Children's personality and its contribution to school grades inequality: Evidence from Mexico

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Abstract

We explore the effect of Big-5 Personality Traits on the level and variation of school grades, using a novel survey of state primary school children in Mexico. The linear school and municipality fixed effects estimates controlling for household income, principal carer's education, IQ and personality traits indicate that Conscientiousness and Agreeableness have substantial and significant effects on grades in all subjects, independent of the child's IQ. A regression-based inequality decomposition analysis (Shorrocks 1982, Fields 2003) shows that a child's personality traits as a whole account for 5.47.8% of the inequality in school grades, depending on the subject.

Keywords: School achievement, Mexico, Big-5 personality traits,

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*Correspondence author: Alfonso Miranda. Circuito Tecnopolo 117, Aguascalientes 20313, Aguascalientes, Mexico. Telephone: +524499945150 ext. 5152. Email: alfonso.miranda@cide.edu. **Acknowledgement**: We would like to thank Regina Medina Rosales, Diana Cristina Alvarez Venzor, and Valeria Gracia Olvera for excellent research assistantship. **Competing interests statement**: All authors declare not to have any conflict of interest. The baseline of EDNA was partially financially supported by the Cátedras CONACYT program [project No. 874], The Hewlett Foundation [project No. 2013-8758], CIDE [project FAI 12171077], and a Newton Mobility Grant [project NMG2R3 100110]. **Author contributions**: All authors equality contributed to this work. **Institutional Review Board (IRB) Approval**: EDNA baseline survey did not have IRB approval because CIDE did not have an IRB at the time of data collection. Despite lacking IRB review, EDNA's research team followed the best international ethical practices including requesting principal carers to sign an informed consent form. Parental permission for the pupil's interview at school was requested in writing. For children, the assent of the participant was verbally requested before starting the interview—copy of the informed consent form can be obtained from the corresponding author. **Data Statement**: All data used for the present paper is publicly available, upon registration, from EDNA's website: www.cide-edna.org. Stata do-files for replication can be obtained from the authors upon request.

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1. Introduction

It has been more than a century since Webb (1915)'s pioneering study on the role of "character" in explaining students' academic performance, on top of the effect of intelligence. Yet, our understanding of the importance of noncognitive effects now is still under-developed, relative to that of the cognitive factors, largely due to difficulties in measuring personality. It was not until the 1990s that the Big-5 Personality Traits (B5PT) model started to be widely adopted by educational researchers as a consistent personality framework (De Raad and Schouwenburg 1996). Meta-analyses of educational research using B5PT measures have since firmly established a robust relationship between academic attainment and B5PT as measured by Extroversion (E), Agreeableness (A), Conscientiousness (C), Neuroticism (N) and Openness (to New Experience) (O) (e.g. Poropat 2009, Richardson et al. 2012).

An emerging literature is concerned with the extent to which cognitive and noncognitive skills interact with each other at different stages of a child's education production. Cunha and Heckman (2007) introduced a theoretical framework of stage-specific cognitive and noncognitive skill formation that allows for dynamic complementarity. This model is generalized by Cunha et al. (2010) to a multi-stage model of the evolution of children's cognitive and noncognitive skills as a function of contemporaneous investment and existing stock of both types of skills. Accounting for both cognitive and noncognitive skills implies that a socially optimal investment strategy to maximize aggregate school attainment is to target the most disadvantaged at younger ages, rather than to target the most advantaged in the early years in traditional models based solely on cognitive skills.

Despite this recent advancement on the theoretical front, direct empirical evidence on the interaction of cognitive and noncognitive skills remains thin, as few (if any) existing surveys collect all the information needed, including measures of family background and school quality, to allow consistent estimations. To bridge this gap in the literature, we design from scratch a new representative survey of primary-school children and their principal carers (PCs) in the Mexican state of Aguascalientes, with both cognitive and noncognitive abilities measured with age-appropriate interviewing techniques used in clinical psychology and adapted for the Spanish language context. With the approval of the local education authorities, this is then matched to the administrative student records on school grades for maths, Spanish and English as well as the exact dates of birth, to form the baseline survey of the Aguascalientes Longitudinal Study of Child Development (EDNA).

Following the literature on the B5PT, we run a field implementation of the Berkeley Puppet Interview Big Five Questionnaire of Measelle et al. (2005), which is an age-appropriate interviewing technique not requiring strict laboratory conditions used in clinical psychology and adapted for the Spanish language context.[1] EDNA's Field Puppet Interview-Big Five Questionnaire Test (FPI-BFQ) appears to show very good reliability for all 5 dimensions of the B5PT as measured by the Omega statistic, with E-omega $= 0.87$, A-omega $= 0.88$, C-omega $= 0.82$,N-omega $= 0.82$, and O-omega $= 0.91$ (Peralta et al. 2021).

Using this novel primary data, we focus on the effect of both B5PT and cognitive abilities of primary-school pupils on the level and variation of their year-averaged school grades, controlling for household income, principal carer's education, IQ and personality traits, as well as school and municipal fixed effects. In the absence of standardized achievement tests, using year-averaged grades has been found to improve the reliability of measures of cognitive skills by substantially reducing measurement errors in high school grades (Guskey 2011) and undergraduate grade point averages (Westrick 2017). Moreover, we also control for the relative age within the school cohort by taking full advantage of the exact date of birth from the administrative student records, given earlier evidence that this could matter (Crawford et al. 2014, Matta et al. 2016).

The benchmark linear (school and municipality) fixed effects estimates show that both Conscientiousness (C) and Agreeableness (A) have substantial and significantly positive effects on grades in all subjects, independent of the child's cognitive abilities as measured by the Intelligence Quo-

[1] The adult version of the B5PT test we use on the principal carers is developed by Benet-Martínez and John (1998) and has good properties for the Mexican population according to Zamorano Reyes et al. (2014).

tient (IQ) scores. Specifically, one standard deviation (referred as sd, hereafter) increment in A increases grades by 0.084, 0.101 and 0.161 sds in maths, Spanish and English, respectively, all significant at 5% at least. Similarly, one sd increment in C increases grades by 0.081, 0.091 and 0.077 sds in maths, Spanish, and English, respectively. While the effects of C on maths and Spanish are statistically significant at 5% and 1% respectively, its effect on English is only marginally significant at 10%.

Using a regression-based inequality decomposition approach (Shorrocks 1982, Fields 2003), we further decompose the effect of personality traits on the inequality in grades, over and above the better-known effects of IQs. The results indicate that a child's personality traits as a whole account for $5.4 - 7.8\%$ of the inequality in school grades, depending on the subject. In relative terms, the contributions of personality traits are equivalent to 64%, 78% and 214% of those of the child's own IQ for maths, Spanish and English, respectively. It is also worth mentioning that even for our unusually rich set of variables, just over half of the variation in pupil grades remain unexplained.

Our results suggest that omitting noncognitive skills results in overestimation of the marginal effects of IQ, by about 14% for maths and Spanish, and 30% for English. On the other hand, excluding the principal carer's IQ and B5PT would leave the effect of the child's IQ virtually identical and the effect of the child's B5PT effects slightly larger. Moreover, we present tentative evidence of heterogeneous effects of cognitive and noncognitive skills by gender. The effect of B5PT is more pronounced for boys, while that of the IQ matters more for girls.

We make at least two contributions to the literature in education economics and child development in this paper. First, we construct a novel primary data, which is the first of its kind in a developing country context, for the study of the effect of **both** cognitive and noncognitive abilities in the learning of primary-school children around age 8. There is strong evidence based on tests of adults that B5PTs vary over the life span (Donnellan and Lucas 2008). Unfortunately, there has been very little direct evidence based on self-reported personality traits of children younger than 9, despite the policy relevance of understanding the malleability of characters in early stages of compulsory education.[2] Secondly, we show a very substantial effect of noncognitive skills as measured by B5PT on primary school students' grades, which is independent of that of the cognitive abilities proxied by IQ. If anything, the magnitude of the effect of personality traits relative to that of cognitive skills appears to be larger than estimates from developed countries.

The rest of the paper is organized as follows. Section 2 introduces the EDNA data used for analysis. Sections 3 and 4 explain how the outcome variables as well as IQ and B5PT measures are derived respectively and present the summary statistics. Section 5 outlines the method of regression-based decomposition of inequality, following (Shorrocks 1982, Fields 2003). Section 6 presents and interprets the empirical analyses. Finally, Section 7 concludes.

2. Data

We use the baseline survey of the Aguascalientes Longitudinal Study of Child Development (EDNA), which is a study of over $1,000$ students in some 100 schools that are representative of the cohort of children who started first grade in 2016 in a public primary school of the state of Aguascalientes, Mexico. EDNA has a stratified two-stage cluster design, with schools sampled in the first stage and pupils sampled in the second stage. More information about EDNA's sample design is available in Miranda et al. (2020).

The baseline survey, collected in $2017/18$, contains information about the child, her primary carer (referred as the PC, hereafter), and her teacher. PCs were interviewed at the child's household; while children were interviewed at their school and teachers in the premises of regional units of education. The main topics covered are: (a) education and civic formation, (b) health and environment, and (c) income and inequality. Detailed anthropometrics are available along a measure of children's cognitive ability and a series of scales measuring personality for both children and PCs.

[2]Existing evidence on personality traits for young children is typically based on proxy interviews of parents or teachers (e.g. Ehrler et al. 1999, Abe 2005).

To allow potential non-response the final issued sample had $1,364$ pupils in 137 schools. A total of $1,143$ PC interviews and $1,118$ children interviews were achieved respectively, amounting to a 84% response rates for PCs and 98% for children—as we only have $1,143$ PCs giving written informed consent to attempt the child's interview. PC interviews started in January 2017 and ended in August 2017 using pen and pencil interviewing, while children interviews were conducted during February to June 2018 using computer assisted personal interviewing (CAPI)—spanning most of the $2017/18$ academic year when children were in Grade 2 and aged between seven and eight.

Our analytical sample contains a total of $1,085$ PC-child pairs. We drop from the analysis 15 (1.4%) observations who report children born in 2017 and 2018 and older children who were grade-retained from previous academic years. Another 66 (6.1%) observations that have missing values on some key variables of analysis are also excluded from the sample. We end up with an analytic sample with $1,004$ observations.

As expected, 97% of PCs are females as in most cases the role is performed by the mother (91%)—though in 4.4% of the cases the PC is the child's grandmother and in 2.4% is the child's father. Because of the involvement of grand mothers the range of ages of the PC goes from 22 to 77, despite the fact that the average CP's age is 33 years (SD 7.9). The great majority of PCs have secondary education (55%). Only 7.4% have professional qualifications. Average household income per moth is around $5,208$ pesos. Table 1 offers detailed descriptive statistics.

Regarding children, 51% are girls. In the analysis that follows, instead of using children's age in years we use age-within-year (see Table 1) as we are dealing with a cohort born in 2010. Age-within-year is measured in days, with day 0 being August 22th (the day the cohort entered first grade in 2016), January 1st being day -234, and December 31th being day 131. Hence, younger pupils have positive age-within-year values. Figure 1 presents a kernel estimate of the distribution of age-within-year. As expected, the distribution is bimodal; with one mode contributed by children born in the spring around day -125 (April 19th 2010) and the other contributed by children born in the summer around day 8 (August 30th 2010). This is the typical behavior of the distribution of birthdays within a year (see, for instance, Crawford et al. 2010; 2014, Matta et al. 2016).

3. Response variables

Our main response variables are pupils' school grades in maths and Spanish for the 2017/18 academic year. These grades are obtained from administrative records of the Instituto de Educación de Aguascalientes (IEA) (Aguascalientes Education Institute), which is the state agency in charge of the education policy. IEA's administrative records contain a permanent unique identification number for each pupil in the population, which allows exact matching to EDNA's child records.

We chose to analyze school grades from the 2017/18 academic year because EDNA's child interview took place between February 2018 to June 2018, including child's IQ and personality measurement; the explanatory variables of main interest in the present study. Despite having available school grades from other academic years—2016/17 and 2018/19—we decided to use in our analysis only data that is contemporaneous to our measurements of child's IQ and personality. On the one hand, while modeling grades from 2016/17 (a year earlier) is clearly interesting, regressing such grades on child's IQ and personality that are measured a year after may lead to potential inverse causality; which is conceptually unsatisfactory. On the other hand, it would be possible to use data from the 2017/18 and 2018/19 academic years to put together a panel at individual level and potentially using panel data methods for the analysis. However, because we only have a child's personality and IQ measured once in 2018, the explanatory variables of main interest in such panel would be time-invariant; excluding the possibility of using panel methods that control for individual unobserved heterogeneity that is potentially correlated with other explanatory variables—i.e. fixed effects estimators. Under such conditions using together data from the 2017/18 and 2018/19 academic years for analysis is less attractive and not better than a contemporaneous cross-section analysis. For these reasons we decided that is conceptually cleaner only to use data from the

2017/18 academic year and cross-section methods in our study.[3]

The 2017/18 academic year lasted 10 moths (August 2017-June 2018, during which children sat exams in maths and Spanish every two months. So, each child has five bimonthly grades for that academic year. For analysis, we average scores over these five bimesters per subject to obtain an average grade for the whole academic year. To ease interpretation, we standardize our response variables so that we end up with a variable that has zero mean and standard deviation of one. Figure 2 presents kernel density estimates for our response variables.

Previous research in educational research criticize the use of school grades for studying how socioeconomic factors affect educational achievement because grades often contain substantial random noise and it is not clear to what degree it reflect learning (Guskey 2011, Anderson 2018). However, it has also been pointed out in the literature that averaging grades over bimesters, quarters, and/or semesters, within an academic year substantially reduces noise (Westrick 2017). Moreover, year-averaged grades have been found to be strongly correlated with results from standardized assessment tests, which are a better measure of learning (Willingham et al. 2002).

As said before, our main interest lies on mathematics and Spanish. However, in our dataset we have available also grades from English. So, for completeness, we include analysis of school grades inequality in English as well, even though English contains significantly more missing values because the subject is not part of the national curriculum—i.e. is not compulsory—and only a subset of primary schools of Aguascalientes offered the subject in 2018.[4]

[3]Though we do control for school, municipality, and interviewer fixed effects. For more details, see section 5.

[4]English was introduced as a subject in some Aguascalientes's primary schools in 1995 as an initiative of the local government, not part of the national curriculum, and subject to budget availability. In 2012 a similar initiative was launched at the national level—Programa Nacional de Inglés en Educación Básica (PNIEB); becoming Programa Nacional de Inglés (PRONI) in 2016; keeping its non compulsory nature and subject to annual budgetary approval. Historically, the budget has been well below what is needed to achieve universal coverage in the state. In fact, only around 30% of schools in Aguascalientes offer English as a subject.

4. IQ and personality measures

One distinctive advantage of EDNA is that it contains measures of IQ and personality for both CPs and children.

While the theory and methods for measuring personality traits for adults were well developed by the end of the 1990s, measuring personality in children has proven harder. Firstly, early literature raised concerns about the age at which a child's personality is well developed and can be reliably measured Edelbrock et al. (1985), Marsh et al. (1998), Roberts and DelVecchio (2000). Secondly, there were doubts as to how well children may self-report aspects of their personality because of a lack of understanding of the questions asked as well as difficulties for expressing their feelings and experiences Welsh and Bierman (2003). For these reasons, initially, measurement of personality in children younger than 9 years old typically relied on indirect reports given by parents and teachers (Ehrler et al. 1999, Asendorpf and Van Aken 2003, Abe 2005, see, for instance,). Dismissing altogether children self-reports, however, was unsatisfactory as parents may not be well/completely informed about their child's problems and emotions.

To bridge the gap, building upon puppet interviewing techniques used in clinical psychology, Ablow and Measelle (1993) developed the 'Berkeley Puppet Interview' (BPI). In the BPI two identical puppets make binary statements—either positive or negative—about their behavior or attributes (for instance, "I'm smart"; "I'm not smart"), and then ask the child to describe her/himself ("How about you?"). To avoid sex preference bias, one puppet is called 'Iggy' while the other is called 'Zyggy'. The interview is performed under laboratory conditions, videotaped, and scored on a $1-7$ Likert scale by professional scorers. The puppets create a playful environment that stimulates the child's interest / engagement and aids communication and understanding. Moreover, the puppets allow children to project their personality while keeping a safe emotional distance; reducing interviewee stress and anxiety. Using the BPI techniques, (Measelle et al. 1998) show that children have a multidimensional self-concept that can be reliably measured. Moreover, Measelle et al. (2005) develop a BPI-Big Five Questionnaire and show that the instrument provides valid and stable measures of $5-7$ year old children.

In the present paper child personality is measured using EDNA's Field Puppet Interview-Big Five Questionnaire test (FPI-BFQ), which is a field implementation of the Berkeley Puppet Interview Big Five Questionnaire of Measelle et al. (2005) that does not require strict laboratory conditions, videotaping, or professional scoring. And, hence, it is easier to implement in surveys with large sample sizes where achieving interviewing conditions is difficult. Peralta et al. (2021) show that the FPI-BFQ provide reliable measures of children in our EDNA sample. The BFQ provides personality scores for the five factors of personality: Extroversion (E), Agreeableness (A), Conscientiousness (C), Neuroticism (N), and Openness to new experiences (O). Peralta et al. (2021) show that the FPI-BFQ scale achieves good reliability, with an Omega statistic (Dunn et al. 2014) of: E-omega $= 0.87$, A-omega $= 0.88$, C-omega $= 0.82$, N-omega $= 0.82$, and O-omega $= 0.91$. To ease interpretation all FPI-BFQ sub-scales are standardized so that they have 0 mean and standard deviation of 1.

Child IQ is measured using a 18-item colored Raven's Progressive Matrices (RPM) test, which is the same instrument implemented by the Mexican Family Life Survey (MxFLS) (Rubalcava and Teruel 2006). RPM is based on pattern recognition and is a widely used in non-verbal test of intelligence and abstract reasoning. At each item a figure with a missing piece is shown and subjects must choose the piece that completes the pattern from a set of 6 or 8 potential options (Raven et al. 1998). Difficulty increases as subject progress from item to item. The colored version of the RPM is suitable for children between 5 and 11. The score ranges from 0 to 17 (mean $= 7.57$, SD $= 2.80$. A kernel estimate of the distribution of the score, which is single peaked, is offered in Figure 3. To ease interpretation children's IQ score is standardized so that it have 0 mean and standard deviation of 1. The 18-item scale achieves a reliability (Cronbach's alpha) of alpha $=$ 0.66, and omega $= 0.65$; which is below 0.7 but still acceptable.

Adult personality (for the CP) is measured using the Spanish version of the Big-Five Personality Test (B5PT) of Benet-Martínez and John (1998) (reliability: E-alpha = 0.81, A-alpha = 0.81, C-alpha = 0.75, N-alpha = 0.79, O- alpha = 0.81), who find that the Spanish version of the Big Five Inventory (BFI) is an "...efficient, reliable, and factorial valid measure of the Big Five for research on Spanish-speaking individuals" (p. 729), and that "...there is little evidence for substantial cultural differences in personality structure at the broad level of abstraction represented by the Big Five dimensions." (p. 729). Zamorano Reyes et al. (2014) investigate the psychometrical properties of the scale in a Mexican population and find a reliability score of alpha = 0.72 and five factor structure in a Principal Component Analysis. Hence, the scale shows good properties for the Mexican population. To ease interpretation all adult BFI sub-scales are also standardized so that they have 0 mean and standard deviation of 1.

Finally, adult IQ is measured using a 12-item RPM test. As in the case of children, EDNA's 12-item RPM for adults is the same instrument implemented by the Mexican Family Life Survey (MxFLS) (Rubalcava and Teruel 2006). Unfortunately, the 12-item scale achieves low reliability; with alpha = 0.43 and omega = 0.23. The score ranges from 0 to 8 (mean = 2.76, SD = 1.25. A kernel estimate of the distribution of the score, which is single peaked, is offered in Figure 4. This 12-item RPM test has been used in previous studies to investigate how health and public policy affects cognitive ability (Venkataramani 2012), the role of maternal cognitive ability on child health (Rubalcava and Teruel 2004), the effect of crime in human capital accumulation (Brown and Velásquez 2017), and the role of cognitive intelligence in explaining the link between height and labor market outcomes (Vogl 2014), among other studies. To ease interpretation the adult IQ score is standardized so that it have 0 mean and standard deviation of 1.

5. Econometric methods

We use regression-based decomposition of inequality based on the Fields (2003) and Shorrocks (1982) methods; discussed and reinterpreted by Cowell and Fiorio (2011), and implemented by Fiorio and Jenkins (2021).

The objective is to decompose the population inequality of a response variable—school grades in our case—in terms of the components given by the data generating process (DGP)

$$y_{gismr} = \mathbf{x}_{igsmr}\beta + c_s + c_m + c_r + u_{gismr},, \tag{1}$$

where y_{gisr} represents the standardized grade (mean zero, sd one) in the $g-th$ subject of the $i-th$ student in the $s-th$ school and the $m-th$ municipality, which was interviewed by the $r-th$ EDNA's interviwer; with $g = \{\text{maths}, \text{Spanish}, \text{English}\}$, $i = 1,\ldots,N$, $s = 1,\ldots,S$, $m = 1,\ldots,M$ and $r = 1,\ldots,R$. Similarly, $\mathbf{x}_{gismr}$ is a $1\times K$ vector of explanatory variables (including the constant), β is a $K\times 1$ vector of coefficients, and u_{gismr} is a random error. There are school level c_s and municipality (county) c_m fixed-effects that control for potential unobserved heterogeneity across schools and across *municipios* in Aguascalientes. We assume that a representative random sample from the population is available for analysis.

EDNA contains an identification number of the interviewer who undertook the principal carer and child interviews. Because different interviewers have different abilities to establish rapport with parents and children, there is possibly some unobserved heterogeneity in the recording of some control variables on the right-hand of equation (1) due to interviewer heterogeneity. Such unobserved variation is likely to be individual specific to each interviewer and time-fixed. Hence, taking advantage that EDNA has information about what person interviewed each household and child, we introduce an interviewer fixed-effect c_r to archive a cleaner specification.

We assume that $E(u|\mathbf{x}) = 0$, so that all explanatory variables—or factors—are exogenous. Under these conditions β can be consistently estimated by OLS with all the required dummies for controlling the fixed-effects at different levels in equation (1). Standard errors are clustered at school level to allow potential correlation of units at that level.

Define the inequality statistic as $I(\mathbf{Y})$, with $\mathbf{Y} = (y_1,\ldots,y_N)'$. Shorrocks (1982) shows that $I(\cdot)$ may be any function of the data. We can interpret (1) in terms of the decomposition of $I(\cdot)$ by factor source with factors $= F_1, \ldots, F_{K+1}$ given by

$$F_j = \beta_j x_j : \quad j = 2, \ldots, K \tag{2}$$

$$F_{K+1} = u. \tag{3}$$

Notice that for inequality decomposition the constant term is irrelevant. We can rewrite equation (1) as

$$y = \beta_1 + F_1 + \ldots + F_{K+1} \tag{4}$$

Now, define the total inequality in terms of its factor sources

$$I(\mathbf{Y}) = \sum_{j=2}^{K+1} G_j\left(F_j\right), \tag{5}$$

where $G_j(\cdot)$ is the contribution of the $j-th$ factor to total inequality. From (5) we can write the proportional contribution of the $j-th$ factor to inequality as

$$g_j = \frac{G_j\left(F_j\right)}{I(\mathbf{Y})}. \tag{6}$$

Finally, from (2)-(6) and the results from Shorrocks (1982), Cowell and Fiorio (2011) show that

$$g_j = \frac{\sigma\left(F_j, y\right)}{\sigma^2(y)} = \beta_j^2 \frac{\sigma^2\left(x_j\right)}{\sigma^2(y)} + \sum_{h \neq j}^{K} \beta_j \beta_h \rho_{j,h} \frac{\sigma\left(x_j\right) \sigma\left(x_h\right)}{\sigma^2(y)} + \beta_j \rho_{j,u} \frac{\sigma\left(x_j\right) \sigma(u)}{\sigma^2(y)}; \quad j = 2, \ldots, K \tag{7}$$

and,

$$g_{K+1} = \frac{\sigma^2(u)}{\sigma^2(y)} + \sum_{j=1}^{K} \beta_j \rho_{j,u} \frac{\sigma\left(x_j\right) \sigma(u)}{\sigma^2(y)}, \tag{8}$$

where $\sigma^2(\cdot) = \mathrm{Var}(\cdot)$, $\sigma(\cdot,\cdot) = \mathrm{Cov}(\cdot,\cdot)$, and $\rho_{\cdot,\cdot} = Corr(\cdot,\cdot)$. Equations (7) and (8) define the inequality decomposition of y in terms of its factor sources.

For implementation we can get a consistent estimator of β, $\widehat{\beta}$, fitting the regression of y on

$\mathbf{x}$ by OLS; including all the required dummies for controlling all fixed-effects included in (1). Variances, covariances and correlations involving observed explanatory variables can be estimated directly from the data. Finally, if we define residuals $\widehat{u}_i = y_i - \mathbf{x}_i\widehat{\beta}$, all variances, covariances and correlations involving the error term can be estimated from the data as well.

6. Results

Table 2 presents regression results for equation (1), fitted by OLS. Fixed-effects at different levels are controlled by adding explicitly the corresponding set of dummies. Standard errors are clustered at the school level. Notice that coefficients can be interpreted as marginal effects. And, because response variables are standardized, marginal effects are measured in terms of standard deviations.

6.1. Effect of mother's characteristics on school grades

Starting by the age of the PC, we find that age is positively associated with higher school grades in maths, Spanish and English. Theoretically, a positive effect is plausible as older parents are more mature and have better parenting skills. The effect, however, is not statistically significant at any standard level. Note that we have a loosely estimated zero, as the size of the standard error is almost the same size of the effect in all cases. Hence, in this case, it is possible that the true effect is positive but with our sample size $N = 1,004$ we simply do not have enough precision to reject the null.[5] A similar result is found for the PC's sex, where female carers carry a positive but insignificant coefficient in regressions for all subjects. Here the effect is further from zero but we still have a sufficiently large standard error to be unable to reject the null.

Moving to education, we find strong evidence that education/qualifications of the PC, in most cases the mother (hence we use PC and mother interchangeably hereafter), is a strong predictor

[5] Age coefficients of an alternative quadratic function are also statistically insignificant for all subjects.

of the child's academic performance.[6] In fact, increasing mother's education from secondary (the control group) to preparatory is associated with an increment on a child's performance in mathematics of about 0.16 standard deviations (sds, hereafter); which is statistically significant at 5%. The education gradient is quite steep. Increasing mother's qualifications to professional studies increases a child's performance in mathematics by around 0.59 sds; which is statistically significant at 1%. Similar findings are reported for Spanish. For English, however, we only find an statistically significant effect of mother's education at the top of the distribution. We speculate that mother's education gradient for English is flat at lower levels because for previous generations English was not a compulsory subject until secondary school and the quality of teaching relatively low. In any case, these results are consistent with Becker's theory of human capital, and what is found empirically in the literature around the globe.

Mother's IQ is found to be statistical insignificant at any standard level of significance. This maybe due to the fact that we control for child's IQ and mother's education, as we discuss later, or because the 12-item version of Raven's progressive matrix test for adults has a relatively low reliability.

In terms of mother's personality, which is measured using the Big-five, we find that mother's Consciousness increases child's performance in math by 0.110 sds (marginally significant at 10%), Spanish by 0.160 sds (significant at 5%), and has no significant effect on English. These results indicate that organized, self-disciplined, and goal-oriented, mothers might be better at helping their children to learn and achieve higher grades at school. On the contrary, Neuroticism is associated with lower child performance on math by -0.093 sds (significant at 10%), on Spanish by -0.109 sds (significant at 5%), and null effect on English. No other personality trait of the mother affects child's school achievement as measured by grades.

Finally, at the household level, income turns out to be a important factor affecting school per-

[6] Though in 4.4% of the cases the PC is the child's grandmother and in 2.4% is the child's father.

formance. In fact, results in Table 2 show that a one-unit increase in household log(income) (an increase of about $4,868$ Mexican peso) results in an increment of 0.138 sds in maths and an increment of 0.134 sds in Spanish; both effects are significant at 5%. No evidence of an income effect is detected for English.

6.2. *Effect of child's characteristics on school grades*

Moving to the effect of the child's characteristics, we find that girls outperform boys by 0.312 sds in maths, 0.428 sds in Spanish, and 0.427 sds in English. All effects are statistically significant at 1%. This is not surprising. Literature in economics and education previous to the 1990s consistently reported girls outperforming boys in language and literature, and boys outperforming girls in math, both in developed and developing countries (see, for instance, Fryer Jr and Levitt 2010, Lindberg et al. 2010, Niederle and Vesterlund 2010). On average, this is still true for the OECD countries OECD (2019b) though since the 1980s girls have caught up and even 'surpassed' boys in maths in many developed and developing countries; mostly where there is a more gender egalitarian culture (Nollenberger et al. 2016, Niederle and Vesterlund 2010). In fact, nowadays, there is evidence that girls outperform boys in most subjects and at all levels of education (see, for instance, Machin and McNally 2005, OECD 2019b, Lindberg et al. 2010).

In the case of Mexico, previous work by Campos-Vázquez and Hernández (2015) using results from ENLACE—a standardized test used in Mexico between 2000 and 2014—find the typical pattern: girls do better than boys in Spanish, and boys do better than girls in maths. Similar results are found in the 2018 PISA: girls outperforming boys in reading by 11 score points and boys outperforming girls in maths by 12 score points OECD (2019a). While we work with school grades rather than with standardized tests, and as such findings have to be interpreted with the due care, as far as we know, the present study is the first in Mexico finding that girls outperform boys in maths as well as Spanish. In general, it is good news to find some evidence that the maths gender gap in Mexico is starting to look like what is observed in developed and gender-equal countries. We hope the result gets confirmed as soon as more data becomes available.[7]

Child's age-within-year is another important control we include in our regressions. As we are dealing with a cohort born in 2010, age-within-year ranges from -234 to 131 with 0 being August 22nd—the day the cohort entered Grade 1 in 2016. Hence, the more positive age-within-year is the younger is a child relative to her/his cohort. Results in Table 2 show that age-within-year carries a negative marginal effect on school grades by -0.001 sds per day in all subjects. These effects are statistically significant at 1% and imply that younger children, relative to her/his cohort, do worse in all subjects. Similar findings for other countries have been reported by Crawford et al. (2010; 2014) and Matta et al. (2016). Two different explanations for the result have been put forward in the literature. First, that older children at the date of entry to first grade are more mature, and hence, have better ability to learn. Second, that older children at school entry spend more time with their parents at home and arrive with higher human capital accumulated; especially those whose parents are highly educated. Whatever the reason older children do better at early stages of primary education, previous results also show that the effect tend to persist over time (see, for instance, Crawford et al. 2010; 2014, Matta et al. 2016).

We now move to discuss the role of children's cognitive ability as measured by the colored Raven's Progressive Matrices test (RPM), which is specially designed for children. As expected, Table 2 shows that children's IQ is a strong predictor of children's school performance. In fact, a one-unit increment in children's IQ, has a marginal effect of 0.252 sds in math, a 0.2284 sds in Spanish, and 0.146 sds in English. All these effects are highly significant at 1% and have a sizable magnitude (more on this later).

Finally, we discuss the role of children's personality; which is the main focus of the present paper. Table 2 shows that a child's personality is a strong predictor of her/his school achievement. A

[7] However, the use and deployment of standardized test in public and private schools in Mexico was discontinued in 2019.

unit increment in Agreeableness (A) has a 0.084 sds marginal effect on maths, a 0.101 sds marginal effect on Spanish, and a staggering 0.162 sds marginal effect in English which is greater than that of IQ. All these effects are significant at 5%. Similarly, a one sd increment in Conscientiousness (C) has a 0.081 sds marginal effect on maths, a 0.091 sds marginal effect on Spanish, and a 0.077 sds marginal effect on English. While the effect of C on maths and Spanish are statistically significant at 5% at least, its effect on English is only marginally significant at 10%. No other child personality trait is significant across all regressions.

That child's Agreeableness positively affects school grades at age 8 is quite interesting. How is it that Agreeableness translates into higher school grades/achievement? Previous research on secondary and high school students find that agreeable students like to be friendly and to "fit in". As a consequence, they are amenable to instructions and requests from parents and teachers; which leads to surface learning and better school performance (Vermetten et al. 2001). Similarly, agreeable students are likely to adopt values the community perceives as desirable. This also translates into an intrinsic motivation for learning (Vermetten et al. 2001, Clark and Schroth 2010). Also, agreeable students have been found to procrastinate less (Lubbers et al. 2010) and to develop good management skills Komarraju et al. (2011). The finding that a child's Conscientiousness positively affects her/his school grades is expected and intuitive. Conscientious individuals have a tendency for being self-disciplined, careful, and diligent; characteristics that are all valuable for good academic performance (Komarraju and Karau 2005, Chamorro-Premuzic and Furnham 2003, Conard 2006, Bidjerano and Dai 2007, McKenzie et al. 2004).

6.3. *Effect of mother and child's characteristics on school grades inequality*

We now turn our study into decomposing how mother's and child's characteristics affect school grades inequality. As discussed in section 5, to perform such a decomposition we use the methods of Shorrocks (1982) and Fields (2003). Table 3 presents results of decomposing the inequality in school grades for maths, Spanish, and English. At the top of Table 3 we report that just over half of the total inequality in standardized mean grades remain *unexplained* for all subjects, even with our unusually rich set of controls which include PC's and child's characteristics and netting out school, municipal and interviewer fixed-effects—as specified by model 1. The bottom panel of Table 3 presents a summary of the results.

We find that PC's education explain about 5.14% of the inequality in school grades in maths, 5.44% in Spanish, and 2.57% in English. This is a relative large contribution to inequality when compared to the contribution of the PC's personality traits; which explain 1.20% of the inequality in maths, 1.44% in Spanish, and only 0.53% in English. Household income only explains 1.44%, 1.46% and 0.65% of the total inequality in maths, Spanish and English, respectively. So, household income only plays a relatively minor role, comparable to that of PC's personality, in determining child's school grade.

Moving to the contribution of children's characteristics, Table 3 shows that child's IQ—as measured by the RPM test—is the largest contributor to grades inequality across all subjects. In fact, IQ explains about 8.51% of the inequality in maths, 7.02% of the inequality in Spanish, and 3.63% of the inequality in English. Finally, we learn that children's personality traits explain about 5.42% of the inequality in maths, 5.50% of the inequality in Spanish, and 7.76% inequality in English.

Overall, the PC's characteristics including household income sum up to a total contribution of 7.64% to the inequality in mathematics, 8.26% to the inequality in Spanish, and 3.74% to the inequality in English. While the contribution of the PC characteristics is important, our findings show that the contribution of children's characteristics is at least twice as important in all subjects. In fact, children's characteristics contribute 16.72% of the inequality in maths, 17.26% of the inequality in Spanish, and 16.27% of the inequality in English.

6.4. Further robustness checks

We present results of further robustness checks in the Appendix. Table *A*1 replicates the fixed-effects regressions in Table 2, but without controlling for the child personality traits. Compared to our main results, the marginal effects of child's IQ increase by about 14% for maths and Spanish, and 30% for English. Therefore, omitting child's noncognitive skills, as in the case of much of existing studies, will lead to overestimates of the effect of cognitive skills.

Table *A*2 replicates the fixed-effects regressions, but without controlling for CP's IQ and personality traits. This results in a slight increase in the estimated marginal effect of household income. Moreover, the marginal effect of the child's IQ is virtually identical, while the marginal effects of the child's B5PT effects are slightly larger. Compared to Table *A*1, this result suggests that the omitted variable bias problem is less serious if the child's own personality traits are properly accounted for.

Tables *A*3 and *A*4 replicate Table 2, but for girls and boys separately. Our main finding appear only to be more robust for boys, as the B5PT estimates are largely statistically insignificant for girls. On the other hand, IQ matters more for girls. However, it is important not to over-interpret these patterns. Unless these findings are confirmed in comparable studies with larger samples, we can not be confident that this is driven by a lack of statistical power in relatively small samples.

Finally, Table *A*5 replicates Table 2, but only using the subsample with the mother as the CP. Using this much more homogeneous group only, we can be more confident that our main results are not driven by unobservable heterogeneity or sorting in the family background variables. It is reassuring that our main results appear to be highly robust to the exclusion of small minority (about 9%) of families where the CP is not the mother.

7. Summary and conclusions

In this paper we investigate how principal carer (PC)'s and children's cognitive and noncognitive skills affect the level and the inequality of children's school grades, for public primary school children—aged 8—in the state of Aguascalientes, Mexico. Data comes from the baseline survey of the Aguascalientes Longitudinal Child Development Survey (EDNA), which is linked to administrative data on grades and dates of birth generated by the Institute of Aguascalientes (IEA)—the state education authority. A major novelty of the primary EDNA data is the collection of detailed information on personality traits of both PCs and children, alongside their cognitive ability as measured by a Raven Progressive Matrix test. Personality is measured using the Big Five Personality Traits model (Digman 1990). For adults, we use the Spanish version of the Big-Five Personality Test of Benet-Martínez and John (1998). For children, EDNA contains a unique and innovative measurement of personality for young children: the Field Puppet Interview-Big Five Questionnaire test (FPI-BFQ) (Peralta et al. 2021). The FPI-BFQ is a field implementation of the Berkeley Puppet Interview Big Five Questionnaire of Measelle et al. (2005) that does not require strict laboratory conditions, videotaping, or professional scoring.

Even with our unusually rich set of controls, education of the PC still plays a major role in explaining school grades inequality (around 5% for both maths and Spanish). Household income's contribution to grades inequality is relatively minor; with an impact of 1.45% in maths and Spanish, and only 0.65% in English. In terms of the PC's personality, we find that one standard deviations (sd) increase in Consciousness increases the child's school grades by about 0.11 sds in maths, and 0.16 sds in Spanish; but has no significant effect on English. In terms of grades inequality, Consciousness of the PC contributes to explaining 0.36% and 0.83% of the total inequality in maths and Spanish respectively. Intuitively, PC's Neuroticism has an impact of -0.093 sds (significant at 10%) on maths, and -0.109 sds in Spanish (significant at 5%). No effect of PC's Neuroticism on English is found. In terms of grades inequality, PC's Neuroticism contributes to 0.80% of total inequality in maths and 0.88% in Spanish. No effect of adult IQ is detected, presumably because we control for both education and B5PT of the CP.

Overall, the contribution of a child's own characteristics to grades inequality is more than double the contribution of the PC—in most cases the mother— characteristics in all subjects. A child's IQ is the most important determinant of school grades, with an impact of 0.252 sds in maths, 0.224 sds in Spanish, and 0.146 sds in English (all significant at 1%). This amounts to a contribution to total grades inequality of 8.5% in maths, 7.0% in Spanish, and 3.6% in English. In terms of child's personality traits, we find that Agreeableness and Conscientiousness have an important effect in both subjects. Agreeableness has a marginal effect of about 0.084 sds, 0.101 sds and 0.162 sds, for maths, Spanish and English respectively. In contrast, the effects of Conscientiousness on the three subjects are more similar, ranging $0.077 - 0.091$ sds. The total contributions of a child's personality traits to grades inequality are 5.4%, 5.5% and 7.84%, for maths, Spanish and English respectively.

In summary, our findings show that a child's personality traits are major factors in explaining the variation in the academic performance of children aged 8. These effects are relatively large, equivalent to 64%, 78%, 214% of the corresponding contributions of the child's IQ for maths, Spanish and English, respectively. The effect of a child's personality traits is as large as that of the education of the PC for maths and Spanish, and three times as large for English. These results are consistent with the findings of Cunha et al. (2010) and Cunha and Heckman (2007), which point out that the development of noncognitive abilities in children are almost as important as the development of cognitive abilities in explaining variations in education and labor market outcomes. Household income explains part of the grades inequality but it's role is relatively minor when compared to the effects of the principal carer's education, child's IQ, or child's personality.

In terms of public policy, our findings underline the relevance of developing the noncognitive skills in school age children. As Cunha et al. (2010) and Cunha and Heckman (2007) point out, interventions that seek to develop good personality traits in children as young as three years old are easier to implement and have substantive impact than interventions focused on improving cognitive skills. Hence, public policy should put more emphasis on interventions that seek to develop good personality traits in children. Moreover, for purposes of evaluation of educational outcomes, it is important to generate information about the evolution of children's personality traits along measurements of children's school achievement and cognitive abilities.

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Table 1. Descriptive statistics of the analytical sample.

Variable	Obs.	Mean	SD	Min	Max
Principal carer characteristics					
Age	1004	33.36	7.89	22	77
Female	1004	0.98	0.16	0	1
Education: none	1004	0.01	0.11	0	1
Education: primary	1004	0.17	0.38	0	1
Education: secondary	1004	0.55	0.5	0	1
Education: preparatory	1004	0.16	0.37	0	1
Education: technical	1004	0.03	0.17	0	1
Education: professsional	1004	0.07	0.26	0	1
Household log(income) per month	1004	2.78	1.25	0	8
Household log(income) missing	1004	1.4	0.76	0	4.33
IQ	1004	0	1	-2.2	4.2
BFQ: E	1004	0	1	-2.3	2.0
BFQ: A	1004	0	1	-2.6	1.8
BFQ: C	1004	0	1	-3.1	1.5
BFQ: N	1004	0	1	-1.9	2.6
BFQ: O	1004	0	1	-2.8	1.9
Child's characteristics					
Girl	1004	0.51	0.5	0	1
Age within year	1004	-47.28	104.31	-234	131
IQ	1004	0	1	-2.7	3.4
FBPI: E	1004	0	1	-4.2	0.8
FBPI: A	1004	0	1	-4.6	1.0
FBPI: C	1004	0	1	-4.8	0.9
FBPI: N	1004	0	1	-1.2	3.4
FBPI: O	1004	0	1	-4.6	0.8

Table 2. Fixed effects regressions for pupils' school grades in the 2017/18 academic year (age $7-8$).

	Math	Spanish	English
	Principal carer characteristics		
Age	0.004	0.003	0.005
	(0.004)	(0.004)	(0.004)
Female	0.274	0.114	0.119
	(0.181)	(0.173)	(0.207)
Education: none	-0.146	-0.356*	-0.114
	(0.231)	(0.213)	(0.151)
Education: primary	-0.174**	-0.176**	-0.116
	(0.087)	(0.087)	(0.091)
Education: preparatory	0.163**	0.190**	0.062
	(0.081)	(0.084)	(0.081)
Education: technical	0.316**	0.360**	0.197
	(0.147)	(0.151)	(0.157)
Education: professional	0.585***	0.521***	0.344**
	(0.109)	(0.103)	(0.146)
IQ	-0.018	0.004	-0.006
	(0.031)	(0.030)	(0.039)
household log(income)	0.138***	0.134**	0.074
	(0.053)	(0.053)	(0.062)
BFQ: E	0.060	0.013	-0.001
	(0.071)	(0.071)	(0.086)
BFQ: A	-0.069	-0.062	-0.060
	(0.074)	(0.074)	(0.074)
BFQ: C	0.110*	0.160**	0.060
	(0.067)	(0.066)	(0.077)
BFQ: N	-0.093*	-0.109**	-0.032
	(0.049)	(0.048)	(0.054)
BFQ: O	-0.088	-0.055	-0.034
	(0.057)	(0.060)	(0.076)

Table 2. (Cont.)

	Math	Spanish	English
	Child's characteristics		
Girl	0.312***	0.428***	0.427***
	(0.058)	(0.057)	(0.069)
Age within year	-0.001**	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)
IQ	0.252***	0.224***	0.146***
	(0.031)	(0.032)	(0.042)
FBPI: E	0.044	0.036	0.017
	(0.034)	(0.036)	(0.046)
FBPI: A	0.084**	0.101***	0.162***
	(0.034)	(0.037)	(0.044)
FBPI: C	0.081**	0.091***	0.077*
	(0.032)	(0.033)	(0.044)
FBPI: N	-0.020	-0.020	-0.003
	(0.035)	(0.035)	(0.037)
FBPI: O	0.044	0.015	0.068
	(0.032)	(0.032)	(0.042)
School fixed-effects	Yes	Yes	Yes
Municipio fixed-effects	Yes	Yes	Yes
Enumerator fixed-effects	Yes	Yes	Yes
N. of obs	1,004	1,004	755
N. of clusters	135	135	115
R^2-within	0.29	0.29	0.26
R^2-between	0.01	0.03	0.10
R^2-overall	0.15	0.18	0.18
ρ	0.33	0.29	0.31

Note. Marginal effects reported with clustered robust standard errors at school level written in parenthesis. *10% significant; **5% significant; ***1% significant.

Table 3. Regression-based decomposition of the inequality in pupils' school grades in the 2017/18 academic year (age 7-8).

	Math	Spanish	English
Unexplained inequality	55.7	56.3	52.7
	Principal carer characteristics		
Age	-0.01	-0.04	0.06
Female	-0.05	-0.06	-0.06
Education: none	0.06	0.24	0.06
Education: primary	0.94	1.08	0.41
Education: preparatory	0.77	1.02	0.23
Education: technical	0.40	0.49	0.27
Education: professional	2.98	2.60	1.61
IQ	-0.07	0.02	-0.01
household log(income)	1.44	1.46	0.65
E	0.13	0.05	0.01
A	0.03	-0.09	0.37
C	0.36	0.83	-0.38
N	0.80	0.88	0.33
O	-0.13	-0.23	0.20
	Child's characteristics		
Girl	2.16	4.32	4.18
Age within year	0.63	0.41	0.71
IQ	8.51	7.02	3.63
FBPI: E	0.57	0.46	0.26
FBPI: A	1.80	2.25	4.51
FBPI: C	1.84	2.17	1.58
FBPI: N	0.33	0.35	0.06
FBPI: O	0.88	0.27	1.35
School fixed-effects	Yes	Yes	Yes
Municipio fixed-effects	Yes	Yes	Yes
Enumerator fixed-effects	Yes	Yes	Yes
Total	100	100	100
	Total contribution of key characteristics		
Principal carer's education	5.14	5.44	2.57
Principal carer's personality	1.20	1.44	0.53
Child's personality	5.42	5.50	7.76
	Total contribution of mother and child characteristics		
Principal carer's characteristics	7.64	8.26	3.74
Child's characteristics	16.72	17.26	16.27

Note. Regression-decomposition of inequality based in Fields (2003) and Shorrocks (1982) methods.

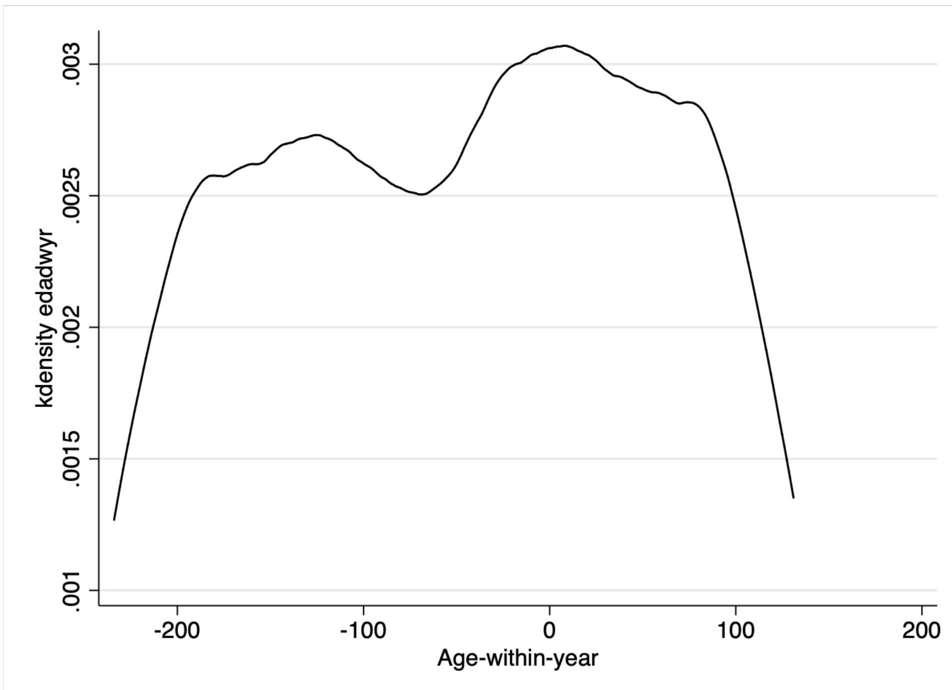

Figure 1. Kernel density estimates for age-within-year. Age-within-year is measured in days, with day 0 being August 22th (the day the cohort entered first grade in 2016), January 1st being day -234, and December 31th being day 131. Younger pupils have positive age-within-year values.

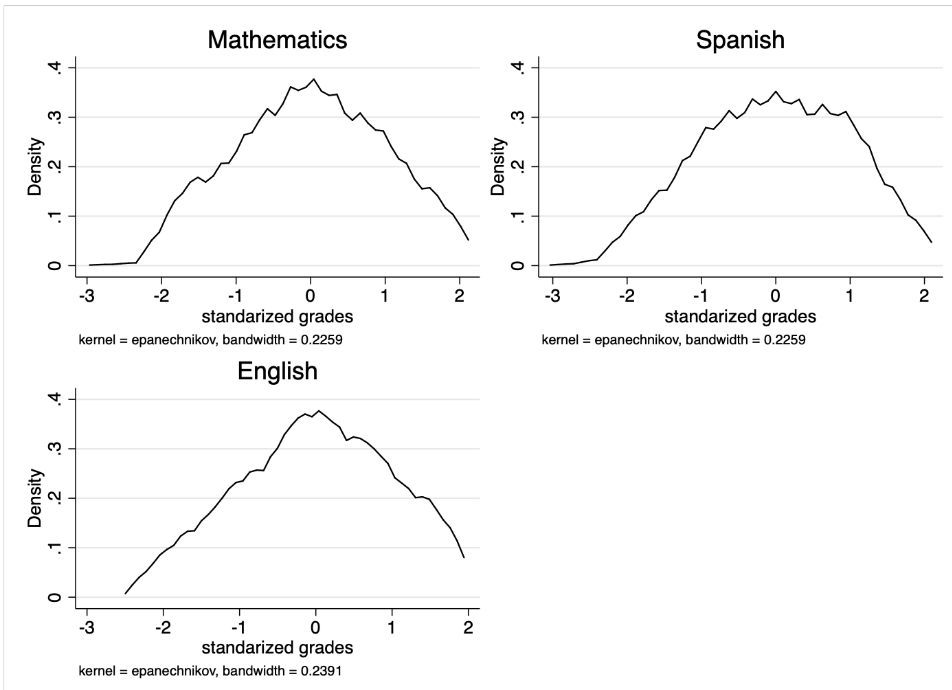

Figure 2. Kernel density estimates for standardized school grades. Academic year 2017/18.

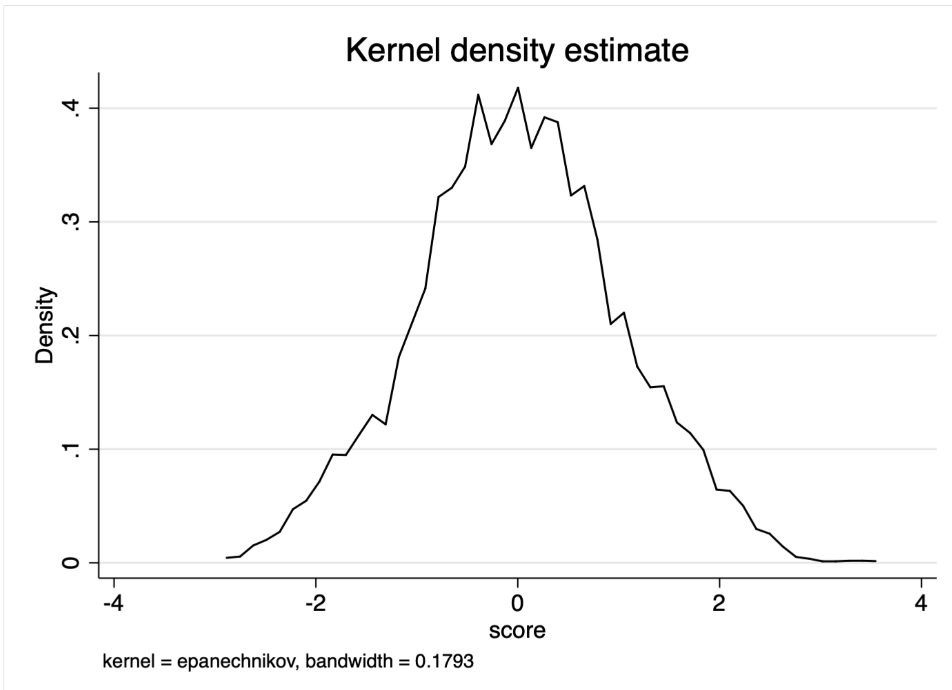

Figure 3. Kernel density estimates for standardized child IQ score (18-item colored Raven's progressive matrix test).

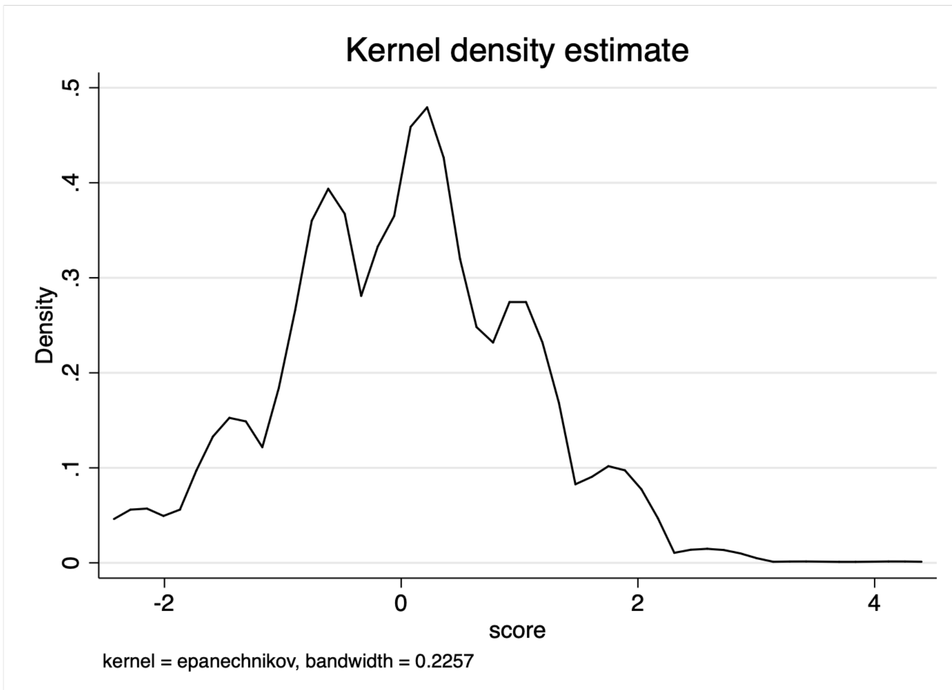

Figure 4. Kernel density estimates for standardized adult IQ score (12-item Raven's progressive matrix test).