The intergenerational transmission of cognitive and non-cognitive abilities[a]

by

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Abstract

We study the intergenerational transmission of cognitive and non-cognitive abilities between fathers and sons using population-wide enlistment data. Measurement error bias in fathers' ability measures is corrected for using two sets of instruments. Results suggest that previous estimates of intergenerational ability correlations are biased downwards; once corrected for, the non-cognitive correlation is close to that of cognitive ability. We also predict mothers' abilities and find the mother-son cognitive ability correlation to be stronger than the father-son correlation. Finally, educational attainment and labor market outcomes of both sons and daughters are strongly related to both parents' cognitive and non-cognitive abilities.

Keywords: Intergenerational ability correlations, cognitive ability, non-cognitive ability, measurement error bias

JEL-codes: J24, J13,I0

1 Introduction

A large literature recognizes the importance of not only cognitive abilities but also of non-cognitive abilities for labor market outcomes (e.g. Bowles, 2001; Heckman et al., 2006; Lindqvist and Vestman, 2011). Despite a growing mass of research on non-cognitive abilities (Borghans et al., 2008), the role of parents in shaping such personality traits is still far from fully understood. A better insight of this is vital for our understanding of how economic outcomes are transmitted between generations. One fundamental problem when studying the relation between parental abilities and the abilities of their offspring is that abilities are likely to be measured with error. As is well known, random measurement errors will lead to an under-appreciation of the influence that parents have on their children (Black and Devereux, 2011). This may be particularly problematic when comparing the intergenerational transmission of cognitive and non-cognitive skills as the measurement problems are likely to be more severe for non-cognitive traits, which may lead to unfounded beliefs that parental influences are less important for non-cognitive than for cognitive abilities.

In this paper we make use of military enlistment records for 37 cohorts of Swedish men, where fathers' and sons' abilities are evaluated at age 18 and where the evaluation methods are comparable over time. This enables us to estimate intergenerational correlations in both cognitive and non-cognitive abilities using the same sample of individuals. We correct for measurement error in fathers' abilities using two different sets of instrumental variables: For a smaller sample ($n \approx 2{,}000$), we use comparable ability evaluations for fathers at age 13. For a larger sample ($n \approx 50{,}000$), ability evaluations of the son's uncle (i.e., the father's brother) are employed as instruments for the father's abilities, thus utilizing the sibling correlation. The two approaches provide similar results. In a series of validity checks we cannot reject the exclusion restriction that uncles have no direct effect on the skills of their nephews. In addition, the second IV strategy enables us to predict mothers' abilities by using the ability evaluations of their brothers, thus bringing both parents into the analysis. In the Appendix we provide the formal conditions for 2SLS when data on the endogenous regressor is unavailable.

Without adjusting for measurement error, we find a father-son correlation of 0.32-0.35 for cognitive and 0.21 for non-cognitive abilities, much in line with previous findings in the literature.[1] When we adjust for measurement error in fathers' abilities, the intergenerational correlation increases to 0.42-0.48 for cognitive, and to around 0.42 for non-cognitive abilities.[2] This suggests that the substantial difference in estimated intergenerational correlations between cognitive and non-cognitive abilities found in the previous literature, to a large extent is due to a higher degree of measurement error in non-cognitive abilities.

We next derive predicted cognitive and non-cognitive ability measures also for mothers using the enlistment evaluations of their brothers; i.e. the maternal uncles. The results show that mother-son correlations in cognitive abilities are somewhat stronger than father-son correlations, while no such difference is apparent for non-cognitive abilities. Previous studies on the relative ability correlations between mothers and fathers have produced inconclusive results; in part due to small sample sizes (see for example Anger and Heineck 2010 and Anger 2011). With the large sample at our disposal, we estimate correlations with a high degree of precision. Since both generations are evaluated at approximately age 18, another advantage of our data is that parental abilities are not influenced by experiences shared by parents and children, a consideration shown to be important in a contribution by Brown et al. (2011).

Finally, we find a strong association between (predicted) parental abilities—both fathers' and mothers'—and educational and labor market outcomes for both sons and daughters.

[1] Black et al. (2009) and Björklund et al. (2010) find intergenerational correlations in cognitive abilities of 0.35-0.38, while the meta-study by Plomin and Spinath (2004) reports 0.4. As for non-cognitive abilities, the meta-study by Loehlin (2005) reports an intergenerational coefficient of 0.15, while Anger (2011) and Dohmen et al (2012) find coefficients of 0.12-0.25.

[2] Note that Bowles and Gintis (2002) argue that the intergenerational correlation in cognitive ability lies between 0.42 and 0.72 when taking measurement error into consideration.

Parents' cognitive abilities are relatively more important for educational outcomes while their non-cognitive abilities are relatively more important for earnings and labor force participation. Previous findings on the labor market effects of cognitive and non-cognitive abilities for men by Lindqvist and Vestman (2011) are thus likely to apply to women as well. Back-of-the-envelope calculations indicate that only a minor part of the earnings premium of parental abilities can be accounted for by increased educational attainment.

These results provide support for recent findings suggesting that the transmission of non-cognitive skills can explain a substantial part of the intergenerational correlation in economic outcomes. For example, in a small sample of US children Osborne Groves (2005) finds that personality traits can explain 11 percent of the earnings transmission, the same number as Blanden et al. (2007) find in a study of 3300 UK children using a measure of non-cognitive skills. Hirvonen (2009) finds that a combination of sons' education, cognitive and non-cognitive skills, as well as a health indicator (BMI) can account for most of the intergenerational correlation in income. In the same vein, Björklund et al. (2010) find that indicators of parental patience can explain a substantial part of sibling income correlations.

2 Methodological considerations

We ideally want to estimate the true population correlation of cognitive and non-cognitive abilities between generations; that is, to estimate the following simple regression model:

$$Y_j^{*son} = \alpha + \beta Y_j^{*father} + \varepsilon_j , \qquad (1)$$

where Y_j^{*i} i={father, son} represents the true cognitive or non-cognitive ability for the father and son in family *j*, and ε_j is an error term, and where the parameter β is the population correlation in true cognitive or non-cognitive abilities between fathers and sons.

A problem—for essentially all studies on the subject—is that observed measures of cognitive and non-cognitive abilities, Y_j^i, typically capture the true underlying abilities with an error $Y_j^i = Y_j^{*i} + \eta_j^i$, where η_j^i is a measurement error. Under the assumption that the measurement error is classical, i.e. an independent random variable, the OLS-estimate of the intergenerational correlation in true abilities can be expressed as:

$$plim\,\beta^{OLS} = \beta \frac{V\left(Y_j^{*father}\right)}{V\left(Y_j^{father}\right)}. \tag{2}$$

This is the usual measurement error bias expression, where the OLS-estimate of the intergenerational correlation is attenuated by the ratio between the variance of fathers' true and observed abilities; i.e. the reliability ratio.

Noisy measures of the true latent ability of fathers are particularly problematic for our purposes, since the extent of measurement error may differ between the cognitive and non-cognitive ability measures. In particular, we suspect the measurement error problem to be more severe for measures of non-cognitive skills than of cognitive skills, which would lead us to draw incorrect conclusions of the relative importance of the intergenerational transmission of different types of skills.

One way of dealing this measurement error is to find an instrument that is strongly related to fathers' abilities but without a direct relation to sons' abilities (see e.g. Ashenfelter and Krueger, 1994). Ideally, this would be an independent ability evaluation undertaken at the same time as the original evaluation. Lacking such evaluations, we instead propose two different sets of instruments: First, we use a set of evaluations of the fathers' abilities conducted at an earlier age, an instrument which comes close to the ideal. As discussed in the next section, this instrument is available only for a limited sample of individuals. Second, we use the draft evaluations of paternal uncles to instrument for fathers' abilities. The main advantage of using this uncle-instrument is that it dramatically increases the sample size and hence the precision of our estimates. We estimate the following first stage relation:

$$Y_j^{father} = \pi + \rho Y_j^{i} + u_j \quad \text{for } i = \text{early age, uncle}, \tag{3}$$

where ρ is the correlation between the different ability evaluations. In the first case, we thus exploit the strong intrapersonal correlation between ability evaluations conducted at different ages to address the measurement error problem. In the second case, we exploit the strong correlation between siblings' abilities. Under the exclusion restriction that there is no direct effect from the father's ability at age 13 or the uncle's ability at age 18 on the son's abilities – other than through the father's ability at age 18 – we correct for the measurement error bias, and thus estimate the intergenerational correlation in the true latent abilities:

$$plim\hat{\beta}_{IV} = \frac{\text{cov}(Y_j^{son}, Y_j^{i})}{\text{cov}(Y_j^{father}, Y_j^{i})} = \beta \frac{\text{cov}(Y_j^{*father}, Y_j^{*father})}{\text{cov}(Y_j^{*father}, Y_j^{*father})} = \beta \quad \text{for } i = \text{early age, uncle}. \tag{4}$$

The exclusion restriction is quite innocent when considering the fathers' own ability evaluations conducted at an earlier age. The validity of the uncle-instrument is more questionable as uncles can have a direct influence on their nephews, or they could share some family factor with their nephews not shared by the father. In such a case, the IV-estimate would overestimate the true transmission in abilities. Another possibility is that the measurement error may not be classic and, in particular, brothers' measurement errors could potentially be correlated. If this is the case, the IV-estimate is likely to underestimate the intergenerational correlation in true skills. In Section 4.2 we will address these and related concerns about the validity of the uncle-instrument.

A second major concern is whether these IV-estimators capture the true population correlation of cognitive and non-cognitive abilities between generations. In principle, it is possible that the intergenerational transmission of the abilities that are stable between the fathers' early and late evaluations, or that are shared between fathers and their brothers, may differ from the intergenerational transmission of fathers total abilities. Thus, any difference between the OLS and the IV-estimates may not only be driven by measurement error, but can also be due to the fact that the estimators exploit different parts of the variation in fathers' abilities. Since we have two different sets of instruments, both exploiting different sources of variation, our approach to address this issue is to compare the different IV-estimates. In section 4.1 we will discuss this concern in more detail.

3 Data

Up until 2010, all Swedish men had to go through the military enlistment if called upon.[3] In most cases, the enlistment took place the year men turned 18. Until the late 1990s, over 90 percent of all men in each cohort went through the whole enlistment procedure. Thereafter the need for conscripts declined and the enlistment became less comprehensive.[4]

The enlistment consisted of a series of physical, psychological and intellectual tests and evaluations. The evaluation of cognitive ability consisted of subtests of logical, verbal, and spatial abilities, as well as a test of the conscript's technical comprehension. The design of the test has been subjected to minor revisions in 1980, 1994 and 2000, but throughout the period it tested for the same four underlying abilities. The test results on these four subtests were combined to a normally distributed stanine scale ranging from 1-9 (mean 5, standard deviation 2), that has been found to be a good measure of general intelligence (Carlstedt, 2000). We standardize this composite measure of general cognitive ability by enlistment year.

Our measure of non-cognitive abilities is based on a standardized psychological evaluation aimed at determining the conscripts' capacity to fulfill the requirements of military duty and

[3] The discussion of the enlistment data draws heavily on an interview by Erik Lindqvist (August 25, 2004) with Johan Lothigius, chief psychologist at the National Service Administration. We are grateful to Erik for sharing his notes with us.

[4] The consequences of refusing the military service include prison in up to one year (1994:1809 Lag om totalförsvarsplikt).

armed combat. Central to this are the abilities to cope with stress and to contribute to group cohesion. The evaluation was performed by a certified psychologist who conducted a structured interview with the conscript. As a basis for the interview, the psychologist had information about the conscript's results on the tests of cognitive ability, physical endurance, muscular strength, as well as grades from school and the answers from a questionnaire on friends, family, hobbies etc. The interview followed a specific, and secret, manual that states topics to discuss and also how to grade different answers.

A conscript's personality is scored along four domains (Mood et al, 2012): social maturity (extroversion, having friends, taking responsibility, independence); psychological energy (perseverance, ability to fulfill plans, to remain focused); intensity (the capacity to activate oneself without external pressure, the intensity and frequency of free-time activities); emotional stability (the ability to control and channel nervousness, tolerance of stress, and disposition to anxiety). It should be noted that motivation for doing the military service was explicitly not a factor to be evaluated. Grades were given on four different sub-scales along the personality dimensions, which were transformed by the enlistment agency to a normally distributed stanine scale ranging from 1 to 9. We standardize this measure by enlistment year, and the correlation between cognitive and non-cognitive abilities is 0.35. To a large extent, the psychological evaluation captures the same personality traits that make up the Big Five domains of personality (Bouchard, 1994), but they are grouped together somewhat differently. As there is no perfect mapping between the sub-indices and personality measures found in the literature, we focus on the composite non-cognitive ability evaluation.[5]

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[5] For a sub-sample of draftees we have access to survey questions evaluating school adaptation and motivation at age 13, and the personality traits in the survey data that roughly correspond to the Big Five domains of personality, load on the draft measure of non-cognitive ability. The relation between the non-cognitive draft evaluation and personality traits based on these responses are described in the online Appendix.

Data on enlistment is collected from the Swedish Military Archive and the National Service Administration, and consists of all Swedish men born between 1950 and 1987. It includes data on date of the enlistment, results on the cognitive ability tests, the psychologist's rating of non-cognitive skills, and height. Information from Statistics Sweden on biological parents has then been used to link fathers and sons, as well as mothers and siblings.

A few restrictions on data have been imposed in the main analysis. All men included in our sample must have a valid enlistment record and have enlisted the year they turned 18, 19 or 20. Since over 90 percent of all men were enlisted up to the late 1990's, representativeness is a minor concern for most of the period studied. During the early 2000's, however, the share of enlisted men fell: For individuals born in the mid 1980s, only 70 percent were enlisted.[6]

In order to correct for measurement error in the fathers' abilities we use two different strategies, both strategies impose separate sample restrictions. For a 10 percent sample of fathers born in 1953 we have alternative measures of cognitive and non-cognitive abilities at age 13. These data originates from the longitudinal study *Evaluation Through Follow-up* (ETF). Within the ETF surveys, individuals were given cognitive ability tests reflecting some of the same abilities as measured during the enlistment. Even though the cognitive tests at age 13 and 18 are not identical, they are supposed to reflect the same cognitive traits. While the ETF data does not include any direct measurement of non-cognitive abilities, it does contain information capturing such personality traits. More specifically the ETF data contains information on grade point average (GPA) in non-academic subjects in the 6th grade and survey information on educational aspirations and peer interaction.[7] We use the residual of

[6] Selective enlistment is not a problem for our results; see footnote 10.

[7] The survey question on educational aspirations contain information on the number of years the student plans to study, while the question on peer interaction captures the extent to which the student spend time outside school alone or with friends.

these measures after regressing them on the ETF-measure of cognitive ability—thus netting out any cognitive ability—as instruments of the father's non-cognitive ability at age 18.

Our second strategy is to use uncles' abilities as instruments for the father's abilities and we therefore restrict the sample to sons with at least one uncle. In addition, by requiring that both the father and the uncle have enlisted before 1980 we guarantee that they have undertaken the same version of the cognitive ability test. Further, to avoid that uncles share more of the same environment with their nephews than with their brothers, we require the age difference between fathers and uncles to be at most seven years.

Subject to these restrictions, our main regression samples consists of almost 2,000 observations (sons) for the ETF-sample and more than 50,000 observations (sons) for the uncle sample. Table 1 shows descriptive statistics for sons, fathers and paternal uncles in our respective samples. As noted above, men are typically enlisted when they are 18 years old. There is some evidence that the sons in our sample have slightly higher cognitive and non-cognitive skills than the population on average, while their fathers have slightly lower cognitive and slightly higher non-cognitive skills than their sons. This pattern is likely to be caused by the age restrictions in the enlistment data (individuals born 1950 to 1987) which implies that the fathers in our sample are slightly younger than fathers in the population as a whole. Paternal uncles are slightly younger than the fathers, since there is no requirement that uncles need to have children. They also have somewhat lower cognitive scores than fathers, possibly due to birth order effects (Black et al., 2011).

[Table 1]

4 Father-son correlations

We start this section by presenting the results for intergenerational correlations in cognitive and non-cognitive abilities between fathers and sons with and without correction for measurement error. In Section 4.2, we thereafter present a number of consistency checks and discussing the validity of the uncle-instrument.

4.1 Correlations with and without correcting for measurement error

Table 2 presents OLS and IV-estimates of the intergenerational correlation in abilities between fathers and sons.[8] In the first column in the top panel of Table 2, we see that the OLS-estimate of the relation between fathers' and sons' cognitive abilities is 0.32 for the ETF-sample. For the uncle-sample, the same estimate, in column 3, is 0.35 which is close to what Black et al. (2009) have found for Norway and Björklund et al. (2010) for Sweden. In the first column in the lower panel, we instrument for fathers' cognitive abilities using the cognitive ability evaluation conducted at age 13. The point estimate increases to 0.42, implying a reliability ratio of 0.76. In the third column, we instead instrument for fathers' cognitive abilities using the enlistment evaluation of their brothers, i.e. the uncle-instrument. The IV-estimate is 0.48 which in turn implies a reliability ratio of 0.73. This ratio is not statistically different from the reliability ratio in column one.

We next turn to the intergenerational ability correlations for non-cognitive abilities. In columns two and four in the top panel, we see that the OLS-estimates are 0.21 both for the ETF- and the uncle-sample, which is in line with previous findings (see e.g. Lohlin 2005, Dohmen et al 2012, and Anger 2011). In the second column in the lower panel, we correct the estimates for attenuation bias using the fathers' non-cognitive ability evaluations at age 13 as instruments. The point estimate then increases to 0.41 which means that the reliability ratio equals 0.51. In the final column, we use the uncle-instrument to correct for measurement error

[8] Overall, there is a strong relation between the instruments and fathers' cognitive and non-cognitive abilities as show by the F-test in Table 2. The exception is the relation between the non-cognitive components of the ETF and the non-cognitive measure at age 18, but the non-cognitive components of the ETF still classifies as strong instruments using the rule of thumb suggested by Staiger and Stock (1997). The first stage regressions are described in the online Appendix.

and get a point estimate of 0.42, very close to the estimate in column two. The reliability ratio for the uncle-instrument equals 0.5 which, again, is not statistically different from the reliability ratio we get in column three.[9]

[Table 2]

Apart from the substantial increases in the intergenerational correlations when correcting for measurement error, the most striking finding in Table 2 is the similarity between the estimates based on the two different set of instruments for fathers' abilities. Recall that the ETF-instruments are measures of the same traits at age 13 for the same individual, thus constituting an all but perfect instrument. The fact that the uncle-instrument and the age 13-instrument yield very similar results is consistent with the assumption that the exclusion restriction holds also for the uncle-instrument.

The similarity between the estimates using different instruments has implications for the interpretation of the estimated intergenerational correlation. The ETF-instruments pick up all genetic components of cognitive and non-cognitive ability and all environmental factors up until age 13. Hence, it will capture the true population correlation unless the fathers' position in the ability distribution changes significantly between age 13 and 18, and that the fathers' abilities at age 13, which do not remain at age 18, have a direct effect on the sons' abilities at age 18. The uncle-instrument, on the other hand, exploits the variation in fathers' skills that is common between brothers. As brothers on average share 50 percent of their genes and part of the environment at age 18, the two instruments exploit rather different sources of variation in the father's abilities at age 18. The fact that the two instruments still produce similar results is

[9] As described above, the composite measure of cognitive and non-cognitive skills are made up of four different sub-indices. The intergenerational correlation does not differ substantially between the different sub-indices, and we therefore focus only on the composite measures. In the online Appendix we describe the intergenerational transmission for each of these components.

consistent with the notion that the sources of father's abilities—genes or environment—have minor impact on the transmission of abilities over generations and that the IV-estimates capture the average intergenerational correlation in abilities in the population.

One additional concern is that the high father-son correlation in non-cognitive ability may be spuriously driven by cognitive ability, as the cognitive ability is omitted in the regressions in columns two and four, and vice versa. In Table 3, however, we find that the point estimates in the uncle-sample are only slightly reduced – to 0.44 for cognitive abilities and to 0.39 for non-cognitive abilities – when controlling for the other ability type. The point estimates are not statistically different from the corresponding estimates in Table 2. Further, the relative size of the correlations in different abilities does not change.

[Table 3]

The results in this section show that OLS-estimates of intergenerational ability correlations are substantially downward biased, in particular for non-cognitive abilities.

4.2 Can we trust the uncle-instrument?

The similarity between the estimates using the two different sets of instruments reported in the previous section lends credibility to the uncle instrument. Still, in this section we perform several consistency checks corroborating the exclusion restriction. This is crucial since a direct impact by uncles on their nephews' abilities would render results based on the uncle-instrument to be invalid.

Table 1 shows that the average uncle is more than 25 years older than his nephew, reducing much of potential shared time-specific environmental influences between uncles and nephews. Still, uncles could have a direct influence on their nephews, and we test for this by using a sub-sample of "absent uncles", defined as uncles who either died or emigrated from Sweden prior to the birth of their nephew. If uncles have a direct effect on their nephews, IV-estimates based on absent uncles—who have had no or very limited contact with their nephews—should be lower than for the average uncle.

Despite the drastic reduction in sample size, column two in Table 4 first shows that the OLS-estimates for cognitive and non-cognitive skills are essentially unchanged compared to the estimates based on the full sample. More importantly, the IV-estimates for the absent uncle sample are, if anything, larger than the IV-estimates based on the full sample of observations, and the reliability ratios are lower. The standard error of these IV-estimates are however large and we cannot reject that the IV-estimates for the different samples are equal. Still, the results do not indicate that the IV-estimates for absent uncles are smaller, or that the reliability ratios are larger, compared to the estimates based on the full sample. This is consistent with a lack of a direct influence of uncles on their nephews' abilities.

[Table 4]

Even if uncles do not influence their nephews directly, they do have a shared environment through the grandparents. Grandparents may have an influence on both their sons and their grandsons, for example by spending time with their grandchildren. Hence, there may be an association between the uncle and his nephew, not shared with the father, potentially biasing the IV-estimates upwards. In order to test for this we utilize sub-samples of children with "absent grandparents", where the direct contact with the grandparents is broken.

We first use a sample of children where *either* the grandmother *or* the grandfather died before their grandson was born. In column three in Table 4, we find the IV-estimates for cognitive and non-cognitive abilities to be essentially unchanged compared with the original estimates. In column four we instead use the small sample where *both* the grandmother and the grandfather died before their grandson was born. For this sample, the IV-estimate for cognitive ability is slightly smaller, while the estimate for non-cognitive ability is larger, than for the full sample, but these differences are not statistically significant. It is important to note that the OLS-estimates also differ somewhat from the estimates based on the full sample, most likely due to this sample being a highly selected one. If the original IV-estimates were upward biased due to a direct influence by grandparents on their grandchildren, we would expect the reliability ratios for the absent grandparents sample to be higher than for the full sample. Again, we find no indication of this. Thus we fail to find evidence of an independent association between the uncle and the nephew through the influence from the grandparents.

Our third strategy to examine the validity of the uncle instrument is to consider a trait with limited measurement error, namely stature. Stature has a strong genetic component but also reflects environmental factors likely to be shared between brothers (Currie and Almond, 2011). If shared genetic or environmental factors captured by uncle stature have a direct impact on child stature, we expect IV estimates to be larger than OLS. If, on the other hand, no direct effects are present, the IV and OLS estimates should be close to identical. Indeed, in Table 5 we find the OLS-estimate of the father-son correlation in height to be 0.48, whereas the IV-estimate is 0.50. Thus, we fail to find indications of direct effects by uncles on their nephews through the shared genetic and environmental factors that are captured by stature.

[Table 5]

Through all the consistency tests performed we fail to find evidence of a direct effect from the uncle to his nephew, either through a direct influence, a shared environment or through a common genetic component not shared by the father.[10] Given the results of these tests and the similarity in results between the two IV-strategies the remaining analysis is based on the uncle-instrument, rather than using the much smaller EFT-sample.

[10] In additional sensitivity analyses we find no evidence that our results would be biased due to some individuals consciously underperforming at the enlistment in the hope of escaping military service. Furthermore, in the early 2000's the share of enlisted men dropped as the need for conscripts decreased: We find no evidence that our results are sensitive to selection issues induced by the sampling frame. For details of these sensitivity tests see Grönqvist, Öckert and Vlachos (2010).

5 Ability correlations using both parents

So far we have only studied father-son correlations even though both parents presumably are important for the transmission of abilities to their children. The focus on fathers is due to data limitations that we share with several other studies on intergenerational ability correlations. Whether or not the inclusion of mothers is important crucially depends on the degree of assortative mating. To bring the mothers into the analysis we generalize our methodological strategy by predicting maternal abilities using the enlistment records of their brothers.

5.1 Deriving maternal abilities

To derive maternal abilities, we use the idea behind the uncle-instrument to predict abilities for both parents using the first stage relation; that is, we use enlistment ability measures of both paternal and maternal uncles. However, since we do not observe mothers' abilities we cannot obtain a direct estimate of the brother-sister correlation in abilities in the first stage equation for mothers. But, using an estimate of the brother-sister correlation at age 18, $\hat{\rho}_{18}^{brother-sister}$, from some other source, we can predict the abilities of mothers from maternal uncles as:

$$\hat{Y}_j^{mother} = \hat{\pi} + \hat{\rho}_{18}^{brother-sister} Y_j^{maternaluncle}. \tag{5}$$

We can then plug mothers predicted abilities, $\hat{Y}_i^{mother}$, into the second stage relation (1). To perform this exercise we need an estimate of $\rho_{18}^{brother-sister}$. If ability correlations between siblings of opposite gender were the same as between same-gender siblings, deriving the implied ability scores for mothers using their brothers' abilities would be trivial. Rather than just assuming that sibling correlations display such a pattern, we use alternative sources of data to produce an estimate of the gender specific sibling correlations.[11]

To this end, we scale the brother correlations from equation (3) by a factor equal to the relative sister-brother to brother-brother correlation for each assessed ability. More specifically, we construct the estimate of the brother-sister correlation to be used in the prediction of mother's abilities as:

$$\hat{\rho}_{18}^{brother-sister} = \hat{\rho}_{18}^{brother} \frac{\hat{\rho}_{18,k}^{brother-sister}}{\hat{\rho}_{18,k}^{brother}} \quad , k=13,\ 16. \qquad (6)$$

For cognitive skills we have ability evaluations at age 13 from the EFT-study for a sample of boys and girls. Using these data we first regress sisters' cognitive ability at age 13 on their brothers' cognitive ability at the enlistment at age 18 to obtain the brother-sister correlation $\hat{\rho}_{18,13}^{brother-sister}$, thereafter we obtain $\hat{\rho}_{18,13}^{brother}$ by regressing the cognitive ability at age 13 of one brother on his brother's cognitive ability at the enlistment. Relating the brother-sister correlation to the brother-brother correlation then gives us the scaling factor for cognitive ability. In the first two columns of Table 6, we find that this sibling correlation in cognitive abilities is 0.41 for men and 0.38 for women. This gives a relative correlation in cognitive abilities for siblings of opposite sex compared to same-sex siblings of 0.92.

[Table 6]

For non-cognitive sibling correlations we do not have any direct measure of non-cognitive abilities for women. What we do have is the GPA from the last year of compulsory school at

[11] There is no consensus regarding the relative correlation in personality traits between same-sex and different-sex siblings. For example, Eaves et al (1999) report opposite-sex correlations in personality traits to vary substantially relative to brother correlations. The relative correlations are 0.61 (*Psychoticism*), 0.94 (*Extraversion*), 1.05 (*Lie*), and 1.25 (*Neuroticism*). Lake et al (2000) find the opposite-sex correlation in *Neuroticism* to be 0.89 relative to the brother correlation in Australia, but 1.25 in the US. This wide range of estimates possibly reflects the fact these studies include a relatively low small number of individuals and that the samples are non-representative of the general population.

age 16. These grades are supposed to reflect how well students perform relative to national standards and grade-setting is aided by standardized national achievement tests in Swedish, English, and Mathematics. GPA records are available from 1988 and we standardize them by school year. The GPA-results are used by students to apply for upper-secondary education and they reflect both cognitive and non-cognitive abilities.[12] In order to obtain a scaling factor for non-cognitive abilities—and an additional estimate of the scaling factor for cognitive abilities—we regress boys' and girls' GPA on their brothers' enlistment evaluations, which gives us $\hat{\rho}_{18,16}^{brother}$ and $\hat{\rho}_{18,16}^{brother-sister}$.

As can be seen in the third and fourth column Table 6, male and female students' GPA-results are strongly related to their brother's cognitive and non-cognitive ability evaluations at the enlistment. The correlation in cognitive abilities between brothers and sisters is 0.92 relative to that between brothers, identical to the relative sibling correlations in cognitive abilities obtained from the estimates in columns one and two. Similarly, the relative sibling correlation in non-cognitive abilities from columns three and four is 0.93.

Based on these estimates, we assume that the scaling factor (the brother-sister correlation relative to the brother-brother correlation) is 0.92 for cognitive abilities and 0.93 for non-cognitive abilities. Using these estimates of the relative gender sibling correlations, we rescale the brother-brother correlation $\hat{\rho}_{18}^{brother}$ to obtain the first stage relation between mothers and their brother's abilities $\hat{\rho}_{18}^{brother-sister}$. We then predict the cognitive and non-cognitive abilities for both fathers and mothers using the abilities of paternal and maternal uncles with enlistment records.

[12] Regressing an individual's GPA at age 16 on his cognitive and non-cognitive abilities at the enlistment yields (n=232,567) a coefficient of 0.56 (0.002) on cognitive abilities and 0.19 (0.002) on non-cognitive abilities (standard errors in parentheses).

In the Appendix we derive the conditions for generating an unobserved endogenous regressor, which is unavailable in other samples, but where an observed variable of the same *type* can be used to generate the missing regressor. In addition to the exclusion restriction that maternal uncles' abilities have no direct effect on their nephew's abilities, we show that the scaling in equation (6) also requires that the alternative ability measure (ability at age 13 or the GPA at age 16) is an equally good proxy variable for both mothers' and fathers' ability at age 18. In the online Appendix we check this condition for cognitive skills in our data. We find that cognitive skills at age 13 have roughly the same association with GPA at age 16 for both mothers and fathers.

5.2 Results for maternal and paternal abilities

Having derived abilities for both mothers and fathers, we can estimate the intergenerational correlation between sons and both of their parents. Note that the attenuation bias due to measurement error is accounted for in the two-stage procedure. We now require that enlistment records are available for both paternal and maternal uncles, which reduces the sample size to around 25,000 sons. In the first column of Table 7, we estimate the father-son correlation in cognitive ability to 0.51; the slight difference to the IV-estimates in Table 2 is due to the somewhat different sample. To account for the regressor being generated, we now bootstrap the standard errors. In column two, we see that the estimated mother-son correlation in cognitive ability is higher, 0.59. The third column shows that the partial correlations for fathers' (0.34) and mothers' (0.43) cognitive abilities are both reduced when entered jointly into the regression, indicating some degree of positive assortative mating. The difference in the intergenerational correlations for fathers' and mothers' abilities is statistically significant; both for the bivariate and partial results.

[Table 7]

For non-cognitive abilities, the mother and father correlations are more similar. The father-son correlation in non-cognitive abilities is 0.46 (column four), the same as the mother-son correlation in column five. When entered jointly, the partial father-son correlation is 0.34 whereas the partial mother-son correlation is 0.30, but the difference between these estimates is not statistically significant.

The results in this section show that mother-son correlations in cognitive abilities are higher than father-son correlations, while the mother-son and father-son correlations are similar for non-cognitive abilities.

6 Long run outcomes of children

In the previous section we predicted both parents' abilities and estimated the intergenerational correlations between parents and their sons. In this section, we use these predicted abilities to estimate the relation between parental abilities and the educational and labor market outcomes among both sons and daughters. In particular, we estimate the relationship between parental abilities on children's compulsory school achievement, years of education, earnings, and labor force participation. These estimates will capture a composite effect of the influence from two components. The first is the ability payoff to the skills transmitted from parents to children. The second is the direct effects of parental abilities on their children's labor market prospects or educational success, including factors such as residential choice, help with homework, and professional networks.

We perform this analysis separately for sons and daughters, thus allowing mothers' and fathers' abilities to have different impact on male and female offspring. Such differences can be due to either a gender specific transmission of parental abilities; differences in the payoff to the same ability for men and women; or a differential direct impact of parental abilities on sons and daughters labor market prospects or educational success. While there is evidence that the same ability can have different payoffs for women and men,[13] less is known concerning the relative importance of paternal and maternal ability transmission.

In this analysis we only require the children to have a paternal uncle and a maternal uncle with a valid enlistment record. We can therefore predict cognitive and non-cognitive abilities also for fathers and mothers born before 1950. Further, in order for these long-term outcomes to be representative for life success, we require the labor market outcomes and years of schooling to be observed when sons and daughters are between 30 and 40 years old.

Table 8 present the results for educational outcomes for sons and daughters. In columns one of the upper panel, we regress standardized test scores on paternal abilities. The test scores reflect academic achievement in English, Swedish and mathematics at age 16. The association between cognitive abilities and student achievement is strong: 0.47 for sons and 0.45 for daughters. The relation between test scores and non-cognitive ability is considerably weaker: 0.09 among sons and 0.14 among daughters. Columns two perform the same analysis using maternal abilities. The association between maternal cognitive ability and student achievement is stronger for sons (0.51) than for daughters (0.43), while the reverse is true for non-cognitive abilities (0.10 for sons and 0.20 for daughters). In columns three, we include both maternal and paternal abilities and find that the same patterns hold: mothers' cognitive abilities are relatively more important for sons while mothers' non-cognitive abilities are relatively important for daughters and there is no difference between sons and daughters for fathers' abilities. Children whose parents both have abilities one standard deviation above the mean achieve on average 0.8 standard deviations higher scores.

[Table 8]

[13] Heckman et al. (2006) provides an analysis of gender specific payoffs of cognitive and non-cognitive abilities. Further, Mueller and Plug (2006) find that women with an antagonistic personality are at a substantial earnings disadvantage compared to women who are more agreeable. For men, this pattern is reversed.

In the lower panel we document the strong relation between total years of schooling and parental abilities. Here some interesting gender differences can be found: Both paternal and maternal cognitive abilities are more strongly related to sons' than to daughters' total years of schooling while both parents' non-cognitive abilities are more important for daughters than for sons. Sons (daughters) whose both parents have abilities one standard deviation above mean attain on average 1.6 (1.5) additional years of schooling.

We next turn to children's labor market outcomes. In the top panel of Table 9 we regress annual earnings on fathers' and mothers' abilities (zero earnings are included). To facilitate interpretation we divide the estimates by the average earnings for sons and daughters in the sample, respectively. Parental non-cognitive abilities are substantially more important than their cognitive abilities for the earnings of their children. Sons (daughters) whose both parents have abilities one standard deviation above the mean on average earn almost 25 (20) percent more. The middle panel shows that one of the reasons behind this result is that parental non-cognitive abilities are strong predictors of labor force participation, while cognitive abilities are not. This relation holds for both sons and daughters, and for both fathers' and mothers' non-cognitive abilities. Among sons, a one standard deviation increase in either fathers' or mothers' non-cognitive ability is associated with about a six percentage point higher probability of being employed. Among daughters, a one standard deviation increase in fathers' non-cognitive abilities increases the probability that daughters are employed with 9 percentage points and the corresponding figure for mothers is 6.4 percentage points.

[Table 9]

In the bottom panel, we estimate the relation between log earnings and parental abilities. For sons, the relation between log income and the cognitive and non-cognitive abilities of their fathers is 0.053 and 0.054, respectively. As for mothers' abilities, the point estimate for cognitive abilities is 0.036 and 0.05 for non-cognitive. The estimated correlation between daughters' log income and parental non-cognitive abilities suggests a somewhat different pattern: the estimate for fathers' cognitive abilities is 0.062 while the association is close to zero for non-cognitive abilities. The relative importance of cognitive abilities also holds true for maternal abilities: the point estimate is 0.053 for cognitive and 0.016 (not statistically significant) for non-cognitive abilities.

The strong relation between parental abilities and child earnings can be due to both a direct impact of abilities on earnings and an indirect impact running through educational attainment. To get a sense of the relative strength of these channels, we conduct a back-of-the-envelope calculation of the implied earnings effect of the relation between parental abilities and child educational attainment. The estimates in Table 8 show that a one standard deviation's increase in fathers' cognitive and non-cognitive abilities is associated with 0.72 and 0.42 additional years of schooling for sons. Given that the returns to an additional year of schooling on the Swedish labor market is 2.5 percent (Öckert, 2010), this corresponds to an earnings increase by 0.018 percentage points for cognitive abilities, and 0.011 for non-cognitive abilities. As shown in Table 9, the total earnings effect of a one standard deviation increase in paternal cognitive and non-cognitive abilities is 0.043 and 0.135 percentage points. Thus, only a minor part of the earnings premium of parental abilities can be accounted for by increased educational attainment. Moreover, the direct earnings effect is substantially stronger for father's non-cognitive than for his cognitive ability. This pattern is more or less the same for daughters and if we use mothers' rather than fathers' abilities.[14]

[14] For daughters the implied (total) earnings impact of increased educational attainment is 0.013 (0.042) for paternal cognitive and 0.016 (0.118) for non-cognitive abilities. Regarding maternal abilities, the implied earnings impact of increased educational attainment is 0.022 (0.013) for cognitive and 0.009 (0.014) for non-cognitive abilities among sons (daughters). The total earnings impact is 0.043 (0.035) for cognitive and 0.133 (0.096) for non-cognitive among sons (daughters).

7 Conclusions

This paper makes several distinct contributions to the literature on the intergenerational transmission of cognitive and non-cognitive abilities. First, we compare intergenerational correlations in cognitive and non-cognitive abilities using large and representative samples of men who are evaluated using the same methods and at the same age. Second, we correct for measurement error bias using two different sets of instruments. In particular, we make a methodological contribution by suggesting that the ability evaluations of a father's brother (a child's uncle) can be used as instruments to correct for measurement error in the father's abilities. Third, we bring mothers into the analysis by predicting their abilities using the ability evaluations of maternal uncles and derive an estimator to this purpose. Forth, we estimate the importance of the transmission in abilities from both parents for outcomes later in life, both for sons and daughters.

We find evidence of measurement error bias in both ability dimensions and once this is corrected for, the intergenerational transmission of non-cognitive abilities is almost as high as that of cognitive skills. This is in contrast to previous research which indicates that the transmission of non-cognitive abilities between generations is substantially lower than that of cognitive abilities. Since measurement error is generally likely to be more severe for non-cognitive than cognitive abilities, these findings have bearing on the interpretation of the results in the existing literature.

When using the predicted abilities for both parents, we find that the mother-son correlation in cognitive abilities is stronger than the father-son correlation while there is no substantive difference for parental non-cognitive abilities. Finally, we find a strong relation between both parents' cognitive and non-cognitive abilities and several educational and labor market outcomes for both sons and daughters. Parental cognitive abilities are relatively important for schooling outcomes, while parental non-cognitive abilities are particularly important for labor force participation among both sons and daughters. Back-of-the-envelope calculations show that only a minor part of the earnings premium associated with parental abilities can be accounted for by increased educational attainment

Our results show that previous findings regarding the importance of cognitive and non-cognitive abilities for male earnings and labor force participation (Lindqvist and Vestman, 2011) are likely to generalize to women. Some noteworthy gender differences are found, however: Relative to parental non-cognitive abilities, cognitive abilities are more important for educational outcomes for sons than for daughters, while parental cognitive abilities are relatively more important for female earnings – provided that the women are in the labor force. A better understanding of these differences is an obvious question for future research.

The finding that families play an important role in shaping both cognitive and non-cognitive abilities raises some doubts concerning the general perception that non-cognitive abilities are relatively malleable, and hence a more appropriate target for policy interventions than cognitive abilities (Carneiro and Heckman, 2003; Knudsen et al, 2006; Cunha and Heckman, 2008). Before drawing any strong conclusion on these matters, however, more research is clearly needed. In particular, it should be stressed that our study presents a descriptive analysis of intergenerational correlations which does not disentangle the mechanisms through which these correlations arise.[15]

[15] These mechanisms are likely to include complex interactions between genetic and environmental factors. A recent study by Cesarini (2009) uses monozygotic and dizygotic twins, as well as different types of siblings to estimate the family component of—among other things—cognitive and non-cognitive abilities. Cunha and Heckman (2007) provide a perspective on the nature-nurture debate. Using a large sample of adopted children, Björklund et al (2006) find that pre- and post-birth parental characteristics interact when influencing child outcomes.

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Tables

Table 1 Descriptive statistics

	ETF-sample		Uncle-sample		
	Sons	Fathers	Sons	Fathers	Paternal uncles
Variables:					
Year of birth	1980.33	1953.00	1981.31	1954.64	1955.46
	(3.78)	(0.00)	(3.91)	(2.52)	(2.68)
Age at draft	18.19	18.73	18.21	18.51	18.44
	(0.33)	(0.51)	(0.35)	(0.56)	(0.56)
Cognitive ability at age 18	0.07	0.01	0.09	-0.03	-0.09
	(0.96)	(0.97)	(0.93)	(0.97)	(1.00)
Non-cognitive ability at age 18	0.04	0.09	0.05	0.07	-0.02
	(0.99)	(0.96)	(0.97)	(0.98)	(0.99)
Cognitive ability at age 13	.	0.04	.	.	.
	.	(0.99)	.	.	.
Non-academic GPA at age 13	.	0.05	.	.	.
(residual)	.	(0.98)	.	.	.
Educational aspirations at age 13	.	-0.03	.	.	.
(residual)	.	(1.01)	.	.	.
Peer interaction at age 13	.	-0.01	.	.	.
(residual)	.	(0.98)	.	.	.
N	1,889	1,465	50,214	40,277	39,599

Notes: Standard deviations are in parentheses. The cognitive and non-cognitive ability measures have been standardized by year of draft in the entire population.

Table 2 OLS and IV-estimates of intergenerational correlation in abilities – alternative instruments

Sample:	ETF-sample		Uncle-sample	
Dependent variable:	Son's cognitive ability	Son's non-cognitive ability	Son's cognitive ability	Son's non-cognitive ability
	OLS		OLS	
Independent variable:				
Father's cognitive ability	0.323 (0.023)		0.350 (0.004)	
Father's non-cognitive ability		0.212 (0.024)		0.210 (0.005)
	IV - Father's ability at age 13		IV - Uncle's ability	
Father's cognitive ability	0.423 (0.031)		0.478 (0.009)	
Father's non-cognitive ability		0.412 (0.050)		0.422 (0.015)
Statistic:				
Reliability ratio	0.764 (0.078)	0.515 (0.209)	0.731 (0.017)	0.497 (0.021)
F-test (first stage)	1713.89	9.45	10251.65	3709.68
N	1,889	1,889	50,172	50,172

Notes: All estimates come from separate regressions. The ability measures have been standardized. Standard errors adjusted for clustering on the father are in parentheses. In the IV-specification, the father's ability has been instrumented with either the father's ability at age 13 or the uncle's ability. Father's non-cognitive ability at age 13 is given by his average verbal, spatial and logical abilities. Father's non-cognitive abilities are given by his non-theoretical school grades, educational aspirations and peer interaction, where the correlation with his cognitive abilities at age 13 has been partialled out. The reliability ratios have been calculated by dividing the OLS-estimates by the IV-estimates, and the standard errors have been computed by means of the delta method.

Table 3 IV-estimates of intergenerational correlations in both cognitive and non-cognitive abilities

Dependent variable:	Son's cognitive ability	Son's non-cognitive ability
Independent variable:		
Father's cognitive ability	0.445	0.043
	(0.014)	(0.015)
Father's non-cognitive ability	0.069	0.391
	(0.019)	(0.021)
n	50,172	50,172

Notes: The ability measures have been standardized. Standard errors adjusted for clustering on the father are in parentheses. The father's abilities have been instrumented with the uncle's abilities.

Table 4 Intergenerational correlation in abilities – alternative restrictions

Sample:	All	Dead or emigrated uncle	Dead grandfather *or* grandmother	Dead grandfather *and* grandmother
Model:	Panel A. Cognitive abilities			
OLS	0.350	0.356	0.329	0.298
	(0.004)	(0.049)	(0.012)	(0.056)
IV	0.478	0.602	0.464	0.414
	(0.009)	(0.104)	(0.025)	(0.117)
Statistic:				
Reliability ratio	0.731	0.591	0.708	0.721
	(0.017)	(0.131)	(0.047)	(0.244)
Model:	Panel B. Non-cognitive abilities			
OLS	0.210	0.259	0.199	0.178
	(0.005)	(0.058)	(0.013)	(0.061)
IV	0.422	0.677	0.415	0.709
	(0.015)	(0.175)	(0.043)	(0.247)
Statistic:				
Reliability ratio	0.497	0.382	0.480	0.251
	(0.021)	(0.131)	(0.059)	(0.123)
N	50,172	311	5,777	258

Notes: All estimates come from separate regressions. The ability measures have been standardized. The father's abilities have been instrumented with the uncle's abilities. Standard errors adjusted for clustering on the father are in parentheses. The reliability ratios have been calculated by dividing the OLS-estimates by the IV-estimates, and the standard errors have been computed by means of the delta method.

Table 5 Instrument validity check: Intergenerational correlations in height

	OLS		IV
Dependent variable:	Son's height	Son's height	Son's Height
Independent variable:			
Father's height	0.483	0.477	0.500
	(0.004)	(0.005)	(0.008)
Uncle's height	.	0.012	.
	.	(0.005)	.
N	52,973	52,973	52,973

Notes: The height has been standardized by year of draft. Standard errors adjusted for clustering on the father are in parentheses. In the IV-specification, the father's height is instrument by the uncle's height, and the sample is restricted to sons who have at least one uncle.

Table 6 Sibling correlations

Dependent variable:	Brother's cognitive ability at age 13	Sister's cognitive ability at age 13	Brother's GPA at age 16	Sister's GPA at age 16
Independent variable:				
Brother's cognitive ability at age 18	0.412	0.379	0.336	0.309
	(0.010)	(0.010)	(0.002)	(0.002)
Brother's non-cognitive ability at age 18	.	.	0.121	0.113
	.	.	(0.002)	(0.002)
Statistics:				
Relative cognitive correlation	0.918		0.918	
	(0.032)		(0.007)	
Relative non-cognitive correlation	.		0.934	
	.		(0.020)	
N	9,186	8,900	291,400	278,816

Notes: All estimates come from separate regressions. The ability measures have been standardized. The standard errors for the relative sibling correlations have been calculated by using the delta method.

Table 7 Father-son and mother-son correlations

Dependent variable:	Son's cognitive ability	Son's cognitive ability	Son's cognitive ability	Son's non-cognitive ability	Son's non-cognitive ability	Son's non-cognitive ability
Independent variable:						
Father's cognitive ability	0.508	.	0.338	.	.	.
	(0.014)	.	(0.017)	.	.	.
Mother's cognitive ability	.	0.589	0.434	.	.	.
	.	(0.015)	(0.019)	.	.	.
Father's non-cognitive ability	.	.	.	0.461	.	0.336
	.	.	.	(0.021)	.	(0.027)
Mother's non-cognitive ability	.	.	.	.	0.464	0.297
	.	.	.	.	(0.023)	(0.030)
N	25,251	25,251	25,251	25, 251	25,251	25,251

Notes: The ability measures have been standardized by year of draft. The father's abilities have been predicted by using the paternal uncle's abilities. The mother's abilities have been predicted by using the maternal uncle's abilities and the relative sibling correlations in Table A3. Bootstrapped standard errors accounting for clusters on the father are in parentheses.

Table 8 Parental abilities and educational success, sons and daughters

	Sons			Daughters		
Model:	(1)	(2)	(3)	(1)	(2)	(3)
Dependent variable:	Academic achievement at age 16					
Independent variables:						
Father's cognitive ability	0.470	.	0.330	0.446	.	0.331
	(0.026)	.	(0.028)	(0.026)	.	(0.028)
Father's non-cognitive ability	0.093	.	0.061	0.138	.	0.071
	(0.035)	.	(0.040)	(0.035)	.	(0.041)
Mother's cognitive ability	.	0.506	0.375	.	0.432	0.293
	.	(0.028)	(0.030)	.	(0.028)	(0.030)
Mother's non-cognitive ability	.	0.104	0.021	.	0.195	0.107
	.	(0.039)	(0.044)	.	(0.039)	(0.044)
n	15,214	15,214	15,214	14,484	14,484	14,484
Dependent variable:	Years of schooling at ages 30-40					
Independent variables:						
Father's cognitive ability	0.715	.	0.482	0.504	.	0.378
	(0.081)	.	(0.088)	(0.081)	.	(0.092)
Father's non-cognitive ability	0.421	.	0.292	0.620	.	0.472
	(0.106)	.	(0.124)	(0.114)	.	(0.135)
Mother's cognitive ability	.	0.906	0.712	.	0.511	0.347
	.	(0.086)	(0.094)	.	(0.094)	(0.103)
Mother's non-cognitive ability	.	0.345	0.147	.	0.572	0.295
	.	(0.116)	(0.137)	.	(0.118)	(0.151)
n	13,231	13,847	13,847	12,380	12,380	12,380

Notes: The ability measures have been standardized. The father's abilities have been predicted by using the father's brother's abilities. The mother's abilities have been predicted by using the mother's brother's abilities, and the relative sibling correlations in Table A3. All models control for fixed effects for year of birth. Bootstrapped standard errors accounting for clusters on the father are in parentheses.

Table 9 Parental abilities and labor market success, sons and daughters

	Sons			Daughters		
Model:	(1)	(2)	(3)	(1)	(2)	(3)
Dependent variable:	Earnings at ages 30-40 (effect relative to the mean)					
Independent variables:						
Father's cognitive ability	0.043	.	0.030	0.042	.	0.035
	(0.018)	.	(0.020)	(0.017)	.	(0.019)
Father's non-cognitive ability	0.135	.	0.104	0.118	.	0.100
	(0.025)	.	(0.029)	(0.024)	.	(0.028)
Mother's cognitive ability	.	0.043	0.024	.	0.035	0.015
	.	(0.022)	(0.024)	.	(0.019)	(0.021)
Mother's non-cognitive ability	.	0.133	0.084	.	0.096	0.045
	.	(0.027)	(0.030)	.	(0.026)	(0.031)
n	13,231	13,231	13,231	12,380	12,380	12,380
Dependent variable:	P(Employed) at ages 30-40					
Independent variables:						
Father's cognitive ability	-0.013	.	-0.019	-0.003	.	-0.004
	(0.011)	.	(0.013)	(0.014)	.	(0.015)
Father's non-cognitive ability	0.065	.	0.050	0.090	.	0.080
	(0.016)	.	(0.019)	(0.018)	.	(0.022)
Mother's cognitive ability	.	0.003	0.006	.	-0.000	-0.005
	.	(0.013)	(0.014)	.	(0.015)	(0.017)
Mother's non-cognitive ability	.	0.060	0.042	.	0.064	0.029
	.	(0.017)	(0.021)	.	(0.021)	(0.024)
n	13,231	13,231	13,231	12,380	12,380	12,380
Dependent variable:	ln(Earnings) at ages 30-40					
Independent variables:						
Father's cognitive ability	0.053	.	0.046	0.062	.	0.051
	(0.010)	.	(0.010)	(0.010)	.	(0.010)
Father's non-cognitive ability	0.054	.	0.046	0.008	.	0.002
	(0.013)	.	(0.015)	(0.013)	.	(0.015)
Mother's cognitive ability	.	0.036	0.016	.	0.053	0.036
	.	(0.011)	(0.012)	.	(0.010)	(0.011)
Mother's non-cognitive ability	.	0.050	0.023	.	0.016	0.006
	.	(0.014)	(0.016)	.	(0.014)	(0.016)
n	10,333	10,333	10,333	8,104	8,104	8,104

Notes: The ability measures have been standardized. The father's abilities have been predicted by using the father's brother's abilities. The mother's abilities have been predicted by using the mother's brother's abilities, and the relative sibling correlations in Table A3. Earnings are measured in 2009. P(Employed) is the probability to earn more than the minimum wage according to collective agreements on a yearly basis (SEK 175,000), and is estimated using a linear probability model. ln(earnings) is restricted to individuals who earn more than the minimum wage on a yearly basis. All models control for fixed effects for year of birth. Bootstrapped standard errors accounting for clusters on the father are in parentheses.

Appendix. Generating missing regressors

This appendix lays out the formal conditions for estimating two-stage least squares with missing endogenous variables. We address the situation when the missing regressor is unavailable in other samples, but where an observed variable of the same *type* can be used to generate the missing regressor. In particular, the observed and unobserved variables are two different *alterations* of the same underlying variable. This can be different training programs (types) for both certified and uncertified teachers (alterations) in a study of school performance, where program participation is only observed for certified teachers; pharmaceutical drugs (types) which are administered in both tablet and fluid form (alterations) in a study of infant health, but where consumption data is available only for tablets; or, as in our setting, both mothers' and fathers' abilities when estimating intergenerational correlations, but where only fathers' abilities are observed.

For each observation we consider the following structural equation:

$$y_i = \boldsymbol{x}_i\boldsymbol{\beta} + \varepsilon_i \; , \tag{1}$$

where $\boldsymbol{x}_i = [\boldsymbol{g}_{1i}\; \boldsymbol{h}_{2i}]$ is a $1 \times (k+l)$ vector of endogenous variables; $\boldsymbol{g}_{1i} = [g_{11i}\; g_{12i} \dots g_{1ki}]$ is a $1 \times k$ vector of variables of alteration 1; and $\boldsymbol{h}_{2i} = [h_{21i}\; h_{22i} \dots h_{2li}]$ is a $1 \times l$ vector of alteration 2 variables. $\boldsymbol{\beta} = [\boldsymbol{\beta}_1\; \boldsymbol{\beta}_2]'$ is the $(k+l) \times 1$ parameter vector of interest, and ε_i is an error term. We have the following first-stages:

$$\boldsymbol{g}_{1i} = \boldsymbol{z}_i\boldsymbol{\gamma}_1 + \epsilon_{1i} \tag{2}$$

$$\boldsymbol{h}_{2i} = \boldsymbol{z}_i\boldsymbol{\gamma}_2 + \epsilon_{2i}, \tag{3}$$

where $\boldsymbol{\gamma}_1$ and $\boldsymbol{\gamma}_2$ are $k \times (k+l)$ and $l \times (k+l)$ matrices of first-stage parameters for the endogenous variables of alteration 1 and 2. $\boldsymbol{z}_i = [\boldsymbol{u}_{1i}\; \boldsymbol{v}_{2i}]$ is the $1 \times (k+l)$ vector of instruments. For each endogenous regressor in $\boldsymbol{g}_{1i}$ and $\boldsymbol{h}_{2i}$ there exists a primary instrument, designated to isolate the exogenous variation in the regressor; $\boldsymbol{u}_{1i} = [\boldsymbol{u}_{11i}\; \boldsymbol{u}_{12i} \dots \boldsymbol{u}_{1ki}]$ includes k instruments for $\boldsymbol{g}_{1i}$, and $\boldsymbol{v}_{2i} = [\boldsymbol{v}_{21i}\; \boldsymbol{v}_{22i} \dots \boldsymbol{v}_{2li}]$ contains l instruments for $\boldsymbol{h}_{2i}$.

Let $\boldsymbol{X}$ and $\boldsymbol{Z}$ denote data matrices of dimension $n \times (k+l)$, and let $\mathbf{Z}$ have the standard properties: $\text{plim}(\boldsymbol{Z}'\boldsymbol{\varepsilon}/n) = 0$ and $\text{plim}(\boldsymbol{Z}'\boldsymbol{X}/n) = \boldsymbol{\Sigma}_{ZX}$, where $\boldsymbol{\Sigma}_{ZX}$ is a finite matrix of full rank. When the regressors of both alteration 1 and 2 are observed, the first stage parameter vectors are estimated as $\widehat{\boldsymbol{\gamma}}^{FS} = (\boldsymbol{Z}'\boldsymbol{Z})^{-1}\boldsymbol{Z}'\boldsymbol{X}$, and the 2SLS estimator is given by:

$$\widehat{\boldsymbol{\beta}}^{2SLS} = \left(\widehat{\boldsymbol{X}}^{FS\prime}\widehat{\boldsymbol{X}}^{FS}\right)^{-1}\widehat{\boldsymbol{X}}^{FS\prime}\boldsymbol{Y}, \tag{4}$$

where $\widehat{\boldsymbol{X}}^{FS} = \boldsymbol{Z}(\boldsymbol{Z}'\boldsymbol{Z})^{-1}\boldsymbol{Z}'\boldsymbol{X}$. This is a consistent estimator of $\boldsymbol{\beta}$ under the standard instrumental variable assumptions:

$$\text{plim}\,\widehat{\boldsymbol{\beta}}^{2SLS} = \text{plim}\left(\widehat{\boldsymbol{X}}^{FS\prime}\widehat{\boldsymbol{X}}^{FS}/n\right)^{-1}\widehat{\boldsymbol{X}}^{FS\prime}\boldsymbol{Y}/n,$$

$$= \text{plim}\,[(\boldsymbol{X}'\boldsymbol{Z}(\boldsymbol{Z}'\boldsymbol{Z})^{-1}\boldsymbol{Z}')(\boldsymbol{Z}(\boldsymbol{Z}'\boldsymbol{Z})^{-1}\boldsymbol{Z}'\boldsymbol{X})/n]^{-1}\boldsymbol{X}'\boldsymbol{Z}(\boldsymbol{Z}'\boldsymbol{Z})^{-1}\boldsymbol{Z}'\boldsymbol{Y}/n$$

$$= \text{plim}\,[\boldsymbol{X}'\boldsymbol{P}_Z{}'\boldsymbol{P}_Z\boldsymbol{X}/n]^{-1}\boldsymbol{X}'\boldsymbol{P}_Z'\boldsymbol{Y}/n$$

$$= \text{plim}\,[\boldsymbol{X}'\boldsymbol{P}_Z\boldsymbol{X}/n]^{-1}\boldsymbol{X}'\boldsymbol{P}_Z'\boldsymbol{X}\boldsymbol{\beta}/n + \text{plim}\,[\boldsymbol{X}'\boldsymbol{P}_Z\boldsymbol{X}/n]^{-1}\boldsymbol{X}'\boldsymbol{P}_Z'\varepsilon/n = \boldsymbol{\beta}, \tag{5}$$

where $\boldsymbol{P}_Z$ is the projection matrix.

Case 1: Homogeneous first stages

Consider the case where $\boldsymbol{g}_{1i}$ is observed but $\boldsymbol{h}_{2i}$ is not. When the first stages are homogenous across the alterations, $\boldsymbol{\gamma}_1 = \boldsymbol{\gamma}_2$, the unobserved regressors of alteration 2, $\boldsymbol{h}_{2i}$, can be generated using the observed variables of alteration 1. Let $\boldsymbol{h}_{1i} = [h_{11i}\; h_{12i} \ldots h_{1li}]$ be a $1 \times l$ vector of regressors of alteration 1 that corresponds to the unobserved regressors of alteration 2. That is, if $\boldsymbol{h}_{2i}$ contains the mother's cognitive skills, $\boldsymbol{h}_{1i}$ contains the father's cognitive skills. For each observation we then have the following *auxiliary stage*:

$$\boldsymbol{h}_{1i} = \boldsymbol{m}_i\boldsymbol{\theta}_1 + w_{1i}, \tag{6}$$

where $\boldsymbol{\theta}_1$ is a $l \times (k+l)$ matrix of auxiliary stage parameters, and $\boldsymbol{m}_i = [\boldsymbol{u}_{2i}\; \boldsymbol{v}_{1i}]$ is a $1 \times (k+l)$ vector of instrumental variables; $\boldsymbol{v}_{1i} = [v_{11i}\; v_{12i} \ldots v_{1li}]$ is a $1 \times l$ vector of primary instruments for the regressors in $\boldsymbol{h}_{1i}$, while $\boldsymbol{u}_{2i} = [u_{21i}\; u_{22i} \ldots u_{2ki}]$ is a $1 \times k$ vector of instruments for the unobserved regressors in $\boldsymbol{g}_{2i} = [g_{21i}\; g_{22i} \ldots g_{2ki}]$. $\boldsymbol{g}_{2i}$ is defined as a

$1 \times k$ vector of variables of alteration 2 that correspond to the variables of alteration 1 in $\boldsymbol{g}_{1i}$. $\boldsymbol{u}_{2i}$ is included for completeness. In our case, $\boldsymbol{v}_{1i}$ could be the paternal uncles' cognitive skills, and $\boldsymbol{u}_{i2}$ the maternal uncles' non-cognitive skills. w_{1i} is a disturbance term.

Let $\boldsymbol{M}$ and $\boldsymbol{H}_1$ be data matrices of dimensions $n \times (k + l)$ and $n \times l$, where $\boldsymbol{M}$ is assumed to have the following properties: $\text{plim}(\boldsymbol{M}'\boldsymbol{\varepsilon}/n) = 0$ and $\text{plim}(\boldsymbol{M}'\boldsymbol{H}_1/n) = \boldsymbol{\Sigma}_{MH_1}$, with $\boldsymbol{\Sigma}_{MH_1}$ being bounded and of full column rank. The auxiliary stage parameters are then estimated as:

$$\widehat{\boldsymbol{\theta}}_1^{AS1} = (\boldsymbol{M}'\boldsymbol{M})^{-1}\boldsymbol{M}'\boldsymbol{H}_1. \tag{7}$$

Under the assumption that the first stage relation is homogenous between alterations 1 and 2, the auxiliary stage parameters (7) can be used in place for the parameters in the unobserved first stage (3). The identifying assumption can be written as:

$$\text{plim}\, \widehat{\boldsymbol{\theta}}_1^{AS1} = \text{plim}\, \widehat{\boldsymbol{\gamma}}_2^{FS}. \tag{IA.1}$$

For later purposes, we denote the elements in the o:th row and p:th column of $\widehat{\boldsymbol{\theta}}_1^{AS1}$ by $\hat{\theta}_{1op}^{AS1}$. Under (IA.1), the prediction of the unobserved data can be written as $\widehat{\boldsymbol{X}}^{AS1} = \boldsymbol{Z}\widehat{\boldsymbol{\gamma}}^{AS1}$, where $\widehat{\boldsymbol{\gamma}}^{AS1} = [\widehat{\boldsymbol{\gamma}}_1^{FS}\ \ \widehat{\boldsymbol{\theta}}_1^{AS1}]$ is a $(k + l) \times (k + l)$ matrix of first stage and auxiliary stage parameters. The structural parameters in (1) can then be estimated as:

$$\widehat{\boldsymbol{\beta}}^{ASLS1} = \left(\widehat{\boldsymbol{X}}^{AS1\prime}\widehat{\boldsymbol{X}}^{AS1}\right)^{-1}\widehat{\boldsymbol{X}}^{AS1\prime}\boldsymbol{Y} = (\widehat{\boldsymbol{\gamma}}^{AS1\prime}\boldsymbol{Z}'\boldsymbol{Z}\widehat{\boldsymbol{\gamma}}^{AS1})^{-1}\widehat{\boldsymbol{\gamma}}^{AS1\prime}\boldsymbol{Z}'\boldsymbol{Y}. \tag{8}$$

Assumption (IA.1) implies $\text{plim}\widehat{\boldsymbol{X}}^{AS1} = \text{plim}\widehat{\boldsymbol{X}}^{FS}$, which yields the standard 2SLS estimator:

$$\text{plim}\, \widehat{\boldsymbol{\beta}}^{ASLS1} = \text{plim}\left(\widehat{\boldsymbol{X}}^{AS1\prime}\widehat{\boldsymbol{X}}^{AS1}/n\right)^{-1}\widehat{\boldsymbol{X}}^{AS1\prime}\boldsymbol{Y}/n = \text{plim}\left(\widehat{\boldsymbol{X}}^{FS\prime}\widehat{\boldsymbol{X}}^{FS}/n\right)^{-1}\widehat{\boldsymbol{X}}^{FS\prime}\boldsymbol{Y}/n = \boldsymbol{\beta}, \tag{9}$$

where the last equality follows from equation (5). Hence under the assumption that the first stage is homogeneous, $\widehat{\boldsymbol{\beta}}^{ASLS1}$ is a consistent estimator for $\boldsymbol{\beta}$.

Case 2: Heterogeneous first stages

The assumption of homogenous first stages can be too strong. In our case, it may seem unlikely that the auxiliary stage parameters (the brother-brother correlations) are equal to the unobserved first stage parameters (the brother-sister correlations). We therefore propose using proxy variables for the unobserved regressors to adjust for the heterogeneity in the unobserved first stage. To this end we utilize $\widetilde{\boldsymbol{h}}_{1i}$ and $\widetilde{\boldsymbol{h}}_{2i}$ which are $1\times l$ vectors of proxies for $\boldsymbol{h}_{1i}$ and $\boldsymbol{h}_{2i}$, respectively. In our case, the proxy variables are compulsory school grades available for boys and girls. The relation between the proxy variables and the corresponding instruments is given by a second auxiliary stage:

$$\widetilde{\boldsymbol{h}}_{1i} = \boldsymbol{m}_i\boldsymbol{\Pi}_1 + e_{1i} \tag{10}$$

$$\widetilde{\boldsymbol{h}}_{2i} = \boldsymbol{z}_i\boldsymbol{\Pi}_2 + e_{2i}, \tag{11}$$

where $\boldsymbol{\Pi}_1$ and $\boldsymbol{\Pi}_2$ are $l \times (k+l)$ matrices of second auxiliary stage parameters, while e_{1i} and e_{2i} are error terms. The second auxiliary stage parameters can be estimated as:

$$\widehat{\boldsymbol{\Pi}}_1^{AS2} = (\boldsymbol{M}'\boldsymbol{M})^{-1}\boldsymbol{M}'\widetilde{\boldsymbol{H}}_1 \tag{12}$$

$$\widehat{\boldsymbol{\Pi}}_2^{AS2} = (\boldsymbol{Z}'\boldsymbol{Z})^{-1}\boldsymbol{Z}'\widetilde{\boldsymbol{H}}_2 \tag{13}$$

where $\widetilde{\boldsymbol{H}}_1$ and $\widetilde{\boldsymbol{H}}_2$ denote data matrices of dimension $n \times l$. Assuming that the relative impact of the instruments in the second auxiliary stages for alterations 1 and 2 can be used to infer the relative effects of the first stages for different alterations, we can use the ratio between the second auxiliary stage parameters to adjust the parameters in the first auxiliary stage. Formally, define $\widehat{\boldsymbol{\theta}}_1^{AS2}$, which is a $l \times (k+l)$ matrix of adjusted first auxiliary stage parameters, where the elements are of the form $\hat{\theta}_{1op}^{AS2} = (\widehat{\Pi}_{2op}^{AS2}/\widehat{\Pi}_{1op}^{AS2})\hat{\theta}_{1op}^{AS1}$. That is, we scale the first auxiliary stage parameters with the ratio between the second auxiliary stage parameters. Hence, we can define the following identifying assumption:

$$\operatorname{plim} \widehat{\boldsymbol{\theta}}_1^{AS2} = \operatorname{plim} \widehat{\boldsymbol{\gamma}}_2^{FS}. \tag{IA.2}$$

Under (IA.2), the predicted observations for the unobserved regressors are given by $\widehat{\boldsymbol{X}}^{AS2} = \boldsymbol{Z}\widehat{\boldsymbol{\gamma}}^{AS2}$, where $\widehat{\boldsymbol{\gamma}}^{AS2} = [\widehat{\boldsymbol{\gamma}}_1^{FS}\ \ \widehat{\boldsymbol{\theta}}_1^{AS2}]$ is a $(k+l)\times(k+l)$ matrix of first stage and adjusted auxiliary stage parameters. The structural parameters in (1) can then be estimated as:

$$\widehat{\boldsymbol{\beta}}^{ASLS2} = \left(\widehat{\boldsymbol{X}}^{AS2\prime}\widehat{\boldsymbol{X}}^{AS2}\right)^{-1}\widehat{\boldsymbol{X}}^{AS2\prime}\boldsymbol{Y} = (\widehat{\boldsymbol{\gamma}}^{AS2\prime}\boldsymbol{Z}'\boldsymbol{Z}\widehat{\boldsymbol{\gamma}}^{AS2})^{-1}\widehat{\boldsymbol{\gamma}}^{AS2\prime}\boldsymbol{Z}'\boldsymbol{Y}. \tag{14}$$

Assumption (IA.2) implies that $\text{plim}\widehat{\boldsymbol{X}}^{AS1} = \text{plim}\widehat{\boldsymbol{X}}^{FS}$, and $\widehat{\boldsymbol{\beta}}^{ASLS2}$ is a consistent estimator for $\boldsymbol{\beta}$ by equation (5).

The credibility of IA.2

To see when assumption (IA.2) is reasonable, consider the data generating process:

$$\tilde{h}_{1ji} = h_{1ji}\kappa_{1j} + n_{1ji} \tag{15}$$

$$\tilde{h}_{2ji} = h_{2ji}\kappa_{2j} + n_{2ji}, \tag{16}$$

where $\tilde{h}_{1ji}$ and $\tilde{h}_{2ji}$ are 1×1 proxy variables for regressor j, while κ_{1j} and κ_{2j} are scalars describing the proxy relation, and $n_{1ji}$and n_{2ji} are error terms. Assuming that $E(\boldsymbol{M}'n_{1ji}) = 0$ and $E(\boldsymbol{Z}'n_{2ji}) = 0$, the parameters for regressor j in the second auxiliary stage is given by:

$$\widehat{\Pi}_{1j}^{AS2} = (\boldsymbol{M}'\boldsymbol{M})^{-1}\boldsymbol{M}'\widetilde{\boldsymbol{H}}_{1j} = (\boldsymbol{M}'\boldsymbol{M})^{-1}\boldsymbol{M}'(\boldsymbol{H}_{1j}\kappa_{1j} + n_{1j}) = (\boldsymbol{M}'\boldsymbol{M})^{-1}\boldsymbol{M}'\boldsymbol{H}_{1j}\kappa_{1j} = \hat{\theta}_{1j}^{AS1}\kappa_{1j} \tag{17}$$

$$\widehat{\Pi}_{2j}^{AS2} = (\boldsymbol{Z}'\boldsymbol{Z})^{-1}\boldsymbol{Z}'\widetilde{\boldsymbol{H}}_{2j} = (\boldsymbol{Z}'\boldsymbol{Z})^{-1}\boldsymbol{Z}'(\boldsymbol{H}_{2j}\kappa_{2j} + n_{2j}) = (\boldsymbol{Z}'\boldsymbol{Z})^{-1}\boldsymbol{Z}'\boldsymbol{H}_{2j}\kappa_{2j} = \hat{\gamma}_{2j}^{FS}\kappa_{2j}, \tag{18}$$

where $\widetilde{\boldsymbol{H}}_{1j}$ and $\widetilde{\boldsymbol{H}}_{2j}$ are $n \times 1$ vectors of observations for $\tilde{h}_{1ji}$ and $\tilde{h}_{2ji}$. Now, consider the elements of $\hat{\theta}_1^{AS2}$ and substitute in elements from equations (17) and (18)

$$\hat{\theta}_{1op}^{AS2} = (\widehat{\Pi}_{2op}^{AS2}/\widehat{\Pi}_{1op}^{AS2})\hat{\theta}_{1op}^{AS1} = (\hat{\gamma}_{2op}^{FS}\kappa_{2op}/\hat{\theta}_{1op}^{AS1}\kappa_{1op})\hat{\theta}_{1op}^{AS1} = \hat{\gamma}_{2op}^{FS}(\kappa_{2op}/\kappa_{1op}) \tag{19}$$

Hence, if $\text{plim}\kappa_{1op} = \text{plim}\kappa_{2op}$ then $\text{plim}\hat{\theta}_{1op}^{AS2}$=$\text{plim}\hat{\gamma}_{2op}^{FS}$. For (IA.2) to hold, the proxy relation in equations (15) and (16) must be homogeneous; i.e. the proxy variables must be just as good measures for the regressors of alteration 1 and 2. In our setting this translates to GPA's being an equally good proxy of skills for both genders.

Standard errors

The sampling errors of the auxiliary stage estimates must be taken into account when calculating standard errors. Therefore, we chose to bootstrap the standard errors. Our findings suggest that the bootstrapped standard errors are not much larger than when ignoring the sampling variability. We believe this is due to our large samples in combination with the strong first stage and auxiliary stage relations.