Whom did Sekolah Desar INPRES benefit? *

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Abstract

Program evaluation often overlooks heterogeneity in treatment effects for subgroups within the population that may vary considerably from the ATE and might be of relevance by themselves. Understanding heterogeneity in treatment effects of such programs will contribute towards better identification of the beneficiaries and more efficient and effective targeting. In this paper, we evaluate how the primary school construction program in Indonesia (Sekolah Desar INPRES) affected children born in good and bad rainfall months differently. We find that INPRES contributed greatly towards narrowing of the gap in attained education between children born in good rain and bad rain months, even though it seems to have almost no impact on those born in good rain months. We show that the evaluations of INPRES might be misleading if one does not account for heterogeneity in treatment effect. We present evidence suggesting that the zero effect for children born in good rain months was as a result of deteriorated teacher quality and increased competition that accompanied the school expansion. Depending on the relative weights assigned to education of children born in good and bad rain months, this has significant implications for the cost benefit analysis of the INPRES program.

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1 Introduction

Sample populations in research studies are heterogeneous . Despite the heterogeneities, while evaluating a program we often estimate average treatment effects. While not all heterogeneities may be of direct interest to the questions being studied, sometimes the treatment effects for subgroups within the population may vary considerably from the ATE and might be of relevance by themselves. Failing to account for heterogeneities in treatment along relevant attributes can mask the effect of the treatment even when it exist.[1] Even in less extreme scenarios, an understanding of heterogeneity in treatment effect can inform policy by better identifying the beneficiaries.

However, it is not wise to go looking for heterogeneity in treatment effect along each dimension that observations in a sample vary in. Selection of such subgroups should be based on prior knowledge or conjectures about the what group attributes might affect an intervention's impact. While heterogeneity analysis along readily observable attributes like ethnicity, gender or age are often explored, investigation of heterogeneity along cognitive abilities, non-cognitive abilities, other health and human capital measures, even though of great importance, is difficult because of the endogenous gradient formation along these variables. In this paper, we argue that natural experiments that affect the subject population before the intervention of interest can be leveraged to unearth these heterogeneities.

The interaction of two exogenous interventions is of interest in its own right. It becomes rather crucial when the interventions target areas of human capital formation like health and education due to their interdependent nature. Such interactions if cooperative in nature are often referred to as 'synergies' in medical literature and the word 'complementarity' has been used in economics to describe the observation.[2][3] Cunha and Heckman (2007a) provides a different theoretical framework that argues it is more reasonable to consider human capital formation as evolutionary process, where investments made in human capital at any given time are likely to be more productive for individuals who received higher investments in the past vis--vis those who received lower investments. Such interaction effects, if significant, can greatly alter the cost benefit calculations of interventions. This possibility, therefore, makes a case for joint evaluation of two or more program, especially if they are contiguous.

Such joint analyses of two or more shocks are important for at least one more reason. Shocks to the early life environment often have long lasting impacts. For example, lack of nu-

[1] For example, consider a hypothetical evaluation that studies the effect of a particular health intervention on a sample population which consists of both men and women. Let us assume that the treatment improves the health of women but worsens the health of men. If we do not control for heterogeneity in treatment effect, we might estimate a zero effect for the sample even though gender specific effects are not zero.

[2] According to Miller-Keane Encyclopedia and Dictionary of Medicine, Nursing and Allied Health, 'synergy' is defined as "coordinated or correlated action of two or more structures, agents, or physiologic processes so that the combined action is greater than the sum of each acting separately."

[3] Cunha and Heckman (2007a), Cunha and Heckman (2007b)

trition or exposure to pollution in early life have been found to affect adult life outcomes like earnings and completed schooling. The magnitudes and frequency of such negative shocks are higher in developing countries in particular. Due to the market imperfections, the ability of individuals to shield themselves from such shocks or to make corrective or compensatory investments is inadequate and the technology at their disposal is often less effective. Most of the corrective or compensatory investments are made by the government in these countries. It is, therefore, important to know what kind of investments can mitigate the negative impacts of what kinds of early shocks? To what extent does such compensations work? Is there an appropriate time in an individual's life that such investments should be made? Since later corrective (or reinforcing) investments are often endogenous, the estimates of catch up obtained from analysis of such investments may be biased. Joint evaluation of two exogenous shocks, however, provides a sound framework to analyse to what degree can a later life positive shock undo the damage done by an early life negative shock.

In this paper, we analyse the extent to which the Sekolah Desar INPRES program (hereafter, INPRES program), a large scale school construction program undertaken by the Indonesian government, mitigated the effects of low rainfall in months of birth for children born in Indonesia during late 1960s and early 1970s. Maccini and Yang (2009) examine the effect of weather shocks around the time of birth of Indonesian women and men born between 1953 and 1974 on the adult health, education, and socio-economic outcomes observed in 2000. They found higher rainfall in birth seasons improved health, education and socio-economic outcomes for women but not for men.[4] According to Duflo (2001), between 1973-1974 and 1978-1979, more than 61,000 primary schools, average of two schools per 1,000 children aged 5 to 14 in 1971, were constructed in Indonesia under the INPRES program. Primary school enrolment rates among children aged 7 to 12 increased from 69 percent in 1973 to 83 percent by 1978. Duflo (2001) finds that every primary school constructed per 1,000 children led to 0.12 to 0.19 extra years of education on average and increased wages by 1.5 to 2.7 percent. It is of interest to examine the impact of this program separately for those who experienced good rainfall in their birth years (hereafter, high rainfall children) and those who did not (hereafter, low rainfall children). According to Maccini and Yang (2009), one of the way in which rainfall might affect adult outcomes is through early life nutrition. Given the interdependence of health and educational outcomes, it is plausible that INPRES had widely different impacts for the higher and the lower rainfall children.

We look at the independent and interactive effects of these two shocks and find that INPRES benefit low rainfall children more than high rainfall children. In that, INPRES allowed low rainfall children to catch up to some extent with high rainfall children. Moreover, even though high rainfall children did considerably better than low rainfall children, INPRES seemed to have had a small negative effect on their schooling attainments on the margin. We

[4] Aguilar and Vicarelli (2011) find similar results for a different weather shock in Mexico.

argue and provide suggestive evidence that this was as a result of deteriorating teacher quality and increasing competition as as result of the rapid expansion in the number of schools.

Our study is similar to Adhvaryu et al. (2014) that studies the impact of rainfall shocks, PROGRESA transfers and their interaction on adult outcomes. While our study contributes by lending external validity to citeadh findings, there are two important differences worth noting. First, while Progresa attempt to manipulate the demand side, INPRES was a supply side intervention. Manipulating demand is often more difficult and more expensive in comparison to altering supply side variables. From an efficiency perspective, therefore, it becomes important to understand how effective supply side measures like INPRES are in comparison to demand side measure like PROGRESA. Second, PROGRESA targeted individuals, INPRES worked on schools. So, while there is a possibility that PROGRESA beneficiaries choose to attend school for the monetary transfer alone and were not motivated enough by the gains in education, INPRES did not interfere with an individual's decision making process directly. The INPRES beneficiaries choose to benefit from such a treatment voluntarily. Stopping the cash transfers in programs like PROGRESA may result in individuals populations reverting back to their old ways and the change in choices made, therefore, might be temporary relative to the changes brought about by INPRES.

Our paper also contributes at a policy level by describing better the pros and cons of a large scale program like INPRES and identifying better the beneficiaries of such programs. It also serves a word of caution for countries and regions attempting to replicate similar programs by bringing to attention how small but crucial elements, like teacher quality, are essential for realization of the full of such programs. It also argues the case for joint evaluation of programs for accurate cost benefit analysis.

The remainder of the paper is organized as follows. Section II gives a brief background of the two treatments, previous evidence about their impacts on outcomes of interest and the plausible mechanisms proposed. Section III describes the data used and the construction of our independent variables. The empirical strategy is presented in section IV. We discuss the results in Section V. Section VI concludes.

2 Background

2.1 Rainfall shocks

Agriculture is one of the most important sources of household income in Indonesia. According to Food and Agriculture Organization of the United Nations as of 2012, a little over 40 percent of the country's labour force was engaged in agriculture. This number was as high as 55 percent during 1980s. Indonesia is the third largest producer of rice in the world and its population has the the highest per capita rice consumption (approximately 139 kilo per capita per year), most of it produced within the country. Agriculture, and rice production in particular, is highly dependent on the timing and amount of precipitation (Levine and Yang (2006), Kishore et al. (2000)). The specific monsoon trajectory varies across years and, as a result, the timing, intensity and duration of precipitation varies a lot across the different rice growing regions in the country in any year and across years within a region.

Planting of rice is done once a certain level of rainwater has accumulated in the fields. Delayed planting in the main agricultural season leads to reduced crop yields not only in that season but also reduces the secondary crop yields by delaying the harvesting of primary season crops and planting of secondary crops. Floods, on the other hand, do not seem so much of a concern. Maccini and Yang (2009) find that the benefits of rainfall do not diminish even at very high levels of rainfall. Due to its equatorial location, other weather related factors such as temperature shows little variation within years and across years.

According to statistics released by Indonesian Ministry of Agriculture, smallholder farmers account for around 90 percent of Indonesia's rice production. Given the high dependence on rice for both home consumption and income, rainfall shocks are one of the most important risk factor faced by households.[5]. Within a household, availability of food, nutrient composition of food, income availability for other consumption purposes, time allocation for adults and children, general level of stress, etc., can all be influenced greatly due to these shocks. Pregnant women and young children are particularly vulnerable to such shocks. The critical-period programming or fetal origins hypothesis, that environmental conditions critical periods in early life can affect a wide gamut of adult outcomes, is well established in developmental biology (Barker (1998)). In economics, the affect of shocks in-utero and in early years of life on adult outcomes related to income, health and educational attainment are being increasingly documented.(Alderman et al. (2006); Almond (2006); Almond and Mazumder (2011)). Maccini and Yang (2009) look at the impact of such rainfall shocks in Indonesia and find that better rainfall is associated with better health, educational and socio-economic outcomes for women born between 1953 and 1974. As Maccini and Yang (2009) acknowledge, other channels, like disease environment, availability of portable water, that link rainfall to child nutrition and health might exist. Their estimates, therefore, are net of all these mechanisms.

2.2 INPRES program

Since 1973, the redistribution of aggregate gains from the oil booms were controlled mainly by the presidential instructions (INPRES) (Ravallion (1988)). Sekolah Dasar INPRES was the flagship program of these instructions. Between 1973-74 abd 1978-79, more than 61,000 primary schools were built. This was an attempt to increase primary enrolment rate for children in the age group 7 to 12, which was around 69 percent in 1973. (Duflo (2001)). The program

[5] Rainfall shocks have been found to be of immense important in other parts of the world as well. (Fafchamps et al. (1998); Giné et al. (2008)

was to planned to target regions of low enrolment first. This created a lot of variation in the timing and intensity of the program across different districts and cohorts. Duflo (2001) utilizes the quasi experimental nature of the program to estimate the impact of the program. Focussing on men alone, it finds that the one extra school constructed per 1000 children increased the educational attainment by 0.12 to 0.19 years. It also finds significant improvements in wages of those exposed.

While the analysis looks for heterogeneity in results across birth cohorts, it does not analyze heterogeneity in impact depending on weather the individual was born in a high rainfall month or low rainfall month. Rainfall, as Maccini and Yang (2009) argues, could affect individual years of schooling through nutrition. It is plausible that better nutrition improves the cognitive ability of children and those with higher cognitive ability make better use of the INPRES program. Alternatively, it is possible that intra-household allocation before the program was such that children who were born in high rainfall months, received better nutrition and had higher cognitive ability were sent to school even before INPRES. With the income effect of INPRES program, even those with lower cognitive ability were sent to school. In such a scenario, INPRES could lead to narrowing gap between years of schooling attainment of children born in high and low rainfall months. In what follows, we re-estimate the affect of rainfall shocks and INPRES on educational attainment, wages and other adult outcomes. We also include for any effect due to the interaction of the two treatments. The interaction effect will tell us about any significant heterogeneity in the effects of these treatments. We describe the data and empirical strategy in the next section.

3 Conceptual framework

According to Maccini and Yang (2009), one of the most plausible mechanism through which good rain affects completed years schooling is by enabling parents to provide better nutrition for their children, an income effect (Also, see Shah and Steinberg (2013)). A possible pathway via which good nutrition in initial years affects years of education is through enhancement of cognitive ability (Liu et al. (2003), Brown and Pollitt (1996), Galler et al. (1983)). To incorporate such a mechanism, in this section, we present a simple endogenous model for schooling decisions which allows for heterogeneity in cognitive ability of individuals in the population. Building on Card(1995) and Duflo(2001), we show effects of a large-scale school constructions on schooling decisions vary across individuals with a different endowment at birth. Following Duflo (2001), an individual's utility function is defined as follows.

$$U(S_{ijk}) = y(S_{ijk}) - h(S_{ijk}), \tag{1}$$

where S_{ijk} is years of schooling of an individual i, born in district j, at date of k, $y(S_{ijk})$ is the income (or the natural log of income) of individual i, born in district j, at date of k at a later date when he starts working and $h(S_{ijk})$ is his cost of schooling. We define returns to schooling and cost of schooling functions as:

$$y(S_{ijk}) = a + b_{ijk}S_{ijk} \tag{2}$$

and

$$h(S_{ijk}) = \frac{1}{2}\phi(Z_{jk}, D_i)S_{ijk}^2 \tag{3}$$

where Z_{jk} indicates the number of schools in district j at date of k and D_i denotes the cognitive ability type of individuals. While the returns to schooling function follows the exact from as in Duflo (2001), the cost function is slightly different from hers but follows closely the form in Card (1994), the one that Duflo (2001) uses for the definition of the cost function. It is worth noting that the benefit function is linear with respect to the years of schooling, and the marginal cost of schooling is determined by the number of schools in a district at the particular time and an individual's type. For simplicity, we assume there are only two types, and denote individuals with high cognition by $D = 1$ and those with with low cognition by $D = 0$. In addition to that, we assume ϕ is decreasing in both the Z_{jk} and D.

$$\phi_1(Z_{jk}, D) < 0,\ \phi_2(Z_{jk}, D_i) < 0, \qquad D_i \,\epsilon\, \{0, 1\} \tag{4}$$

That is an increases in the number of schools in a district decreases the cost of schooling. Such a decrease, for example, might come about due to decreased commutation costs. Also, children with better ability might require lower investments, such as amounts of time and efforts or private tutoring, to complete each year of schooling vis-a-vis those with lower ability. The assumptions, therefore, look realistic. As the individuals maximize their expected utility, optimal levels of schooling in the equilibrium is given by:

$$S_{ijkD} = \frac{E_k b_{ijk}}{\phi(Z_{ijk}, D_i)}, \tag{5}$$

Therefore, years of schooling increase in expected benefits from schooling, the number of schools in the district and ability. We control for indvidual level heterogeneity by modelling it additively: $b_{ijk} = b_{jk} + e_i$.

Next, we define regional returns to education as a linear function of supply and demand for workers with different levels of educations. On the supply side, benefits from higher years of education depend average education of all cohorts of similar ability in that district and quality of learning at any given time. The demand side is summarised in v_jD, which represents regional economic circumstance that affect individuals with ability D.[6] It is likely that increases

[6] We make the simplifying assumption that the returns from education for an individual of type D depends on the

in the average education leads to decrease in return to education and that quality of learning has positive impact on return. Therefore, we write the benefit function of education as follows.

$$b_{jkD} = 2\beta_1 S_{jD} + \beta_2 q_{jk} + v_{jD}, \qquad \beta_1 < 0,\ \beta_2 > 0 \tag{6}$$

where S_{jD} denotes the average years of schooling and q_{jk} denotes the quality of learning for individuals of type D in district j at a time when cohort k is participating in the market .

We make two simplifying assumptions at this point. First, we assume there are only two cohorts in our world, those who are out of school in 1974 (not treated by INPRES) and those who begin school in 1974 or later. Subscript takes value of 0 for the older cohort and 1 for the younger cohort. The assumption implies

$$S_{jD} = \frac{1}{2}(S_{j0D} + S_{j1D}), \quad D_i \,\varepsilon\, \{0, 1\}$$

Second, as in Duflo (2001), we assume that the generation which started education before 1974 did not expect new school constructions in period 0. In other words, given individual's type,

$$E_0\phi(Z_{j0}, D) = E_0\phi(Z_{j1}, D)$$

Using the assumptions together with the equation (5), we obtain that for cohort 0

$$S_{j0D} = E_0 S_{j0D} = E_0 S_{j1D}$$

That is, individuals of the older cohorts of a particular type are aware of their own schooling attainments and expect the regional average years of schooling to be identical for the older and newer cohorts of that type when making its schooling decisions. Combining this result with equation (5) and equation (6), we get

$$(\phi(Z_{j1}, D) - \beta_1)S_{j1D} - (\phi(Z_{j0}, D) - \beta_1)S_{j0D} = \beta_2(q_{j1} - q_{j0}) + E_1 v_j - E_0 v_j \tag{7}$$

Total differentiation with respect to Z_{j1} yields

$$\pi = \frac{dS_{j1D}}{dZ_{j1}} = -\frac{\phi_1(Z_{j1}, D)S_{j1D}}{\phi(Z_{j1}, D) - \beta_1} > 0 \tag{8}$$

According to the equation (7), under the assumptions made, years of schooling in district j after the introduction of INPRES depends on both the number of newly constructed schools and the quality of learning. Consistent with our intuition, equation (6) suggests that educational

average level of schooling of other individuals of type D in the region and not on individuals with a different level of ability. Relaxing this assumption will not change the results of the model but will make it computationally involved.

attainments of an individual in district j who start schooling after 1973 increases with increase in the number of school in the district. However, this positive impact of INPRES on education varies across ability type. Differentiating equation (8) with respect to D_i, we get

$$\frac{d\pi}{dD} = -\frac{(\phi_{12}(Z_{j1}, D)S_{j1D} + \phi_1(Z_{j1}, D)\frac{dS_{j1D}}{dD})(\phi(Z_{j1}, D) - \beta_1) - \phi_1(Z_{j1}, D)S_{j1D}\phi_2(Z_{j1}, D)}{(\phi(Z_{j1}, D) - \beta_1)^2} \tag{9}$$

Using (8), this can be simplified to $\frac{d\pi}{dD} = -\frac{(\phi_{12}(Z_{j1},D)S_{j1D}+\phi_1(Z_{j1},D)\frac{dS_{j1D}}{dD}+\phi_2(Z_{j1},D)\frac{dS_{j1D}}{dZ_{j1}})}{(\phi(Z_{j1},D)-\beta_1)}$ The sign of $\frac{d\pi}{dD_i}$ can be determined from data. Based on the sign of $\frac{d\pi}{dD_i}$ and equation (9), one can comment on the sign of ϕ_{12}. For example, if we find that $\frac{d\pi}{dD_i} < 0$, it is possible only if $\phi_{12} > 0$. That is, if the positive impact of INPRES school construction is higher for lower ability children, it must be that the reduction in cost brought about by the school construction program was higher for children with lower ability. If $\frac{d\pi}{dD_i} > 0$, both $\phi_{12} > 0$ and $\phi_{12} < 0$ are feasible.

Note that for those who were not going to school or dropping out earlier before INPRES school construction program was implemented, the quality of education in grades they did not complete was of a second order importance. A situation with increased access to schools and teacher, even if that of lower quality, was better than no or little access. For individuals already in these higher years, the decrease in access cost is not as important as the increase in competition and the decrease in school quality. It is, therefore, possible that the school construction had a positive impact on those who would have otherwise not gone to school or dropped out earlier but had a negative impact on those who would have gone for higher years even without INPRES school construction. It is likely that those who were of higher ability went for higher years of schooling even before INPRES, and, therefore, suffered more due to the quality deterioration. However, conditional on being enrolled in a class, the impact of lower school quality can be expected to have lower impact on high ability children than on low ability children. That is, high ability children in a certain class where the teacher quality, for example, deteriorates might still be able to learn better than the low ability children in the same class.

From (8), the impact of INPRES on schooling (or completion of a certain level of schooling) is positive for all those who were exposed to INPRES. However, if we extend the model to incorporate the impact of schooling construction on quality of schooling, we replace o $\beta_2 q_{jk}$ by $\beta_2 q_{jkD}$ as the mean of $\beta_2 q_{j0D}$ and $\beta_2 q_{j1D}$, where cohort 0 expects the two to be same while cohort 1 realizes that $\beta_2 q_{j0}$ ¡ $\beta_2 q_{j1}$ due to the construction of extra schools. Under these assumptions, (8) changes to

$$\pi' = \frac{dS_{j1D}}{dZ_{j1}} = \frac{\beta_2 \frac{dq_{j1}}{dZ_{j1}} \phi_1(Z_{j1}, D) S_{j1D}}{\phi(Z_{j1}, D) - \beta_1} \tag{10}$$

The sign of this depends on the relative magnitudes of the impact of school construction on quality of schools and the impact of school construction on the direct cost of schooling. A high level of deterioration of school quality due to school construction could imply reduction in schooling or completion of a certain level of schooling. If this deterioration of quality has different impact on the quality of learning for individuals of different types, (9) changes to

$$\frac{d\pi}{dD} = \frac{(\beta_2 \frac{d^2 q_{j1D}}{dZ_{ji} dD} + \phi_{12}(Z_{j1}, D) S_{j1D} + \phi_1(Z_{j1}, D) \frac{dS_{j1D}}{dD} + \phi_2(Z_{j1}, D) \frac{dS_{j1D}}{dZ_{j1}})}{(\phi(Z_{j1}, D) - \beta_1)} \tag{11}$$

We test the prediction from the model, equation (8) to (11) in our empirical analysis. We use our results to decide which of the two models - no impact on quality of learning or detrimental impact on quality of learning - explains the situation better. The next section describes the data and the empirical specification we use.

4 Data and Empirical Strategy

For our analysis, we leverage the quasi-random nature of rainfall shocks and exposure to the INPRES program. For constructing our rainfall shock variable, we use the publicly available Global Historical Climatology Network (GHCN) Precipitation and Temperature Data (Version 2). Not every every kabupaten (district) in Indonesia has a weather station and rainfall information from the existing stations was also sometimes missing. Therefore, we use a weight average of data from all of the stations within a 200 kilometer radius of the center of a kabupaten instead of the observation from the nearest station. We weigh the observations from different stations by the inverse of the distance between a kabupaten and the station and calculate the difference between logarithm of rainfall in a month of any year in a kabupaten and logarithm of the a hundred year average rainfall of that month in that kabupaten . Then, we generate a dummy variable that takes value '1' if the rainfall deviation in a month of an year in a kabupaten is greater than the median rainfall deviation, '0' otherwise. This serves as our rainfall shock. Using this procedure, a total of 162 out of 228 kabupaten are matched with the constructed rainfall data.

The INPRES treatment definition draws on variation in program intensity across kabupaten and across years. In this we follow Duflo (2001). Despite the fact that INPRES targeted children born after 1968, it is plausible that children who were born not long before 1968, might have benefit from the primary school construction as well, given late enrolment is prevalent in developing countries. For this reason, we define individuals who had little or no exposure to the program (those 13 to 17 year old in 1974) as controls, while considering those who were 2 to 6 in 1974 to be treated by INPRES.

We then match these two treatment definitions with data from the fourth round of Indonesian Family Life Survey (IFLS 4) using kabupaten identifiers. IFLS 4, carried out in 2007, is the fourth round of on-going longitudinal survey IFLS-series since 1993/4 by RAND. The survey respondents are representative of about 83% of Indonesian population and contains over 30,000 individuals living in 13 of the 27 provinces in the country (Strauss et al. (2009)). We use information from a previous round of the survey, IFLS1-3, to replace any of missing observations for variables that were useful control variables (such as education, place of birth, migration, mother/father education, religion, ethnicity and so on). We then estimate:

$$S_{ijmt} = \alpha + \beta_1 R_{jsmt} + \beta_2 I_{jt} + \beta_3 R_{jmt} * I_{jt} + \gamma` X_{ijmt} + \delta_t + \nu_j + \mu_m + \epsilon_{ijmt} \quad (12)$$

where R_{jmt} is the dummy that takes value '1' if the rainfall deviation for month m in year t in a kabupaten j is greater than the median of rainfall deviation of that season in that kabupaten , '0' otherwise, I_{jt} represents the INPRES intensity in year t in a kabupaten j . δ_t are year fixed effects, ν_j are kabupaten fixed effects, and μ_m is a month fixed effect. In this regression, we compare respondents born in between 1968 and 1972 (treatment group) to respondents born in between 1956 and 1960 (control group). Kabupaten fixed effects control for unobservable static differences across districts. (X_{ijmt}) is a vector of controls that includes type of residence (urban or rural), parental education, gender dummy, ethnic and religion dummies. Standard errors are clustered at the kabupaten level. We use the specification to look at impact of these variables on years of schooling, weekly and monthly wages, cognitive ability and mental health. When analysing the impact on wages, we use Heckman-two step method to control for selection. β_1 captures the main effect of good rainfall, β_2 represents the main effect of INPRES program and the coefficient of the interaction term, β_3, is the additional effect of INPRES for children born in good rainfall years vis-a-vis those born in bad rainfall years. A positive β_3 is an indication of synergies or complementarity in investments made in human capital at different stages in life. A negative β_3 will suggest catch up or that one treatment might inhibit the effect of the other.

While one could have used data from the Indonesia Intercensal Population Survey (SUPAS) of 1995 (or later years) or the set used by Duflo (2001), which is a sample of male individuals from SUPAS 1995. However, there are at least four reasons why we decided to use IFLS instead. Given the relative richness of the IFLS data, it was possible to study the impact of the treatments on other outcomes and explore the plausibility of a wider variety of mechanisms. Second, migration related issues can be studied much better using the panel nature of IFLS surveys and because it notes the district of residence at birth and at age 12. Third, important covariates like parental education have a lot many missing observations in SUPAS and is not available in data from Duflo (2001). Month of birth is another important variable not available in data from Duflo (2001). Also, data from Duflo (2001) uses a sample of males only. It is, however, of interest to see how INPRES, an intervention that reduced commutation cost amongst other things, affected the educational attainment of women. Fourth, the rainfall and individual level observations match is significantly better for the IFLS data set where less that five percent of the sample has missing rainfall information. While the comprehensive nature of IFLS 4 allows us to test for the impact of these treatments on a variety of outcomes, it comes at a price. The number of observations we work with is significantly lower than that used by Duflo (2001). Given our smaller sample, we will interpret the results based on the consistency in their magnitudes and signs and not just their level of significance. Wherever possible, we will use data from Duflo (2001) and SUPAS 1995 to provide robustness checks for our results.

Finally, to provide suggestive evidence supporting the mechanism that we propose were instrumental, we use the Indonesian Population Surveys of 1971 and 1980 and the Intercensal Population Survey of 1976.[7] We extract out the sample that reports their occupation as school teachers from the census survey for our analysis using the occupation code information in these surveys.

5 Results

The most important results from this analysis are summarized in Tables 2. Column (1) presents the impact of the being born in a good rainfall. Being born in a good month increased an individual's years of schooling by 0.14 years. Even though the sign is as expected, the coefficient is not significant. Column (2) presents the impact of one more school construction per 1000 children under the INPRES program. One more school increased an individual's years of schooling by 0.116 years on average. Even though the estimate is insignificant, the magnitude is very close to that reported by Duflo (2001) even though a different dataset is used in her analysis. Duflo (2001) reports an increase of 0.124 years of schooling for each school built. Adjusting for the fact that we use the 1957-61 cohort as our control group, the impact, as per Duflo's analysis would have been an increase of 0.115 years. Including both good rainfall dummy and the INPRES treatment intensity in one specification does not improve the fit of the model and leads to only a slight increase in the magnitudes of the impact. In column (4), include both the treatment indicators and their interaction. Not only do the independent impact of the two treatments significant, their magnitudes are around two to three times the magnitudes in column (1), (2) and (3). The interaction itself is significant. Being born in a good month seems to increase an individual's years of schooling by 0.55 years. For those born

[7] These survey data were drawn from IPUMS international. See Minnesota Population Center. Integrated Public Use Microdata Series, International: Version 6.4 [Machine-readable database]. Minneapolis: University of Minnesota, 2015. The original producer of the survey data is Statistics Indonesia.

in bad rainfall months, years of schooling increased by 0.33 years for each new school built per 1000 children. However, for those born in good rainfall months, INPRES had very little or no effect. INPRES gave those born in bad rainfall months an opportunity to catch up with those born in good rainfall months. Such a catch up effect has been observed in other studies as well (Adhvaryu et al. (2014)). Mani (2012) uses earlier rounds of IFLS survey to track cohorts who are 3 months to 6 years old in 1993 over the next seven years and finds that there is partial recovery from effects of childhood malnutrition in on adolescence height for children in Indonesia. It seems plausible that such a catch up might be possible even for educational attainments provided the right investments are made. It is, therefore, no surprise that in a standalone analysis, rainfall seemed to have very little or no effect. Similarly, while INPRES had a substantial impact for those born in bad rainfall months, it had almost no impact on those born in good rainfall months, leading to a lower average treatment effect estimate.

The gender dummy suggests that women, on average, complete lower years of education, an observation common in developing countries (King and Hill (1997)). Education level of both father and mother of a child had a big impact on the years of education completed; education level of mothers seem to matter slightly more than that of fathers. Not including these covariates leads to a change of 0.1 to 0.05 points in the estimated treatment effects and is indicative of their importance. For example, parents education could be correlated with the degree to which parents are able to shield their children from the negative effects of a rainfall shock. To be sure that our estimates for the treatment effects and the effect of other covariates is not out of order, we estimate the effect of good rainfall dummy on the cohorts born between 1950 and 1961.[8] The results are presented in column (5) of table 9. Children born in good rainfall months are likely to complete 0.48 more years of education. The magnitude of the treatment effect is very close to the ones we get in table 2. Education levels of father and mother seems to be as important here as in table 2. Gender differences in education were larger in earlier cohorts. To check for robustness, we look at the impact of the good rainfall dummy using SUPAS 1995 data. The results are presented in table A3. It is important to remember that the SUPAS analysis does not include important covariates like father's and mother's education, which are extremely important for the analysis. We, therefore, focus on the sign and not the magnitude of these estimates. We find that the signs are consistent with improved educational attainment of those born in good rainfall months.

However, the magnitudes of the interaction in tables 2 and **??** raise certain other questions. What could have led to a close to zero impact of INPRES for children born in good rainfall years? Before suggesting possible mechanisms, we check for the consistency in the sign of the interaction effect by estimating the specification used in table 2 using data used in Duflo (2001) and data from SUPAS 1995. The results are presented in 7 and A2, respectively. Interaction

[8]Indonesia was a Dutch colony before 1945 and the Dutch recognised Indonesia's independence at the end of 1949. Many structural and policy changes came hand in hand with independence. To avoid the influence of such factors, we focus on the cohorts born between 1950 and 1961.

coefficient has a negative sign in both these tables. Also, there is a sizable change in the magnitudes of the independent impact of good rainfall and INPRES once the interaction term is included in the specification.[9] We, now, look at some plausible mechanisms behind this negative impact of the interaction.

We talk about two of the many possible mechanism that could have resulted in a negative interaction effect. It is important to note that apart from improving access to primary schools, the INPRES program brought about some other significant changes. An important one amongst those was the decrease in the teacher quality of the newly recruited teacher. Teacher quality has been a concern in Indonesia for quite sometime. According to a 2009 report released by Ministry of National Education, Government of Indonesia, in collaboration with World Bank more than 60 percent of the total 2.78 million teachers in 2006 had not completed the level of academic qualification of a four-year bachelor's degree. Majority of them had either a two-year diploma or a senior secondary certificate qualification. Most teachers from this group (about 70 percent) taught in the primary schools. Arze del Granado et al. (2007) report that teacher absenteeism in Indonesia is as high as in some parts of Sub-Saharan African and India. According to the 2009 report:

".. [T]he quality of the teachers began to decline with the expansion of the primary school (SD Inpres) program. In order to meet the surge in demand for teachers created by the rapid increase in the number of primary schools, quality was sacrificed for quantity. In general, recruitment into these programs became less selective and the average ability of teachers fell. Consequently, the prestige of teachers also fell. Teacher salaries have declined in real terms when compared to national average salaries in inverse proportion to the number of teachers inducted into the profession and there has been less incentive for the brighter students to enter the teaching service."

While there is no clear consensus on what makes a good teacher, we test this hypothesis in a few ways. We separate out individuals who report their main occupation as primary school teachers from the SUSENAS rounds of 1971 and 1980 and the SUPAS 1976 round. Out of these, SUPAS 1976 and SUSENAS 1980 are from years after the school construction program while SUSENAS 1971 was before the school construction. We pool the data and check how the composition of teachers have changed over the years in regions with high and low intensity of INPRES school construction. The results are presented in tables 3 and 4. The minimum qualification to be a primary school teacher in Indonesia around the time was a diploma degree (DIPLOMA III or DIPLOMA IV) after completing high school. The results suggest that the average education of the primary school teachers over the years improved considerably. This is consistent with the trend in education in general in Indonesia (insert citation) over this period. Regions where school construction was more intense, high INPRES

[9] The negative effect of INPRES in table A2 is puzzling. It is, however, a possibility if the intercensal population survey missed out on those born in bad rainfall months more than those born in good rainfall months, which is likely given the lower income and education of those born in low rainfall years.

intensity region, had teachers who were less likely to have completed high school or diploma III to begin with. However, what is more important, is that as clear from table 3, the teachers in regions with high intensity of school construction post INPRES school construction were much less likely to have completed high school. As clear from the table, the teachers in primary schools in high intensity INPRES school construction region were also less likely to have completed the teaching diploma. This difference was bigger in 1976. Perhaps, with more time to hire and fire teachers, school were able to improve the quality of teachers over time. However, this difference was significant even towards the end of the decade.

It is believed that if a teacher understands the culture of the region in which teaches, she is better able to communicate with and understand the students. In table 4, we look at teacher characteristics. Column (1) and (2) present the results for the specification where the dependent variable is whether a primary school teacher was born in the same district that she teaches in. Teachers in regions with high intensity of school construction post the program were much less likely to be born in the same district. For the specification in column (3), the dependent variable takes a value 1 if the teacher's previous district of residence was the same district as the one she is teaching in, 2 if her previous district was in the same province but a different district, 3 if it was in a different province but from the same country and 4 if the teacher is from a different country. Again, post program teachers in high intensity school construction regions were much more likely to be form outside the district. For column (4), the dependent variable takes value 1 if the teacher is teaching in the same district she was in five years ago, 2 if she migrated from a different district in the same province, 3 if she migrated from a different province but from within the country country and 4 if the teacher came from a different country. Again, teacher is high intensity regions post program were much more likely to have migrated from a relatively far off place. The last column has the duration of stay at the present district as the dependent variable. Teachers in high intensity regions post program had, on average, spent around four years less in the district they are teaching in than teachers in low intensity regions even after controlling for any initial differences.

Second, there is a possibility that the increase in number of middle and secondary schools could not keep up with the expansion in primary school. As a result, there could have been increased competition to get into middle and secondary school after children completed primary school. If one looks at the probability of middle and high school completion, according to Table 5 while individuals born in good rainfall years were more likely to complete middle and high school in comparison to those born in bad rainfall years, those who were born in good rainfall years and were in regions with high intensity of INPRES treatment did not complete middle and high school as often those who were born in good rainfall years but grew up in regions with low intensity of INPRES treatment. There was no significant difference in the average rate of completion of primary school for these groups. Since the resource bottleneck was created at higher levels of education, no impact on primary school completion and lower rate of completion of middle and high school is suggestive of the competition effect in particular. The impact of INPRES that we observe, therefore, is the net of the positive effect improved access and negative effects of increased competition and decreased teacher quality.

As mentioned before, one possible pathway via which good nutrition due to better rainfall during birth months (Maccini and Yang (2009)) affects years of education is through enhancement of cognitive ability. According to Cunha and Heckman (2007a), the lack of initial cognitive ability endowment can be compensated for by investments in the early years. The degree of substitutability, however, declines as one grows up. Quality of primary school teachers, therefore, should be expected to play an important role in developing the cognitive ability of children in their early years. The deteriorating quality of teachers in areas of high intensity of INPRES, therefore, might lead to lower cognitive development of children in these areas. Therefore, while the improvement in access might have resulted in higher years of schooling, the decline in teacher quality might have led to lower cognitive ability development.

Unfortunately, we do not have cognitive ability measurements for children exposed to INPRES program during their school years or at the time of their graduation. However, we do have information on their performance on a word recall test that was administered to them as a part of the IFLS4 survey in 2010. When we examine the impact of the two interventions and their interactions on the performance on this word recall test (ref. to Table 6), we find that even though the impacts are mostly insignificant, the signs are in the expected direction and the magnitudes relatively large. However, as argued before, given the small sample size, we will base our interpretation on magnitudes and consistency of signs. Also, it is worth noting that these word recall tests were given to these cohorts in 2007, about 30 years. Age and experience might have some bearing on these scores. Therefore, we have to be cautious and not rely too much on these results. . From column (2), INPRES seems to have had a negative effect on word recall scores of boys and a positive affect on girls. This negative effect for boys is slightly counter intuitive. The results start making more sense as we move to column (3) and (4), where we control for good rainfall and the interaction of the two treatments. While INPRES has a small negative impact for boys, girls witness a much larger, significant positive affect on their word recall scores. As argued before and clear from table 9, children born in low rainfall months had poorer access to schools. Girls had an even lower access in this group. So, while INPRES improved access to girls more than that for boys even in this group, it increase the competition and decreased the quality for the few already at school who were, more often, boys. Being born in a good rainfall year, as expected, was associated with a higher score on the word recall test while the interaction has a negative effect on the score, observation consistent with the worsening teacher quality and increasing competition hypothesis. We also look at the impact of these treatments and their interaction on other indicators that might be related to cognition. In particular, we look for impact on grade repetitions, ability to read and write in a second language. While none of the impacts are statistically significant, the signs of the impacts are all significant with the mechanisms put forth. Good rainfall and INPRES seem to decrease repetitions and increase ability to read an write in another language. Their interaction, however, tends to increase grade repetitions and decrease the ability to read and write in a second language.

It seems that while INPRES succeeded in generating higher enrolment and educational attainment on average, it might have come at some cost. The cognitive development of some might have been inhibited by lower quality of newly appointed teachers. However, given the lack of significance for cognitive ability results and the time lag since treatment, any strong claims will be unwarranted. What is clearer is that INPRES did affect negatively the schooling attainment of children born in good rain years. Higher years of education have led to higher levels of happiness but do not seem to have a clear impact on wages.

6 Conclusion

Considering the immediate goal of INPRES was to increase primary school enrolment, it was, arguably, a big success. However, our analysis provides a good exposition of some of the major trade offs and challenges faced by almost all policies implemented at such a large scale. Often such immediate goals are set in pursuit of bigger goals of a better educated populace and economic development. INPRES is redistributive in more than one way in that it increased the educational attainment for one group at a small cost to another group. While such redistributions, given the overall gain, might still be well justified and even desired, understanding the heterogeneity in its impact is beneficial for future policy planning. It is important to realize that the benefits of the intervention could have been bigger had it been accompanied by other improvements in infrastructure. Proper personnel training and simultaneous expansion of middle and secondary school infrastructure might have mitigated the negative effect for children born in good rainfall months and would have resulted in higher gains from INPRES. The harmful effect of deteriorating infrastructure on cognition, even though insignificant is suggestive evidence that infrastructural investments in human capital at early stages, like primary school teacher quality, can affect cognitive development of children. In Indonesia, and in particular for the cohort analysed, evidence support catch-up in production of human capital and not one of complementarity between interventions.

The study also serves to emphasize the importance of a general equilibrium approach to evaluation of large scale interventions of this nature. While higher education is of value by itself, visible in its impact on subjective well being measures, its impact on the labour market competition and wages need to be understood better to ensure that its full potential is realized. In developing regions of the world, low levels of and high fluctuations in incomes and missing credit markets limit the possibilities of private investment in human capital accumulation. State run policies, therefore, are of extreme importance in ensuring higher levels of human capital

(Easterlin (1981)). Given the limited state budget, the decision of whether or not to roll out a particular program depends a lot on the cost and benefit of the program. In such cost-benefit analyses, different welfare weights for benefits to different subgroups might be desirable. One has to be aware of the average costs and benefits to each of these subgroups to be able to evaluate the net gains of such policies. Heterogeneity analysis of this nature, therefore, might be important in such evaluations.

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Table 1: Summary statistics

		Treatment Cohort (born 1968-72)		Control Cohort (born 1961-57)	
		Good rain	Bad rain	Good rain	Bad rain
Individuals					
	N	1499	1099	958	651
Education (completed years)	Mean	9.02	9.23	6.73	6.55
	SD	3.96	3.90	4.40	4.29
	N	753	486	402	290
Monthly earnings (in Rupiah)	Mean	828801.1	811470.1	891542.5	776842.2
	SD	1259791	937684.3	1317236	850244.5
	N	619	409	314	238
Weekly earnings (in Rupiah)	Mean	11600000.0	11600000.0	13600000.0	11200000.0
	SD	14100000.0	15500000.0	17400000.0	11500000.0
Kabupaten					
Primary gross school enrolment (%)	Mean	96.43	95.17	88.58	87.90
Primary gross school enrolment for males (%)	Mean	98.34	97.41	97.41	92.44
Primary gross school enrolment for females (%)	Mean	94.47	92.86	92.86	83.79
Primary school completion (%)	Mean	83.01	84.11	58.68	58.04
Middle school completion (%)	Mean	55.25	58.65	33.42	32.19
High school completion (%)	Mean	40.21	42.41	22.66	22.11
Gender composition (%)	Mean	49.29	49.17	50.78	52.49
Ethnicity = Javanese (%)	Mean	41.37	41.70	42.36	48.36
Water and Sanitation program intensity	Mean	0.48	0.48	0.49	0.46
	SD	0.18	0.19	0.19	0.17
INPRES schools per 1000 childen	Mean	2.02	2.08	0.00	0.00
	SD	1.01	1.08	0.00	0.00
INPRES schools per 1000 childen (High intensity region)	Mean	2.51	2.68	0.00	0.00
	SD	1.09	1.09	0.00	0.00
INPRES schools per 1000 childen (Low intensity region)	Mean	1.47	1.56	0.00	0.00
	SD	0.50	0.76	0.00	0.00
Historical annual rainfall average (mm)	Mean	1931.55	2035.93	1992.91	1884.55
	SD	335.14	474.45	376.69	412.51

Table 2: Impact of Rainfall and INPRES on Years of Schooling

VARIABLES	(1) Years of Schooling	(2) Years of Schooling	(3) Years of Schooling	(4) Years of Schooling
Good Rainfall	0.1741		0.1653	0.4678**
	(0.1510)		(0.1506)	(0.1851)
INPRES		0.1433	0.1332	0.2275*
		(0.1188)	(0.1188)	(0.1309)
Good Rainfall * INPRES				-0.2270**
				(0.1026)
Gender Dummy (=1, if Female)	-1.0312***	-1.0311***	-1.0338***	-1.0278***
	(0.1048)	(0.1038)	(0.1047)	(0.1043)
Mother's education	2.3033***	2.3155***	2.3078***	2.3116***
	(0.1725)	(0.1741)	(0.1728)	(0.1734)
Mean of dependent variable	7.53	7.33	7.53	7.53
Observations	3,659	3,672	3,659	3,659
R-squared	0.3561	0.3560	0.3563	0.3572

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses. The standard errors are clustered at Kabupaten level. Other controls include season of birth, year of birth and kabupaten of birth fixed effects, majority ethnicity dummy and a dummy for urban residence.

Table 3: Inpres and Teacher qualifications

VARIABLES	(1) High School	(2) High School	(3) Diploma III	(4) Diploma III	(5) Diploma IV	(6) Diploma IV
High intensity dummy * Survey 1976	-0.0685*	-0.0679*	-0.0617**	-0.0633**	-0.0514***	-0.0523***
	(0.0403)	(0.0403)	(0.0293)	(0.0300)	(0.0182)	(0.0179)
High intensity dummy * Survey 1980		0.0019		-0.0149		-0.0248***
		(0.0133)		(0.0130)		(0.0083)
High INPRES intensity regions	-0.0231*	-0.0199*	-0.0233*	-0.0174	0.0010	0.0039
	(0.0119)	(0.0117)	(0.0127)	(0.0121)	(0.0076)	(0.0075)
Survey year 1976	0.7360***	0.7345***	0.0918***	0.0945***	0.0671***	0.0688***
	(0.0217)	(0.0214)	(0.0259)	(0.0267)	(0.0159)	(0.0154)
Survey year 1980		0.8470***		0.0593***		0.0491***
		(0.0098)		(0.0113)		(0.0062)
Gender Dummy (=1, if Female)	-0.0280**	0.0293***	-0.0553***	-0.0553***	-0.0231***	-0.0312***
	(0.0119)	(0.0043)	(0.0100)	(0.0044)	(0.0069)	(0.0030)
Urban dummy (=1, if Urban)	0.0380**	0.0337***	0.0460**	0.0758***	0.0326***	0.0502***
	(0.0153)	(0.0051)	(0.0180)	(0.0078)	(0.0086)	(0.0049)
Constant	0.0427***	0.0209**	0.0490***	0.0284**	0.0075	-0.0012
	(0.0133)	(0.0104)	(0.0169)	(0.0115)	(0.0057)	(0.0051)
Observations	2,979	32,534	2,979	32,534	2,979	32,534
R-squared	0.5363	0.2884	0.0354	0.0293	0.0275	0.0211

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses. The standard errors are clustered at Kabupaten level.

Table 4: Inpres and Teacher characteristics

VARIABLES	(1) Born here	(2) Born here	(3) Previous district	(4) Migrated from	(5) Years at current location
High intensity dummy * Survey 1976	-0.1783***	-0.1820***			
	(0.0636)	(0.0645)			
High intensity dummy * Survey 1980		-0.1749***	0.1560***	0.0322	-3.7267**
		(0.0514)	(0.0507)	(0.0238)	(1.5440)
High INPRES intensity regions	0.1670***	0.1819***	-0.1672***	-0.0175	1.9659
	(0.0563)	(0.0632)	(0.0622)	(0.0227)	(1.4181)
Survey year 1976	0.1080**	0.1147**			
	(0.0466)	(0.0492)			
Survey year 1980		0.1031**	-0.1291***	0.9507***	20.5882***
		(0.0435)	(0.0416)	(0.0164)	(0.8271)
Gender Dummy (=1, if Female)			0.0042	0.0065*	-4.0628***
			(0.0058)	(0.0037)	(0.2031)
Urban dummy (=1, if Urban)	-0.2002***	-0.1258***	0.1271***	0.0231***	-1.8710***
	(0.0506)	(0.0310)	(0.0306)	(0.0078)	(0.7092)
Constant	0.8889***	0.8375***	1.1998***	1.0674***	13.0934***
	(0.0334)	(0.0499)	(0.0476)	(0.0162)	(0.6338)
Observations	2,980	32,546	31,425	30,474	29,787
R-squared	0.1133	0.0503	0.0508	0.4384	0.1086

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses. The standard errors are clustered at Kabupaten level. (1) & (2) 'Born here' takes value 1 if the teacher teaches in the province he was born. 'Previous district' pertains to the political distance of last district of residence. It takes value 0 if the individual was previously living in the same minor administrative unit, 1 if in same major administrative unit but different minor administrative unit, 2 if in another province, 3 if outside country. 'Migration from' pertains to migration within the last five years. It takes value 0 if the individual has not migrated in last five years, 1 if he has migrated from a place within the same minor administrative unit, 2 if he has migrated from a place within the same major administrative unit but different minor administrative unit, 3 if from other province, 4 if from outside the country.

Table 5: Impact on School Completion

VARIABLES	(1) Primary School	(2) Middle School	(3) High School
Good Rainfall	0.0487**	0.0477**	0.0527**
	(0.0191)	(0.0215)	(0.0219)
INPRES	0.0092	0.0369**	0.0331*
	(0.0167)	(0.0165)	(0.0171)
Good Rainfall * INPRES	-0.0202*	-0.0318***	-0.0301**
	(0.0104)	(0.0110)	(0.0127)
Gender Dummy (=1, if female)	-0.0987***	-0.1110***	-0.0988***
	(0.0128)	(0.0141)	(0.0122)
Mother's education	0.1484***	0.2476***	0.2212***
	(0.0183)	(0.0197)	(0.0209)
Observations	3,659	3,659	3,659
R-squared	0.2539	0.3104	0.2740

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses. The standard errors are clustered at Kabupaten level. Other controls include month of birth, year of birth and kabupaten of birth fixed effects, majority ethnicity dummy and a dummy for urban residence.

Table 6: Impact on Cognitive Ability

VARIABLES	(1) recall	(2) recall	(3) recall	(4) recall
Good Rainfall			-0.0016	0.0009
			(0.0254)	(0.0389)
INPRES	-0.0055	-0.0180	-0.0083	-0.0252
	(0.0144)	(0.0169)	(0.0160)	(0.0213)
Good Rainfall * INPRES			0.0059	0.0161
			(0.0119)	(0.0214)
Good Rainfall * Gender				-0.0070
				(0.0457)
INPRES * Gender		0.0222**		0.0309*
		(0.0108)		(0.0181)
Good Rainfall * INPRES * Gender				-0.0184
				(0.0256)
Gender Dummy (=1, if female)	-0.0896***	-0.1143***	-0.0905***	-0.1108***
	(0.0200)	(0.0269)	(0.0202)	(0.0470)
Father's education	0.0783***	0.0796***	0.0785***	0.0787***
	(0.0232)	(0.0233)	(0.0245)	(0.0247)
Mother's education	0.1119***	0.1103***	0.1113***	0.1091***
	(0.0208)	(0.0208)	(0.0209)	(0.0208)
Observations	3,776	3,776	3,762	3,762
R-squared	0.1776	0.1783	0.1769	0.1780

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses. The standard errors are clustered at Kabupaten level. Other controls include month of birth, year of birth and kabupaten of birth fixed effects, majority ethnicity dummy and a dummy for urban residence. The word recall score represents percentages of words that respondents correctly remember.

Table 7: Grade Repetitions, Reading and Writing

VARIABLES	(1) Repetitions	(2) Repetitions	(3) Read	(4) Read	(5) Write	(6) Write
Good Rainfall	-0.0222	-0.0243	0.0693***	0.0583**	0.0441*	0.0299
	(0.0285)	(0.0409)	(0.0233)	(0.0271)	(0.0243)	(0.0293)
INPRES	-0.0058	-0.0047	0.0251	0.0217	0.0267	0.0200
	(0.0153)	(0.0196)	(0.0212)	(0.0221)	(0.0228)	(0.0233)
Good Rainfall * INPRES	0.0135	0.0036	-0.0210*	-0.0184	-0.0124	-0.0107
	(0.0126)	(0.0201)	(0.0123)	(0.0147)	(0.0115)	(0.0135)
Good Rainfall * Gender		0.0063		0.0217		0.0283
		(0.0486)		(0.0325)		(0.0359)
INPRES * Gender		-0.0024		0.0063		0.0120
		(0.0182)		(0.0117)		(0.0120)
Good Rainfall * INPRES * Gender		0.0184		-0.0048		-0.0031
		(0.0230)		(0.0169)		(0.0159)
Gender Dummy (=1, if female)	-0.0877***	-0.1008***	-0.0740***	-0.0911***	-0.0649***	-0.0930***
	(0.0170)	(0.0383)	(0.0136)	(0.0259)	(0.0133)	(0.0301)
Mother's education	0.0031	0.0039	0.0778***	0.0775***	0.0810***	0.0803***
	(0.0188)	(0.0188)	(0.0203)	(0.0204)	(0.0206)	(0.0208)
Observations	2,776	2,776	3,176	3,176	3,176	3,176
R-squared	0.1190	0.1191	0.2852	0.2855	0.2957	0.2966

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. The standard errors are clustered at Kabupaten level. Other controls include season of birth, year of birth and kabupaten of birth fixed effects, majority ethnicity dummy and a dummy for urban residence.

Table 8: Impact on Wage: Heckman Two-Step Model

	Pooled		Men		Women	
VARIABLES	(1) Log of Weekly Income	(2) Log of Monthly Income	(3) Log of Weekly Income	(4) Log of Monthly Income	(5) Log of Weekly Income	(6) Log of Monthly Income
Income Regression						
Good Rainfall	0.2829***	0.4394***	0.2290**	0.3044**	0.5292**	0.8340**
	(0.0933)	(0.1217)	(0.1001)	(0.1407)	(0.2172)	(0.3814)
INPRES	-0.0258	0.0894	-0.0302	0.0762	-0.0165	0.2369
	(0.0628)	(0.0828)	(0.0596)	(0.0840)	(0.2730)	(0.4431)
Good Rainfall * INPRES	-0.1230**	-0.2066***	-0.1486***	-0.2157***	-0.3588**	-0.5679**
	(0.0480)	(0.0628)	(0.0520)	(0.0728)	(0.1434)	(0.2282)
Working Status Regression						
Good Rainfall	0.0113	0.0125	0.4221	0.4593	-0.0609	-0.0884
	(0.1404)	(0.1394)	(0.3261)	(0.3249)	(0.1912)	(0.1893)
INPRES	-0.0588	-0.0663	-0.3374	-0.3589	0.1283	0.1107
	(0.1011)	(0.1011)	(0.3828)	(0.3739)	(0.1674)	(0.1668)
Good Rainfall * INPRES	-0.0781	-0.0741	-0.2788	-0.2586	-0.0389	-0.0264
	(0.0709)	(0.0706)	(0.2127)	(0.2086)	(0.0973)	(0.0972)
lambda	-0.3491	-0.3311	0.0488	0.3715	0.6063	1.827
	(0.2344)	(0.3139)	(0.3036)	(0.4232)	(1.711)	(2.770)
Observations	1,550	1,560	756	762	794	798

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. The standard errors are clustered at Kabupaten level. Other controls include season of birth, year of birth and kabupaten of birth fixed effects, majority ethnicity dummy and a dummy for urban residence. The working status denotes 1 if respondents work past week and 0 otherwise. The lambda represents covariance of error terms in each regression. it is never significantly different from zero at the 10 percent level.

Table 9: Before INPRES

VARIABLES	(1) Primary School Enrolment	(2) Primary School	(3) Middle School	(4) High School	(5) Years of Schooling
Good Rainfall	-0.0076	0.0244	0.0468**	0.0488***	0.4570***
	(0.0067)	(0.0208)	(0.0181)	(0.0184)	(0.1664)
Gender Dummy (=1, if female)	-0.0098	-0.1411***	-0.1490***	-0.1251***	-1.4997***
Father's education	0.0119	0.1013**	0.1263***	0.1178***	1.4672***
	(0.0169)	(0.0479)	(0.0407)	(0.0316)	(0.3358)
Mother's education	0.0059	0.1374***	0.1788***	0.1484***	1.6651***
	(0.0113)	(0.0499)	(0.0413)	(0.0349)	(0.3866)
Observations	1,148	1,148	1,148	1,148	1,148
R-squared	0.1579	0.3000	0.3375	0.3122	0.3602

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. The standard errors are clustered at Kabupaten level. Other controls include year of birth and kabupaten of birth fixed effects, majority ethnicity dummy and a dummy for urban residence.

Table A1: Robustness Check: Importance of Interaction (Data from Duflo(2001))

VARIABLES	(1) Education	(2) Education	(3) Education	(4) Education	(5) Education	(6) Education	(7) Education	(8) Education	(9) Education
Rainfall shock				0.0738*	0.0849**	0.0922**	0.0968*	0.1131**	0.1264**
				(0.0426)	(0.0426)	(0.0443)	(0.0571)	(0.0564)	(0.0590)
INPRES	0.1149***	0.1419***	0.1850***	0.0883*	0.0732	0.1225**	0.0982*	0.0853*	0.1369**
	(0.0421)	(0.0448)	(0.0486)	(0.0507)	(0.0503)	(0.0570)	(0.0522)	(0.0498)	(0.0551)
Rainfall shock * INPRES							-0.0205	-0.0252	-0.0302
							(0.0328)	(0.0319)	(0.0328)
Constant	7.3915***	7.3861***	7.2215***	7.3940***	6.7274***	6.5484***	7.3795***	6.7172***	6.5234***
	(0.0496)	(0.0489)	(0.1029)	(0.0578)	(0.2507)	(0.3161)	(0.0624)	(0.2552)	(0.3141)
Observations	72,152	71,908	66,965	63,404	63,243	58,331	63,404	63,243	58,331
R-squared	0.1992	0.2000	0.1744	0.2039	0.2048	0.1764	0.2039	0.2049	0.1764

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses. The standard errors are clustered at Kabupaten level. Column (1),(4) & (7) include year of birth and kabupaten of birth fixed effects and interaction of year of birth dummies with children population in that kabupaten in 1971. Column (2),(5) & (7) includes interaction of year of birth dummies with enrolment rate in that kabupaten in 1971 in addition to those in (1),(4) & (7). Column (3), (6) & (9) includes interaction of year of birth dummies with water and sanitation program intensity in that kabupaten in 1971 in addition to those in (2),(5) & (8).

Table A2: Robustness Check: Importance of interaction(SUPAS 1995))

VARIABLES	(1) Education	(2) Education	(3) Education	(4) Education	(5) Education	(6) Education	(7) Education	(8) Education	(9) Education
Good Rainfall				0.0324	0.0186	0.0239	0.0680**	0.0420	0.0542*
				(0.0241)	(0.0229)	(0.0242)	(0.0331)	(0.0306)	(0.0318)
INPRES	-0.1168***	-0.0668*	-0.0121	-0.1361***	-0.0807**	-0.0354	-0.1215***	-0.0716*	-0.0246
	(0.0428)	(0.0345)	(0.0386)	(0.0454)	(0.0361)	(0.0416)	(0.0446)	(0.0363)	(0.0420)
Good Rainfall * INPRES							-0.0312*	-0.0205	-0.0247
							(0.0171)	(0.0160)	(0.0161)
Observations	79,369	79,002	62,645	75,837	75,470	59,113	75,837	75,470	59,113
R-squared	0.2097	0.2115	0.2055	0.2100	0.2119	0.2060	0.2100	0.2119	0.2060

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses. The standard errors are clustered at Kabupaten level. Column (1),(4) & (7) include gender, month of birth, year of birth and kabupaten of birth fixed effects and interaction of year of birth dummies with children population in that kabupaten in 1971. Column (2),(5) & (7) includes interaction of year of birth dummies with enrolment rate in that kabupaten in 1971 in addition to those in (1),(4) & (7). Column (3), (6) & (9) includes interaction of year of birth dummies with water and sanitation program intensity in that kabupaten in 1971 in addition to those in (2),(5) & (8).

Table A3: Robustness Check: Before INPRES (SUPAS 1995))

VARIABLES	(1) Enrolled in Primary School	(2) Completed Primary	(3) Completed Middle School	(4) Completed High School	(5) Years of education
Rainfall shock	0.0057**	0.0083*	0.0061	0.0104*	0.0642*
	(0.0026)	(0.0049)	(0.0063)	(0.0062)	(0.0347)
Gender Dummy (= 1, if Female)	-0.0392***	-0.0976***	-0.1274***	-0.1154***	-0.8445***
	(0.0041)	(0.0066)	(0.0063)	(0.0078)	(0.0347)
Observations	32,073	32,073	32,073	32,073	32,073
R-squared	0.0685	0.1331	0.1872	0.1447	0.1912

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses. The standard errors are clustered at Kabupaten level. Other controls include month of birth, year of birth and kabupaten of birth fixed effects and a dummy for urban residence