Applied Economics and Finance
Vol. 7, No. 3; May 2020
ISSN 2332-7294 E-ISSN 2332-7308
Published by Redfame Publishing
URL: http://aef.redfame.com

The Impact of Education on Fluid Intelligence

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Received: February 14, 2020 Accepted: March 2, 2020 Available online: March 18, 2020

doi:10.11114/aef.v7i3.4774 URL: https://doi.org/10.11114/aef.v7i3.4774

Abstract

Fluid intelligence, which refers to the ability of a person to solve novel problems independent of previously acquired knowledge, is a highly crucial factor in learning and has a big impact on educational and professional success. However, the impacts of formal education on fluid intelligence has been neglected in the literature. In this paper, we apply an exogenous variation in years of schooling to explore the impacts of education on fluid intelligence. From 1971 to the end of 1973, the global price of crude oil increased over 400%. Such an increase in oil price improved the revenue of the Indonesian government from oil production. Indonesia invested most of the new income on central government's construction projects famous as "Presidential Instructions" (INPRES), which aimed to improve regional equity in the country. The largest INPRES program, known as Sekolah Dasar INPRES, also remains the largest school construction project in history. The government built over 60 thousand elementary schools all over the country from 1973 to 1978. Duflo (2001) studies the impacts of the program on years of education. We have received INPRES data from Duflo and combined it with the Indonesian Family Life Survey (IFLS), which contains individual cognitive ability tests. This dataset represents 83% of the population of 13 out of 26 Indonesian provinces. The results show positive and statistically significant impacts of years of schooling on the fluid intelligence of both females and males.

Keywords: schooling, cognitive skills, fluid Intelligence

1. Introduction

Studies on the return to education generally find positive impacts of the years of schooling on wages. Also, the hypothesis that years of schooling improves crystallized intelligence is generally accepted. Nevertheless, the impacts of education on fluid intelligence are not clearly identified in the literature. First, the number of studies that focus on the impacts of education on fluid intelligence is limited. Second, the existing studies have found mixed results. In the following paragraphs, I will explain what fluid intelligence means and why it is important to understand the impacts of education on fluid intelligence.

Cattell (1971) identifies fluid intelligence and crystallized intelligence as two factors of general intelligence. Jaeggi et al. (2008) defines fluid intelligence (Gf) as "the ability to reason and to solve new problems independently of previously acquired knowledge". Fluid intelligence (Gf), which is necessary for all sorts of logical problem-solving tasks, includes both inductive and deductive reasoning. Gf is the capability of a person in understanding patterns and relationships and using logic and abstract reasoning to analyze and solve novel problems. Fluid intelligence is a highly crucial factor in learning and has a big impact on educational and professional success (See Neisser et al., 1996; Deary et al., 2007; Rohde and Thompson, 2007; and te Nijenhuis et al., 2007 among others)

Crystallized intelligence, however, is the ability to apply experience, knowledge, and skills in solving new problems, and it relies on the information in the long-term memory. Crystallized intelligence (Gc) indicates the life-long acquisition of knowledge through education, language, and culture, and the ability of thinking and reasoning using words and numbers. Therefore, Gc interacts with fluid intelligence as well. Belsky, J. (1990) believes that, because crystallized intelligence relies on knowledge and information, it may start decreasing at an age where the rate of forgetting exceeds the ability to acquire new knowledge.

Fluid intelligence and crystallized intelligence rely on the function of the two separate sections of the brain. Gc is a function of the sections of the brain that are critical for long-term memories such as the hippocampus, but Gf relies on the functions of those parts of the brain that are involved with short memories and attention such as the anterior cingulate cortex and dorsolateral prefrontal cortex (Geary, 2005). Appendix A represents some graphics that show where the hippocampus, anterior cingulate cortex, and dorsolateral prefrontal cortex are located in the brain.

In the literature, the correlation between fluid intelligence and crystallized intelligence is emphasized because people with higher levels of fluid intelligence typically acquire more crystallized intelligence (Baltes, 1993; Cunha and Heckman, 2007; Dahmann, 2017).

Among the various measures designed to assess fluid intelligence, Raven's Progressive Matrices (RPM), introduced by Raven (1936), is the most common and widely used. Each question in RPM is a multiple-choice question. The test taker sees a window that contains a three by three (or two by two in abbreviated versions) set of drawings, and the last one of them is dropped (i.e. supposed to be nine drawings, but since one of them is dropped the test taker can see eight). The test taker then has to pick the correct dropped drawing among another eight (or six in abbreviated versions) offered choices. Finding the correct answer requires abstract reasoning and identifying one or more underlying relevant features.

Whether Gf can be improved or not has been a topic of debate. At least two studies suggest that training can improve fluid intelligence. In a study by Klingberg et al. (2002) conducted over a period of five weeks, children with ADHD were trained 20 minutes per day and four to six days per week via fluid reasoning computer-based training programs. The children showed an improvement in their working memory and received higher marks in the Raven test scores compared to the control group. In addition, Klingberg et al. (2002) finds a positive impact from a training program on the fluid intelligence of adults, which was assessed by Raven test scores.

Multiple studies have investigated the effects of schooling on cognitive skills (see e.g. Cahan and Cohen, 1989; Ceci, 1991; Herrnstein and Murray, 1994; Stelzl et al., 1995; Neal and Johnson, 1996; Winship and Korenman, 1997; Jacob, 2002; Hansen, Heckman, and Mullen, 2004; Cascio and Lewis, 2006; Cliffordson and Gustafsson, 2008; Carlsson et al., 2015; Dahmann, 2017; Checchi and Paola, 2018; Castro and Rolleston, 2018; Bietenbeck et al., 2019; Jagannathan et al., 2019). The previous literature suggests that years of schooling improve crystallized intelligence, but the findings on fluid intelligence do not show similar results. The findings of the studies about the impacts of education on fluid intelligence are much more mixed than those of crystallized intelligence. While most of the empirical studies, such as Carlsson et al. (2015) and Cliffordson and Gustafsson (2008), find that the length of education has a positive and significant impact on crystallized intelligence, they identify no significant impact on fluid intelligence. Even Cliffordson and Gustafsson (2008), who do not find any significant impact of schooling on fluid intelligence, suggest a negative impact of age on fluid intelligence. However, other researchers such as Cahan and Cohen (1989) and Stelzl et al. (1995) maintain that schooling may influence fluid intelligence.

Note that even though the literature about the potential impacts of schooling on fluid intelligence is mixed, both fluid and crystallized intelligence improved year after year during the 20th century, a phenomenon known as the Flynn Effect. Several explanations such as schooling and test familiarity, generally more stimulating environment, nutrition, and a higher control on infectious diseases are proposed as explanations for the Flynn Effect[1]. One explanation provided by Blair et al. (2005) suggests a neurodevelopmental schooling hypothesis for the Flynn Effect. Based on this hypothesis, an increase in access to school and in cognitively demanding math courses explains the Flynn Effect.

Perhaps the research most similar to our study is Dahmann (2017) that studies the impacts of a high school reform at the state level in Germany between 2001 and 2007. The reform shortened the number of total years of schooling from 13 to 12 years but did not make any other changes to the education programs. The results show that the decline in years of schooling led to significantly lower Raven test scores, but Dahmann (2017) argues that this effect could be due to the variation in biological age not the reform. Hence her findings on the impacts of length of education on fluid intelligence should be taken with precaution. It is worth noting that she does not find any significant impact of the reform on the crystallized skills of the students. Dahmann's (2017) study is similar to ours because she investigates the impact of a variation in years of schooling on fluid intelligence. However, her research could be also considered as an opposite case of our study because the years of schooling decreased while we consider the impact of an increase in years of schooling.

Jonsson et al. (2017) finds positive impacts of schooling on fluid intelligence in Nordic Countries, but they mention that this impact is not equal in all Nordic Countries. They argue that differences in the quality of offered math courses, as Blair et al. (2005) emphasizes, might be the reason behind the differences.

Several studies have investigated the impacts of schooling on Armed Forces Qualification Test Scores (AFQT) which is available on NLSY dataset. These studies usually find a positive impact of schooling on AFQT scores (Herrnstein and

[1] Research suggests that, in the 1990s, a decline in IQ scores began in industrial countries such as France, Norway, the Netherlands, Denmark, Australia, Sweden, Finland, Britain, and German-speaking countries (Cotton et al., 2005; Flynn, 2012; Dutton & Lynn, 2013, 2015; Pietschnig and Gittler, 2015)

Murray, 1994; Neal and Johnson, 1996; Winship and Korenman, 1997; Hansen, Heckman, and Mullen, 2004; Cascio and Lewis 2006). Hansen, Heckman, and Mullen (2004) find an average of two to four percentage points increase in AFQT scores, which is twice as large as what Herrnstein and Murray (1994) find, but it is almost equal to the findings of Neal and Johnson (1996) and Winship and Korenman (1997). In addition, most of the studies, such as the one by Hansen, Heckman, and Mullen (2004), find a linear impact of schooling across schooling levels. Also, they argue that the impacts on test scores are bigger for participants with lower levels of latent ability[2].

Ceci (1991) finds a positive impact of schooling on general intelligence. However, he argues that, while quantity of schooling positively affects cognition in western nations, this impact is systematically irrelevant to the quality of education. Furthermore, Gustafsson (2016) finds positive and lasting impacts of schooling on adult numeracy performance and literacy in 20 industrial nations.

Based on what has been explained above, the existing literature finds some impacts of education on crystallized intelligence, but it does not present any clear image of the effects of education on fluid intelligence. However, investigating the impacts of education on fluid intelligence is extremely important. First, fluid intelligence plays a significant role in every problem-solving task that a human being executes. Understanding how the current education systems impact fluid intelligence and finding ways to improve education systems such that they could better serve fluid intelligence is highly important. Moreover, because the quality of schools differs between developing countries and developed nations, it is crucial to understand how the education systems in developing countries affect fluid intelligence. In addition, finding the impacts of education on fluid intelligence helps with an old debate of labor economics: signaling versus human capital views. Positive impacts of education on fluid intelligence is in favor of human capital view rather than signaling.

One important debate in labor economics is the contrast between the Michael Spence's Job Market signaling view and Human Capital view by Gary Becker and others. According to the Signaling view by Spence (1973), a school degree aids prospective employees in revealing their abilities to a potential employer by sending her a signal. In other words, the credential sends a signal to the employer about the unobserved ability of the employee, and that signal enables the employer to distinguish between high and low ability workers from each other. Based on Signaling view, education serves an important role in determining the amount of the starting wages of the employees. However, after employees start working, the role of education in determining wages diminishes since their abilities get revealed. Hence, after the employee starts working, the role of ability in determining the amount of income increases over time. According to this theory, people with higher levels of productivity choose higher levels of education to signal their ability to the employers.

According to the Human Capital theory, investment in education increases productivity and therefore income. Credentials do not serve employees only because of their informational value in sending signals to the employers (Becker, 1964; Ben-Porath, 1967). Becker (1992) argues in favor of the Human Capital theory as follows:

> *Tangible forms of capital are not the only type of capital. Schooling, a computer training course, expenditures on medical care, and lectures on the virtues of punctuality and honesty are also capital. That is because they raise earnings, improve health, or add to a person's good habits over much of his lifetime. Therefore, economists regard expenditures on education, training, medical care, and so on as investments in human capital. They are called human capital because people cannot be separated from their knowledge, skills, health, or values in the way they can be separated from their financial and physical assets. Education, training, and health are the most important investments in human capital (p. 1.).*

Arcidiacono et al. (2010) apply the Armed Forces Qualification Test (AFQT) as a measure of ability and provide some insights about education and revealing ability. They find that the ability of college graduates is observed almost perfectly in the job market, but the ability of high school graduates is revealed gradually to the job market over time.

Because of the endogeneity of education and the heterogeneity in individuals' productivity levels, clearly distinguishing signaling effects from human capital in empirical studies is difficult. Therefore, researchers are interested in studying the exogenous variations in education to find support for each of the mentioned views.

We apply an exogenous variation in years of education to study the impacts of education on fluid intelligence. Our results show positive impacts of education on fluid intelligence, which could be interpreted as a finding that is in favor of the human capital view rather than signaling.

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[2] AFQT measures the skill and knowledge of participants in the areas of arithmetic reasoning, word knowledge, paragraph comprehension, and numerical operations. Hence, it mostly measures crystallized intelligence.

The rest of this paper is designed as follows. Section 2 explains the data and identification strategy. Section 3 outlines the empirical design of the paper. Section 4 provides the results and section 5 presents the conclusion of the study.

2. Data and Identification Strategy

The data in this research comes from two sources: the Indonesia Family Life Survey (IFLS) and data from Sekolah Dasar INPRES program in Indonesia. The IFLS data is available online. The author has received the Sekolah Dasar INPRES program's data from Esther Duflo[3], an economist from Massachusetts Institute of Technology (MIT). We use IFLS5 which is constructed in 2014 and combine it with Sekolah Dasar INPRES data. Appendix B shows the coverage of IFLS dataset and intensity of Sekolah Dasar INPRES program on map of Indonesia.

2.1 Sekolah Dasar INPRES Program

Due to the boom in the global price of oil, oil revenues increased in 1973. The government of Indonesia accessed a higher income to finance the central government's development plans, which is known as "Presidential Instructions" (INPRES). Because of the increase in oil income, the Indonesian government's real expenditure on regional development increased by over 100%. One of the first and by far the biggest programs that took place was Sekolah Dasar INPRES, which remains one of the largest school construction projects in human history. From 1973 to 1978, 61,807 elementary schools were constructed all over the country. The number of schools constructed in each region was decided based on the number of primary school aged children in the region who were not enrolled in school in 1972. The stock of the schools doubled between 1971 and 1978. Figure 1 shows the ratio of the total INPRES schools constructed each year (i.e. the number of INPRES schools constructed each year divided by the number of all INPRES schools constructed from 1973 to 1978). In 1973 and 1974, less than 10 percent of the schools were built each year. In 1975 and 1976, over 16 percent of the schools were constructed each year. Finally, in 1977 and 1978, over 23 percent of the schools were built annually.

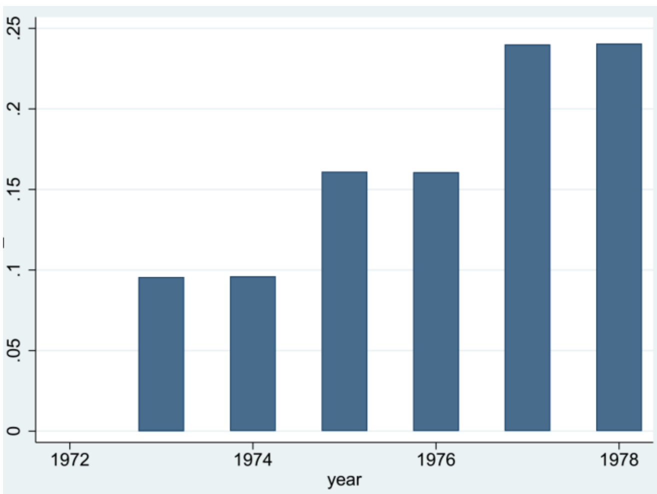

Figure 1. Ratio of the INPRES schools constructed each year
Each bar shows the number of INPRES schools constructed in a particular year divided by the number of all INPRES schools constructed from 1973 to 1978

At the same time, the government initiated a parallel program to increase the number of teachers. New teachers were hired such that the stock of the teachers increased by 43%. Each INPRES school was designed for three teachers and 120 students (Duflo, 2001). Daroesman (1971) argues that the minimum qualification requirements for hiring teachers did not significantly worsen over this period. Hence, the quality of education has not changed significantly.

2.2 Indonesia Family Life Survey (IFLS)

The Indonesia Family Life Survey (IFLS) is a continuing longitudinal health and socioeconomic survey that has published data in five waves so far. The data has been conducted by RAND[4] in collaboration with the Demographic Institute at the University of Indonesia, UCLA, Population Research center at the University of Gadjah Mad, the center for Population and Policy Studies (CPPS) of the University of Gadjah Mada, and Survey METRE. In the first wave in 1993, the sample of the households in the dataset represented 83% of the population of 13 out of 26 Indonesian

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[3] https://economics.mit.edu/faculty/eduflo

[4] Research ANd Development (RAND) is an American nonprofit global policy think tank.

provinces. The second, third, fourth, and fifth waves (i.e., IFLS2, IFLS3, IFLS4, IFLS5) were collected in the years 1997, 2000, 2007, and 2014, respectively. IFLS5, which is the dataset that we use in this research, contains the data of 16,204 households and 50,148 interviewed individuals.

IFLS5 was chosen for this study because in wave five for the first time the respondents of all ages were asked to take an abridged version of the Raven's test, which is a test designed to measure fluid intelligence (Gf). Although participants aged 7-24 were asked to take the same test in IFLS3 and IFLS4, data from IFLS5 was used because we need the respondents who, at the time of taking the Raven's test in 2014, were old enough to be exposed to Sekolah Dasar INPRES program, which took place between 1973 and 1979. The Raven's test used in IFLS5 is available in Appendix C.

2.3 Identification Strategy

Exposure to the Sekolah Dasar INPRES program depends on the age of the person and region of birth. Since Indonesian children attend elementary school between ages 7 and 12, children aged between 2 and 6 years in 1974 could benefit from the program. However, the ones who were born in 1962 and earlier were too old to go to elementary school. Hence, they did not benefit from the program. The impact of the program for those aged 12 and older in 1974 should be close to zero. For the younger children, exposure is a function of their date of birth. We expect bigger effects from the program on younger children aged 2 to 12 in 1974. The younger the children are the bigger the impact should be.

Region of birth is another factor that determines exposure to the program. Since the goal of the INPRES program was to increase regional equality in Indonesia, the highest numbers of INPRES schools were built in the regions where they were needed the most. As mentioned before, the decision for the numbers of schools built in each region was based on the number of elementary school aged children who were not enrolled in school.

Note that region of education could be endogenous with respect to the program. Duflo (2001) elaborates this point as follows:

> *Because the program intensity was related to enrollment rates in 1972, which differed widely across regions, region of birth is a second dimension of variation in the intensity of the program. Region of birth is highly correlated with the region of education: 91.5 percent of the children in the IFLS sample were still living in the district where they were born at age 12. However, unlike region of education, it is not endogenous with respect to the program given that all individuals in the sample were born before the program was started (p. 798.).*

In this paper, region of birth fixed effect is used in all of the regressions. "Region," here, refers to Indonesian Kabupatens. A Kabupaten in Indonesia is a subregion of a province. If provinces can be considered to be similar to the states in the United States, the Kabupaten could be considered similar to counties.

In our difference-in-differences (DID) estimations, we apply the interactions of INPRES *program intensity* in the region of birth and the *young* to study the impact of the program on education and fluid intelligence. "Program intensity in the region of birth" is the number of constructed INPRES schools in the Indonesian Kabupatens, where an individual was born per 1,000 children. "Young" in our regressions is a binary variable that equals one if someone was 2 to 6 years old in 1974, and it equals to zero for the ones aged 7 to 12.

3. Empirical Design

In this paper, the difference-in-differences (DID) approach is applied to estimate the impacts of the INPRES school construction program on years of schooling and fluid intelligence. Two-stage least-squares (2SLS) approach is applied to investigate the impacts of education on fluid intelligence. The basic DID specification is as follows:

$$Y_{ijk} = c_1 + \gamma_1(intens_j \times Young_i) + \delta_1(\boldsymbol{C}_j \times Young_i) + \alpha_j + \beta_k + \varepsilon_{ijt} \tag{1}$$

where Y_{ijk} is the outcome variable for individual *i*, born in year *k* in region *j*. $Young_i$ is a variable that indicates that individual *i* has been in the young cohort that benefits from the program (i.e. individual *i* ages 2 to 6 in 1974). $Young_i$ is a dummy variable that takes the value one if the age of individual *i* has been 2 to 6 in 1974, and it takes value zero if the person's age has been 12 to 17 in 1974. The individuals aged 6 to 12 in 1974 are dropped since they partially benefited from the program. $intens_j$ measures the intensity of the program in region *j*. It is the number of Sekolah Dasar INPRES schools built in the Kabupaten of births per 1000 children in the region. $\boldsymbol{C}_j$ indicates a vector of control variables. $\boldsymbol{C}_j \times Young_i$ controls for the time-varying region-specific factors that might affect the outcomes. α_j is region of birth fixed effect and β_k is the cohort of birth fixed effect. ε_{ijt} is the error term.

The basic specification in 2SLS approach is:

$$Gf_{ijk} = d + \theta Edu_{ijk} + \alpha_j + \beta_k + \mu_{ijt} \qquad (2)$$

where Gf_{ijk} is the fluid intelligence of individual *i* born in year *k* in region *j*. Edu_{ijk} is the years of education of individual *i* born in year *k* in region *j*. ε_{ijt} is the error term, and the rest of the variables have been introduced before.

We apply the interaction between the region of birth and the age of the person as an instrument in 2SLS estimates since this instrument is plausibly exogenous after controlling cohort of birth and region of birth effects. Card and Krueger (1992), Card and Lemieux (1998), and Duflo (2001) apply a similar approach.

4. Empirical Results

In this section of the paper, the details of the empirical method as well as the empirical results are presented.

4.1 Effect on Education

In this section the results of our estimations regarding the impacts of the elementary school construction program on education outcomes are provided.

4.1.1 Basic Results

We apply a difference-in-differences (DID) specification to study the impacts of the treatment (i.e. Sekolah Dasar INPRES in Indonesia) on years of education:

Table 1 represents the estimations of equations 1 where the outcome variables is years of education. Three columns are provided in the table. The columns differ based on the control variables used in the regressions. The results are provided in two panels. In Panel A, which is our experiment of interest, $Young_i$ is as described before. It indicates the young cohort who was exposed to the program versus an older cohort who wasn't exposed to the program. It is equal to one for children aged 2 to 6 in 1974, and is equal to zero for those aged 12 to 17 in 1974. The impact of the school construction program is associated with an increase of 0.29 to 0.35 years of schooling. Panel B represents our control experiment. In panel B, instead of "young" in panel A, we use a dummy variable that sets to one if someone is aged 12 to 17 in 1974, and takes value zero for the ones aged 18 to 24 in 1974. Note that we do not expect to see any significant impact of the program in panel B since people aged 12 to 24 in 1974 were not exposed to the program. As expected, the results of panel B show significantly smaller coefficients with no significant impact from the school construction program on years of schooling.

Table 1. the Impacts of the School Construction Program on Years of Education: Basic Results

	Years of Education		
$intens_j \times Young_i$	(1)	(2)	(3)
Panel A: experiment of interest			
Aged 2 to 6 in 1974	0.352***	0.323**	0.291***
Control: Aged 12 to 17 in 1974	(0.108)	(0.145)	(0.110)
Number of observations	4,188	3,962	3,737
R squared	0.242	0.241	0.318
Panel B: control experiment			
Aged 12 to 17 in 1974	-0.038	-0.108	0.011
Control: Aged 18 to 24 in 1974	(0.096)	(0.109)	(0.097)
Number of observations	3,364	3,205	2,986
R squared	0.175	0.175	0.234
Control variables:			
Year of birth × enrollment rate in 1971	Y	Y	Y
Year of birth × water and sanitation program		Y	Y
Other control variables[1]			Y

Dependent variables: Years of Education
Region of birth and year of birth fixed effects are included in all regressions.
[1] Other control variables include city, village, family size, and electricity. City is a binary variable that indicates whether a person lives in a city. Village is a binary variable that indicates whether a person lives in a village. Family size shows the actual number of household members that live in family. Electricity is a binary variable that determines whether electricity is available in the region of birth.
Young in panel A is a binary variable that takes the value one if someone aged 2 to 6 in 1974, and takes value zero for the ones aged 12 to 17 in 1974.

The difference between Panel A and Panel B is that, in panel B, we have used a different binary variable instead of young in Panel A. In Panel B, this variable takes value one if someone aged 12 to 17 in 1974 and takes value zero for the ones aged 18 to 24 in 1974.
All regressions are clustered by number of family members in each household.
Standard errors are in parentheses.
*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

4.1.2 Reduced-Form Evidence

The identification strategy of the paper could be generalized by estimating the following regression:

$$Edu_{ijk} = c_1 + \gamma_{1l}\sum_{l=2}^{23}(intens_j \times d_{il}) + \delta_{1l}\sum_{l=2}^{23}(C_j \times d_{il}) + \alpha_{1j} + \beta_{1k} + \varepsilon_{ijt} \quad (3)$$

where d_{il} is year of birth dummy variable. It takes value one if individual i ages l in 1974. Hence, each coefficient of the interaction of program intensity in the region of birth and d_{il} shows the impact of the program on cohort l. Individuals aged 2 to 24 in 1974 are considered in the range of the estimations, but the ones aged 24 are omitted hence they form the control group. This equation enables us to generalize equation 1 and estimate it cohort by cohort. Because the children aged over 12 in 1974 were not exposed to the program, this regression should not show significant impacts of the treatment on education levels of the cohorts older than 12 years old.

The estimated γ_{1l}s which show the impact of the program on cohort l, are plotted in Figure 2. Also, the same results are presented in Table 2. In Figure 2, the solid line shows γ_{1l}s, and the dashed lines are the 95 percent confidence intervals. γ_{1l} is the coefficient of the interaction of the program intensity (i.e. number of INPRES schools constructed in the region of birth per 1000 children in the region of birth) and cohorts of birth. As expected, since children older than 12 are not exposed to the program, the coefficients for the ones older than 12 randomly vary around zero and are not statistically significant. However, for the cohorts 2 to 12 years-old in 1974, the impact of the program is an increasing function of cohort of birth. The younger children between 2 and 12 are the bigger the impact of the program is on their years of education. These results are expected, and they show that the identification strategy of the paper is correct.

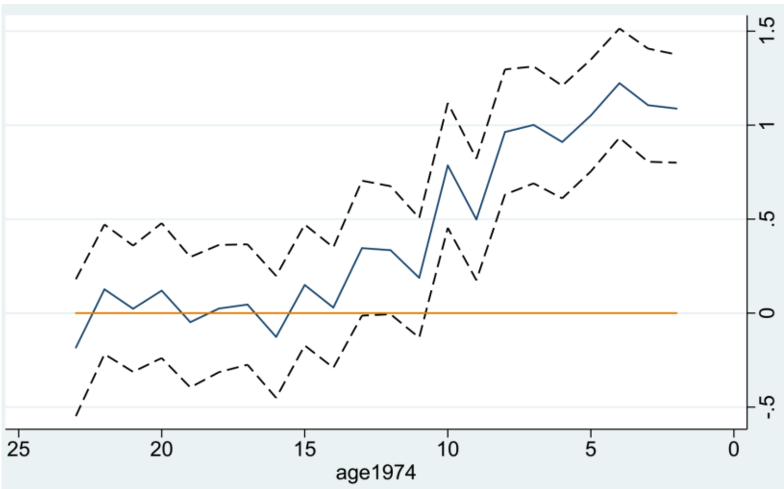

Figure 2. Impacts of the School Construction Program on Years of Education: Reduced-Form Evidence
Dependent variable: Years of Education
The solid line between the two dashed lines show the coefficient of the interaction of cohort of birth and program intensity in the region of birth.
The dashed lines represent the 95 percent confidence interval.
Age in 1974 is on the horizontal axis.
Years of Education are on the vertical axis.

Table 2. the Impacts of the School Construction Program on Years of Education: Reduced-Form Evidence

Age in 1974	$\boldsymbol{intens_j \times d_{il}}$	schooling
23	$intens_j \times d_{i23}$	-0.183 (0.185)
22	$intens_j \times d_{i22}$	0.126 (0.175)
21	$intens_j \times d_{i21}$	0.023 (0.171)
20	$intens_j \times d_{i20}$	0.119 (0.183)
19	$intens_j \times d_{i19}$	-0.048 (0.176)
18	$intens_j \times d_{i18}$	0.024 (0.172)
17	$intens_j \times d_{i17}$	0.045 (0.163)
16	$intens_j \times d_{i16}$	-0.126 (0.165)
15	$intens_j \times d_{i15}$	0.149 (0.164)
14	$intens_j \times d_{i14}$	0.029 (0.163)
13	$intens_j \times d_{i13}$	0.345^{*} 0.183)
12	$intens_j \times d_{i12}$	0.334^{*} (0.173)
11	$intens_j \times d_{i11}$	0.187 (0.162)
10	$intens_j \times d_{i10}$	0.785^{***} (0.169)
9	$intens_j \times d_{i9}$	0.498^{***} (0.164)
8	$intens_j \times d_{i8}$	0.963^{***} (0.169)
7	$intens_j \times d_{i7}$	1.00^{***} (0.158)
6	$intens_j \times d_{i6}$	$0\ .910^{***}$ (0.152)
5	$intens_j \times d_{i5}$	1.05^{***} (0.151)
4	$intens_j \times d_{i4}$	1.223^{***} (0.148)
3	$intens_j \times d_{i3}$	1.106^{***} (0.153)
2	$intens_j \times d_{i2}$	1.088^{***} (0.146)
	Number of observations	7,581
	R squared	0.211

Dependent variable: Years of Education
All regressions are clustered by member of family members in each household.
Standard errors are in parentheses.
*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

4.1.2 Restricted Estimation

In the previous section, we tested whether the impact of the program on years of education of the children older than 12 in 1974 is zero. In this section, however, children older than 12 are omitted from the regression and form the control group. This approach provides us with more precise estimations of the program on the cohorts exposed to it. Estimates of equation 4 provide us with such results.

$$Edu_{ijk} = c_1 + \gamma_{1l}\sum_{l=2}^{12}(intens_j \times d_{il}) + \delta_{1l}\sum_{l=2}^{12}(C_j \times d_{il}) + \alpha_{1j} + \beta_{1k} + \varepsilon_{ijt} \tag{4}$$

The estimates of γ_{1l} are presented in Table 3. The dependent variable in columns (1) to (3) is years of schooling (i.e. from the first year of elementary to the highest levels of education). The dependent variable in columns (4) to (6) is years of elementary schooling (i.e. 6 years of education in elementary school). In each case, the regressions are presented in three different columns based on the control variables used in the estimations. As can be seen in the table, for children aged 2 to 10 years-old, the impact of the program on years of education is positive and statistically significant. For the ones aged 11 and 12, however, the coefficients are smaller, and they are not statistically significant. These results show that the older students did not benefit from the school construction program as much as students of the younger cohorts did.

Table 3. Impacts of the School Construction Program on Years of Education: Restricted Estimations

		Years of Education			Years of Education at Elementary School		
Age in 1974	$intens_j \times d_{il}$	(1)	(2)	(3)	(4)	(5)	(6)
12	$intens_j \times d_{i12}$	0.282**	0.082	0.044	0.005	-0.016	-0.020
		(0.121)	(0.124)	(0.128)	(0.045)	(0.046)	(0.047)
11	$intens_j \times d_{i11}$	0.135	-0.106	-0.121	0.024	-0.002	0.004
		(0.104)	(0.109)	(0.115)	(0.041)	(0.043)	(0.045)
10	$intens_j \times d_{i10}$	0.731***	0.463***	0.443***	0.182***	0.151***	0.156***
		(0.116)	(0.123)	(0.129)	(0.039)	(0.042)	(0.044)
9	$intens_j \times d_{i9}$	0.443***	0.142	0.129	0.037	0.003	0.009
		(0.109)	(0.118)	(0.126)	(0.039)	(0.042)	(0.046)
8	$intens_j \times d_{i8}$	0.908***	0.566***	0.540***	0.191***	0.154***	0.160***
		(0.118)	(0.128)	(0.137)	(0.038)	(0.042)	(0.046)
7	$intens_j \times d_{i7}$	0.947***	0.568***	0.535***	0.234***	0.196***	0.203***
		(0.102)	(0.116)	(0.126)	(0.032)	(0.037)	(0.042)
6	$intens_j \times d_{i6}$	0.856***	0.459***	0.451***	0.224***	0.181***	0.190***
		(0.092)	(0.107)	(0.122)	(0.031)	(0.037)	(0.043)
5	$intens_j \times d_{i5}$	0.997***	0.568***	0.541***	0.246***	0.199***	0.203***
		(0.089)	(0.109)	(0.125)	(0.028)	(0.036)	(0.042)
4	$intens_j \times d_{i4}$	1.168***	0.699***	0.674***	0.317***	0.266***	0.276***
		(0.086)	(0.108)	(0.127)	(0.026)	(0.034)	(0.042)
3	$intens_j \times d_{i3}$	1.052***	0.554***	0.536***	0.301***	0.246***	0.252***
		(0.093)	(0.117)	(0.136)	(0.030)	(0.039)	(0.046)
2	$intens_j \times d_{i2}$	1.034***	0.479***	0.455***	0.384***	0.324***	0.332***
		(0.080)	(0.113)	(0.135)	(0.026)	(0.038)	(0.047)
	Control variables:						
	Year of birth × enrollment rate in 1971		Y	Y		Y	Y
	Year of birth × water and sanitation program			Y			Y
	Number of observations	7,581	7,538	7,112	8,776	8,726	8,193
	R squared	0.209	0.216	0.214	0.113	0.113	0.112

Dependent variables: Years of Education (columns (1) to (3)) and Years of Education in Elementary School
All regressions are clustered by number of family members in each household.
Standard errors are in parentheses.
*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

4.1.3 Impact on Levels of Education

In this section, we investigate the impact of the school construction program on levels of education. Also, we run separate regressions for females and males to see how differently they get affected by the program. To do so, the following regression is estimated:

$$Edu_{ijkm} = c + k_m(intens_j \times Young_i) + \alpha_j + \beta_k + \varepsilon_{ijt} \tag{5}$$

where Edu_{ijkm} is a binary variable that sets to one if individual *i* in region *j* born in year *k* has completed *m* years of education or above. This binary variable takes value zero otherwise. We have estimated this regression for m=0 to 13 separately. The results are provided in Figure 3 and Table 4. The solid line between the two dashed lines in Figure 3. A, B, and C. represent the coefficients of the interaction of program intensity and binary variable $Young_i$ (i.e. k_m). The plotted coefficients in Figure 3 are represented in the form of numbers in Table 4. Part A of Figure 3 and the first column of Table 4 show that the program does not have significant impacts on people with 10 or more years of education. Part B of Figure 3 and the second column in Table 4 show the results of estimations of equation 5 for females. As the results show, the program has a significant impact on years of education of females in elementary school but has no significant impact on completing 7 years of education or above. Part C of Figure 3 and the third column in Table 4 represent the results of estimations of equation 5 for males. As can be seen, the program has benefited the males to the last year of high school (i.e. 12 years of education). However, it does not have much impact on 13 years of education and above.

An interesting point in these regressions is that the impact of the program on some years of elementary school education (m=3 to m=6) of the females is larger than that of the males even though the program does not have any significant impact on their education level above elementary school education. One reason for such results could be that, in the poorer areas of the country, the female children would not be sent to school unless the school is nearby. Hence, the school construction program provided a chance for the young women to attend school. This could be the case for a large portion of the male children as well, but in a much smaller rate than that of the female children. Perhaps higher rates of male children were sent to school even if the school was far away from where they lived.

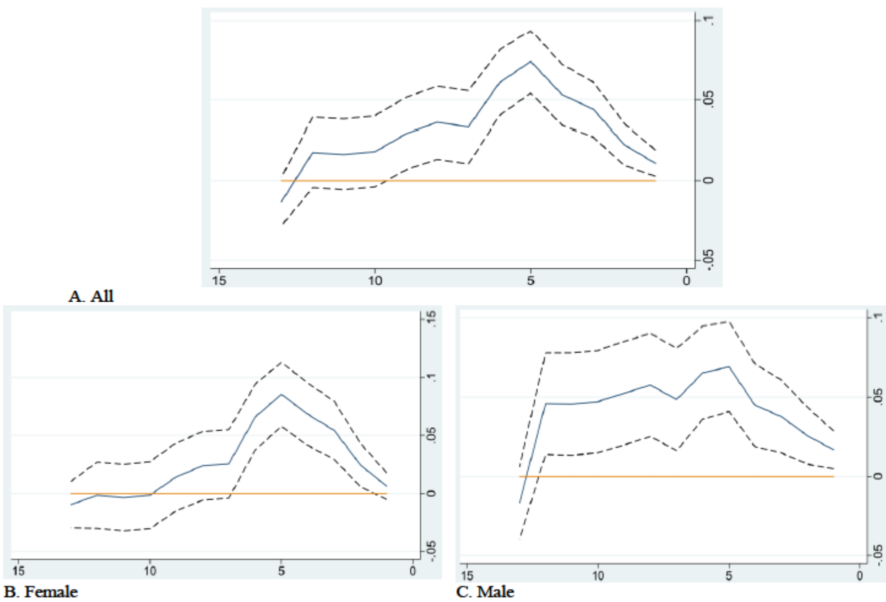

Figure 3. The impact of the program on levels of education. A: All children, B: Female, and C: Male

Dependent variables: Binary variables that take value one if a person completed m years of education or above and they take value zero otherwise. These variables (i.e. Edu_{ijkm}) are on horizontal axes. Region of birth and cohort of birth fixed effects are included in all regressions. Also, the interactions of year of birth and enrolment rate in the region of birth is included in all of the regressions

The solid line between the two dashed lines show the coefficients of the interactions of cohort of birth and program intensity in the region of birth. The dashed lines represent the 95 percent confidence interval. All regressions are clustered by number of family members in each household.

Coefficients (i.e. k_m) are on vertical axes.

Table 4. the Impacts of the School Construction Program on Levels of Education

Edu_{ijkm}	All	Female	Male
m=1	0.010**	0.011	0.016***
	(0.004)	(0.005)	(0.006)
m=2	0.022***	0.024**	0.025***
	(0.006)	(0.009)	(0.009)
m=3	0.044***	0.054***	0.037***
	(0.008)	(0.012)	(0.011)
m=4	0.053***	0.068***	0.044***
	(0.009)	(0.013)	(0.013)
m=5	0.085***	0.073***	0.069***
	(0.014)	(0.010)	(0.014)
m=6	0.065***	0.073***	0.065***
	(0.014)	(0.010)	(0.014)
m=7	0.025*	0.017	0.048***
	(0.015)	(0.011)	(0.016)
m=8	0.035***	0.023	0.057***
	(0.011)	(0.015)	(0.016)
m=9	0.029**	0.014	0.052***
	(0.011)	(0.014)	(0.016)
m=10	0.017	-0.001	0.047***
	(0.011)	(0.014)	(0.016)
m=11	0.016	-0.003	0.045***
	(0.011)	(0.014)	(0.016)
m=12	0.017	-0.005	0.045***
	(0.011)	(0.014)	(0.016)
m=13	-0.013*	-0.009*	-0.016*
	(0.007)	(0.010)	(0.011)
Year of birth × enrollment rate in 1971	Y	Y	Y

Dependent variables: Binary variables that take value one if a person completed m years of education or above and they take value zero otherwise. Region of birth and cohort of birth fixed effects are included in all regressions. Also, the interactions of year of birth and enrolment rate in the region of birth is included in all of the regressions. The upper numbers in each cell show the coefficient of the interaction of program intensity and $Young_i$ (i.e. k_m). Standard errors are in parentheses. All regressions are clustered by number of family members in each household.
*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

Here, we use specifications of equation 1 to further investigate the impact of the program on years of education of females and males. The results of the estimations are provided in Table 5. In the first three columns of the table, both genders are represented. However, in columns (4) to (6), only females are included in the regressions. In columns (8) to (10), only males are represented. The table shows the coefficient of interactions of school construction intensity in the region of birth and being in the young cohort (i.e. γ_1 in equation 1). The dependent variable in columns (1), (4), and (7) is years of elementary schooling education. Also, the dependent variable in columns (2), (5), and (8) is a binary variable that sets one if a person has completed 6 years of education and above. This variable takes value zero if someone has completed 5 or less years of education. The dependent variable in columns (3), (6), and (9) is a binary variable that sets one if a person has completed 7 years of education and above. This variable takes value zero if someone has completed 6 or less years of education. Note that the impact of the program on the mentioned binary variables is estimated in Table 4, but we have added extra control variables to our estimations in Table 5. Besides the fixed effects, the interactions of year of birth, and enrolment rate in the region of birth, other control variables including the water and sanitation program, city, village, family size, and electricity are added to the regressions. The results confirm our previous findings regarding the impact of the program on education level of females and males.

The results show that the program had a positive impact on the elementary school education level of the females, but did not have any significant impact their years of education above elementary school. Although we saw that the impact of the program on years 3 to 6 of elementary school education of the females was larger than that of the males in the previous table, the results in Table 5 suggest that the overall impact of the program on elementary school education of the males could be larger than that of the females.

Table 5. the Impacts of the School Construction Program on Education: By Gender

	All			Female			Male		
	(1) Elem. Edu	(2) 6 years & above	(3) 7 years & above	(4) Elem. Edu	(5) 6 years & above	(6) 7 years & above	(7) Elem. Edu	(8) 6 years & above	(9) 7 years & above
$intens_j \times Young_i$	0.198*** (0.039)	0.060** (0.011)	0.023** (0.012)	0.197*** (0.055)	0.064** (0.015)	0.015 (0.110)	0.213*** (0.060)	0.064*** (0.016)	0.038** (0.017)
Number of observations	3,980	3,737	3,737	2,149	1,974	1,974	1,831	1,763	1,763
R squared	0.172	0.222	0.278	0.216	0.279	0.340	0.184	0.238	0.304

Elem. Edu shows the number of years of elementary school that a person has completed. 6 years & above is a binary variable that sets one if a person has completed 6 years of education and above. This variable takes value zero if someone has completed 5 or less years of education. 7 years & above is a binary variable that sets one if a person has completed 7 years of education and above. This variable takes value zero if someone has completed 6 or less years of education.
Region of birth and cohort of birth fixed effects are included in all regressions. The interactions of year of birth and enrolment rate in the region of birth is also included in all of the regressions. The rest of control variables include the water and sanitation program, city, village, family size, and electricity. City is a binary variable that indicates whether a person lives in a city. Village is a binary variable that indicates whether a person lives in a village. Family size shows the actual number of household members that live in family. Electricity is a binary variable that determines if electricity is available in the region of birth.
All regressions are clustered by number of family members in each household.
Standard errors are in parentheses
*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

4.2 Effect on Fluid Intelligence

Table 6 represents the estimations of equations 1 where the outcome variables is standardized Raven test score. Three columns are provided in the table. The columns differ based on the control variables included in the regressions. The results are presented in two panels. In Panel A, which is our experiment of interest, $Young_i$ indicates the young cohort who was exposed to the program versus an older cohort who was not exposed to the program. It is equal to one for children aged 2 to 6 in 1974, and it equals to zero for those aged 12 to 17 in 1974. The impact of the program on the standardized Raven test score varies from 4.3 to 5.7 percentage points. Panel B represents our control experiment. In panel B, instead of “young” in panel A, we use a dummy variable that sets to one for those aged 12 to 17 in 1974 and takes value zero for the others that aged 18 to 24 in 1974. Note that we do not expect to see any significant impact of the program in panel B because people aged 12 to 24 in 1974 were not exposed to the program. As expected, the results of panel B show significantly smaller coefficients with no significant impact of the school construction program on standardized Raven test score.

Table 6. the Impacts of the School Construction Program on Raven Test Scores: Basic Results

	Standardized Raven Test Scores		
$intens_j \times Young_i$	(1)	(2)	(3)
Panel A: experiment of interest			
Aged 2 to 6 in 1974	0.056***	0.057***	0.043**
Control: Aged 12 to 17 in 1974	(0.020)	(0.021)	(0.019)
Number of observations	4,763	4,473	3,980
R squared	0.117	0.121	0.212
Panel B: control experiment			
Aged 12 to 17 in 1974	-0.005	-0.006	-0.013
Control: Aged 18 to 24 in 1974	(0.017)	(0.017)	(0.017)
Number of observations	3,987	3,777	3,322
R squared	0.112	0.114	0.171
Control variables:			
Year of birth × enrollment rate in 1971	Y	Y	Y
Year of birth × water and sanitation program		Y	Y
Other control variables[1]			

Dependent variables: Raven Test Scores. Region of birth and year of birth fixed effects are included in all regressions. Other control variables include city, village, family size, and electricity. City is a binary variable that indicates whether

a person lives in a city. Village is a binary variable that indicates whether a person lives in a village. Family size shows the actual number of household members that live in family. Electricity is a binary variable that determines whether electricity is available in the region of birth.
Young in panel A is a binary variable that takes the value one if someone aged 2 to 6 in 1974 and takes value zero for the ones aged 12 to 17 in 1974.
The difference between Panel A and Panel B is that, in panel B, we have used a different binary variable instead of young in Panel A. In Panel B, this variable takes value one if someone aged 12 to 17 in 1974 and takes value zero for the ones aged 18 to 24 in 1974.
All regressions are clustered by number of family members in each household.
Standard errors are in parentheses.
*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

In Table 6, some basic results of the impact of the program on fluid intelligence measured by Raven test scores are presented and discussed. In this section, we further investigate the impacts of the program on fluid intelligence. Note that our results so far show that the school construction program increased years of education. This provides an exogenous variation in the years of schooling when controlling for region of birth and cohort of birth effects, which enables us to investigate the causal impacts of education on fluid intelligence.

4.2.1 Reduced-Form Evidence

In this section, the estimates of equation 6 provides us with reduced-form evidence where the impact of the program on standardized Raven test scores of cohorts aged 2 to 23 in 1974 is investigated. l=24 is omitted to form our control cohort. The coefficients of the interactions of the program intensity in the region of birth and the cohort dummies determine the impact of the program on Raven test score.

$$Raven_{ijk} = c_2 + \gamma_{2l} \sum_{l=2}^{23} (intens_j \times d_{il}) + \delta_{2l} \sum_{l=2}^{23} (C_j \times d_{il}) + \alpha_{2j} + \beta_{2k} + \epsilon_{ijt} \quad (6)$$

where d_{il} stands for year of birth dummy variables. It takes a value of one if individual i was age l in 1974. Hence, each coefficient of the interaction of program intensity in the region of birth and d_{il} shows the impact of the program on cohort l. $Raven_{ijk}$ shows the standardized Raven test score of individual i in region j born in year k. α_{2j} and β_{2k} show the region of birth and cohort of birth fixed effects, respectively.

Figure 4 and Figure 5 plot the described coefficients above (i.e. γ_{2l}). Also, the associated results are provided in Table 7. The difference between the mentioned figures comes from the control variables that are applied in the estimations of the regressions. The dashed lines in the figures show the 95 percent confidence interval.

The results show that the program has a positive and significant impact on Raven test score of the children aged 2 to 5 in 1974, but does not confirm any significant impact of the program on the Raven test score of the other cohorts. As expected, the results show that, for the ones aged 12 and older in 1974, the coefficients randomly vary around zero and are not statistically significant. For cohorts younger than 11 years-old in 1974, the size of the coefficients is bigger than that of those 12 years-old and above, but they are not statistically significant.

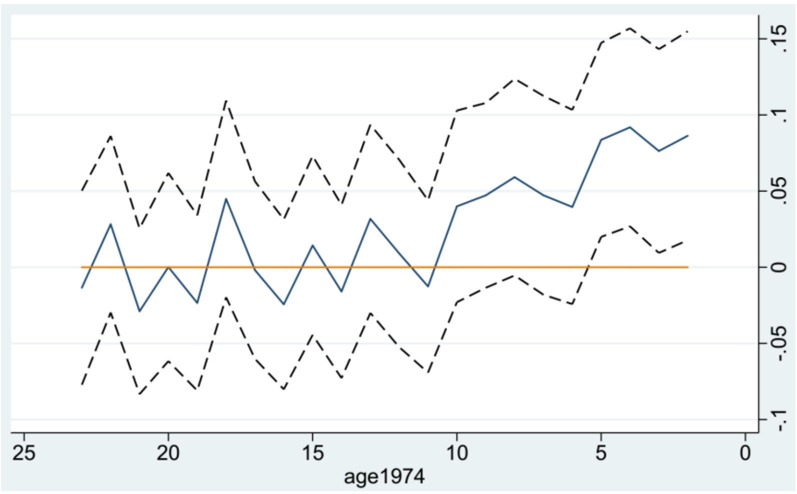

Figure 4. Impacts of the School Construction Program on Raven test score: Reduced-Form Evidence

Dependent variable: standardized Raven test score
The solid line between the two dashed lines show the coefficient of the interaction of cohort of birth and program intensity in the region of birth.
Region of birth and cohort of birth fixed effects are included in all regressions.
The dashed lines represent the 95 percent confidence interval.
Age in 1974 is on horizontal axis.
Standardized Raven test score is on vertical axis.
Year of birth × enrollment rate in 1971 is included.

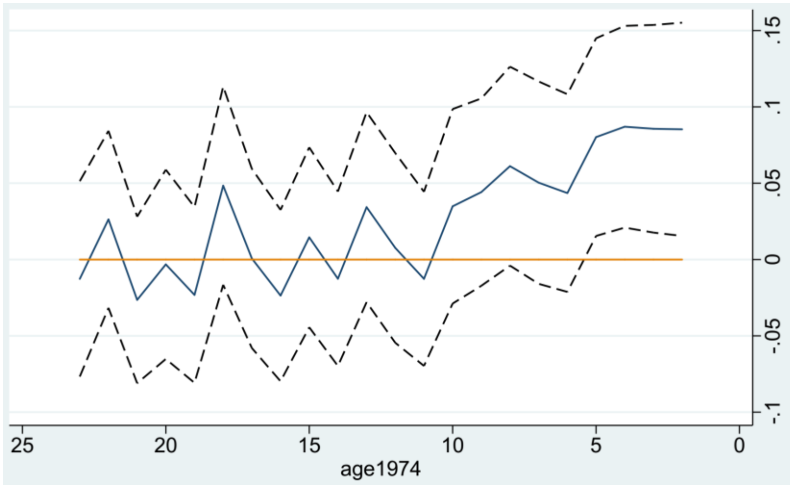

Figure 5. Impacts of the School Construction Program on Raven test score: Reduced-Form Evidence
Dependent variable: standardized Raven test score
The solid line between the two dashed lines show the coefficient of the interaction of cohort of birth and program intensity in the region of birth.
Region of birth and cohort of birth fixed effects are included in all regressions.
The dashed lines represent the 95 percent confidence interval.
Age in 1974 is on horizontal axis.
Standardized Raven test score is on vertical axis.
Year of birth × enrollment rate in 1971 is included.
Year of birth × water and sanitation program is included.

Table 7. Impact of the School Construction Program on Fluid Intelligence: Reduced-Form Evidence

Age in 1974	$\boldsymbol{intens_j \times d_{il}}$	**(1)**	**(2)**
23	$intens_j \times d_{i23}$	-0.013	-0.012
		(0.032)	(0.032)
22	$intens_j \times d_{i22}$	0.028	0.026
		(0.029)	(0.029)
21	$intens_j \times d_{i21}$	-0.028	-0.026
		(0.027)	(0.002)
20	$intens_j \times d_{i20}$	0.0001	-0.003
		(0.031)	(0.031)
19	$intens_j \times d_{i19}$	-0.023	-0.023
		(0.029)	(0.029)
18	$intens_j \times d_{i18}$	0.044	0.048
		(0.032)	(0.033)
17	$intens_j \times d_{i17}$	-0.001	0.0007
		(0.029)	(0.029)
16	$intens_j \times d_{i16}$	-0.024	-0.023
		(0.028)	(0.028)
15	$intens_j \times d_{i15}$	0.014	0.014
		(0.029)	(0.030)
14	$intens_j \times d_{i14}$	-0.015	-0.012
		(0.029)	(0.029)
13	$intens_j \times d_{i13}$	0.031	0.034
		(0.031)	(0.031)
12	$intens_j \times d_{i12}$	0.0090	0.007

		(0.031)	(0.031)
11	$intens_j \times d_{i11}$	-0.012 (0.028)	-0.012 (0.029)
10	$intens_j \times d_{i10}$	0.039 (0.032)	0.034 (0.032)
9	$intens_j \times d_{i9}$	0.047 (0.030)	0.044 (0.031)
8	$intens_j \times d_{i8}$	0.059* (0.032)	0.061** (0.033)
7	$intens_j \times d_{i7}$	0.047 (0.033)	0.050 (0.033)
6	$intens_j \times d_{i6}$	0.039 (0.032)	0.043 (0.033)
5	$intens_j \times d_{i5}$	0.083** (0.032)	0.080** (0.033)
4	$intens_j \times d_{i4}$	0.091*** (0.033)	0.087** (0.033)
3	$intens_j \times d_{i3}$	0.076** (0.034)	0.085** (0.034)
2	$intens_j \times d_{i2}$	0.086** (0.034)	0.085** (0.035)
	Control variables:		
	Year of birth × enrollment rate in 1971	Y	Y
	Year of birth × water and sanitation program		Y
	Number of observations	8,722	8,189
	R squared	0.108	0.112

Dependent variable is standardized Raven test score in all cases. Region of birth and cohort of birth fixed effects are included in all regressions. All regressions are clustered by number of family members in each household. Standard errors are in parentheses.

*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

4.2.2 Restricted Estimations

Estimations of equation 7 give us a more precise understanding of the impacts of the program on Raven test scores. Children aged over 12 in 1974 are dropped from the regressions to form the control group:

$$Raven_{ijk} = c_2 + \gamma_{2l}\sum_{l=2}^{12}(intens_j \times d_{il}) + \delta_{2l}\sum_{l=2}^{12}(C_j \times d_{il}) + \alpha_{2j} + \beta_{2k} + \epsilon_{ijt} \tag{7}$$

where d_{il} stands for year of birth dummy variables. This variable takes value one if individual i ages l in 1974. Each coefficient of the interaction of program intensity in the region of birth and d_{il} shows the impact of the program on cohort l. As mentioned before, cohorts aged 13 to 24 in 1974 are omitted from the estimations to form the control group. $Raven_{ijk}$ shows the standardized Raven test score of individual i in region j born in year k and α_{2j} and β_{2k} show and region and cohort of birth fixed effects, respectively.

The results are presented in Table 8. In column (1) of Table 8, where region of birth and cohort of birth fixed effects are included but not any other control variables, the impact of the program on standardized Raven test score of the cohorts aged 2 to 10 in 1974 is positive and statistically significant. However, the impact of the program on cohorts aged 11 and 12 is much smaller and statistically significant only at 10 percent level. In column (2), besides region of birth and cohort of birth fixed effects, the interactions of year of birth and enrollment rate in 1971 are included as control variables. In column (2), the coefficients are smaller than those of column (1), but they are also statistically significant for the cohorts aged 2 to 10 in 1974. In column (3), besides our usual fixed effects and the interactions of year of birth and enrollment rate in 1971, interactions of year of birth and water and sanitation program are included as control variables. The results in column (3) show significant impacts of the program on the standardized Raven test score of cohorts younger than 9 years old. In column (3), the size of the coefficients is not too different from those of column (2). The size of the coefficients in column (1) is as big as 18.6 percentage points but varies from 3.7 to 8.9 percentage points in column (2), and from 3.9 to 8 percentage points in column (3).

Table 8. Impact of the School Construction Program on Fluid Intelligence: Restricted Estimations

		standardized Raven test score		
Age in 1974	$\boldsymbol{intens_j \times d_{il}}$	**(1)**	**(2)**	**(3)**
12	$intens_j \times d_{i12}$	0.041*	0.007	0.004
		(0.021)	(0.022)	(0.022)
11	$intens_j \times d_{i11}$	0.030*	-0.013	-0.015
		(0.017)	(0.018)	(0.018)
10	$intens_j \times d_{i10}$	0.087***	0.038**	0.031
		(0.021)	(0.022)	(0.023)
9	$intens_j \times d_{i9}$	0.101***	0.045**	0.040*
		(0.018)	(0.020)	(0.021)
8	$intens_j \times d_{i8}$	0.120***	0.057**	0.057**
		(0.021)	(0.023)	(0.023)
7	$intens_j \times d_{i7}$	0.113***	0.045**	0.046**
		(0.020)	(0.023)	(0.023)
6	$intens_j \times d_{i6}$	0.110***	0.037*	0.039*
		(0.019)	(0.022)	(0.022)
5	$intens_j \times d_{i5}$	0.160***	0.081***	0.075***
		(0.018)	(0.021)	(0.021)
4	$intens_j \times d_{i4}$	0.175***	0.089***	0.082***
		(0.018)	(0.022)	(0.023)
3	$intens_j \times d_{i3}$	0.166***	0.073***	0.080***
		(0.019)	(0.023)	(0.024)
2	$intens_j \times d_{i2}$	0.186***	0.083***	0.079***
		(0.018)	(0.024)	(0.024)
	Control variables:			
	Year of birth × enrollment rate in 1971		Y	Y
	Year of birth × water and sanitation program			Y
	Number of observations	8,772	8,722	8,189
	R2	0.102	0.107	0.111

Dependent variable is standardized Raven test score in all columns. Region of birth and cohort of birth fixed effects are included in all regressions. All regressions are clustered by number of family members in each household. Standard errors are in parentheses.

*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

4.3 Two-Stage Least-Squares Estimates

Consider the following equation that estimates the impacts of years of education on Raven test scores:

$$Raven_{ijk} = d + \theta Edu_{ijk} + \alpha_j + \beta_k + \mu_{ijt} \quad (8)$$

where all the variables are introduced before. If years of education is not endogenous, then least-square estimates of this equation would reflect the causal effect of education on Raven test scores. However, if there is a correlation between education and error term in equation 8, the result of the least-square estimation is biased.

One of the most famous examples of endogeneity in empirical economics is when education is one of the right-hand-side variables in an equation. Endogeneity of education when wage is the dependent variable has been heavily discussed in the return to education literature. In recent decades, many researchers have discussed that education is an endogenous variable in such regressions due to omitted variable bias. A variable that plausibly affects both education and wages is innate ability. In general, a good measurement of innate ability is not available in most of the datasets because it is not an easy variable to measure. When innate ability is omitted from a return to education regression, it will automatically be included in the error term of the regression. Therefore, the innate ability that affects both education and wages and has been included in the error term of the regression, causes a correlation between wages and education. This will cause biased estimates of return to education if least-square estimation is applied. In the case of our research where we are concerned with the impacts of education on fluid intelligence, omitted variables might cause endogeneity and biased estimations. To overcome this issue, we apply the instrumental variables (IV) approach. The interactions between cohorts of birth and program intensity in the region of birth are used as instruments in our 2SLS estimates. We modify equation 8 to incorporate the control variables in the following specification:

$$Raven_{ijk} = d + \theta Edu_{ijk} + \pi_l \sum_{l=2}^{12}(C_j \times d_{il}) + \alpha_j + \beta_k + \mu_{ijt} \quad (9)$$

Also note that equation 4 has been used as the first stage of the two-stage least-square estimates. We have presented the results of least-square estimates in Table 8 and those of the two-stage least-square estimates in Tables 9 and 10.

In Table 8, θs (i.e. the coefficients of years of schooling, Edu_{ijk}) are presented in the table. In the first two columns, both female and male children are represented, while columns (3) and (4) include only female children, and columns (5) and (6) include only male children in the regressions. The findings presented in Table 8 show that an extra year of education is associated with an average of 6.2 to 6.6 percentage points increase in standardized Raven test score.

Table 9. the Impact of Years of Education on Fluid Intelligence: Least Square Estimations

	All		Female		Male	
	(1)	(2)	(3)	(4)	(5)	(6)
Schooling	0.066***	0.066***	0.067***	0.068***	0.062***	0.065***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Number of observations	7,653	6,787	3,920	3,554	3,733	3,233
R squared	0.214	0.277	0.267	0.287	0.206	0.285
Control variables:						
Year of birth × enrollment rate in 1971	Y	Y	Y	Y	Y	Y
Other control variables[1]		Y		Y		Y

Dependent variable is standardized Raven test score in all columns.
All regressions include region of birth and cohort of birth fixed effects.
All regressions are clustered by number of family members in each household.
Standard errors are in parentheses.
*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

As previously discussed, the results in Table 9 could be biased due to endogeneity of education. Hence, we have provided the results of 2SLS estimates in Table 10 and Table 11. The estimations in Table 10 include both genders, but separate regressions have been estimated for females and males in Table 11.

The overall results of the 2SLS estimates show that the program has a positive and significant impact on the Raven test scores of both genders. The coefficients in Table 8 vary between 15.3 to 17.7 percentage points. That means that an extra year of education is associated with an average of 15.3 to 17.7 percentage points increase in the standardized Raven test score. At the same time, these findings confirm the positive and significant impact of the school construction program on Raven test scores.

Table 10. Impact of Years of Education on Fluid Intelligence: Two-Stage Least-Square Estimations

		(1)	(2)	(3)
Schooling		0.153***	0.154***	0.177***
		(0.002)	(0.009)	(0.013)
Test of Week instruments	F	43.006	40.789	24.179
Tests of overidentifying restrictions	Sargan (score) chi2	11.482	9.536	15.623
		(p=0.321)	(p=0.491)	(p=0.110)
	Basmann chi2	11.160	9.160	15.147
		(p=0.345)	(p=0.516)	(p=0.126)
Year of birth × enrollment rate in 1971		Y	Y	Y
Water and sanitation program			Y	Y
Other control variables[1]				Y
Number of observations		7,577	7,151	6,718
R squared		0.049	0.051	0.008

Dependent variable is standardized Raven test score in all columns.

All regressions include region of birth and cohort of birth fixed effects.
All regressions are clustered by number of family members in each household.
Standard errors are in parentheses.
*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

In Table 11, the results of the 2SLS estimates are provided for females (columns (1) to (3)) and males (columns (4) to (6)) separately. Again, the results show positive and significant impacts of the school construction program on Raven test scores. The findings show that an extra year of education is associated with an average of 15.8 to 16.6 percentage points increase in the standardized Raven test score of the females. Also, an extra year of education is associated with an average of 14.6 to 18.4 percentage points increase in standardized Raven test score of the males.

Table 11. Impact of Years of Education on Fluid Intelligence by gender: Two-Stage Least-Square Estimations

		female			male		
		(1)	(2)	(3)	(4)	(5)	(6)
Schooling		0.158***	0.158***	0.166***	0.146***	0.147***	0.184***
		(0.011)	(0.011)	(0.016)	(0.015)	(0.016)	(0.019)
Test of Week instruments	F	30.300	28.658	15.586	15.827	15.128	9.724
Tests of overidentifying restrictions	Sargan (score) chi2	9.966 (p=0.443)	7.383 (p=0.688)	10.341 (p=0.411)	3.605 (p=0.963)	3.699 (p=0.959)	10.11 (p=0.430)
	Basmann chi2	9.945 (p=0.489)	6.987 (p=0.726)	9.761 (p=0.461)	3.404 (p=0.970)	3.487 (p=0.967)	9.498 (p=0.485)
Control variables:							
Year of birth × enrollment rate in 1971		Y	Y	Y	Y	Y	Y
Water and sanitation program			Y	Y		Y	Y
Other control variables[1]				Y			Y
Number of observations		3,886	3,667	3,521	3,691	3,484	3,197
R squared		0.095	0.095	0.094	0.055	0.057	0.049

Dependent variable is standardized Raven test score in all columns.
All regressions include region of birth and cohort of birth fixed effects.
All regressions are clustered by number of family members in each household.
Standard errors are in parentheses.
*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

5. Conclusion

Fluid intelligence, defined as the ability of a person to reason, find patterns, and solve novel problems independent of previously acquired knowledge, is highly crucial in learning, accomplishing any logical-solving problem, and has a big impact on educational and professional success (Neisser et al. 1996; Deary et al., 2007; Rohde and Thompson, 2007; and te Nijenhuis et al., 2007, Jaeggi et al., 2008).

Generally, in the literature it is accepted that years of schooling improves crystallized intelligence, but its impacts on fluid intelligence has not been clearly identified. Studies on the impacts of length of education on fluid intelligence are rare, and the ones that exist have reported mixed results.

Another reason why fluid intelligence is important as a focus of research relates to the new ways of life in a high tech and complicated world. As time passes, high-tech companies shape the world and hire people with capabilities of understanding new technologies. The new generations of laborers have to be capable of solving cognitively demanding novel problems much more than what was expected in the past. As time passes and a larger portion of the world's wealth goes to people with better understanding of technology, the ones who lack the required skills of the new world will be left behind much more than in the past.

In addition, schools are the main institutions that civilized societies have designed for the purpose of education. Education is expensive and time consuming. People in wealthier nations spend one or two decades of their lives on education. However, such an investment is not affordable to billions of people in poorer nations and developing countries. The return to education literature finds positive impacts of length of education on wages. Therefore, the gap between those who can afford to invest in education and those who cannot grow bigger. Moreover, another question relates to the impact of formal education on cognitive abilities. If formal years of schooling affects cognitive abilities, the inequality between rich and poor will be affected. Previously, studies have found positive impacts of years of schooling on crystallized intelligence, and that is not surprising because crystallized intelligence is about acquiring knowledge. How does years of schooling affect fluid intelligence, which is about reasoning and applying logic independent of any acquired knowledge? The answer to this question is essential not only because it tells us about the contribution of formal education to inequality, but also because it is highly essential for the labor market. It is important to know whether more educated employees have stronger capabilities in solving novel problems applying reason and logic.

Furthermore, the answer to this question also helps with the old debate of signaling and human capital of labor economics. According to the signaling view a school degree is important because of its informational value. Credentials reveal the ability of prospective employees to the employers. However, according to the human capital view, investment in education increases productivity and therefore income of the employees.

One issue in studying the impacts of education on wages or intelligence is the endogeneity of education. An exogenous variation in years of schooling helps to overcome this issue. This research applies the Indonesian Sekolah Dasar INPRES school construction program, which took place between 1973 and 1978, as an exogenous variation in education to study the impacts of schooling on fluid intelligence.

The results show that the Indonesian Sekolah Dasar INPRES school construction program had a positive and significant impact on years of schooling. In addition, we find positive impacts of years of education on fluid intelligence.

One of the results of this paper is that the program does not equally affect the years of schooling of males and females. It has a significant impact on the years of elementary schooling education of females but does not have any impact on their levels of education beyond 6 years of schooling. It has a slightly smaller impact on years of elementary schooling of males, but the effect on the education of males continues to the last years of high school. The program does not have any impact on years of education beyond high school. Moreover, even for males, the impact on years of high school is significant, but it is not as big as that of the elementary school.

We find significant and positive impact of the program on years of education of the females to the end of their elementary school education, but we did not find any significant impact on their years of education above elementary school. However, our results suggest that the impact of the program on years of education of the males is significant and positive to the end of high school even though it does not have significant impacts on their education beyond high school. Findings of our two-stage least-square specifications suggest that the impact of years of education on fluid intelligence of both females and males is significant and positive and it is not too different across gender.

The findings show that an extra year of education is associated with 15.8 to 16.6 percentage points increase in the standardized Raven test score of females. Also, an extra year of education is associated with 14.6 to 18.4 percentage points increase in the standardized Raven test score of the males.

The findings of this paper are intrinsically important because they tell us about the impacts of education on fluid intelligence. Furthermore, these findings could complete a part of the puzzle of the return to education literature in the labor market that is concerned with wages. Our findings help with understanding why schooling improves wages. Based on the results of this research, one answer is that more educated employees have higher capabilities to find patterns, apply reason, and knowledge in solving novel problems. This finding supports Gary Becker's human capital rather than Michael Spence's signaling view.

Acknowledgments

I sincerely thank Esther Duflo for her support and providing me with the INPRES data. Also, I thank Teresa Molina, Sang-Hyop Lee, Timothy Halliday, Nori Tarui, Jennifer Darrah, Michael Roberts, John Lynham, Inessa Love, and Ekaterina Sherstyuk, and other faculty members of Economics Department at the University of Hawaii at Manoa for valuable inputs and comments. I am especially grateful to Andrew Mason my Ph.D. committee chair for guiding me during this research. I bear sole responsibility for the content of this paper and all errors remain mine.

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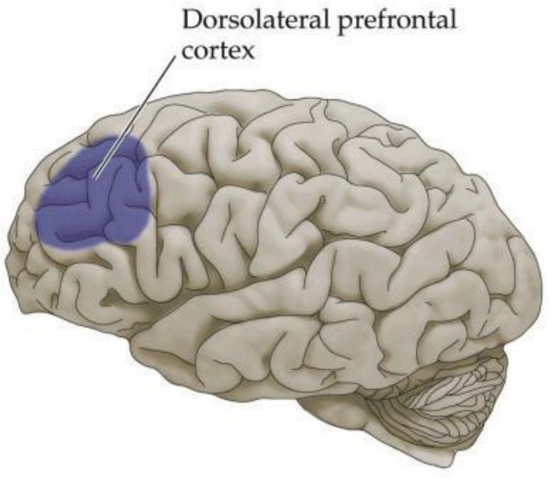
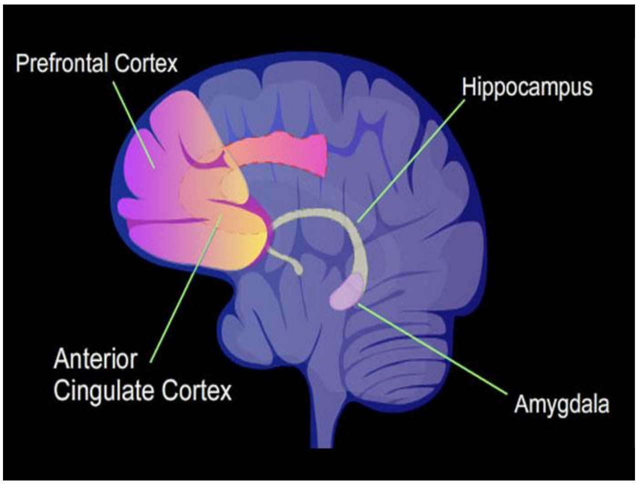
Appendix A





A. B.

Figure 6. Dorsolateral prefrontal cortex, anterior cingulate cortex, and the hippocampus

Figure 6. A and B show dorsolateral prefrontal cortex, anterior cingulate cortex, and the hippocampus in the brain. Fluid intelligence relies on function of the anterior cingulate cortex and dorsolateral prefrontal cortex, while crystallized intelligence is dependent on the function of the hippocampus.
Source of image in Figure 6.A is https://www.sicotests.com/psyarticle.asp?id=191
Source of image in Figure 6.B is National Institute of Mental Health

Appendix B

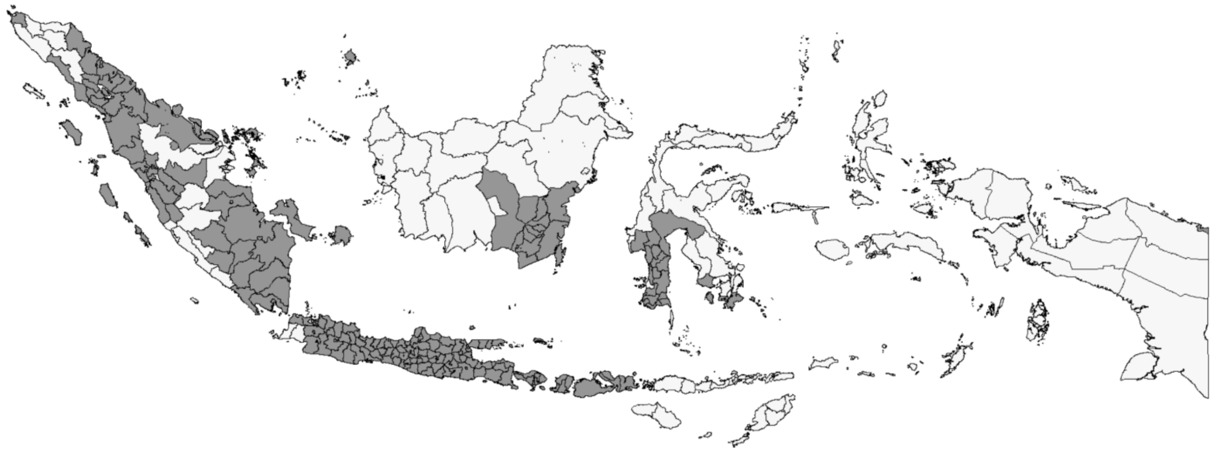


Figure 7. Map of Indonesia. Districts in gray are covered by Indonesian Family Life Survey (IFLS)

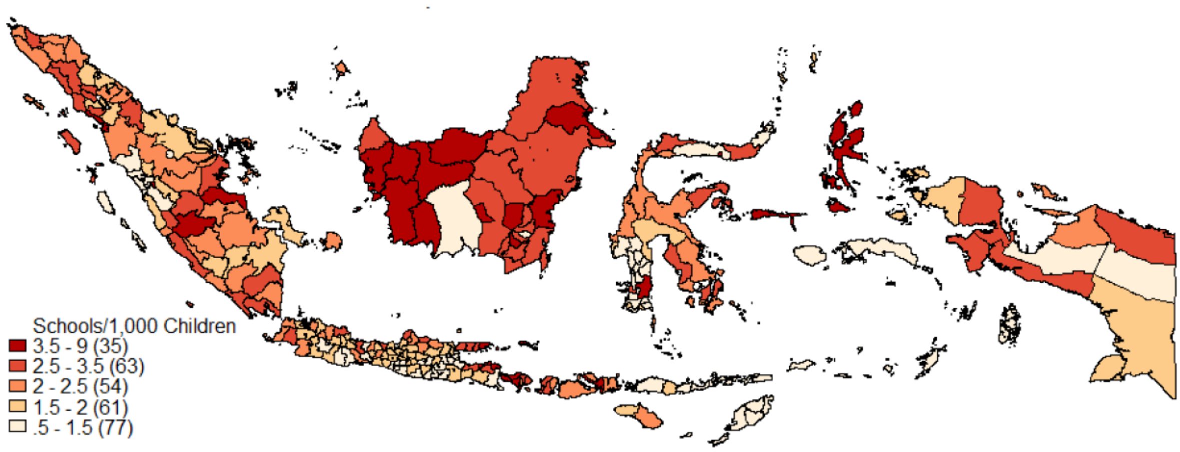
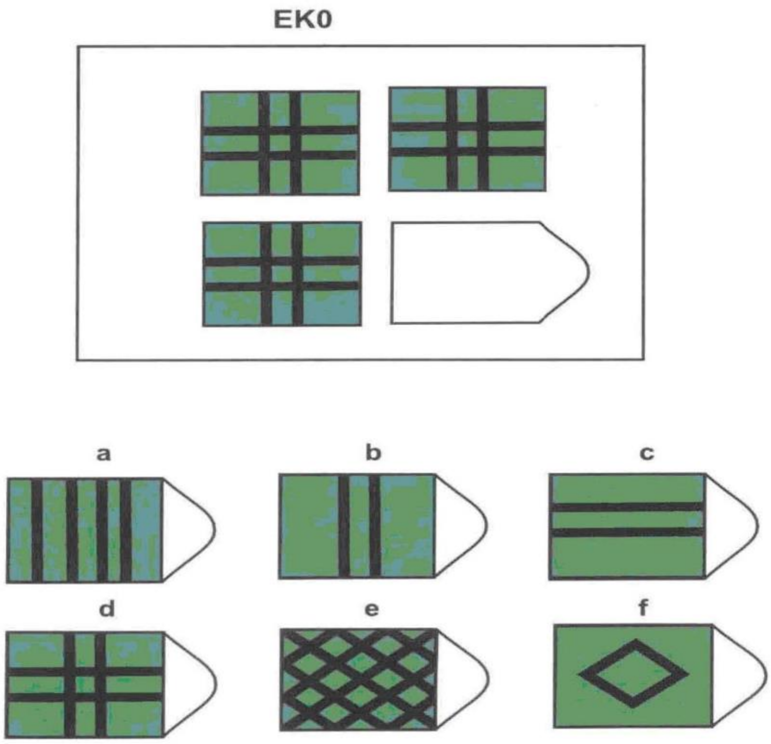


Figure 8. Map of Indonesia. Intensity of the INPRES program from 1973-1978

The darker colors show that number of constructed INPRES schools per 1,000 children is greater than the lighter ones.

Appendix C

The followings are the Raven Progressive Matrices (RPM) that are used in the Indonesian Family Life survey (IFLS).



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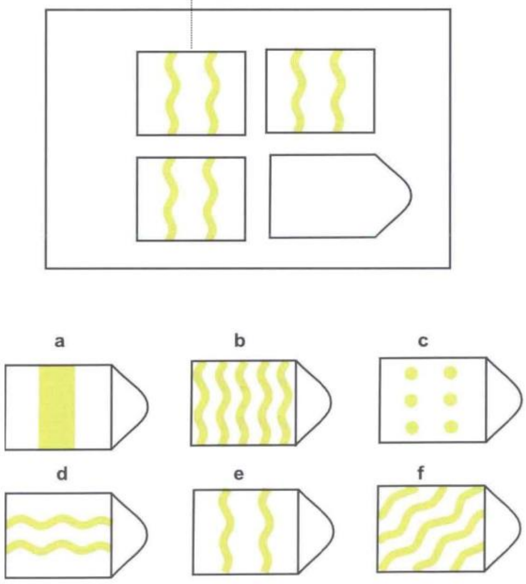

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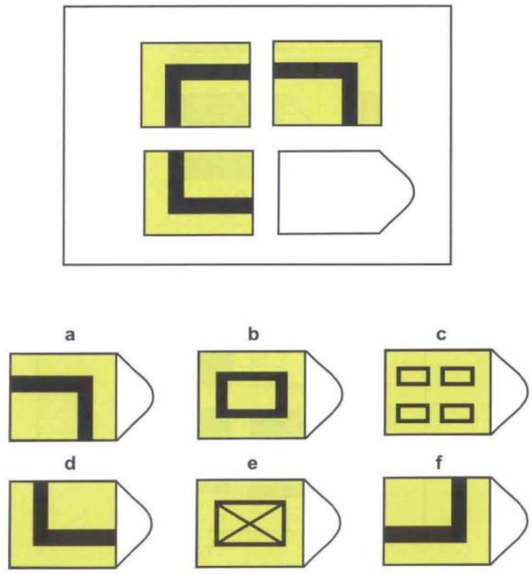

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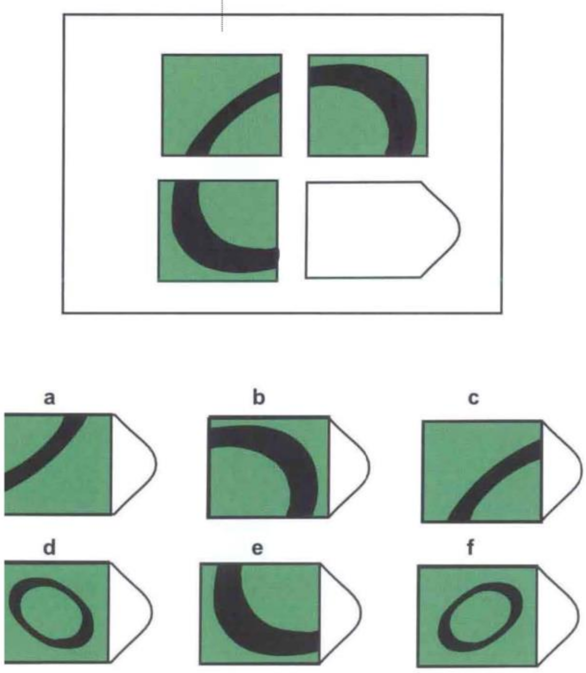

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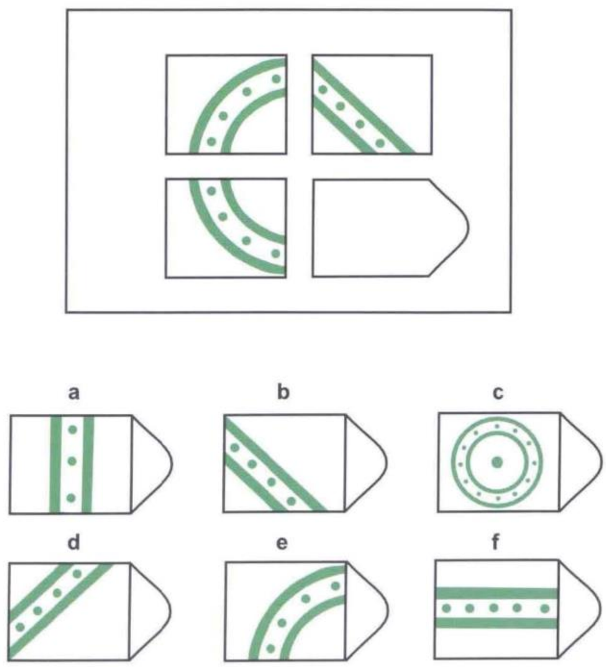
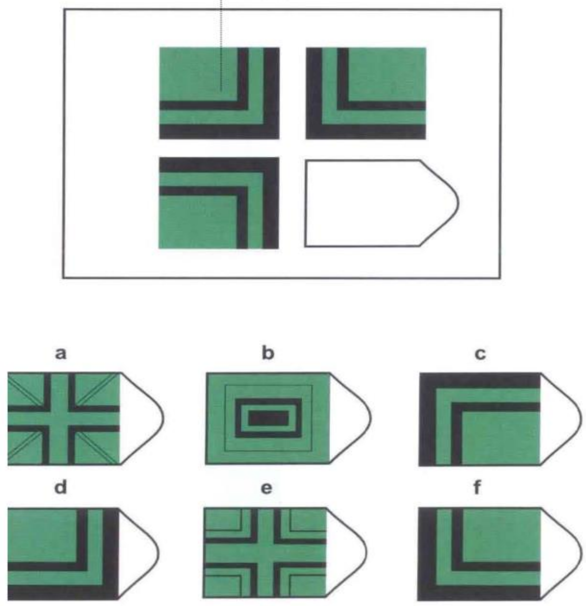
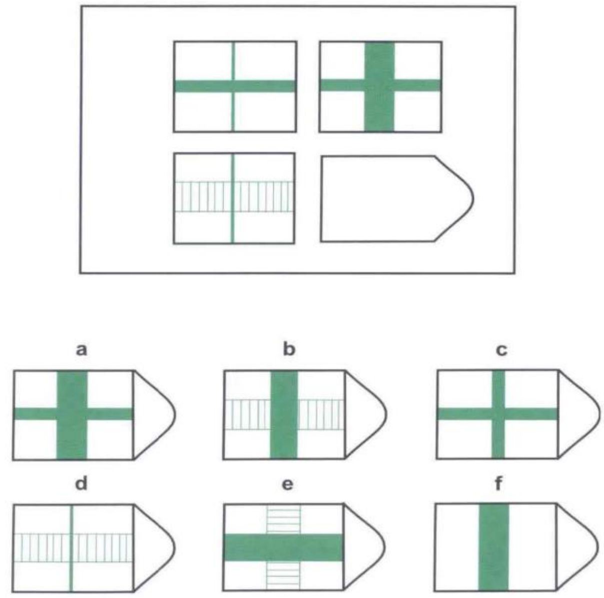


EK5



EK6



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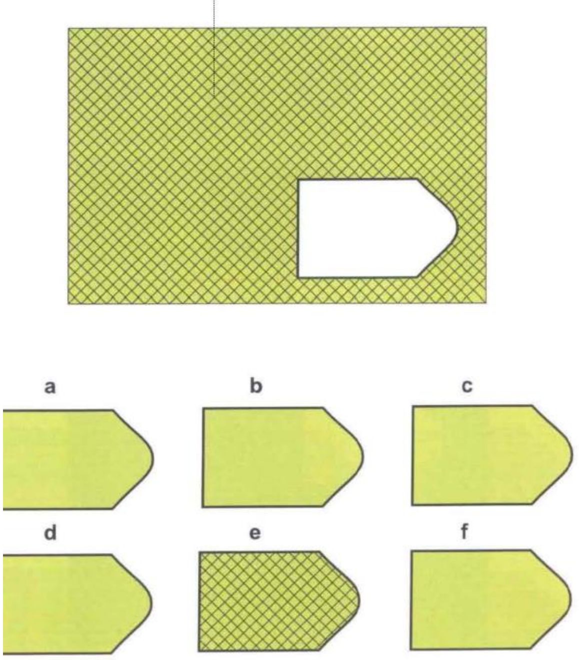
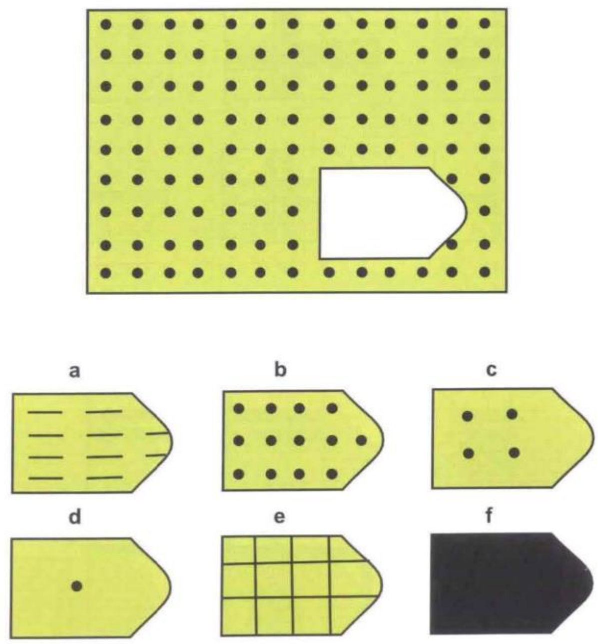
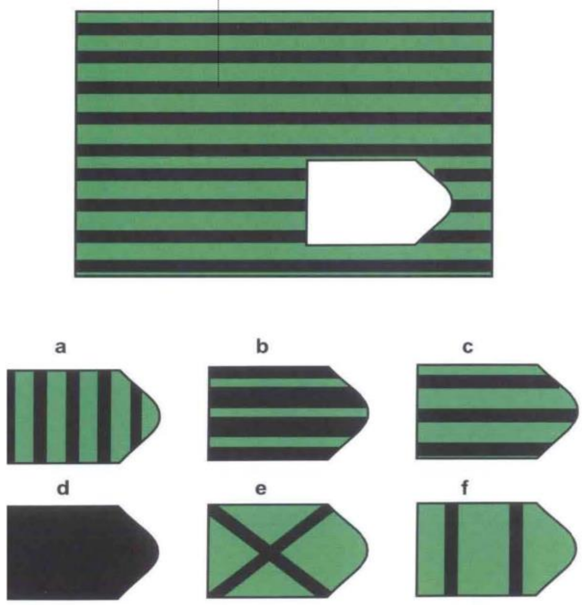


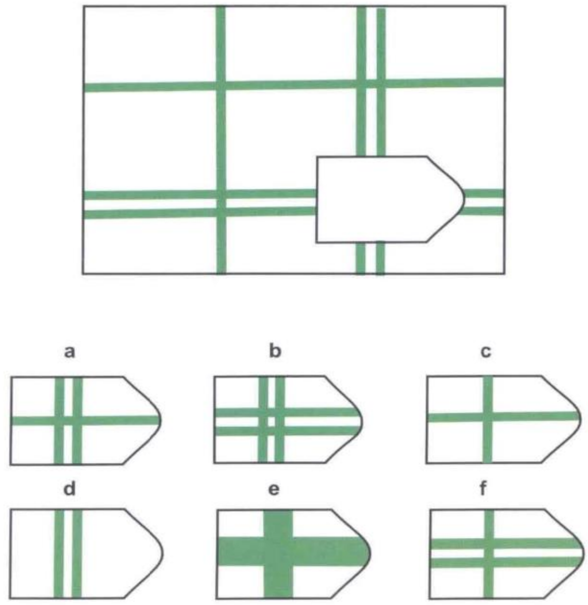
EK8



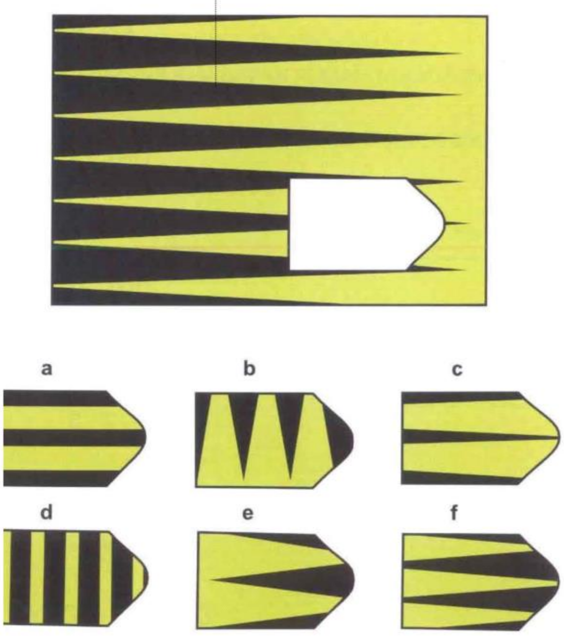
EK9



EK10



EK11



EK12