment in our data

Level	Duration	Specification
6 Postgraduate education	64 Doctoral programme	640 Doctoral programme
	62 Licentiate programme	620 Licentiate programme
	60 Other/unspecified postgraduate programme	600 Other/unspecified postgraduate programme
5 Post-secondary education, two years or longer	55 Five years or longer	557 Vocationally oriented programme at university/college
		556 General programme at university/college
		555 Vocationally oriented programme, not university/college
		550 Other/unspecified post-secondary programme
	54 Four years (at least four but not five years)	547 Vocationally oriented programme at university/college
		546 General programme at university/college
		545 Vocationally oriented programme, not university/college
		540 Other/unspecified post-secondary programme
	53 Three years (at least three but not four years)	537 Vocationally oriented programme at university/college
		536 General programme at university/college
		535 Vocationally oriented programme, not university/college
		532 At least 120 higher education credits, no degree
		530 Other/unspecified post-secondary programme
	52 Two years (at least two but not three years)	527 Vocationally oriented programme at university/college
		526 General programme at university/college
		525 Vocationally oriented

Level	Duration	Specification
		programme, not university/college 522 At least 80 higher education credits, no degree 520 Other/unspecified post-secondary programme
4 Post-secondary education, less than two years	41 Less than two years (at least one semester)	417 Vocationally oriented programme at university/college 415 Vocationally oriented programme, not university/college 413 Upper secondary supplementary programme 412 At least 20 higher education credits in one subject 410 Other/unspecified post-secondary programme
3 Upper secondary education	33 Three years	337 Vocationally oriented programme 336 Theoretical programme/ prep. for higher studies 333 Vocationally oriented Programme, incomplete 332 Theoretical prog./prep. for higher studies, incomplete 330 Other/unspecified upper secondary programme
	32 Two years (at least two but not three years)	327 Vocationally oriented programme 326 Theoretical programme/ prep. for higher studies 323 Vocationally oriented Programme, incomplete 322 Theoretical prog./prep. for higher studies, incomplete 320 Other/unspecified upper secondary programme
	31 Less than two years (at least one semester)	317 Vocationally oriented programme 316 Theoretical programme/

Level	Duration	Specification
		prep. for higher studies 313 Vocationally oriented Programme, incomplete 312 Theoretical prog./prep. for higher studies, incomplete 310 Other/unspecified upper secondary programme
2 Primary and lower secondary education, 9 (or 10) years	20 Primary and lower secondary education, 9 (or 10) years	206 Compulsory school education, years 7–9 204 Lower secondary school education 200 Other/unspecified primary and lower secondary education
1 Primary and lower secondary education, less than 9 years	10 Primary and lower secondary education, less than 9 years	106 Elementary school education 102 Compulsory school education, years 1–6 100 Other/unspecified primary and lower secondary education

Notes: Information from Statistics Sweden (2000).

We use the two-digit code (column "Duration") to do the following classification:
10= 7 years of schooling
20= 9 years of schooling
31= 10 years of schooling
32= 11 years of schooling
33= 12 years of schooling
41= 13 years of schooling
52= 14 years of schooling
53= 15 years of schooling
54= 16 years of schooling
55= 17 years of schooling
60= 18 years of schooling
62= 19 years of schooling
64= 21 years of schooling

Appendix C Additional results

Table C1 Grades and years of schooling explained by military draft skills (imputed for both men and women)

Column:	**(1)**	**(2)**	**(3)**	**(4)**
Outcome:	**Grade (std)**	**Grade (std)**	**Years of schooling**	**Years of schooling**
Sample:	**Men**	**Women**	**Men**	**Women**
Cognitive	0.3749***	0.3300***	0.7677***	0.6464***
ability (std)	(0.0048)	(0.0047)	(0.0051)	(0.0049)
Non-cognitive	0.1471***	0.1270***	0.2324***	0.2331***
ability (std)	(0.0049)	(0.0048)	(0.0051)	(0.0050)
Observations	42,535	41,139	224,807	213,224
Mean of dep.	-0.0980	0.2540	12.0068	12.3707
Variation	All	All	All	All

Notes: Relates to Table 3 in the main paper. For men and women with brothers who have participated in the military draft we impute values on cognitive and non-cognitive ability based on the test results of the brothers. We follow a procedure presented in Grönqvist et al. (2017). The grades are standardized (std) with mean 0 and standard deviation 1 for each examination year. The skill measures are standardized (std) with mean 0 and standard deviation 1 for each draft year. We include year of birth dummies in all regressions. In parentheses we present robust standard errors. Asterisks indicate that the estimates are significantly different from zero at the ***1% level, **5% level, and *10% level.

Table C2 Fertility explained by military draft skills (imputed for both women and men)

Column:	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	# of children	# of children	1[children>0]	1[children>0]	AFB	AFB
Sample:	Men	Women	Men	Women	Men	Women
Cognitive	-0.0300***	-0.0575***	-0.0095***	-0.0179***	0.8584***	0.9942***
ability (std)[a]	(0.0029)	(0.0028)	(0.0010)	(0.0008)	(0.0143)	(0.0128)
Noncognitive	0.0704***	0.0006	0.0306***	0.0073***	0.2513***	0.4326***
ability (std)[a]	(0.0028)	(0.0028)	(0.0010)	(0.0008)	(0.0144)	(0.0129)
Observations	239,292	225,226	239,292	225,226	183,908	190,734
Mean of dep.	1.7260	1.9709	0.7612	0.8464	29.3784	26.5907
Variation	All	All	All	All	All	All

Notes: Relates to Table 6 in the main paper. For men and women with brothers who have participated in the military draft we impute values on cognitive and non-cognitive ability based on the test results of the brothers. We follow a procedure presented in Grönqvist et al. (2017). AFB=Age at first birth. The outcomes in columns (1–4) are measured at age 45. The skill measures are standardized (std) with mean 0 and standard deviation 1 for each draft year. We include year of birth dummies in all regressions. In parentheses we present robust standard errors. Asterisks indicate that the estimates are significantly different from zero at the ***1% level, **5% level, and *10% level.
a=Original estimates of the association between females' abilities and fertility based on these data were produced by Öckert et al. (2017).

Table C3 Fertility explained by years of schooling – overall associations and associations using between twin-pair variation

Column:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Outcome:	**# of children**	**# of children**	**1[children>0]**	**1[children>0]**	**AFB**	**AFB**
A. Women						
Years of	-0.0412***	-0.0420***	-0.0049***	-0.0096***	0.6629***	0.9095***
schooling	(0.0003)	(0.0041)	(0.0001)	(0.0012)	(0.0014)	(0.0190)
Observations	2,180,083	20,244	2,180,083	20,244	1,898,864	15,228
Mean of dep.	2.0061	1.9239	0.8706	0.8487	25.4741	25.6951
Variation	All	Between	All	Between	All	Between
B. Men						
Years of	0.0055***	0.0077*	0.0061***	0.0051***	0.4524***	0.6513***
schooling	(0.0003)	(0.0041)	(0.0001)	(0.0014)	(0.0015)	(0.0216)
Observations	2,233,137	19,758	2,233,137	19,758	1,801,464	12,724
Mean of dep.	1,8312	1.7444	0,7994	0.7697	28,4467	28.4442
Variation	All	Between	All	Between	All	Between

Notes: Relates to Table 4 in the main paper. In columns (1), (3) and (5) we reproduce the estimates from the same columns in Table 4. AFB=Age at first birth. The outcomes in columns (1–4) are measured at age 45. In columns (1), (3) and (5) we include year of birth dummies. In parentheses we present robust standard errors. Asterisks indicate that the estimates are significantly different from zero at the ***1% level, **5% level, and *10% level.

Table C4 Fertility explained by compulsory school grades – overall associations and associations using between twin-pair variation

Column:	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	# of children	# of children	1[children>0]	1[children>0]	AFB	AFB
A. Women						
Grade (std)	-0.0579***	-0.0092	-0.0058***	0.0018	2.0571***	2.1627***
	(0.0028)	(0.0317)	(0.0008)	(0.0106)	(0.0124)	(0.1717)
Observations	201,634	2,110	201,634	2,110	171,479	1,486
Mean of dep.	1.8760	1.7777	0.8500	0.8180	28.0331	28.4159
Variation	All	Between	All	Between	All	Between
B. Men						
Grade (std)	0.0356***	0.0317	0.0132***	0.0128	1.3831***	1.4433***
	(0.0027)	(0.0311)	(0.0009)	(0.0113)	(0.0134)	(0.1698)
Observations	207,679	2,070	207,679	2,070	160,250	1,322
Mean of dep.	1.6507	1.6440	0.7684	0.7614	30.5544	30.3472
Variation	All	Between	All	Between	All	Between

Notes: Relates to Table 5 in the main paper. In columns (1), (3) and (5) we reproduce the estimates from the same columns in Table 5. AFB=Age at first birth. The outcomes in columns (1–4) are measured at age 45. In columns (1), (3) and (5) we include year of birth dummies. The grades are standardized (std) with mean 0 and standard deviation 1 for each examination year. In parentheses we present robust standard errors. Asterisks indicate that the estimates are significantly different from zero at the ***1% level, **5% level, and *10% level.

Table C5 Fertility explained by cognitive and non-cognitive skills – overall associations and associations using between twin-pair variation

Column:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Outcome:	**# of children**	**# of children**	**1[children>0]**	**1[children>0]**	**AFB**	**AFB**
Men						
Cognitive	-0.0212***	-0.0474***	-0.0072***	-0.0176***	1.0491***	1.3475***
ability (std)	(0.0013)	(0.0164)	(0.0004)	(0.0056)	(0.0067)	(0.0928)
Noncognitive	0.1662***	0.1880***	0.0686***	0.0866***	0.1731***	0.4098***
ability (std)	(0.0013)	(0.0174)	(0.0004)	(0.0059)	(0.0068)	(0.0990)
Observations	1,076,204	10,784	1,076,204	10,784	840,106	6,718
Mean of dep.	1.7340	1.6942	0.7732	0.7517	29.3557	29.4408
Variation	All	Between	All	Between	All	Between

Notes: Relates to Table 6 in the main paper. In columns (1), (3) and (5) we reproduce the estimates from the same columns in Table 6. AFB=Age at first birth. The outcomes in columns (1–4) are measured at age 45. In columns (1), (3) and (5) we include year of birth dummies. The skill measures are standardized (std) with mean 0 and standard deviation 1 for each draft year. In parentheses we present robust standard errors. Asterisks indicate that the estimates are significantly different from zero at the ***1% level, **5% level, and *10% level.

Table C6 Fertility explained by years of schooling (close siblings)

Column:	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	# of children	# of children	1[children>0]	1[children>0]	AFB	AFB
A. Women						
Years of	-0.0412***	-0.0138***	-0.0049***	0.0008**	0.6629***	0.3317***
schooling	(0.0003)	(0.0014)	(0.0001)	(0.0004)	(0.0014)	(0.0064)
Observations	2,180,083	350,536	2,180,083	350,536	1,898,864	274,690
Mean of dep.	2.0061	2.0413	0.8706	0.8792	25.4741	25.3493
Variation	All	Within family	All	Within family	All	Within family
B. Men						
Years of	0.0055***	0.0291***	0.0061***	0.0112***	0.4524***	0.2203***
schooling	(0.0003)	(0.0014)	(0.0001)	(0.0004)	(0.0015)	(0.0072)
Observations	2,233,137	377,500	2,233,137	377,500	1,801,464	254,140
Mean of dep.	1,8312	1.8430	0,7994	0.8036	28,4467	28.2077
Variation	All	Within family	All	Within family	All	Within family

Notes: Relates to Table 4 in the main paper. In columns (1), (3) and (5) we reproduce the estimates from the same columns in Table 4. AFB=Age at first birth. The outcomes in columns (1–4) are measured at age 45. In columns (1), (3) and (5) we include year of birth dummies. We implicitly control for year of birth also in columns (2), (4) and (6) since close siblings are born within three years from each other. In parentheses we present robust standard errors. Asterisks indicate that the estimates are significantly different from zero at the ***1% level, **5% level, and *10% level.

Table C7 Fertility explained by compulsory school grades (close siblings)

Column:	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	# of children	# of children	1[children>0]	1[children>0]	AFB	AFB
A. Women						
Grade (std)	-0.0579***	-0.0233	-0.0058***	-0.0001	2.0571***	1.0501***
	(0.0028)	(0.0174)	(0.0008)	(0.0056)	(0.0124)	(0.0885)
Observations	201,634	18,214	201,634	18,214	171,479	13,554
Mean of dep.	1.8760	1.9059	0.8500	0.8541	28.0331	28.0857
Variation	All	Within family	All	Within family	All	Within family
B. Men						
Grade (std)	0.0356***	0.0808***	0.0132***	0.0217***	1.3831***	0.5172***
	(0.0027)	(0.0176)	(0.0009)	(0.0063)	(0.0134)	(0.1014)
Observations	207,679	19,216	207,679	19,216	160,250	12,078
Mean of dep.	1.6507	1.7026	0.7684	0.7778	30.5544	30.5176
Variation	All	Within family	All	Within family	All	Within family

Notes: Relates to Table 5 in the main paper. In columns (1), (3) and (5) we reproduce the estimates from the same columns in Table 5. AFB=Age at first birth. The outcomes in columns (1–4) are measured at age 45. The grades are standardized with mean 0 and standard deviation 1 for each examination year. In columns (1), (3) and (5) we include year of birth dummies. We implicitly control for year of birth also in columns (2), (4) and (6) since close siblings are born within three years from each other. In parentheses we present robust standard errors. Asterisks indicate that the estimates are significantly different from zero at the ***1% level, **5% level, and *10% level.

Table C8 Fertility explained by cognitive and non-cognitive skills (close siblings)

Column:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Outcome:	**# of children**	**# of children**	**1[children>0]**	**1[children>0]**	**AFB**	**AFB**
Men						
Cognitive	-0.0212***	0.0537***	-0.0072***	0.0174***	1.0491***	0.3104***
ability (std)	(0.0013)	(0.0056)	(0.0004)	(0.0019)	(0.0067)	(0.0310)
Noncognitive	0.1662***	0.1439***	0.0686***	0.0560***	0.1731***	-0.1186***
ability (std)	(0.0013)	(0.0050)	(0.0004)	(0.0017)	(0.0068)	(0.0281)
Observations	1,076,204	190,910	1,076,204	190,910	840,106	122,312
Mean of dep.	1.7340	1.7750	0.7732	0.7823	29.3557	29.2542
Variation	All	Within family	All	Within family	All	Within family

Notes: Relates to Table 6 in the main paper. In columns (1), (3) and (5) we reproduce the estimates from the same columns in Table 6. AFB=Age at first birth. The outcomes in columns (1–4) are measured at age 45. The skill measures are standardized (std) with mean 0 and standard deviation 1 for each draft year. In columns (1), (3) and (5) we include year of birth dummies. We implicitly control for year of birth also in columns (2), (4) and (6) since close siblings are born within three years from each other. In parentheses we present robust standard errors. Asterisks indicate that the estimates are significantly different from zero at the ***1% level, **5% level, and *10% level.

Table C9 Parental effort and investment in skills – standardized data (standard deviation equal to one for both fertility and education)

Column:	**(1)**	**(2)**	**(3)**	**(4)**
Type of regression:	**Parent regressions (first stage)**		**Child regressions (second stage)**	
Outcome:	**Fertility (F)**	**Education (E)**	**N-C difference**	**N-C difference**
Cognitive (C)	-0.0122***	0.4643***		
skill (std)	(0.0011)	(0.0009)		
Non- cognitive (N)	0.1359***	0.1371***		
skill (std)	(0.0011)	(0.0009)		
Residual correlation (F, E)	*-0.0214*			
Parent residual			0.0215***	0.0228***
difference (F-E)			(0.0022)	(0.0022)
Child overall				0.0078***
skills (N+C)				(0.0014)
Observations	1,027,581	1,027,581	167,956	167,956

Notes: Relates to Table 7 in the main paper. The only difference is that fertility and education have been standardized before running the regressions in columns (1) and (2). Fertility=number of children at 45. Education=years of schooling at 35. In columns (1) and (2) we include year of birth dummies. In parentheses we present robust standard errors. Asterisks indicate that the estimates are significantly different from zero at the ***1% level, **5% level, and *10% level.

Appendix D Summary of our results

Table D1 Associations between fertility and skills/schooling in our data

Column:	(1)	(2)	(3)	(4)	(5)	(6)
Ind. variable:	Years of schooling		Cognitive ability/grades		Non-cognitive ability	
Variation:	All	Within-family	All	Within-family	All	Within-family
Women						
AFB	+	+ (↓)	+	+ (↓)	+	N/A
# of children	-	- (↑)	-	0 (↑)	0	N/A
1[children>0]	-	0 (↑)	-	0 (↑)	+	N/A
Men						
AFB	+	+ (↓)	+	0 (↓)	+	0 (↓)
# of children	+	+ (↑)	+/-	+ (↑)	+	+ (↓)
1[children>0]	+	+ (↑)	+/-	+ (↑)	+	+ (↓)

Notes: The arrows show how the coefficient moved relative to the "All" coefficient. AFB=Age at first birth. # of children and 1[children>0] are measured at age 45.

Appendix E Optimization of effort and skill investments (extensions)

Optimization of effort

$$U(Y^E, Y^F) = eY^E + (1-e)Y^F$$
$$= e[\theta^{CE}C + \theta^{NE}N + ln\mu^E] + (1-e)[\theta^{CF}C + \theta^{NF}N + ln\mu^F]$$

Assume that $\mu^E + \mu^F = 1$

$$e[\theta^{CE}C + \theta^{NE}N + ln\mu^E] + (1-e)[\theta^{CF}C + \theta^{NF}N + ln\mu^F]$$
$$= e[\theta^{CE}C + \theta^{NE}N + \ln(1-\mu^F)] + (1-e)[\theta^{CF}C + \theta^{NF}N + ln\mu^F]$$

First order condition with respect to μ^F:

$$\frac{-e}{1-\mu^F} + \frac{1}{\mu^F} - \frac{e}{\mu^F} = 0$$

Solving for μ^F:

$$-e\mu^F + 1 - \mu^F - e + e\mu^F = 0$$

$$\mu^F = 1 - e$$

$$\mu^E = e$$

Optimization of skill investments

$$U(Y^E, Y^F) = eY^E + (1-e)Y^F$$
$$= e[\theta^{CE}ln\pi^C + \theta^{CE}(\alpha + u) + \theta^{NE}ln\pi^N + \theta^{NE}(\alpha + u) + ln\mu^E]$$
$$+(1-e)[\theta^{CF}ln\pi^C + \theta^{CF}(\alpha + u) + \theta^{NF}ln\pi^N + \theta^{NF}(\alpha + u) + ln\mu^F]$$

Assume that $\pi^C + \pi^N = 1$

$$U(Y^E, Y^F) = eY^E + (1-e)Y^F$$
$$= e[\theta^{CE}ln\pi^C + \theta^{CE}(\alpha + u) + \theta^{NE}ln(1-\pi^C) + \theta^{NE}(\alpha + u) + ln\mu^E]$$
$$+(1-e)[\theta^{CF}ln\pi^C + \theta^{CF}(\alpha + u) + \theta^{NF}\ln(1-\pi^C) + \theta^{NF}(\alpha + u) + ln\mu^F]$$

First order condition with respect to π^C:

$$\frac{e\theta^{CE}}{\pi^C} - \frac{e\theta^{NE}}{1-\pi^C} + \frac{\theta^{CF}}{\pi^C} - \frac{\theta^{NF}}{1-\pi^C} - \frac{e\theta^{CF}}{\pi^C} + \frac{e\theta^{NF}}{1-\pi^C} = 0$$

$$e\theta^{CE} - \pi^C e\theta^{CE} - \pi^C e\theta^{NE} + \theta^{CF} - \pi^C\theta^{CF} - \pi^C\theta^{NF} - e\theta^{CF} + \pi^C e\theta^{CF} + \pi^C e\theta^{NF}$$
$$= 0$$

Assume that $\theta^{CE} = \theta^{NF} = 1$ and $\theta^{NE} = \theta^{CF} < 1$

$$e - \pi^C e - \pi^C e\theta^{NE} + \theta^{NE} - \pi^C\theta^{NE} - \pi^C - e\theta^{NE} + \pi^C e\theta^{NE} + \pi^C e = 0$$
$$e + \theta^{NE} - \pi^C\theta^{NE} - \pi^C - e\theta^{NE} = 0$$

$$e + \theta^{NE} - e\theta^{NE} = \pi^C + \pi^C\theta^{NE}$$

$$\theta^{NE} + e(1 - \theta^{NE}) = \pi^C(1 + \theta^{NE})$$

$$\pi^C = \frac{\theta^{NE} + e(1 - \theta^{NE})}{1 + \theta^{NE}}$$

$$\pi^N = 1 - \frac{\theta^{NE} + e(1 - \theta^{NE})}{1 + \theta^{NE}} = \frac{1 - e(1 - \theta^{NE})}{1 + \theta^{NE}}$$

Optimization of effort under complementarity (i.e. effort in education also affects fertility)

$$U(Y^E, Y^F) = eY^E + (1 - e)Y^F$$
$$= e[\theta^{CE}C + \theta^{NE}N + ln\mu^E] + (1 - e)[\theta^{CF}C + \theta^{NF}N + ln\mu^F + \rho ln\mu^E]$$

Assume that $\mu^E + \mu^F = 1$

$$e[\theta^{CE}C + \theta^{NE}N + ln\mu^E] + (1 - e)[\theta^{CF}C + \theta^{NF}N + ln(1 - \mu^E) + \rho ln\mu^E]$$

First order condition with respect to μ^E:

$$\frac{e}{\mu^E} - \frac{(1 - e)}{1 - \mu^E} - \frac{(1 - e)\rho}{\mu^E} = 0$$

Solving for μ^E:

$$e - e\mu^E - \mu^E + e\mu^E + (1 - \mu^E)(1 - e)\rho = 0$$

$$e - \mu^E + (1 - \mu^E)(1 - e)\rho = 0$$

$$e - \mu^E + \rho - \rho e - \rho\mu^E + \rho e\mu^E = 0$$

$$\mu^E + \rho\mu^E - \rho e\mu^E = e + \rho - \rho e$$

$$\mu^E(1 + \rho - \rho e) = e + \rho(1 - e)$$

$$\mu^E = \frac{e + \rho(1 - e)}{(1 + \rho - \rho e)} = \frac{e + \rho(1 - e)}{1 + \rho(1 - e)}$$

$$\mu^F = 1 - \frac{e + \rho(1 - e)}{1 + \rho(1 - e)} = \frac{1 + \rho(1 - e) - e - \rho(1 - e)}{1 + \rho(1 - e)} = \frac{1 - e}{1 + \rho(1 - e)}$$

$$\frac{\partial \mu^E}{\partial \rho} > 0, \frac{\partial \mu^E}{\partial e} > 0$$

$$\frac{\partial \mu^F}{\partial \rho} < 0, \frac{\partial \mu^F}{\partial e} < 0$$