Three Essays on Well-Being in Africa

By

Yayo Ake Paul Michel

Dissertation

Submitted to

KDI School of Public Policy and Management

In Partial Fulfillment of the Requirements

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Approval as of August, 2021

ABSTRACT

THREE ESSAYS ON WELL-BEING IN AFRICA

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This dissertation analyses the effect of diverse policies on well-being in Africa. The chapter 1 assesses the causal effects of School Feeding Program (SFP) on socio-economic outcomes in Cote d'Ivoire. Using a Difference in Difference methodology (DID), we found that the impact of this intervention is rather mixed and some educational outcomes appeared to be gender-specific. The chapter 2 examines the impact of aid development projects on child's nutrition in West Africa. We made use of two-way fixed effects estimators with heterogeneous treatment effects methodology and found evidence that development aid projects significantly increase child's nutrition status of those close to project locations compared to those who are far. The chapter 3 analyses the effect of new mining activities on local populations' living conditions. To reach our objective, we utilized a Difference in Difference methodology and found that mining activities in our selected area impact positively and significantly the living condition of the local population. Based on each finding, we drew some policy implications.

Keywords: Well-being; Difference in Difference; Endogeneity; Income; Employment; Child's Health; Education; Cote d'Ivoire.

Dedicated to
My Parents: Yayo Pierre and Yayo Marie

ACKNOWLEWLEGEMENTS

I would like to express my sincere gratitude to my main supervisor, Prof. Taejong Kim, for his continuous support all along my Ph.D. journey in KDIS. He really pushed hard to go beyond my own capacities throughout the researching and writing of this dissertation. Besides my advisor, I would like to thank the other members of my dissertation committee: Professor Jinsoo, Lee; Professor Dongseok, Kim; Professor Cheol, Liu and Professor Chungeun, Yoon for their insightful comments and their openness any time I reached out to them. Finally, I would like to thank my family and friends who have supported me since my primary school up to this stage. Without my God and all of you, I sincerely do not think I could have reached this step.

TABLE OF CONTENT

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE : Socio-economic impacts of school feeding programme in Cote d'Ivoire.

ABSTRACT

This study assesses the causal effects of School Feeding Program (SFP) on socio-economic outcomes in Cote d'Ivoire. Contrary to previous studies that were focused only on educational outcomes, we extend the analysis by exploring the effects on variables that may also be impacted by this program, namely child labor and household expenditure. We also include in our study a cost-effectiveness analysis which was overlooked in other studies. To reach our goals, we use schools and households' surveys provided by the national institute of statistics in Cote d'Ivoire. We then utilize a difference in difference methodology (DID) to solve endogeneity issues and measure the effect of this intervention. After analysis and robustness tests, we found that the impact of this intervention is rather mixed and some educational outcomes appeared to be gender-specific. Finally, we find evidence that if the aim of the policymaker is to improve students' performance or reduce significantly dropout rate, deworming programs may be more cost effective than school feeding programs.

1.1 Introduction

Education as a component of human capital, has always been perceived as a key element for economic growth and human development. Countries where the level of education is higher on average have better levels of growth compared to others. Aware of that many countries have been implementing reforms in their education system in order to improve educational outcomes specially in primary school. Indeed, early childhood intervention is perceived as one of the most cost-efficient investments in human capital that is conducive to a country's sustainable development. Some researchers have shown evidences that early childhood programs, are vital for they help alleviate the effects of adverse early experiences which if not addressed could result into negative consequences in the long run (UNICEF, 2020).

To improve schooling outcomes, many developing countries have acted on demand and supply sides by initiating divers interventions which includes conditional cash transfers (CCT) and unconditional cash transfers (UCT) (De Janvry et al., n.d.; Filmer & Schady, 2011; Glewwe et al., 2015) with mixed results. In Kenya, non-governmental organizations (NGO) have distributed school uniforms to children from poor areas(Evans et al., 2009). Also some countries have provided free medication (Miguel & Kremer, 2004) and a combination package of benefits such as uniforms, textbooks and classroom construction (Angrist et al., 2002). Other countries have excluded school fees for public primary education, by implementing programmes called UPE (Universal Primary Education) or FPE (Free Primary Education). Many other countries following UPE, have been working to reach the forth Sustainable Development Goal (SDG) which is to achieve quality education. To reach this goal, governments have since implemented some policies in order to reduce the costs associated to schooling mostly among those who cannot afford it easily. Thus, one of the policies which is found to be appropriate to improving educational outcomes, particularly among the vulnerable population is the School Feeding Programme (SFP). This programme has been implemented in many countries around the world such as Kenya(WFP, 2019), Bangladesh (Meng & Ryan, 2010) , Senegal (T. T. Azomahou et al., 2019) etc. with mixed results according to the environment.

Empirical studies are inconclusive about the real impacts of SFP. The points of view are rather mixed. Indeed, a study in Malawi by the World Food Program in 1996 has revealed that SFP has engendered 5 percent higher enrolment rate and 36 percent higher attendance rate. However, a study run this time in Kenya has shown no significant impact of this intervention(Martens, 2007).

In order to improve schooling outcomes in primary school and fight against poverty, the Ivorian government, following the example of some African countries, with the help from WFP launched this programme in 2015 in some specific regions which have not received this program before. So, what could be the potential effects of school feeding programme in the case of Cote d'Ivoire?

By investigating these issues, we can obtain better assessments of the impact of school feeding programme for Cote d'Ivoire and use it as an example for other countries that are planning to implement it. Furthermore, based on the results of this study, we can know whether or not government and donors should scale up the program and expand it to other regions of the country. Finally, this study will help us perceive in which way the program should be improved in order to make it more successful.

To provide an answer to the above question, this study takes advantage of a recent data set from Cote d'Ivoire and represents as far as we may be aware of the first evaluation of SFP in Cote d'Ivoire. The aim of this intervention can be divided into two parts. The first one is the reduction of hunger and the improvement of health and nutrition in the northern part of the country. As for the second one, it is related to the improvement of educational outcomes. In our study, we focus on the latter.
Particularly in this paper we investigate the causal effect of this intervention on socio-economic outcomes. Specifically, we study the impact not only on educational outcomes (absenteeism, dropout, enrollment and performance in test score) but also on variables that are considered to be important from prospects of school-age children: child work. Second, we explore the indirect impact on household's expenditure given that providing meals to students can help their parents reallocate their resources and increase or decrease their demand for other goods all things being equal. Third, we investigate gender disparities in educational outcomes and finally we run a cost effectiveness analysis compared to deworming intervention in Senegal which also was targeting the same outcomes. The gender specific effect could help us discern whether both groups (boys and girls) are equally or differently likely to respond to the program. Thus, depending on the result, policymakers can design effective policy targeting each group.

It is worth noticing that the effects of SFP on educational performance are not straight forward. From one hand, the improvement of nutrition may not be enough to engender an increase in some educational outcomes such as learning. In some cases additional educational inputs may also be needed for an increase in school performance (Chakraborty & Jayaraman, 2019). From another hand, the impacts received from food can lead to wonder whether the target children were already well-off before the intervention, or whether the intervention induces some households to increase the amount of food consumed by the other members of the family who don't benefit from the intervention. Also, SFP as any other programs might seem to be impactful before implementation yet might not succeed in generating expected effects. Thus, the evident need for this analysis is to help policymakers figure out whether or not interventions are producing intended impacts and to help better understand what works, what does not. Finally, the opportunity costs face by parents and students may cause the program to fail in reaching its intended goals. Therefore, studying the impact of SFP is an important empirical investigation.

We hypothesize that SFP by reducing the cost associated to schooling can decrease absenteeism, dropout rate in school and increase enrollment. Also, since this indirect transfer frees up some resources that households can reallocate to other expenditures, we hypothesize that the program increases consumption expenditure. We also hypothesis that by maintaining students in school this program help reduces child labor. We finally posit that the program increases students' performance since it may likely improve their health, increase their concentration in class and reduce their probability to miss classes.

To reach our goals, we use two rounds of schools and households' surveys in 2015 and 2016 provided by the national institute of statistics in Cote d'Ivoire. We then utilize a difference in difference methodology (DID) to measure the effect of this intervention on diverse outcome variables. Our identification strategy may be weakened by potential confounding factors such policy changes and the failure to prove parallel trends assumption in our outcome variables. We cannot fulfil all these criteria. However, we try to show the strength of our findings within the limitations of our data by running some sensitivity tests.

Our study contributes to a growing literature using quasi-experimental methodology to analyze the effect of SFP in developing countries. However, we extend this literature in two main aspects. First of all, contrary to previous studies that were focused only on educational outcomes, we extend the analysis by exploring the effects on variables that may also be impacted by this program, namely child labor and household expenditure. Secondly, we also include in our study a cost-effectiveness analysis which was overlooked in many other studies.

After analysis and robustness tests, we found that the impact of this intervention is rather mixed. More specifically, the programme significantly decreased dropout and absenteeism rate in the group of students who took up but did not succeed in raising significantly the enrolment rate and child labour. Moreover, the intervention does not indirectly succeed at significantly decreasing household expenditures. Finally, our analysis could not show any significant effect of the intervention on reading scores even if the relationship between them is positive. The heterogeneity effect analysis reveals however gender disparities in terms of educational outcomes. Indeed, girls are less likely to miss classes and drop out from school compared to boys. However, the program does not show any heterogeneity effect according to gender in terms of enrolment and students' performance. Furthermore, this analysis reveals that the impact on drop out and absenteeism is most likely to be driven by students in lower grades and also school facilities and inputs have a significant impact in improving educational outcomes. Finally, we show that if the aim of the policymaker is to improve students' performance or reduce significantly dropout rate, deworming programs may be more cost effective than school feeding programs.

Our study is organized as follow: the second section explores literature review related to the study, the third one is about description of the programme. The fourth section focuses on data description and methodology while the fifth section deals with descriptive statistics. The part 6, gives way to discussion of our results and in section 7 we run our cost-effectiveness analysis. We end our study in section7 and provide some policy recommendations.

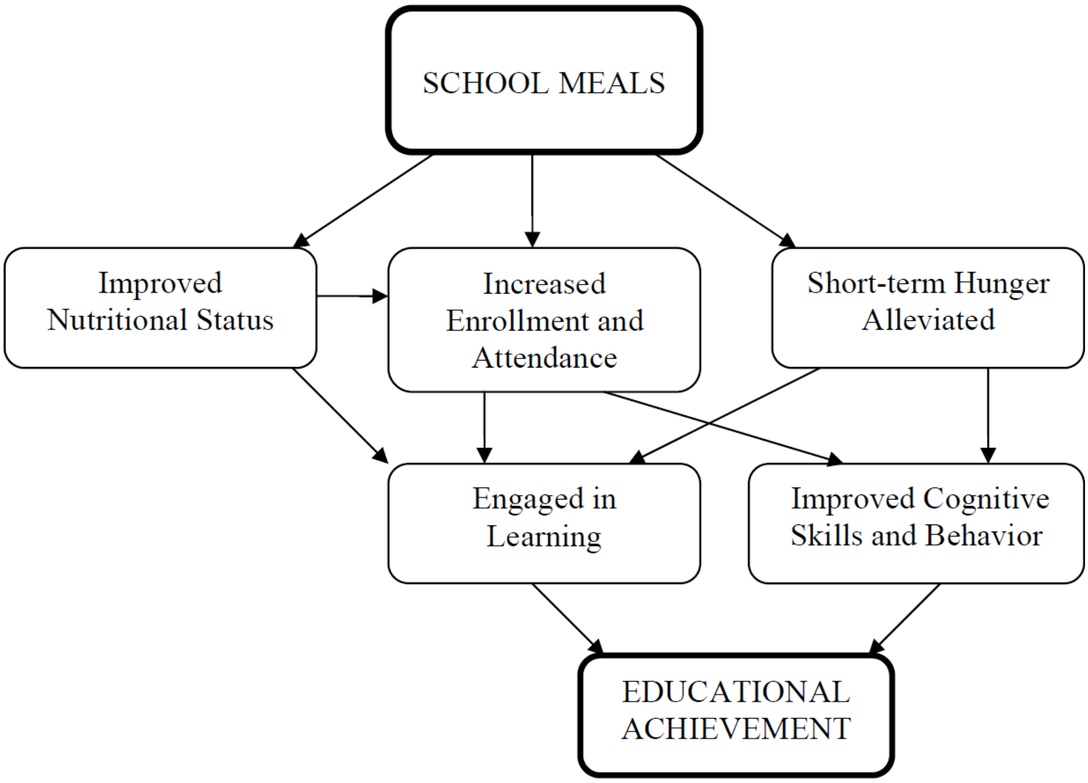
1.2 Literature review

1.2.1 Theoretical and conceptual framework

Our study is built on the expectancy theory of motivation developed by Vroom (1964). This theory stipulates that an individual propensity to act in a particular way depends on the expected outcome that will follow his action. In our case, the SFP acts like an incentive to entice children to school and facilitate their learning process. The expectancy is the conviction regarding the probability that participating in the program will help solve their hunger and nutrition issues. It is the confidence that regular attendance will deliver them the pain of hunger. Moreover, the expected outcome for students and their parents is also the belief that their regular attendance will help them receive quality education and this education will in turn free them from starvation in the long run. Thus, the final result of this expected outcome could lead to an increase of attendance, enrollment and a decrease in dropout rate.

Conceptually, the increase of educational outcomes caused by the program can occur through three main channels as illustrated by the Figure 1. Firstly, SFP can increase the attendance by reducing the opportunity costs of attending more regularly and offering extra motivations to do so. This latter situation may lead to an increase of the time children spend in school and the time they can devote towards learning. The second channel is through the attenuation of hunger which may increase their concentration during lectures. The final mechanism is through the improvement of children's nutrition which can improve their health and help them attend school regularly.

Figure 1. Relationship between SFP and potential outcomes and impacts on school children



Source: Adapted from Grantham-McGregor et al. (1998) and Jacoby et al. (1998).

1.2.2 Concept of School Feeding Program and empirical literature

School feeding programmes are broadly perceived as provision of food freely or sometimes against a small amount of money to a target unit in school. There are many modalities but we can summarize them in two main groups: within-school meal (WSM) and take-home rations (THR). For the first modality, students eat in the school canteen for free while for the second one, students can bring back food to home whenever they attend. Within SFP has two modalities as well: intervention that supply high-energy biscuits or snacks and programmes that provide students with meals. According to their respective costs, each of the modalities has advantages and trade-offs (Bundy and al., 2009).

Concerning the meals, the type of food provided is sometimes designed in line with territorial preferences and can be costlier than snacks. The snacks are akin with meals in increasing students' performance, but may provide lesser effects in maintaining students at school. Moreover, they require less infrastructure and can touch many students compared to within SFP. As for the take-home ration, it may provide better outcomes compared to others but may not always be beneficial to intended children since the food can be shared once at home with the other members of family (Martens, 2007).

Three main reasons guide the implementation of school feeding programmes: the first one is to respond to social need issues; the second objective is to increase educational outcomes and finally to enhance nutrition in the target unit. Concerning educational benefit, SFP may be a tool to maintain students in school through improving enrolment and attendance rate. A higher attendance may be translated into an increase in school performance, since students can now cope with hunger which was an impediment to their concentration(Jukes et al., 2007).

Basically, the impact of SFP on human capital development is related to education and health. Mostly, SFP by providing healthy food to students, increases their attendance which can help them learn more. By attending school more often, students can perform well and increase their probability to complete their exams and degrees. Consequently in the future they may have greater possibility to find better jobs with higher incomes (Jomaa et al., 2011 , Psacharopoulos & Patrinos, 2018).

As said above, the impacts of SFP come from an improvement in quality and quantity of time spent at school by students, which later improve human capital efficiency. But the magnitude of the impacts may also rest on the organization and set up of the programme. Particularly, intervention oriented to disfavoured areas may provide greater results. SFP can also have an indirect effect on local investments. Indeed, local population by providing sometimes raw materials and other inputs for canteen may improve substantially their economic situation indirectly. This additional source of income may increase the purchasing power in areas where the programmes are implemented.

Moreover, according to Samuelson (1956) and Becker (1973), families where children eat free lunch in school will consider this new opportunity in their consumption and investment plans. Consequently, they will reallocate their consumption based on this indirect transfer. This model, called resource allocation model stipulates that SFP, may be more efficient at enhancing particular household members' outcomes than transfers targeting the whole household.

Previous empirical works are not conclusive about the impact of SFP on educational outcomes. A study by WFP (2019) revealed that fortified biscuits in Bangladesh has significantly led to a rise in school enrolment by about 14.2% and a reduction in the probability of drop-out rate by about 7.5%. Furthermore 45 studies of SFP in different countries have shown that students in the treatment groups attend school 4-7 days more than those in the treatment group (WFP, 2019). Additionally Afridi (2011) using the DID method found that the attendance rate of girls has increased by 10.5% comparatively to boys in India but did not find any positive effect on enrolment rate. SFP has also helped reduce inequality in the dropout rate between boys and girls. Indeed in Madagascar, THRs intervention led to a decrease in dropout rates, particularly for girls by over 40% (UNEP, 2016) and in Burkina Faso, it has significantly increased the enrolment of girls aged 6-12 by 6% (World Bank Group, 2018).

Dercon et al.(2014) equally contribute to extending the literature related to SFP. Indeed, using instrumental variable methods, they find that the intervention was successful in compensating for the adverse impacts of drought on child health.

The effect of SFP on school performance has also been analysed through randomized control trial method. Indeed, an RCT in Burkina Faso after one year of intervention did not show any impactful result on student performance. The key finding in this study is that girls compared to boys spent less time to solve their test (Kazianga et al., 2012). Furthermore a RCT study after one year of intervention in Jamaica, has equally not found any improvement in students' spelling or reading ability but has revealed an important increase in their mathematics ability(Powell et al., 1998). Another RCT conducted in South Africa with intervention providing students with biscuits have revealed a significant impact on cognitive abilities after one year(van Stuijvenberg et al., 1999).

Evidences about SFP impact on drop-out rates are also inconclusive even if some studies have limitations in disentangling the effects of the intervention from several other factors. A. U. Ahmed (2004) showed that the SFP (School lunch) in Bangladesh significantly lowered the dropout rate in the treatment group by around 7.5 percent compared to the control group. Before the previous study, the author in collaboration with Del Ninno has found that the THR has a significant impact on dropout rate as well. This impact was evaluated at about 6 percent in the treatment group. However this study suffers from the difficulty to eliminate other factors affecting the outcome variable (A. Ahmed & del Ninno, 2002). Other authors used a DID method to estimate the causal effect of SFP on dropout. It is the case of Tan et al.(1999). These authors assess the effects of similar intervention in the Philippines. More specifically they used differences between pre and post intervention data and have found no significant effects of the programme on dropout rate.

Contrary to the other outcome variables, studies about the effects of the programme on student absenteeism is very rare. Only Kazianga et al.(2009) using a DID methodology found that those who were receiving meals at school have 0.7 days less absenteeism compared to the control group. By studying the heterogeneity effects according to gender, they found that the programme did not have any effects on boy's absenteeism but revealed a significant effect on girls.

Our study extends the literature on this topic in three ways. First, from our knowledge, it is the first empirical paper about the impact of SFP in Cote d'Ivoire and secondly contrary to other studies we also investigate the indirect effects on households' expenditure and the effect on other social outcome variables we think are of greater importance for child development namely child labor and finally we include a cost effectiveness analysis which is has been overlooked in many previous studies.

1.3. Background of SFP in Cote d'Ivoire

After the end of the post-election crisis in 2011, the country's economic situation renewed with improvement, with the country having one of the highest growth rates in sub-Saharan Africa. Based on the World Bank's latest Living Standards Measurement Survey from 2015, the poverty rate dropped from around 51 percent in 2011 to 46 percent in 2015. This increase generated by recent economic recovery has impacted both rural and urban areas. Nevertheless, poverty is still an important rural phenomenon, marked by inequalities in access to important services and gender disparities. Around 30 percent of children under 5 years old suffer chronic malnutrition and 13 percent of the population suffer from food insecurity.

Women face typically serious challenges in schooling. In 2012, 63 percent of women in the country were illiterate, compared to 49 percent of men. Girls were also more often educationally badly off than boys. Only 14 percent of girls made it to secondary school, compared to 30 percent of boys. In primary school, 9 girls were enrolled for every 10 boys, and 34 percent of girls dropped-out from school prematurely, compared to 28 percent of boys.

After the independence in 1960, Côte d'Ivoire promised to reach a schooling rate of 100 percent. As a result, it has put education as a national main concern by allocating more than 40 percent of the budget in the sector. In September 2015, the government of Cote d'Ivoire (GoCI) made school mandatory and free for children between 6 and 16 years old. However, a number of factors slowed down this objective, including the problem of additional cost related to education and noon hunger, which was soon faced by many children whose schools were positioned several kilometres from their family's home. The satisfactory and inclusive response to this important problem required the conduct of a social policy based particularly on school meals.

Since 1989, the government of Cote d'Ivoire has administered a national SFP with the support of WFP. In 2000, they integrated nutritional aspects in addition to educational objectives, targeting for sustainability by fostering the production of local communities. This national program, called the "Integrated Program for the Sustainability of School Canteens" (PIPCS), tries to address the problems of chronic child malnutrition, evaluated at 23.2 percent for boys and 19.9 percent for girls under 5 years old, and poor performance in primary education, with 63 percent of the population being illiterate and only 75.1 percent of children with primary school education level in 2016 (MICS, 2016). In April 2014, the Government, through the Directorate of School Canteens (DCS), with the technical assistance of the WFP and UNDP, established the strategy for the national SFP. The areas of the intervention were designed through an analysis based on a composite indicator of gross completion rate, level of food insecurity, prevalence of chronic malnutrition and gross enrolment rate. Thus, the following regions have been identified as priority areas for school feeding interventions: priority 1 (Cavally, Guémon, Poro, Bagoué, Tchologo, and Bafing), priority 2 (Worodougou, Béré) and priority 3 (Gontougo and Bounkani). This new program concerns only the regions which did not receive it before and consists of providing lunch to students in public primary schools. Specifically, the program provided fortified food (iron-enriched rice, split peas and vitamin A-enriched vegetable oil) during lunch time. Moreover, voluntary contributions of fresh vegetables and protein sources such as dried fish from the community members to the school canteens further contributed in diversifying and enhancing the school meals.

The program covered 1,634 school canteens in the 10 priority regions. Building on the progress from this project, WFP conducted a vulnerability analysis and mapping (VAM) exercise to select the most food insecure communities within 7 of the 10 priority regions for the 2015-2020 MGD project, in coordination with the DCS, though WFP continues to provide school meals with funding from other donors in 6 other regions in Côte d'Ivoire (which are not included as part of this evaluation).

1.4 Data and methodology

1.4.1 Data

In order to analyse empirically our topic, we use data from National Institute of Statistics (NIS) in Cote d'Ivoire. As sampling strategy, they firstly designated the geographic areas (regions) for the intervention from which they selected a sample of eligible schools. Then, from this sample of eligible schools, a second random sampling led to choose a subsample of schools to take part in the project. To minimise the costs of the survey, a random draw was conducted at each school level which helps determine the students to be surveyed in order to have information about their characteristics as well as those of their family and the environment in which they were living. The baseline data were collected in 2015 prior to the beginning of the programme and it is mainly information about schools, households and students' characteristics such as: number of students enrolled, number of teachers and school facilities as well as information about child labour. The follow up data was collected in 2016. The data was collected at the same time in both the treatment and control group. Out of 813 schools sampled, 801 were correctly surveyed (610 beneficiary schools and 191 non-beneficiary schools), i.e. 98.4% of achievement. At the level of the household survey, out of 3636 households initially planned, 3624 households were actually interviewed in both the baseline and follow up survey, for a response rate of 97.6% (which falls within the acceptable limits described in the methodology). In terms of reading assessment, out of 100 schools initially planned, 99 schools (56 beneficiary schools and 43 control schools) were correctly surveyed. Also, out of 1200 pupils expected for the survey about reading performance, 1181 pupils (711 in the treatment group and 410 in the control group) were correctly surveyed. These limits do not affect the quality of the estimates that have been made from the data collected. All this selection was done in 7 regions namely: Bafing, Bagoue, Bounkani Cavally, Gontougo, Poro and Tchologo.

1.4.2 Methodology

Our main concern in this analysis is to explore the causal impact of SFP exposure on educational outcomes, child labour and households' expenditure. Even if we control for individual and school characteristics, we may have biased estimates of the real impact of the school programme with ordinary least squared (OLS). In other words, even though the list of observable characteristics is extensive, the decision for parents to let their kids take up the programme may be based on unobservable individual characteristics which we cannot account for. Therefore, the results to obtain using OLS may include not only the causal effect of the program but also the indirect effect of other factors not included but correlated with our outcome variables. Hence in order to reduce the bias and obtain a consistent estimate

we resort to a DID (difference in difference) approach. Basically, we calculate the difference of outcome before and after the program in the treatment group and use the control group to factor out any contemporaneous changes that may occur during that period. By doing so, we are controlling both for the effects of unobserved and observed time invariant characteristics. We assume that there are no time varying differences between the two groups. Two main reasons comfort us in our assumption. Firstly, the time difference between the baseline and the follow up surveys is short (1 year) and secondly since all the schools included in the surveys are in the northern part of the country we can assume that there are no major changes that can affect disproportionately one of the two groups. Finally, this method helps us control for any measurement error in the records provided that the degree of propension to inflate participation figures does not vary before and after the implementation of the programme.
We formulate our equation as follow:

$$\mathbf{Y_{ist}} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{Treat}_{is} + \boldsymbol{\beta_2}\mathbf{Time}_{it} + \boldsymbol{\beta_3}\mathbf{Treat}_{is} * \mathbf{Time}_{it} + \boldsymbol{\beta_4}\mathbf{X_{ist}} + \boldsymbol{\tau_s} + \mathbf{U_{ist}} \qquad (1)$$

Y_{ist} : Outcome variable of individual i (school, household or student) in region s at time t.
Treat_{is}: Treatment dummy, equals 1 if school or individual is in the treatment group, 0 otherwise.
Time_{it}: Time dummy, equals 1 if information is from baseline survey, 0 otherwise.
$\mathrm{Treat}_{is} * \mathrm{Time}_{it}$: Treatment effect indicator
X_{ist} : School and individual characteristics;
τ_s: region fixed effects
U_{ist}: Error term.
Depending on the outcome variable, i represents school, household or student.

It is worth highlighting the fact that our DID approach measures the Intent to Treat (IIT) effect (Imbens & Rubin, 1997). That is the difference in outcomes between the units assigned to the treatment group and the unit assigned to the control group irrespective of whether the unit assigned to the treatment arm actually receives the program. If noncompliance occurs only in the treatment group, the IIT can still be relevant because in most cases, policy makers can only offer a program and cannot force the program participation in the treatment group. However, if non-compliance occurs in the control group, the IIT effect can be biased downward. Clearly, the potential effects of the program may be underestimated if students in the control group have access to meal. This situation is minimized since some teachers included in the programme management in each school checked the identity of the students before they enter the canteen. Another potential source of underestimation is the possibility for students who eat to share food with others. This situation is also unlikely to happen since students have the obligation to eat in the canteen and cannot go out with some food. Within school externality minimized (checking) even cross school externality because of distance. However, since the program selected the most food insecure communities, we may expect our results to be down-biased.

1.5 Descriptive statistics (Balance test)

The table1, 2 and 3 respectively show schools, households and students descriptive statistics depending on whether they belong to the treatment or control group (variable description is presented in the annex pages). These tables help us to know whether the control and treatment group are balanced in terms of average characteristics. Although this balancing test is not fundamental in difference in difference approach, it is generally reassuring when it is satisfied. From table 1, it appears that there are not significant differences in terms of characteristics between schools in control and treatment group. On the contrary the table 2 shows some significant differences in households characteristics. Households in control group seem to be better off compared to the treatment group at the baseline. This shows that any regression by OLS may not only reflect the impact of the programme but also the differences between the two groups. Moreover, the summary statistics of students selected for the reading test in table 3 shows that there are also significant differences between the treatment and the control group.

Table1.1: School characteristics

Variable	Treatment	Control	Diff
Total teachers	5.07	3.81	1.258
	[0.06]	[0.14]	[1.141]
Locality	1.94	1.98	-0.043
	[0.01]	[0.01]	[1.018]
Number of classrooms	4.91	3.59	1.318
	[0.19]	[0.15]	[1.178]
Warehouse	1.61	2	-0.389*
	[0.03]	[1.00]	[0.230]
School co-operative	1.21	2	-0.789*
	[1.02]	[0.00]	[1.317]
water	1.52	1.65	-0.131
	[1.02]	[0.03]	[1.041]
Drinkable water	4.75	4.26	0.484
	[1.08]	[0.15]	[1.163]
Toilets	1.47	1.71	-0.243
	[0.02]	[1.03]	[1.041]
Separate toilets	1.2	1.29	-0.09**
	[0.02]	[0.06]	[0.045]
Kindergarten	1.84	1.83	0.011
	[0.01]	[0.03]	[0.030]
Parents’ association	1.13	1.28	-0.15
	[1.01]	[0.03]	[1.031]
Library	1.91	1.88	0.031
	[0.01]	[0.02]	[0.025]
Electricity	1.89	1.92	-0.028
	[0.01]	[0.02]	[0.025]
Teachers receive training	1.61	1.65	-0.043
	[0.02]	[0.03]	[0.040]

Absenteeism	3.8	3.62	-0.184
	[0.49]	[0.87]	[1.002]
drop out	4.14	3.57	0.562
	[0.26]	[0.46]	[0.523]
Enrollment	204.96	147.84	57.117*
	[28.78]	[27.79]	[30.049]

Note: significance levels: * < 10% ** < 5% ***<1%. Robust standard errors in brackets.

Table 1.2: Household characteristics

Variable	Treatment	Control	Diff
Gender of head household	1.12	1.11	0.009
	[0.01]	[0.01]	[0.013]
Age of head household	45.43	44.66	0.767*
	[0.21]	[0.42]	[0.466]
Education level	1.51	1.49	0.013
	[0.01]	[0.03]	[0.033]
Child fertility	0.05	0.04	0.01
	[0.00]	[0.00]	[0.008]
Child labor	0.25	0.22	0.031
	[0.02]	[0.01]	[0.017]
Family size	2.18	2.07	0.11
	[0.04]	[0.08]	[0.089]
Distance to school	0.35	0.2	0.147
	[0.11]	[0.04]	[0.205]
Number of people working in house	2.82	2.87	-0.048
	[0.04]	[0.07]	[0.085]
Food expenditure	9893.15	9844.99	48.152
	[881.01]	[394.86]	[887.055]
Health Expenditure	4645.66	5002.42	-356.752*
	[93.50]	[226.50]	[214.995]
Agriculture Expenditure	6952.49	7629.37	-676.886
	[394.78]	[647.54]	[830.849]
House equipment expenditure	4584.2	5348.22	-764.015
	[780.38]	[468.16]	[987.913]
Log (food expend)	7.52	7.63	-0.11
	[0.08]	[0.19]	[0.169]
Log (health expenditure)	8.14	8.06	0.075**
	[0.01]	[0.03]	[0.035]
Log (agriculture expenditure)	8.55	8.53	0.023
	[0.01]	[0.03]	[0.035]
Log (house equipment expenditure)	9.59	9.43	0.158
	[0.06]	[0.14]	[0.149]
Bicycle	1.29	1.34	-0.049***
	[0.01]	[0.02]	[0.019]
Car	1.98	1.98	-0.005

	[0.00]	[0.01]	[0.005]
Motorcycle	1.32	1.35	-0.031
	[0.01]	[0.02]	[0.019]

Note: significance levels: * < 10% ** < 5% *** < 1% . Robust standard errors in parentheses

Table 1.3: students characteristics

Variables	Treatment	Control	Diff
Gender	1.5	1.49	0.007
	[0.02]	[0.02]	[0.030]
Reading score	1.63	2.33	-0.693
	[0.43]	[0.42]	[0.474]
age	9.41	9.3	0.11
	[0.08]	[0.10]	[0.067]
education level	3.46	3	0.458
	[0.06]	[0.08]	[1.099]
book at home	2.2	1.99	0.211**
	[0.07]	[0.06]	[0.095]
other kind of books	1.93	1.93	-0.006
	[0.01]	[0.01]	[0.015]
read with family members	1.67	1.68	-0.009
	[0.02]	[0.02]	[0.028]
read alone at home	1.51	1.47	0.047
	[0.02]	[0.02]	[0.030]
like reading	1.34	1.18	0.161*
	[0.08]	[0.09]	[0.096]
father age	44.48	44.49	-0.018
	[0.41]	[0.54]	[0.671]
parent's education	1.51	1.42	0.094
	[1.03]	[1.04]	[1.048]
Number of brothers going to school	1.56	1.6	-0.036
	[0.05]	[0.06]	[0.072]
number of sisters going to school	1.58	1.56	0.021
	[0.14]	[0.21]	[0.246]
Number of brothers not going to school (6-14 years	1.82	1.79	0.026
	[0.02]	[0.02]	[0.029]
Number of sisters not going to school (6-14 years)	1.87	1.8	0.067***
	[0.01]	[0.02]	[0.024]
distance to school	0.22	0.2	0.017
	[0.03]	[0.03]	[0.039]
N	711	470	1181

Note: significance levels: * < 10% ** < 5% *** < 1% . Robust standard errors in parentheses

1.6 Results and discussion

As already mentioned the impact of the programme is obtained by using a DID approach. Our estimate is likely to be biased for two reasons if we use simple OLS. Firstly, only those who are likely to benefit from the programme will take it. Secondly, as already shown in the summary statistics, some observable characteristics differ in both groups. For educational outcome variables, we present the main results and heterogeneity effects based on gender and also on grade. The heterogeneity analysis will help us highlight any inequality in terms of gender in educational outcomes. The gender effect of the program is relevant for policy makers since it can help discern whether girls and boys will respond equally or differently to SFP. Furthermore, in all our results, we cluster standard error at school or village level in order to allow for possible correlation of information provided by individuals within the same cluster of schools or villages. For school related outcome variables, we control for school facilities as well as other school inputs such as number of students, teachers etc. As for households related outcome variables, we also control for household specific characteristics. For child labour and student performance, additional to school and household characteristics, we control for child specific features such as age, grade etc. Our investigation is conducted in several steps, where each result motivates the subsequent component of our analysis.

1.6.1 Drop out

Table 4 reports the results on drop out. By drop-out we mean the number of students who abandoned school for a reason or another. Hence, a negative coefficient indicates that children in the treatment group are on average less likely to drop out of school compared to others.

The results on full sample; column (1) show that compared to the control group, the treatment group is 4.2 percent less likely to drop out from school. In other words, in schools with free lunch, 4.2 percent fewer children drop out compared to the control group. Therefore, the programme provides parents with an incentive to keep their kids in school or the programme gives the children themselves an incentive to enjoy staying in school during the first year of the programme. The reason may be that since most of the people in this part of the country are poor and sometimes lack food, parents may prefer keeping their children in school. Ahmed (2004) shows similar effects in the case of SFP implemented in Bangladesh.

From column (2) and (3), it appears that the programme significantly affects girls' dropout rate but does not for boys. The reason is, parents may consider opportunity costs in their decision about their kids' studies. Basically, they will consider two fundamental choices: give the kids the possibility to increase their education level or let them earn money for the family. Since this opportunity cost seems higher for boys, SFP may not significantly affect their decision to prevent their sons from dropping out of school. Moreover, the heterogeneity effect analysis in table 5 highlights the fact that the program does not impact the students in higher grades or older students but impacts significantly the younger grade group. The impact is therefore driven by students in lower grades. This is likely to expose the fact that the cash value of the food provided through the program does not change while the costs associated to schooling rise with the grade, due to the higher direct costs associated with school material (uniforms, books, etc) and opportunity costs (value of home and labour market production). The total cost associated with schooling seems to be higher in higher grades compared to lower ones and may influence parents and child's decisions. This result is in line with Dora et al. (2015) who also find that SFP in India is more efficient at increasing school participation in lower grades than in higher ones. Furthermore, school facilities seem to have a positive impact on dropout rate. Indeed, this rate significantly decreases due to the presence of electricity, water, library in schools. The total number of classrooms also plays a significant role in decreasing school dropout rate. On the contrary the total number of students increases the likelihood of drop out of school.

Table 1.4: Impact on drop out

	Drop out		
VARIABLES	Full sample	Boys	Girls
Treat*Post	-0.042**	-0.017	-0.036**
	(0.0211)	(0.076)	(0.016)
Garden	-0.0256	-0.0194	-0.0350
	(0.0299)	(0.0495)	(0.0402)
Electricity	-0.037***	-0.0336	-0.0404***
	(0.004)	(0.220)	(0.0189)
Library	-0.021***	-0.0312	-0.0217**
	(0.002)	(0.195)	(0.0089)
Total teacher	-0.00253	-0.0165	-0.0241
	(0.0561)	(0.0836)	(0.0799)
Total Classrooms	-0.0190***	-0.027***	-0.018**
	(0.0032)	(0.0056)	(0.0079)
Water	-0.091***	-0.094***	-0.0802
	(0.0068)	(0.002)	(0.137)
Locality	-0.0153***	-0.0166	-0.0323**
	(0.0097)	(0.135)	(0.0128)
Kindergarten	-0.036*	-0.024	-0.028
	(0.020)	(0.076)	(0.179)
Parents' association	-0.00763*	-0.00861	-0.00696
	(0.00394)	(0.00572)	(0.00564)
Separate toilets	-0.142	-0.183	-0.0789
	(0.118)	(0.173)	(0.168)
Warehouse	0.00763*	0.00861	0.00696
	(0.00394)	(0.00572)	(0.00564)
Teacher's training	0.000569	-0.000890	-0.0675
	(0.0102)	(0.0111)	(0.0519)
Number of students in school	0.0537***	0.0491**	0.0688***
	(0.0165)	(0.0238)	(0.0244)
Constant	-2.039	0.139	-4.567**
	(1.406)	(1.998)	(2.058)
School Fixed effects	YES	YES	YES
Observations	596	596	596
R-squared	0.179	0.151	0.266

Notes: The dependent variable in this regression is the natural log of the number of students who drop-out from primary school in our concerned areas. The unit of observation is school. Full detail of the control variables included are provided in variables description (Appendix). The variable of interest is Treat*Post. Coefficients are reported with standard errors in parentheses clustered at school level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.5: Heterogeneity effects of drop out based on student's grade

VARIABLES	Grade1	Grade 2	Grade 3	Grade 4	Grade 5	Grade 6
Treat*Post	-0.0651*	-0.0782**	-0.0212**	-0.0144**	-0.0573	-0.00933
	(0.0390)	(0.0395)	(0.0187)	(0.0072)	(0.0483)	(0.0311)
Garden	-0.00710	-0.00370	-0.00272	-0.00293	-0.00245	-0.00502
	(0.0106)	(0.00649)	(0.00749)	(0.00743)	(0.00608)	(0.00479)
Electricity	-0.0629*	-0.0430	-0.0346***	-0.0392*	-0.0200	-0.0106
	(0.0323)	(0.197)	(0.0173)	(0.0226)	(0.0185)	(0.0146)
Library	-0.0550*	-0.0219	-0.0221	-0.0365*	0.0273	0.0311**
	(0.0299)	(0.0183)	(0.0211)	(0.0209)	(0.0171)	(0.0135)
Total teacher	-0.00111	-0.00441	-0.00768	-0.0100	-0.00391	-0.00686
	(0.0234)	(0.0143)	(0.0165)	(0.0164)	(0.0134)	(0.0106)
Locality	-0.0119	-0.0321	-0.0609*	-0.0469	0.0317	-0.0502**
	(0.0443)	(0.271)	(0.0313)	(0.0310)	(0.0254)	(0.0200)
Kindergarten	-0.00499**	-0.00277*	-0.00212	-0.00163	-0.000120	-0.00145
	(0.00248)	(0.00152)	(0.00175)	(0.00174)	(0.00142)	(0.00112)
Classrooms	-0.0767***	-0.0356	-0.0118	-0.0264*	-0.00806	0.0101*
	(0.0122)	(0.0746)	(0.0862)	(0.0155)	(0.0699)	(0.0551)
Water	-0.0193	-0.0385***	-0.0235	-0.0213	-0.0130	-0.0178
	(0.0223)	(0.0101)	(0.0157)	(0.0156)	(0.0128)	(0.0136)
Warehouse	-0.0314	-0.0513***	-0.0269*	-0.0277	-0.105	-0.151
	(0.204)	(0.0125)	(0.0144)	(0.143)	(0.117)	(0.0921)
Separate toilets	-0.0151	-0.0809	0.0113	0.0134	-0.0641	-0.0513
	(0.0267)	(0.163)	(0.0188)	(0.187)	(0.153)	(0.120)
Teacher training	-0.0611	-0.0122	-0.0191	-0.0507	-0.0377	-0.0646
	(0.0681)	(0.027)	(0.0186)	(0.176)	(0.0962)	(0.0758)
Parents' association	-0.0143	-0.00417	-0.00979	-0.00891	-0.00812	-0.00230
	(0.00893)	(0.00546)	(0.00631)	(0.00625)	(0.00512)	(0.00403)

Number of students in school	0.0523	0.0151	0.0531*	0.0134	0.0176	0.0446**
	(0.0384)	(0.0235)	(0.0271)	(0.0269)	(0.220)	(0.0183)
Constant	-1.130	0.919	-0.671	-4.383*	-5.331***	-4.184***
	(3.391)	(2.073)	(2.393)	(2.374)	(1.942)	(1.529)
Observations	596	596	596	596	596	596
R-squared	0.187	0.169	0.139	0.167	0.153	0.156
School FE	YES	YES	YES	YES	YES	YES

Note:The dependent variable in this regression is the natural log of the number of students who drop-out from primary school in our concerned areas. Each column displays the result of the corresponding grade. The unit of observation is school. Full detail of the control variables included are provided in variables description (Appendix). The variable of interest is Treat*Post. Coefficients are reported with standard errors in parentheses clustered at school level. *** p<0.01, ** p<0.05, * p<0.1.

1.6.2 Absenteeism

Absenteeism is measured by the number of students who have more than 10 days of absenteeism in each school. The table 6 shows that on average the programme reduces significantly the probability of absenteeism in the treatment group by 3.1 percent compared to the control group. This result can be explained by the fact that the programme by providing students with food rich in nutrients reduces their probability to have health issues related to malnutrition which can prevent them from attending school. Moreover, since the take up is conditional on attendance, students are motivated to attend school sometimes. Also, since the food provided by the school is considered to be more delicious than home-made food for most of the students, they prefer attending school rather than staying at home. The heterogeneity effect analysis based on gender reveals that SFP does not significantly reduce boys' absenteeism while it does for girls. Kazianga et al. (2009) reach the same conclusion in their study. This effect can be due to the fact that the opportunity cost for letting a boy go to school is higher than that of girls. The reason is that boys are most likely those who help their parents in farms. Thus sometimes, especially during raining or harvest seasons parents prefer going to farms with their boys instead of letting them go to school. Indeed, this situation is more common in this part of the country where boys can sometimes spend one week with their fathers farming or harvesting before resuming school. The analysis of the heterogeneity effect according to student's grade in table 7 points out that the effect is most likely to be driven by students in lower grades. Indeed, for students from grade 1 to grade 4 the effect is significant while it is the opposite for students in grade 5 and 6. Students in grade 5 and 6 are generally older and therefore constitute an important labour force for domestic and external activities which can prevent them to attend classes regularly mostly when parents are poor. As in the previous results about dropout rate, the presence of school facilities (library, water, warehouse, total number of classrooms) reduces significantly absenteeism while the likelihood of absenteeism increases significantly due to the total number of students.

Table 1.6: Impact on absenteeism

	Absenteeism		
VARIABLES	Full sample	Boys	Girls
Treat*Post	-0.031**	-0.023	-0.048**
	(0.0147)	(0.027)	(0.0228)
Garden	-0.00479	-0.0297	-0.0206
	(0.0253)	(0.0385)	(0.0358)
Distance to school	-0.00326	-0.00275	-0.0319
	(0.00516)	(0.00532)	(0.0505)
Library	-0.0162***	-0.00914	-0.0218***

	(0.00480)	(0.00702)	(0.00674)
Electricity	-0.0432	-0.00453	-0.100
	(0.109)	(0.157)	(0.158)
Total teacher	-0.0452**	-0.0533**	-0.0361
	(0.0158)	(0.0275)	(0.0265)
Separate toilets	-0.00692	-0.00734	-0.00805
	(0.0439)	(0.0637)	(0.0630)
Locality	-0.0408**	-0.0353	-0.0472**
	(0.0202)	(0.0226)	(0.0212)
Total Classrooms	-0.0795**	-0.0676	-0.0846**
	(0.0370)	(0.0524)	(0.0336)
Water	-0.036***	-0.0132	-0.0528***
	(0.0138)	(0.0111)	(0.0109)
Kindergarten	-0.012*	-0.015	-0.010*
	(0.0072)	(0.0849)	(0.0059)
Warehouse	-0.0243**	-0.0182	-0.0280*
	(0.0100)	(0.0145)	(0.0143)
Teachers training	-0.000749	-0.00236	0.00846
	(0.0109)	(0.0117)	(0.0411)
Number of students	0.0465***	0.0521***	0.0416***
	(0.0120)	(0.0177)	(0.0171)
Parents' association	-0.00364	-0.00649	-0.00127
	(0.00317)	(0.00458)	(0.00449)
Constant	1.115	0.673	1.671
	(0.835)	(1.196)	(1.183)
School Fixed effects	YES	YES	YES
Observations	596	596	596
R-squared	0.042	0.000	0.099

Notes: The dependent variable in this regression is the natural log of the number of students who miss more than 10 days of classes. The unit of observation is school. Full detail of the control variables included are provided in variables description (Appendix). The variable of interest is Treat*Post. Coefficients are reported with standard errors in parentheses clustered at school level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.7: Heterogeneity effect of absenteeism based on grade

VARIABLES	Grade1	Grade2	Grade3	Grade4	Grade5	Grade6
Treat*Post	-0.017*	-0.0449**	-0.0437***	-0.0182**	-0.0170	-0.0186
	(0.0101)	(0.0229)	(0.0149)	(0.0074)	(0.0113)	(0.0651)
Garden	-0.00228	-0.00227	-0.00229	-0.00221	-0.00228	-0.00220
	(0.00229)	(0.00229)	(0.00229)	(0.00229)	(0.00229)	(0.00229)
Library	-0.0166*	-0.0168*	-0.0165*	-0.0168*	-0.0169*	-0.0175**
	(0.00873)	(0.00873)	(0.00872)	(0.00873)	(0.00874)	(0.00876)
Electricity	-0.00874	-0.0220	-0.00387	-0.0113	-0.00394	-0.00854
	(0.0696)	(0.0705)	(0.0696)	(0.0696)	(0.0705)	(0.0695)
Kindergarten	-0.00588	-0.0147	-0.0170	-0.0143	-0.00746	-0.0147
	(0.0655)	(0.0647)	(0.0113)	(0.0651)	(0.0645)	(0.0649)
Teachers' training	-0.0137	-0.00863	-0.00790	-0.00746	-0.0163	-0.0315
	(0.105)	(0.104)	(0.104)	(0.105)	(0.104)	(0.106)
Total teacher	-0.0429**	-0.0639**	-0.0425**	-0.00394	-0.00380	-0.00437
	(0.0179)	(0.0279)	(0.0176)	(0.0276)	(0.0276)	(0.0276)
Locality	-0.0181	-0.0123	-0.0739**	-0.0278*	-0.0399	-0.0454
	(0.0957)	(0.0963)	(0.0356)	(0.0157)	(0.0958)	(0.0957)
Classrooms	-0.0677***	-0.0964***	-0.0107	-0.0886***	-0.0703	-0.0465
	(0.0263)	(0.0264)	(0.0265)	(0.0264)	(0.0263)	(0.0264)
Water	-0.0424**	-0.0145	-0.0194	-0.0105	-0.00971	-0.00977
	(0.0181)	(0.0488)	(0.0494)	(0.0485)	(0.0492)	(0.0483)
Kindergarten	-0.0149	-0.0183	-0.0145	-0.0110	-0.0136	-0.0108
	(0.0441)	(0.0441)	(0.0440)	(0.0442)	(0.0441)	(0.0442)
Warehouse	-0.0598***	-0.0180	-0.0169	-0.0351	-0.0422	-0.0647
	(0.0218)	(0.0598)	(0.0599)	(0.0599)	(0.0598)	(0.0598)
Separate toilets	-0.0120	-0.0216	-0.0202	-0.0171	-0.0136	-0.0135
	(0.0576)	(0.0581)	(0.0578)	(0.0579)	(0.0577)	(0.0575)

Prents’association	-0.0265	-0.0213	-0.0378	-0.0278	-0.0251	-0.0265
	(0.0832)	(0.0827)	(0.0832)	(0.0827)	(0.0827)	(0.0827)
Total number of students	0.0592	0.0598*	0.0585	0.0594	0.0598*	0.0601*
	(0.0363)	(0.0362)	(0.0362)	(0.0362)	(0.0362)	(0.0362)
Constant	0.912	0.827	0.914	0.871	0.893	0.856
	(0.738)	(0.733)	(0.730)	(0.732)	(0.731)	(0.732)
Observations	596	596	596	596	596	596
R-squared	0.046	0.048	0.049	0.047	0.047	0.048
School FE	YES	YES	YES	YES	YES	YES

Notes: The dependent variable in this regression is the natural log of the number of students who miss more than 10 days of classes. Each column displays the result of the corresponding grade. The unit of observation is school. Full detail of the control variables included are provided in variables description (Appendix). The variable of interest is Treat*Post. Coefficients are reported with standard errors in parentheses clustered at school level. *** p<0.01, ** p<0.05, * p<0.

1.6.3 Impact on enrolment

The results in table 8 show the impact on enrolment in grade1. The enrolment here is measured by the total number of students registered in grade 1. The result points out that contrary to the attendance and dropout rate in previous results, SFP has not significantly increased new enrolment rate. There are also no heterogeneity effects based on gender. Afridi (2011) also finds the same results in an analysis about SFP in India. One explanation for this may be that, the opportunity cost for parents to enrol their kids is higher than keep them working to provide revenue for their family. The existence of direct and indirect costs related to school (purchasing of school supplies and hardware for learning, payment of social contributions for parents' association) may also deter parents from enrolling their kids. Indeed, the World Bank (2004) has contended that user fees are the main hindrance to universal education in developing countries. However, we can notice that the presence of school facilities such as libraries, and the number of school teachers has a positive impact on enrolment.

Table 1.8: Impact on enrolment

	Enrolment		
VARIABLES	Total sample	Boys	Girls
Treat*Post	0.0860	0.0946	0.0634
	(0.147)	(0.156)	(0.141)
Garden	-0.00262	-0.0140	0.00770
	(0.00756)	(0.0124)	(0.00819)
Locality	0.00150**	0.00152***	0.0173***
	(0.000571)	(0.000482)	(0.00486)
Separate toilets	0.00749	0.00830	0.0111*
	(0.00537)	(0.00667)	(0.00610)
Electricity	0.0866	0.183**	0.0214
	(0.0808)	(0.0822)	(0.0753)
Library	0.0376**	0.0426**	0.0280
	(0.0163)	(0.0184)	(0.0231)
Total teacher	0.0172***	0.0184***	0.0160***
	(0.00342)	(0.00384)	(0.00280)
Water	0.0774	0.00886	0.112
	(0.0873)	(0.0906)	(0.0803)
Classrooms	0.0183***	0.0188**	0.0206**
	(0.0081)	(0.00846)	(0.00882)
Warehouse	0.0211	0.0619	-0.0174
	(0.0638)	(0.0643)	(0.0657)
Kitchen	0.0227	0.0237	0.0372
	(0.0783)	(0.0855)	(0.0750)
parents' association	0.0186	0.0164	0.0218
	(0.0172)	(0.0221)	(0.0218)
Teacher's training	0.00145	0.00297**	-0.0118

	(0.00159)	(0.00124)	(0.0104)
Observations	596	596	596
R-squared	0.656	0.648	0.699
School FE	YES	YES	YES

Notes: The dependent variable in this regression is the natural log of the number of students enroll in grade1. The unit of observation is school. Full detail of the control variables included are provided in variables description (Appendix). The variable of interest is Treat*Post. Coefficients are reported with standard errors in parentheses clustered at school level. *** p<0.01, ** p<0.05, * p<0.1.

1.6.4 Reading score

To assess the impact on reading score of school children and analyse the change in skills over time, the evaluation team administered the same reading assessment tool, ASER (Annual Status of Education Report). Due to the possibility that either students have access to the test from their older cohorts or teachers have become aware of the assessment and started preparing students for the test, the evaluation team revised the version of the test. To avoid any possible bias in reading outcomes, the test content has been updated while keeping the same level of difficulty.

We expect a positive impact on reading. The reason is, for children who eat free lunch, the programme may increase their reading outcomes through regular attendance and also by reducing hunger and health issues, the programme may increase children's ability to focus more during lectures. To measure this effect, we control not only for school characteristics but also, we control for households' characteristics as well as students' specific characteristics such as grade, age etc. Before showing the impact on students' performance, we first try to detect if there is any significant attrition bias.

1.6.4.1 Attrition bias

Common threats to internal validity of a quasi-experimental analysis include attrition and spillovers effect. Attrition arises when respondents drop out of the study or data on them cannot be recovered. A significant difference in terms of characteristics between attritors and non-attritors after the baseline survey may lead to biased estimates of program effects, with the risk of bias increasing with the attrition rate. However, if attrition is not correlated with treatment assignment and outcomes, it will decrease power as a result of the sample size decreasing but will not affect the treatment effect on average. In our case, we may suspect the good students to enroll in private schools after the baseline survey and create a selection bias problem. Also, weaker students are more likely to have higher absenteeism and miss the tests. To evaluate this possibility, we regress attrition on treatment assignment and a set of observables (student's and their respective household characteristics). The results in table 9 show that there is not a significant difference between attritors and non-attritors in most of our variables and also, the attrition rate seems very small (73/1181= 0.0618).

Table 1.9: Test for differential attrition

Variable	Non attritors	Attritors	Difference
Reading score	3.02	3.29	0.266
	[0.09]	[0.39]	[0.359]
Like reading	1.28	1.19	-0.087
	[0.01]	[0.05]	[0.054]
Read at home with parents	1.68	1.63	-0.046
	[0.01]	[0.06]	[0.057]
Have book at home	2.15	2.17	0.02
	[0.05]	[0.05]	[0.193]
Grade	3.3	2.95	-0.354*
	[0.05]	[0.20]	[0.203]
Age	9.52	9.6	0.087
	[0.07]	[0.26]	[0.271]
Gender	1.49	1.48	-0.015
	[0.02]	[0.06]	[0.060]
Distance to school	0.2	0.34	0.138*
	[0.02]	[0.09]	[0.080]
Father's age	1.47	1.53	0.062
	[0.02]	[0.11]	[0.097]
House equipment expenditure	4285.97	5421.92	1135.952*
	[160.00]	[639.54]	[644.576]
agriculture expenditure	4738.22	7302.05	2563.833
	[435.54]	[1342.90]	[1731.737]
Education expenditure	5579.74	6945.89	1366.152
	[490.16]	[1210.82]	[1935.174]
Car	1.99	1.97	-0.014
	[0.00]	[0.02]	[0.014]
Bicycle	1.33	1.21	-0.126**
	[0.01]	[0.05]	[0.056]
Mill	1.99	2	0.006
	[0.00]	[0.00]	[0.009]
N	1108	73	1181

Significance levels: * < 10% ** < 5% *** < 1%. Standard errors in parentheses. The unit of observation is students.

1.6.4.2 Impact on reading score

The table 10 shows the impact on reading score. We can see that the intervention has no significant impact on the reading ability. Equally the heterogeneity effects based on the gender show that even if girls perform better than boys, the effect is not any significant at all. Many reasons can explain this result which is opposite to what we expected before. First, it may be due to the fact that students had a very bad level in reading to begin with. Indeed, the average reading score before intervention is only 1.63. In this case the implementation of the programme cannot change significantly their previous level just in only two years of exposure. Second the school level organization may not be well appropriate to translate the intervention into an increase in schooling performance. Chand and al (1998) have even highlighted a negative effect of SFP on student performance in Jamaica that they related to school organization. Particularly, they noticed that SFP is likely to have a negative or no effect in schools which are not so well organized. In our case, since teachers have been assigned to the management of the programme, it may be that they spent more time for daily management and organization of food distribution while reducing time for preparing class material.

Table 1.10: Impact on reading score

VARIABLES	(1) Test score total	(2) Boys	(3) Girls
Treat*Post	1.068	0.945	1.159
	(2.074)	(2.319)	(3.175)
Garden	-0.0457	-0.0472	-0.105
	(0.111)	(0.200)	(0.165)
Father's education	0.0385	0.190	-0.199
	(0.260)	(0.444)	(0.433)
Distance to school	-0.0914	-0.695	0.0293
	(0.285)	(0.461)	(0.431)
Number of people with Job at home	0.0431	0.0991	0.154
	(0.0726)	(0.127)	(0.112)
Total number of people at home	0.00140	0.00583	-0.0316
	(0.0286)	(0.0484)	(0.0315)
Electricity	1.751	6.531***	1.758
	(1.561)	(2.298)	(2.084)
Library	1.302**	2.792***	1.153
	(0.578)	(0.847)	(0.855)
Parent's association	0.898	1.864	1.103
	(1.057)	(1.372)	(1.405)
Total teachers	0.0390	0.597	0.397
	(0.274)	(0.445)	(0.415)
Classrooms	0.117	0.549	-0.247
	(0.311)	(0.480)	(0.469)
Water	0.653*	0.258	1.212**
	(0.351)	(0.571)	(0.466)
Canteen	0.162	0.154	0.145
	(0.356)	(0.542)	(0.519)
Kitchen	0.475	1.117	1.789
	(0.694)	(0.882)	(1.152)
Separate toilets	0.270	0.0432	1.174
	(0.615)	(0.699)	(1.212)
Father age	-0.00435	0.0233	-0.0170
	(0.0149)	(0.0218)	(0.0241)
Teacher's training	-0.00558	0.00173	0.0679

	(0.0248)	(0.0276)	(0.181)
Total students	0.623	2.030*	-0.853
	(0.767)	(1.045)	(1.264)
Age	0.0148	0.121	-0.0778
	(0.185)	(0.278)	(0.252)
Grade	1.149***	1.039***	1.231***
	(0.240)	(0.373)	(0.296)
Book at home	0.0596	0.0188	0.159
	(0.143)	(0.220)	(0.192)
Other books	0.173	0.662	0.814
	(0.676)	(0.981)	(1.042)
Read with family member	0.835**	0.103	1.183**
	(0.402)	(0.730)	(0.591)
Constant	-1.611	-1.782	-2.615
	(7.056)	(8.775)	(10.07)
School Fixed effects	YES	YES	YES
Observations	782	408	374
R-squared	0.635	0.714	0.703

Notes: The dependent variable is reading score. It is measured on a scale (ladder) from 0 to 11. 0 being the worst score and 11 the best. The unit of observation is student. Full detail of the control variables included are provided in variables description (Appendix). The variable of interest is Treat*Post. Coefficients are reported with standard errors in parentheses clustered at school level. *** p<0.01, ** p<0.05, * p<0.1

1.6.4.3 Heterogeneity of the performance based on wealth level

This average effect of the program on students' performance may mask important disparities that depend on their parents' wealth. Indeed, SFP may differently affect student's performance depending on the level of their parents' wealth. Those who are poor may mostly take advantage and gain more benefit. To better explore this possibility, we study the effect on students' performance based on wealth level. Since the wealth index is not available for each survey round, we use household assets availability such as access to car, bicycle, wheelbarrow, motorcycle, cart, tractor, crusher, sprayer, mill, net radio and TV. We construct an asset index using principal component analysis (PCA) strategy. More precisely, we code the wealth index as a binary variable: poor or rich, where poor households are those below the median and rich households are those above the median. The results in table 11 show that the program has a significant effect on students from poor households compared to rich households. Indeed, there is a significant increase of the test score of students from poor households by 0.1426 sd. Also, even if students from rich households perform better, the effect is not significant.

Table 1.11: Heterogeneity based on wealth level

VARIABLES	(1) Poor	(2) Rich
Treat*Post	0.862**	1.243
	(0.439)	(0.847)
Garden	-0.00683	0.599
	(0.129)	(0.383)
Father's education	0.221	-1.826
	(0.254)	(0.870)
Distance to school	0.0415	-0.00589
	(0.307)	(0.672)
Number of people with Job at home	0.0916	0.261
	(0.0758)	(0.228)
Total number of people at home	0.00323	1.142
	(0.0238)	(1.000)
Electricity	0.483**	0.780
	(0.200)	(0.849)
Library	1.397**	-0.214
	(0.542)	(1.231)
Total teachers	0.209	4.899*
	(0.309)	(1.876)
Classrooms	-0.0893	1.237
	(0.290)	(0.926)
Water	-0.370	2.684
	(0.386)	(1.623)
Father's age	-0.00409	0.0138
	(0.0159)	(0.0398)
Total students	-0.454	1.434
	(0.315)	(0.887)
Age (student)	0.0855	-1.300*
	(0.137)	(0.467)
Grade (student)	1.082***	2.107**
	(0.191)	(0.600)
Book at home	-0.0406	-0.0352
	(0.160)	(0.385)
Other books	0.340	2.169
	(0.693)	(2.592)
Read with family member	-0.749*	1.045
	(0.425)	(1.035)
Constant	-12.67**	15.09
	(6.333)	(11.53)
Observations	980	191
R-squared	0.691	0.986
School FE	YES	YES

Notes: The dependent variable is reading score. It is measured on a scale (ladder) from 0 to 11. 0 being the worst score and 11 the best. The unit of observation is student. Column 1 show the result for the poor and column 2 for the rich. Full detail of the control variables included are provided in variables description (Appendix). The variable of interest is Treat*Post. Coefficients are reported with standard errors in parentheses clustered at school level. *** p<0.01, ** p<0.05, * p<0.1

1.6.5 Impact on child labour

School feeding program can also have an indirect impact on child labour. Based on the information provided by household's survey asking whether or not child participated in farming activities during the previous week, we are able to study this effect. Given that the program reduces absenteeism and drop-out rate, we assume that it will also help reduce child labour activities. Another reason supporting our hypothesis is that SFP by providing students with meals, decreases families' expenditures. This extra revenue can help parents reallocate their resources in hiring more labour force and consequently reduces the necessity for child to work. For a better assessment of this impact, we control for school characteristics, household characteristics as well as student characteristics. Unfortunately, it appears from our results in table 12 that school feeding program does not significantly reduce child labour. Many explanations can lie behind this observed result. One of them can be the opportunity cost analysis as in the previous cases (comparison between revenue to earn or to save through child's work and future revenue to earn). Furthermore, cultural principles play a crucial role in encouraging child labour in some societies. In developing countries such as Cote d'Ivoire, some people believe that work has a positive impact on character development and helps build skills since childhood. There is a custom in some families, where children should follow the parents' footsteps and learn the job from an early age. With this kind of thinking and belief, it is less likely for SFP to have an impact on child labour.

Table 1.12: Impact on child labour

	Child Labour
VARIABLES	Full sample
Treat*Post	-0.0540
	(0.0472)
Gender	0.0771**
	(0.0381)
Grade	-0.00526
	(0.0119)
Garden	-0.00219
	(0.0136)
Father's education	-0.151**
	(0.0747)
Total number of people at home	-0.0175
	(0.0743)
Distance to school	-0.0510**
	(0.0231)
Number of people with job at home	-0.0435**
	(0.119)

Electricity	0.0670
	(0.0634)
Library	0.0478
	(0.0588)
Total teacher	0.00997
	(0.0251)
Classrooms	-0.00480
	(0.0240)
Water	0.0489
	(0.0437)
Separate toilets	-0.00450
	(0.0522)
Father's age	0.00259
	(0.00177)
Teacher's training	0.00246
	(0.00459)
Constant	-0.306
	(0.665)
Observations	3136
R-squared	0.046
Village FE	YES

Notes: The dependent variable in this regression is child labor. It is based on the question: Did selected child participate in heavy farming activities? The unit of observation is household. Full detail of the control variables included are provided in variables description (Appendix). The variable of interest is Treat*Post. Coefficients are reported with standard errors in parentheses clustered at school level. *** p<0.01, ** p<0.05, * p<0.1

1.6.6 Impact on household's expenditure

The indirect impact of SFP on expenditures has been less studied maybe due to the difficulties to collect data on households. This survey included a module to collect information about some students and their respective families. Based on these data, this study assesses the impact of SFP on diverse expenditures. The expenditures have been classified into four main categories namely food, health, agriculture and house equipment. They measure the amount in monetary value spent monthly on each category mentioned. Since the school provides children with food we should expect the average expenditure on food to be reduced and expenditure on other items to be increased. Moreover, since the food provided by the school is rich in nutrients and healthy which can make students less likely to be sick, we should expect on average less expenditure related to health issues. Expenditure may most likely depend on household characteristics. We therefore control for them in our regression.

As shown in the table 14, the programme reduces expenditure allocated to food and health while it increases expenditure for agriculture and house equipment. However, these impacts are not significant. Even if they are not significant, the positive sign related to agriculture and house equipment expenditure can be explained by the fact that, by decreasing food and health expenditures, the programme frees up resources which can be allocated to other expenditures. However, these resources may not be large enough to significantly decrease household expenditures.

Table 1.14: Impact on household expenditure

VARIABLES	(1) Food	(2) Health	(3) Agriculture	(4) House equipment
Treat*Post	-0.0401	-0.0198	0.0119	0.0320
	(0.262)	(0.0599)	(0.115)	(0.226)
Asset index	-0.0421	-0.0437***	-0.0411*	-0.0712***
	(0.0295)	(0.0114)	(0.0210)	(0.0239)
Head household's age	0.00430	0.00135	0.00172	-0.00358
	(0.00644)	(0.00119)	(0.00224)	(0.00489)
Head household's education	0.184**	0.150***	0.0788**	0.144**
	(0.0799)	(0.0161)	(0.0361)	(0.0627)
Marital status	-0.196***	-0.0824***	-0.130***	0.0416
	(0.0667)	(0.0162)	(0.0422)	(0.0934)
Gender	0.0655	-0.00763	0.0839	0.0157
	(0.142)	(0.0265)	(0.0516)	(0.107)
Total students in family	0.0506	0.000229	0.00390	-0.000319
	(0.0525)	(0.00257)	(0.00284)	(0.0157)
Distance to school	-0.253	-0.000336	0.00591**	0.0826
	(0.395)	(0.00232)	(0.00240)	(0.0763)
Aware of the program	-0.187	-0.162***	-0.0421	0.338
	(0.282)	(0.0578)	(0.104)	(0.233)
Total people working in house	-0.0200	0.0560***	0.0785***	0.0667**
	(0.0657)	(0.00756)	(0.0117)	(0.0269)
Constant	-580.8**	-60.79	-58.39	295.6
	(274.5)	(57.28)	(109.3)	(220.0)
Observations	2,210	3,552	2,240	1,594
R-squared	0.092	0.059	0.033	0.044
Village FE	YES	YES	YES	YES

Notes: The dependent variable in each column measures the natural log value of expenditure devoted to each item. The unit of observation is household. Full detail of the control variables included are provided in variables description (Appendix). The variable of interest is Treat*Post. Coefficients are reported with standard errors in parentheses clustered at village level. *** p<0.01, ** p<0.05, * p<0.1

1.7 Validity of our results

Since we make use of the DID method to assess the impact of the programme, our results must satisfy one main assumption: parallel trend. This assumption means that the outcomes in the treatment and control group would follow the same trend in the absence of the program. Unfortunately, we could not have access to pre-treatment data to check the pre-treatment results but at least our balancing test suggests that there are not too many differences in characteristics between our treatment and control group. Moreover, these differences have been controlled for in our different regressions. Nevertheless, we implement some robustness tests to make sure of the strength of our results.

1.7.1 Ordered probit and logit

To ascertain the veracity of our finding about the impact on test score, we use another approach. Since our dependent variable is ordinal, the estimation with a DID approach may result in issues related to heteroskedasticity. To deal with it we use two alternative estimation methods: ordered logit and ordered probit. The results of this new estimation, presented in Table 15 show no significant impact of the programme on reading score and the coefficients are also almost conform to the previous results.

Table 1.15: Test score, ordered logit and probit

VARIABLES	(1) Ordered Probit	(2) Ordered Logit
Participation	0.807	0.984
	(0.315)	(0.570)
Garden	-0.0394	-0.0806
	(0.0659)	(0.112)
Father's education	0.138	0.251
	(0.141)	(0.242)
Distance to school	-0.00934	0.0222
	(0.170)	(0.285)
Number of people with Job	0.0187	0.0360
	(0.0446)	(0.0775)
Electricity	0.955	1.629
	(0.848)	(2.564)
Aware of the program	0.452	0.840
	(0.324)	(0.579)
Total teacher	0.179	0.342
	(0.164)	(0.300)
Locality	0.685	1.205
	(1.174)	(1.815)
Classrooms	0.222	0.431
	(0.155)	(0.275)
Library	0.566***	0.954**
	(0.213)	(0.371)
Separate toilets	0.162	0.250
	(0.271)	(0.493)
Father's age	0.00278	0.00385
	(0.00841)	(0.0144)
Teacher's training	-0.0122	-0.0199
	(0.0189)	(0.0318)
Total student	0.244	0.460
	(0.401)	(0.698)
Gender	-0.158	-0.259

	(0.174)	(0.306)
Age	0.0196	0.0452
	(0.0752)	(0.129)
Grade	0.676***	1.135***
	(0.110)	(0.193)
Book at home	0.186	0.300
	(0.149)	(0.252)
Another book	0.0947	0.124
	(0.383)	(0.660)
Read with family member	0.495**	0.849**
	(0.230)	(0.407)
Observations	674	674

Notes: The dependent variable is reading score. It is measured on a scale (ladder) from 0 to 11. 0 being the worst score and 11 the best. The unit of observation is student. Full detail of the control variables included are provided in variables description (Appendix). The variable of interest is Participation. Coefficients are reported with standard errors in parentheses clustered at school level. *** p<0.01, ** p<0.05, * p<0.1

1.7.2 Test score: Instrumental variable approach

Since particularly for reading score we have sufficient information about student characteristics and non-compliance is most likely to happen only in treatment arm, we can estimate the treatment on the treated effect (TOT). The TOT is the difference in outcome between the students who actually eat free meal from school and those who are in the control group. To measure this effect, we use an instrumental variable approach. Specifically we instrument the treatment with initial randomization at the school level which is whether the school was assigned to treatment or control school (Angrist et al., 1996). Concretely we have the following equations:

1. First stage: estimate the effect of offering the program on actual participation.

$$\mathbf{P_{isr} = \beta_0 + \beta_2 Z_{sr} + \beta_k X_{isr} + \gamma_{isr}} \quad (2)$$

$\boldsymbol{Z_{sr}}$**:** randomized exposure to the program; equal 1 if school in region r have been assigned to the treatment group, 0 otherwise. $\mathbf{P_{isr}}$: Participation of student i in school s and region r.

2. Second stage: estimate the Treatment- On- Treated effect of the program (TOT).

$$\mathbf{Y_{isr} = \beta_0 + \beta_{LATE} \widehat{P}_{isr} + \beta_k X_{isr} + \epsilon_{isr}} \quad (3)$$

The result in table16 shows that our instrument is strong (First stage t-squared greater than 10). However, the program did not succeed at increasing significantly student performance even if the correlation is positive.

Table 1.16 : Instrumental variable result of the impact on reading score (Second stage)

VARIABLES	Reading score
Participation	0.842
	(0.735)
genders	-0.309**
	(0.128)
Age	-0.0504
	(0.0469)
Grade	1.180***
	(0.0636)
Book at home	-0.0801*
	(0.0416)
Read at home	-0.569***
	(0.141)
Read alone	0.287**
	(0.136)
Like reading	-0.341**
	(0.160)
Constant	1.152**
	(0.518)
First stage t-squared	40.39
School Characteristics	YES
Family Characteristics	YES
Observations	1,181
R-squared	0.452

Notes: The dependent variable is reading score. It is measured on a scale (ladder) from 0 to 11. 0 being the worst score and 11 the best. The unit of observation is student. Full detail of the control variables included are provided in variables description (Appendix). The variable of interest is Participation. Coefficients are reported with standard errors in parentheses clustered at school level. *** p<0.01, ** p<0.05, * p<0.1

1.7.3 Difference in difference plus PSM

Although we use DID methodology to estimate our results, we may still be worried that some disparities in school, household and students' characteristics are associated with different trends in our outcome variables. Thus, to further prove the validity of our analysis we use DID plus PSM (Propensity Score

Matching). One weakness of the PSM method is that it does not account for unobservable characteristics. However, it seems plausible that groups of schools that are similar in terms of observable features might also be similar in terms of unobservable features. The PSM method creates a quasi-experimental design that matches the take up groups with non-take up groups and assess any difference in outcome variables between these two groups. For school related outcomes, the variables on which we match include the total number of students and teachers, school infrastructure (classrooms, electricity, water, toilet). As for household related outcomes we match based on asset index, father's education, number of children in school and age. More specifically, we first apply a probit model to estimate the probability of participation based on the selected variables. We then use the predicted values from probit to generate propensity score, after that we restrict our sample to common support and match treated units using a matching algorithm. Finally, we check the balancing and calculate the treatment effect. As matching algorithms, we make use of "nearest neighbour" which select m closest comparison units. The results in table 17 show that even if the magnitudes of the results are not perfectly the same with previous ones, they have the same sign and the same level of significance for some outcome variables.

Table 1.17: DID plus PSM

VARIABLES	(1) Drop out	(2) Abs	(3) Enrol	(4) Reading	(5) Child labour	(6) Food	(7) Health	(8) Agriculture	(9) House equipment
Post	-0.028	-0.058	-0.0784	-0.851**	0.175	0.0187	0.0146	0.0387	-0.0235*
	(0.383)	(0.440)	(0.119)	(0.391)	(0.145)	(0.0146)	(0.0286)	(0.0536)	(0.0123)
Treat	-0.060**	-0.0244*	-0.0968	0.111	0.0533**	118.0	-28.58	7.324	-307.4
	(0.031)	(0.012)	(0.0648)	(0.382)	(0.0220)	(344.0)	(64.97)	(123.2)	(275.5)
Treat*Post	-0.058**	-0.0306**	0.0274	0.386	-0.0411	-0.0586	0.0141	0.00363	0.0153
	(0.029)	(0.022)	(0.117)	(0.484)	(0.139)	(0.171)	(0.0322)	(0.0611)	(0.0137)
Cons	1.338***	1.168***	5.692***	3.453***	0.00188	-369.4	-21.51	-69.85	482.3*
	(0.239)	(0.387)	(0.0559)	(0.310)	(0.00161)	(294.8)	(57.62)	(108.0)	(248.2)
Observations	428	428	428	964	2028	2028	2028	2028	2028

Note: results in column 1-4 are at school level, and from column 5-9 at household level. Coefficients are reported with standard errors in parentheses clustered at region level. *** p<0.01, ** p<0.05, * p<0.1. The unit of observation from column 1-3 is school. The unit of observation for column 4 is students. The unit of observation for column 5-9 is household.

1.7.4 Confounding factors

While our results are robust to different estimation methods, other school policies such as provision of school inputs implemented by the government might have coincided with the introduction of the SFP. Therefore, in order to rule out this possibility, and check if contemporaneous change in some school inputs affect our outcome variables, we re-estimate our difference in difference model while taking as outcome variables school inputs such as number of classrooms and teachers, the existence of water, electricity, toilets in school and teaching materials. The result in table 18 shows that most of the inputs are insignificant (column 1- 4). For those which are significant, they display a wrong sign (column 5 and 6). We can therefore say that these results do not offer convincing proof that our main findings related to schooling outcomes are affected by contemporaneous changes in school inputs.

Table 1.18: Confounding factors

VARIABLES	(1) Teachers	(2) Classrooms	(3) Water	(4) Electricity	(5) Toilets	(6) Teaching materials
Treatment	1.649***	1.228***	-0.142*	-0.115***	0.0494	-0.00407
	(0.313)	(0.337)	(0.0808)	(0.0436)	(0.0468)	(0.0231)
Post	-0.0214	-0.0794	-0.00605	0.00379	-0.136	0.00793
	(0.0533)	(0.0815)	(0.0187)	(0.00704)	(0.0995)	(0.0561)
Treat*Post	-0.0426	0.0132	0.0212	0.00403	-0.143**	-0.0828*
	(0.134)	(0.181)	(0.0417)	(0.0184)	(0.0708)	(0.0491)
Constant	47.12	164.1	13.83	-5.681	-98.24	9.420
	(107.5)	(164.3)	(37.61)	(14.21)	(94.32)	(46.52)
Observations	595	596	596	596	580	591
R-squared	0.113	0.072	0.010	0.017	0.030	0.008
School FE	YES	YES	YES	YES	YES	YES

Notes: The dependent variable in column 1 and 2 measures the total number of teachers and classrooms while in column 3-5 it measures the existence or not of each of the items in school. The column 6 measures the provision of school materials (books, chalks, blackboards) by the government. The unit of observation is school. Full detail of the control variables included are provided in variables description (Appendix). The variable of interest is DID. Coefficients are reported with standard errors in parentheses clustered at school level. *** p<0.01, ** p<0.05, * p<0.1

1.8 Cost-effectiveness analysis

The effectiveness of policies to impact any outcome variable is determined not only by the effects of these policies but also by their costs. The main idea behind this analysis is to know whether other options or policies aiming at the same outcome variable may be more effective or beneficial compared to the evaluated program. In a context of limited resources, the cost effectiveness analysis will help us suggest better alternatives among other policies aiming at improving the same outcome variables. The alternative option we use in our case is deworming. The reason behind this choice is that deworming and SFP have both been cited in literature as improving education outcomes (Kazianga et al., 2012; Miguel & Kremer, 2004). Furthermore, the two programs are designed to provide similar benefits: enhancing development outcomes of children through nutrition. In order to run the analysis, we need to know the annual cost of each programme (school feeding programme and deworming) per student. Based on the information provided by the National Institute of Statistics, the annual cost per student is about 24,800 CFA francs. As for the cost of deworming, it is at most about 100 CFA francs for students in primary school according to Word Health Organization[1]. Given the cost associated with each programme and their impact, we can calculate the cost effectiveness ratios. To do that, we divide the cost of each intervention by its marginal impact and obtain the cost related to one unit of a given outcome. The percentage for additional impact of deworming on dropout and test score is from T. Azomahou et al.(2014) who also studied the impact of school meal and deworming programmes in Senegal. The choice of this study is due to the similarity between Cote d'Ivoire and Senegal. The result in table 19 reveals that the deworming programme is more cost effective in reducing drop out and improving test score compared to school feeding programme. Therefore, in a context of resources constraint, if the goal of the policymaker is to improve test score or reducing dropout rate, prioritizing deworming would be a better solution.

Table 1.19: Cost effectiveness analysis

		Dropout	Test score
Cost			
	School Meal	24800	24800
	Deworming	100	100
Percentage of marginal impact			
	School meal	4.2	0.862
	Deworming	1.44	0.656
Cost per percentage of additional impact			
	school Meal	5904.761	28770.301
	deworming	69.444	152.439

Note: The cost is expressed in CFA[2] francs (currency of Cote d' Ivoire).

[1] https://www.who.int/intestinal_worms/resources/at_a_glance_french.pdf?ua=1
[2] 1 CFA = 0.02 $ USD

1.9 Conclusion and policy recommendation

The objective of our paper was to analyse the socio-economic impacts of SFP in Cote d'Ivoire. Using two rounds of schools and households survey data coupled with a quasi-experimental design (difference in difference), we arrived at the conclusion that the impact of this intervention is rather mixed. More specifically, the programme decreased significantly dropout rate and absenteeism in the group of students who took up but did not succeed in raising significantly the enrolment rate and child labour. Moreover, the intervention does not indirectly succeed at decreasing significantly household expenditures. Finally, our analysis could not show any significant effect of the intervention on reading scores even if the relationship between them is positive. The heterogeneity effect analysis reveals however gender disparities in terms of educational outcomes. Indeed, girls are less likely to miss classes and drop out from school compared to boys. However, the program does not show any heterogeneity effect according to gender in terms of enrolment and students' performance. Furthermore, this analysis reveals that the impact on drop out and absenteeism is most likely to be driven by students in lower grades and also school facilities and inputs have a significant impact in improving educational outcomes. Finally, we show evidence that deworming may be more cost-effective compared to school meals if the objective of policymakers is to improve students' performance or reduce dropout rate.

To prove the validity of our estimates, we conducted some robustness checks by using ordered probit-logit regression, propensity score matching methods coupled with DID and an analysis about the potential existence of confounding factors. After the robustness checks, we believe that our results stand even if we could not eliminate all the possibilities of bias in the results specifically those which may be caused by unobserved factors. However, based on our specifications and robustness checks we can assign most of the potential impacts to the programme. According to WFP (2013) who summarized the results of many other studies related to impact evaluation of SFP, this intervention can only be efficient in increasing education outcomes if the other factors that are fundamentals for learning such as school inputs are already in place. Since many of these factors are lacking in Cote d'Ivoire, it is therefore not surprising to see such a mixed result.

In general, SFP succeeded in keeping students at school (less absenteeism and drop-out). However, enrolment and child labour do not respond to this programme. Thus, further policy interventions may be necessary to respond to the reasons of this failure. One main reason which can guide parents and students in their decision making about education is the comparison between the opportunity cost of pursuing studies and present and future revenue to earn. When the perspectives are not good or when income of the family cannot afford it, parents or students may choose not to enrol or attend more regularly. Thus, policy intervention such as conditional or unconditional cash transfers or any other intervention aiming at reducing the cost of education or providing better incentives should follow SFP for more efficiency. Moreover, as shown in the results, school inputs are associated with higher educational outcomes. Therefore, supply-side interventions such as improving school inputs could also help in achieving better educational outcomes.

It is worth noticing that we are studying the effects of the intervention after only one year of implementation. We can expect that with a long-lasting intervention, students' performance in reading would have been impacted significantly.

We also want to highlight that SFP may have greater socio-economic impacts that have not been considered in this study. One of the extensions of this study is to consider the broader socio-economic impacts on the local economy. Another extension would be to analyse the impact of this intervention on students' performance in a longer-term. If in the long run the effect of the programme on students' performance is still insignificant, it would imply that it is not hunger which harms students' achievement but maybe school inputs or motivation to learn. If this latter relationship were true, effort to improve students' outcome should be oriented to improve school inputs or design curricula to stimulate students' interest rather than simply provide them with food. Our quasi experimental approach is, however, not without drawbacks. One concern is the unavailability of data to help us conduct more robustness and placebo tests. Ideally, it would have been preferable to show that there were parallel trends prior to the implementation of the program but unfortunately, our data set does not cover such a period of time. It is reasonable to think that the parallel trends assumption holds in our case because of many reasons. First of all, as the balancing test suggests, there are not many significant differences between treatment and control group at school, household and student level before the rolling out of the program. Second, our analysis of confounding factors shows that there are not significant contemporaneous changes that can influence our education related outcomes variables. Finally, we are not aware of any other policies or sectoral trends going on that have affected differently any group or any other shock in the economy that might cause the post-treatment trends to differ and might be a threat to our findings. Reason being, the treatment and control groups are located in the northern part of the country and the time difference between baseline and follow-up surveys is relatively short. To conclude, this program offers a mixed result. Therefore, policymakers should consider the environment, their goals and cost effectiveness analysis if they want to scale-up this program. Also, it is very crucial to take into account all aspects (gender, economic conditions, culture etc.) of a society when designing and evaluating programs.

Appendix A

Table A1: First stage results the impact on reading performance.

VARIABLES	Exposure to the Program
Participation	0.784***
	(0.0184)
Genders	0.00831
	(0.0174)
Age	0.0226***
	(0.00640)
Grade	-0.0163*
	(0.00868)
Book at home	0.00394
	(0.00563)
Read at home	0.0398**
	(0.0192)
Read alone	0.0154
	(0.0185)
Like reading	0.0433**
	(0.0214)
Constant	-0.184***
	(0.0707)
First stage t-squared	40.39
School Characteristics	YES
Family Characteristics	YES
Observations	1,181
R-squared	0.633

Table A2: Variable description

Variables	Description
Grade	Student's grade
Gender	Student gender, 1 if Male, 0 otherwise
Father age	Student father age
father education	Father education level, from no education to superior
Boys in school	Total boys going to school in family
Girls in school	Total girls going to school in family
Boys no school (6-14 years)	Total boys not going to school in family
Girls no school (6-14 years)	Total girls not going to school in family
Distance to school	Distance to school
Number of people working at home	Number of people working at home
Daily expenditure	Total daily expenditure of the household
Monthly expenditure	Monthly expenditure of the household
Expenditure in energy	Expenditure in energy at home
Expenditure in communication	Expenditure in communication at home
Expenditure in health	Expenditure in health at home
Home equipment	Expenditure for home equipment
Debt reimbursement	Debt reimbursement
Expenditure agriculture	Expenditure in agriculture
Expenditure seed	Expenditure for see payment
Expenditure education	Expenditure in education
drinkable water at home	Whether there is drinkable water at home or not
Total student in school	Total number of students in a given school
Total teacher	Total number of teachers in a given school
Locality	Locality of student, 1 if Urban, 0 otherwise
Classrooms	Number of classrooms in a given school
Warehouse	Whether there is warehouse or not at school, 1 if yes, 0 otherwise
Water	Whether there is drinkable water or not in school, 1 if yes, 0 otherwise
Distance to water	Distance to water point in school
Toilet	Whether there is toilet or not in school, 1 if yes, 0 otherwise
Kinder garden	Whether there is kinder garden or not in school, 1 if yes, 0 otherwise
Parents ‘association	Whether there is parent's association or not in school, 1 if yes, 0 otherwise
Library	Whether there is library or not in school, 1 if yes, 0 otherwise
Electricity	Whether there is electricity or not in school, 1 if yes, 0 otherwise
Age	Age of the student
Book at home	Whether or not there is book at home, 1 if yes, 0 otherwise
Other kind of books	Whether or not student there is other books at home beside those used in school
Read with family members	Whether or not student read with family's member at home, 1 if yes, 0 otherwise
Teacher training	Whether or not teacher receive training in sanitary issues, 1 if yes, 0 otherwise
Garden	Garden, 1 if yes, 0 otherwise
Total number of people at home	Family size

Child labour	Whether or not the chosen student did heavy farming work last year, 1 if yes, 0 otherwise
Kindergarten	Whether or not there is kindergarten in school
Enrolment	Total students enrolled in grade 1
Absenteeism	Total number of students who missed more than 10 days of classes
Drop out	Total students who dropped out in a given school
Separate toilets	Whether or not there are separate toilets in a given school
Read alone at home	Whether or not student read alone at home, 1 if yes, 0 otherwise
Like reading	Whether or not student like reading, 1 if yes, 0 otherwise
Father age	Father age

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CHAPTER TWO: Impact of aid development projects on child's nutrition in West Africa.

ABSTRACT

This study assesses the impact of aid development projects on child's nutrition in West Africa. Since cross-national studies may be biased by countries' specific characteristics, we opt for a more micro-level analysis. More specifically, we analyze the extent to which the inflow of aid in terms of development projects in an area can significantly impact child's health status in West Africa. As health outcomes, we analyze weight-for height ratio among under five children. To reach our objective, we combine Demographic and Health Surveys (DHS) data in West Africa with information about the precise localization of development aid projects obtained from Word Bank. After controlling for a wide number of variables which may influence our outcome, we use two-way fixed effects estimators with heterogeneous treatment effects methodology to reduce biases caused by endogeneity issues. Moreover, we conduct some heterogeneity analyses based on the individual location and sector specific project. We find evidence that development aid projects significantly increase child's nutrition status of those close to project locations compared to those who are far and this effect is stronger in low developed areas compared to developed areas. Moreover, this relationship is most likely to be transmitted through employment and development of economic activities channels.

2.1 Introduction

Under nutrition among children under-fives is prevalent globally, particularly in developing countries. Recent estimates show that about six million kids are touched by serious malnutrition problems in West and Central Africa. Particularly in West Africa, the occurrence of stunting among under-fives kids is 29.2% which is bigger compared to the global average of 21.9%. Moreover, the prevalence of wasting in the same group of children reaches 8.1% which is also bigger compared to the global average of 7.3%(*Western Africa Nutrition Profile - Global Nutrition Report*, 2019). Undernutrition in the earlier stages of kids' lives can lead to permanent effects in the long run. For thousands and thousands of kids, it implies that they may be, forever, stunted. Smaller than their non-stunted peers, stunted kids seem more prone to illnesses and in class they often underperform (*UNICEF*, 2018).

In order to tackle this situation in West Africa, most of the governments of those countries adopted national development programs with the support of international donors. However, despite these efforts, countries in West Africa are still far from reaching the SDG 3 which is to reduce child mortality rate to 25 deaths per

1000 live births by 2030 (*UNICEF,2018*). Moreover, regardless of the flux of international aid in these countries, it happens to not seem to follow social development pace. The latter situation has intensified the discussion about the effectiveness of international aid in significantly impacting human capital namely health and education. The extent to which aid development projects help improve recipients' health principally child nutrition status is the object of our analysis in this paper.

Many studies have analyzed the relationship between international aid in terms of development projects and human development. However, most of those studies were inconclusive. One reason that can explain this inconclusiveness is the fact that most of the studies were focused on cross country analyses. This kind of investigations may not take into account differences across countries, which may sometimes lead to imprecise estimation of the real impact of development aid (Odokonyero et al., 2015). Another reason explaining the weak relationship between aid and other outcome variables is the fact that the size of aid is sometimes too small and localized in a specific area to significantly impact aggregate outcomes (Dreher & Lohmann, 2015). Also, for Harttgen et al. (2013), aid received from developed countries sometimes only targets particular areas or sectors and expecting those funds to impact significantly national outcomes within a few years may be naïve. Therefore, if such investments do not succeed in directly boosting national aggregates, it does not automatically mean that aid allocations were not impactful. Furthermore, since aids are mainly offered in terms of projects to satisfy specific needs such as infrastructures or health facilities, their impact may be more noticeable at the sectoral level. Even so, cross country analyses can still be useful even though they might ignore project level and sectoral characteristics, which are easily taken into account in micro-level studies (Kotsadam et al., 2018).

Thus, using micro-based approach, recent studies have turned away from macro-level analyses and have assessed the impact of aid on various outcome variables including health (Cameron et al., 2016). With geographic data comprising information about the location of aid projects De et al.(2015) find that international aid lead to reduced occurrence of diarrhea in Malawi, while Marty et al.(2017) reveal that aid also has succeeded in decreasing the probability to have malaria as well as in improving the quality of population health in the same country.

Driven by the fact that cross-national studies may be biased by countries' specific characteristics, we opt for a more micro-level analysis. Thus, in the same line with other micro-based studies, we study the causal impact of aid on health. More specifically, we analyze the extent to which the inflow of aid in terms of development projects in an area can significantly impact child's health status in West Africa. As health outcomes, we analyze weight-for height ratio among under five kids. Low weight-for-height ratio called in other words wasting, is a signal of severe undernutrition.

Wasting and other patterns of malnutrition decrease a kid's likelihood to survive, while also preventing him from a better growth and health. For example, wasting inhibits brain development, which may probably be detrimental to cognitive ability, performance in school and future incomes in the long run. This in turn may affect the potential development of nations. A great number of countries are extending their nutrition programs targeting under five kids. The world health organization (WHO) established the objective of reaching a 40 percent increase in nutrition status among kids under 5 years old by 2025 (UNICEF, 2013). Knowing to what extent aid development project direct and spillover effects may also help reach this goal is therefore an important empirical question worthy to be investigated.

Given the direct and spillover effects development projects can have in terms of creating new employments or improving living standards of people close to them, we hypothesize that this initiative helps reduce the probability for children to face stunting. To reach our objective, we combine Demographic and Health Surveys (DHS) data in West Africa with information about the precise localization of development aid projects obtained from WB. Thereby, we link projects financed by the WB with health outcomes of children in the neighborhood of the given projects (those who are more likely to benefit from the projects) and compare these individuals to those who cannot benefit from it due to the distance (those who are less likely to benefit from the projects). We obtained information about child nutrition status from five countries[3] located in West Africa. The choice of these countries is due to data availability.

While controlling for a wide number of variables which may influence our outcome, we use two-way fixed effects estimators with heterogeneous treatment effects methodology which is a variant of difference in difference approach to reduce biases caused by endogeneity issues. This approach reduces bias coming from omitted variables, which is sometimes eluded in cross-country analyses. Moreover, we conduct some heterogeneity analyses based on the individual location and sector specific project. Finally, we analyze the mechanism through which our results can be explained and run various robustness tests to prove the validity of our findings.

Our study reveals that development aid projects significantly increase child's nutrition status of those close to project locations compared to those who are far and this effect is stronger in low developed areas compared to developed areas. Moreover, this relationship is most likely transmitted through employment and development of activities channels. However, development aid projects do not appear to significantly affect local GDP even if the relationship is positive. We also come to know from this study that there is a significant and positive link between the funding allocated to projects and their impacts. Furthermore, we reveal that distance to project location also matters. The closer people are from project location, the more likely they are to be positively affected. Finally, we provide evidence that water and sanitation aid projects are have higher effect in improving child's nutrition status compared to health and agriculture projects. However, we cannot really compare them since they may have different objectives.

[3] Togo, Liberia, Nigeria, Mali, Sierra Leone.

Our analysis contributes to the literature in many ways. First of all, while there are many country-level studies about the effectiveness of aid, not many of them have focused on the effectiveness of aid below the country level. Our study aims at filling this gap. Previous studies (De et al., 2015) and (Odokonyero et al., 2015) use the same methodology to assess the effectiveness of development projects on different outcome variables in Africa but were focused only in one country. The latter studies, although providing new findings, may lead to spurious effects of aid since they fail to control for differences within countries. Secondly, we also analyze the heterogeneity effects and the mechanism behind this effect, which was overlooked in previous analyses. Finally, we conduct a cost effectiveness analysis to show which sector policymakers should prioritize when they have limited resources and want to improve child's nutrition. This latter analysis is less common in literature about aid projects.

For a better understanding of our topic, we organize our study according to this plan: Section 2 shows the related literature. The data and the methodology used are explained in section 3. Then, in section 4, we expose the results obtained after the different regressions, robustness checks as well as the mechanisms. Section 5 concludes our study followed by some policy recommendations.

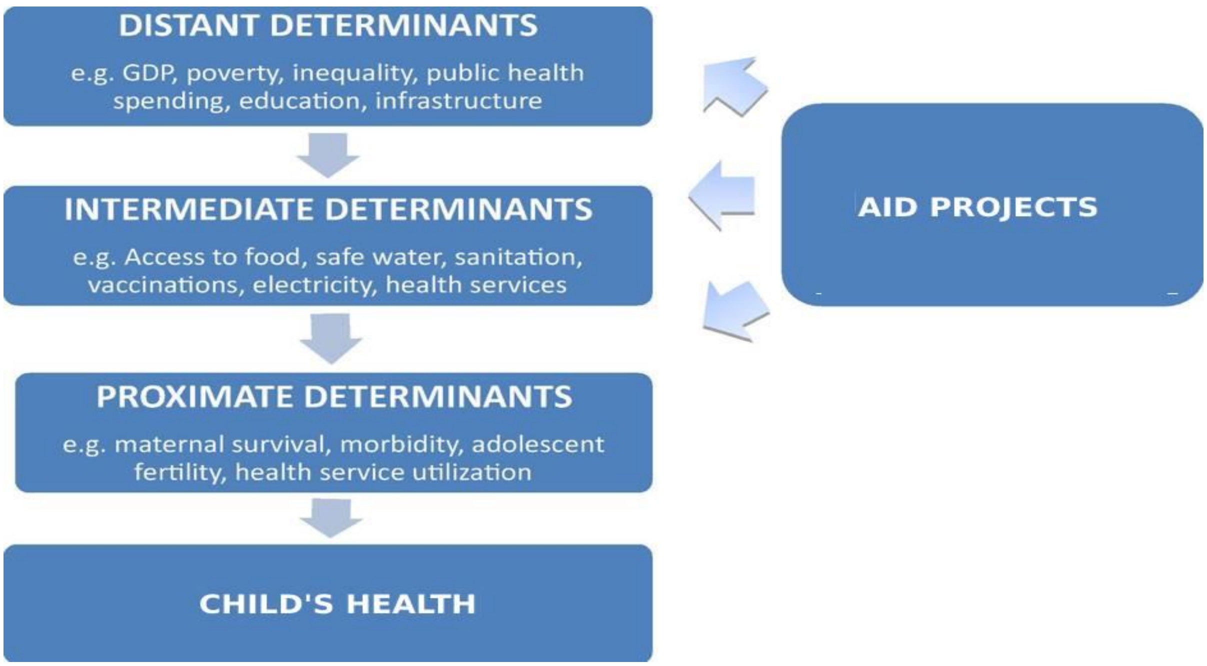
2.2 Related literature

In this part, we first review the theoretical and conceptual framework of our analysis following by the debate about aid effectiveness, then the determinants of child malnutrition in Africa and we end by showing the health benefits of development aid.

2.2.1 Theoretical and conceptual framework

Our study is based on child survival's theory. Child's survival is related to various indirect and direct factors according to the conceptual framework developed by Mosley and Chen (1984). The main idea underlying this framework is that child's environment such as economic and social system impact its survival probability though a set of distant, intermediate and proximate factors as illustrated by the figure 1. Therefore, since diverse factors are involved in the determination of child's health, it is more rational to consider the effect of aid on a larger specter rather than narrowing the analysis by targeting only health sector.

Figure 2.1: Conceptual framework.



Source: Schel et al (2007)

2.2.2 Aid effectiveness debate

Aid effectiveness appears to be one of the most divisive debates in development economics. Our investigation reveals that three main points of views come out of this debate. While some scholars reveal that aid is ineffective, others display an utterly different opinion. Yet still others have found a common ground between the two main sides: for them even if aid is said to be not impactful, it can have a strong effect when some conditions are fulfilled. The first point of view is defended by Easterly (2014) and Moyo (2008) who relate that official aid can engender dependency, increase corruption and currency overvaluation, which can in turn harm its expected results. They also argue that aid agencies are bureaucratic, risk averse, innovate slowly and act like monopolies by charging too much and delivering little services. Of course, the promoters of this idea don't deny the fact that aid was also helpful in improving health and education indicators in many countries. But in general, they stipulate that aids conducted through rigid and monopolistic government agencies are mostly unproductive and sometimes constitute just a waste of money.

The second point of view is promoted by authors such as (Sachs, 2005) who, although critical about development aid management system in the previous years, formulates that if this aid is properly provided, and if directed toward fighting particular issues (diseases, provision of better infrastructures, etc.) can lead to the improvement of well-being in the short run. For Sachs (2005), most aid programs should be oriented toward big five development intervention: agricultural, basic health, infrastructure (communication, transport) and safe and drinkable water for everyone, provision of power.

A third group of authors such as Collier (2009) display rather an intermediate position. Aid effectiveness issue is neither black or white. For him, most developing countries are caught in four main traps which are: conflict, natural resources, landlocked and bad governance. Although aid can help solve the first two issues, it can unfortunately do little to tackle the last two ones. He goes on to say that aid can turn out to be more impactful if a large part is dedicated toward increasing the skills and abilities of the population in a given country, as well as government officials who are in charge of implementing projects.

Aside from Easterly-Sachs arguments, other authors have also fueled the debate about aid effectiveness. Thus, some authors will advance the idea that aid may be impactful when certain conditions such as: democracies; Boone (1996) , good governance; Dietrich (2015), less vulnerability to external shocks; Guillaumont et al. (2001) are fulfilled. On the contrary Clemens et al.(2012) support the hypothesis of unconditional aid. They find that aid significantly impacts growth albeit at a decreasing return and more importantly, the impact is not related to the institutional framework in the recipient countries.

Other authors through their empirical investigation contribute also to extending this topic. Their findings can be classified according to whether aid is effective (Asteriou et al., 2009; Kotsadam et al., 2018; Mekasha & Tarp, 2013; Roodman, 2007), ineffective (Rajan & Subramanian, 2008) to improving growth. As for Bourguignon and Sundberg (2007), they argue that the inconclusiveness of studies related to debt effectiveness come from the existence of multiple channels that can directly or indirectly affect the outcome variables. Thus, for them, the fact to consider all kinds of aids (emergency assistance, program aid, project aid) as homogeneous may be misleading. They rather propose to disentangle all the causality channels and the black box of international aid so as to better measure the real impact of aid.

As the macro analyses have not succeeded in giving any significant value added to the comprehension of the complexities of aid effectiveness due to the existence of multiple channels, it has inspired many other authors to prospect alternative micro approaches. One of them is Randomized Control Trial (RCT), an approach advocated by Banerjee and Duflo (2011). For them, some projects financed by aid have produced encouraging outcomes in terms of improving well-being while other projects fail considerably. The key is to find an appropriate method in order to evaluate the effectiveness of each project (Banerjee and Ester , 2011). This method, although efficient, has suffered many criticisms from Deaton (2013). For him, the success of a project at a micro level does not guarantee the same success at macro level and RCTs reveal only local information that may not be feasible in other contexts. Moreover, RCT approach just tells the local average effect and does not tell how and when it works.

2.2.3 Health benefit of development aid

Another tendency of aid effectiveness analysis emphasis the effect of aid on outcomes not related to growth. Supporters of this approach stipulate that by focusing only on growth, authors may fail to notice other important impacts such as its effect on health. Thus, Mishra et al. (2009) using a panel composed of 118 countries between 1973 and 2004 coupled with a Generalized Method of Moment (GMM) reveal that health aid succeeded in significantly affecting infant mortality. Likewise, Yogo & Mallaye (2015) find that health aid has helped improve respondents' health in SSA countries by utilizing a sample of 34 countries spanning from 1990-2012. They also show that the main channel of this effect is through the increase of female education. On the contrary some analyses fail to prove any causal relationship between aid and health outcomes (Wilson, 2011 *;* Kosack & Tobin, 2006).

Moreover, in assessing aid effectiveness, some authors have tried to measure the effects of specific aid in agriculture, water and sanitation sectors on the improvement of people's health conditions. Thus, Botting et al. (2010) show that access to drinkable water is higher in countries that receive higher amounts of aid from developed countries compared to those who receive less. Likewise, Wayland (2019) using propensity score matching (PSM) method points out that households located near health-related projects in Africa experience an improvement in the quality of water, sanitation and health status. Finally, more recently, some authors have used geocoded aid data to measure the impact of aid projects on recipients' health. It is the case of Kotsadam et al.(2018) who, using a quasi-experimental approach, come to the conclusion that geographic closeness to aid projects decreases infant mortality in Nigeria. Likewise, Odokonyero et al. (2015) adopt a DID methodology to assess the contribution of aid on key health outcomes. Its study reveals that health aid has significantly succeeded in decreasing illness occurrence. De et al. (2015) follow the same line of investigation as the previous two authors. Thus, through both Instrumental variable (IV) and PSM difference in differences methods they come out to the point that aid significantly and negatively affects disease severity and also water aid decreases significantly diarrhea incidence in Malawi. Finally, Christina et al (2020) by collecting data from 38 developing countries between 1986 and 2017 and applying fixed effects estimation methods show that aid projects reduce importantly the time needed to fetch water and infant mortality for those who close compared to those who are far from those projects.

2.2.4 Child malnutrition in Africa

For WHO, "malnutrition is described as a pathological state stemming from the shortage or excess, relative or absolute, of one or more vital nutrients. It can be assessed by clinical measures, biochemical or anthropometric analyses. However, when it comes to statistical measures of the prevalence of child malnutrition, most nutritional surveys use anthropometric indicators. We must distinguish four forms: undernourishment, specific deficiencies, overfeeding and nutritional imbalance (Derrick, 1969). For under 5 years old kids, the most commonly used indicators are height-for-age, weight-for-age, and weight-for-height. Statistically, these indicators are expressed as the number of standard deviation units (Z-score) compared to the median international reference population. The standard measure of nutrition status for kids suggested by the WHO is height-for-age, weight-for-height and weight-for-age divided into two levels of severity: moderate level of malnutrition if the index (Z-score) is less than 2 standard deviations (this is the conventional measure used by WHO); severe level of malnutrition (severe condition), when the index (Z-score) reaches minus 3 standard deviations. It is worthwhile notifying that:

- Height-for-age is an indicator of stunting and helps to identify so-called chronic malnutrition or rickets. This is a structural situation in a long-term scope;
- Weight-for-height measures individual's thinness or wasting;
- Weight-for-age is a good reflection of a child's overall nutritional status and can be used to track a child's weight gain. However, it does not differentiate wasting from stunting.

The UNICEF, the WHO and the WB assessed in 2015 that around 159 million kids under five were touched by chronic malnutrition around the world (UNICEF, 2015). Three quarters of them are found in Africa and Asia, with a higher prevalence of child malnutrition in Sub Saharan Africa (32%) than in Asia (25%).

West and Central Africa are the most affected by child malnutrition (with a rate of 35%): the number of under-five children stunted rose from 19.9 million in 1990 to 28 million in 2014 (included Sahelian countries) compared to a worldwide reduction from 255 million in 1990 to 159 million in 2014. About half (45%) of deaths of children under five are attributable to undernutrition, which would cause the loss of life of at least 3 million children in the world each year (UNICEF, 2015, page 1). The level of mortality of children under five in SSA is the highest worldwide due, among other things, to the undernutrition of children. Out of 1,000 live births, there are approximately 86 deaths in children under 5, double the global average of 43 deaths per 1,000 live births. Children's food and nutrition insecurity also contributes to reducing their chances of education: an estimated 33 million school-age children in SSA are out of school. Black et al.(2008) have highlighted specific factors for child malnutrition which include both socio-economic factors at community and household level, behavioral factors of care and biomedical and socio-demographic factors at the individual level.

The consequences of malnutrition in children are multiple both at the individual and national level:

decreased immune protection against disease, decreased intellectual capacity of the child leading to school failure, low cost benefit of health care, and reduction productivity. Demographically, the persistence of a high level of infant and child mortality, due in large part to child malnutrition, contributes to maintaining a low life expectancy at birth in developing countries and reduces efforts of policies aiming at controlling fertility through parental resistance to family planning in view of the high risk of child death. Also, intellectual capacity deficiencies reduce academic performance in terms of transition rates, success or completion of studies.

2.3 Data and methodology

In this part, we first of all provide information about the source of our data set, the countries and time period covered and then elaborate more about our methodology.

2.3.1 Data

The data used to analyze the effect of development aid projects on malnutrition in west Africa are from two main sources: the WB AidData project and Demographic Health Surveys (DHS). The AidData project contains information about the projects sponsored by the World Bank. The development projects in our study spans from 2000 to 2017 and each project has its precise beginning and ending dates, as well as GPS evidence (latitude and longitude) about the precise location of each project. These projects cover many sectors. They range from agriculture, health, education, banking, infrastructure, sanitation, water and additional services. Our data set has totally 1438 development projects. As for DHS, it is mostly sponsored by USAID. It gathers nationwide information about households in more than 90 countries since 1984. Sample size in each country generally ranges from 5000 to 30000 and surveys are conducted regularly to help follow individual characteristics over time. In our analysis, we make use of DHS groups of household respondents into geographical clusters. Each cluster has a number and the center of each of them is indicated by geographic coordinates (latitude and longitude). Sampling clusters surveyed are determined randomly. We use three DHS surveys for each country covering the period 2001-2017. DHS survey makes available information about the child, the mother, the household as well as geographic area characteristics. Thus, using different rounds of DHS surveys will help us capture the variation in those characteristics.

2.3.2 Methodology

Many approaches have been used to study aid effectiveness as already highlighted by our literature review. Unfortunately, few of those previous studies provide robust conclusions. The main difficulty comes from the endogeneity issue which can make the results biased. Three potential sources of endogeneity can be determined: reverse causality, omitted variables and measurement error. In our case, donors may have the incentive to assign aid to countries or areas within countries that have the potential to manage it very well. In other words, they can allocate aid to environments which have minimum conditions to make it successful. In this case, an inappropriate method can upward bias the results. On the contrary, in order to promote development, donors may also have the incentive to allocate aid to areas which do not have strong capacity to absorb it or areas endowed with unfavorable conditions. In this latter case, the estimates can be downward biased. In order to consider these two possibilities, we use an appropriate identification strategy.

We analyze whether a child under five years old at the time of the survey, born by female respondents in the DHS cluster living in proximity to WB project experiences an improvement in his nutrition status compared to a child living far from the development projects. In a similar setting, some researchers have used two-way fixed effects methodology which control for group and time fixed effects to estimate the effect of the treatment on some outcome variables (Christina & Stadelmann, 2020). When the treatment effect is constant across groups and over time, such regression estimates that effect provided the fulfillment of parallel trend assumption. However, it is sometimes not possible to have a constant treatment effect. For example, in our case, the effect of development projects on child nutrition may vary across countries and also over time since all projects did not start at the same time. To solve this issue and obtain a less biased estimate we resort to a two-way fixed effects estimators with heterogeneous treatment effects methodology recently developed by (de Chaisemartin & D'Haultfœuille, 2020). That estimator is a variant of DID and therefore relies on parallel trends assumption of potential outcomes, which we try to show in our different regressions. Our treatment group is individuals living in the vicinity of world bank projects (those who are most likely to benefit from the projects) and our control group represent the individuals living far from aid projects sites (those who are less likely to benefit). Thus, we specify our empirical equation as follows:

$$\mathbf{Nutrition_{isct} = \alpha + \beta_1 AidProject_{sct} + \gamma X_{isct} + \pi_s + \delta_{ct} + \epsilon_{isct}} \tag{1}$$

The dependent variable, $Nutrition_{isct}$ is the WHZ score of an under-five child i in cluster s, country c at time t. It captures the extent of wasting of each child under the age of 5 born by a female respondent in the DHS surveys. We use weight-to-height (WHZ) index as a measure of nutrition status in our analysis. Lower values of WHZ score indicate a higher risk of undernutrition. Values are given in percentage of a standard deviation from the median. We multiply the score by 100 to make the interpretation easier.

The treatment variable, $AidProject_{sct}$ is aid project in cluster s, country c at time t. It is a binary variable equals to 1 if the respondent has spent more than one year and lives within 50 kilometers of any aid project location, 0 otherwise. The control group is therefore the individual in the same country but not exposed to any aid project. Later on, we distinguish between aid projects based on sector. We also check the robustness of our estimates by restricting our treatment group and taking individuals who have been living more than one year within 25 kilometers radius of any aid project. We consider only residents living more than one year in an area to limit the impact of migration. By doing this we lose some observations but we can have better estimates.

$\mathbf{X_{isct}}$ **:** vector of control variables. It includes individual as well as area characteristics $\boldsymbol{\pi_s}$: cluster fixed effects. We include them with the purpose of capturing time-invariant codeterminants of exposure to development aid projects and our outcomes variables at the local level such as weak state capacity and or local political instability (ethnic cleavages). $\boldsymbol{\delta_{ct}}$: Country $\times$ year fixed effects. They help wash out all country wide time varying characteristics affecting our outcomes variables (for example war). The purpose of doing this is to make sure that our results are not influenced by country level dynamic differences. $\boldsymbol{\epsilon_{isct}}$: error term. The effect of aid development projects is thus determined by the comparison between the change in outcomes for individuals that are close to the location of projects in a given year and the change in outcomes for individuals in other locations in the same country that are considered to be far at the same point in time. We exclude projects implemented in capitals due the higher level of migration. The underlying assumption is that locations that are close to and somewhat farther away from aid projects were on parallel trends in child's nutrition outcomes before the implementation of those projects.

On the one hand, our strategy helps us control for both cluster and time-period fixed effects so that all time invariant differences across countries and clusters- such as food preferences, geography or institutions (as long as they vary slowly over time)- and secular changes over time- such as improvement in sanitation, health and technology- are considered. On the other hand, our method supposes that there are also no other shocks or policies happening during the same time period where aid projects were implemented that can affect our outcome variable. Even if this assumption is less likely to be plausible, we address this possibility by adding other time and country varying variables that can bias our results. Also, we lack statistics about other potential aid projects, some of them may have affected the control groups. Therefore, the real impact of development aid is possibly bigger than what we have found. However, since the WB group is the biggest sponsor of aid development projects in West Africa (more than 80 percent), we can be sure that the effect we capture is close to the true effect.

2.4 Descriptive statistics and empirical results

In this section, we show detailed information about the variables used and then present the results from our regression.

2.4.1 Summary statistics

Tables 2.1: variables description

Variables	Description	Source
WHZ-100	Weight-for-height Z-score*100 for children of female respondent under 5 years of age	Demographic and health surveys (DHS)
Aid project	existence of development aid project within 50km (25km) radius of respondent's survey cluster.	AidData
Agriculture Aid	existence of Agriculture aid project within 50km (25km) radius of respondent's survey cluster.	AidData
Health Aid	existence of Health aid project within 50km (25km) radius of respondent's survey cluster.	AidData
Water Aid	existence of Water aid project within 50km (25km) radius of respondent's survey cluster.	AidData
Age	age of the child (Months)	DHS
Gender	child gender=1 if male, 0 otherwise	own coding based on DHS
Religion	female respondent's religion= 1 if Christian, 2 if Muslim, 0 otherwise	own coding based on DHS
Employment status	female respondent's employment= 1 if has a job, 0 otherwise	own coding based on DHS
Education level	female respondent's education level= 0 if no educ, 1 prim educ, 2 second educ, 3 higher educ	own coding based on DHS
Mother’s age	female respondent's age	DHS
Family size	Number of persons living with respondent	DHS
Residency	Respondent's area=1 if rural; 0 if urban	own coding based on DHS
Night light	night light composite index of respondent's cluster	DHS
Precipitation	Rainfall quantity in respondent's cluster	DHS
Distance to Urban area	travel time for respondent to reach major urban city (hours)	DHS
Population	Population in respondent's cluster	DHS
Gross cell production	Gross cell production in respondent's cluster	DHS
Disbursement	Amount spent for the project in million (dollars)	AidData
Duration of project	Duration (number of years) of the project (years)	AidData
Number of projects	number of projects in respondent's cluster= 1 if more than 3 aid projects; 0 otherwise	AidData

Table 2.2: Descriptive statistics

VARIABLES	N	Mean	Sd	Min	Max
Z-scores	88,890	-51.67	102.8	-400	198
Residency	88,890	0.307	0.461	0	1
Age	88,890	33.220	0.414	0	1
Gender	88,890	0.505	0.500	0	1
Respondent within 50km of any aid project	88,890	0.408	0.491	0	1
Agriculture Aid	63,477	0.170	0.376	0	1
Health Aid	54,824	0.0394	0.195	0	1
Water Aid	59,958	0.122	0.327	0	1
Number of projects	67,873	0.224	0.417	0	1
Respondent within 25km of any aid project	88,890	0.230	0.421	0	1
Education Level	88,886	0.670	0.890	0	3
Population	88,890	12.47	1.319	6.726	15.77
Gross cell Production growth	88,890	-2.789	1.568	-9.148	1.874
Distance to Urban city	88,890	5.267	0.530	4.173	8.243
Duration of project	88,890	8.925	4.124	1	14
Night light	88,890	0.489	2.658	0.00976	61.58
Precipitation	88,890	383.4	485.1	0.123	3,275
Disbursement	68,909	6.966e+07	1.411e+08	284,990	3.000e+09
Mother’s age	88,890	30.25	10.15	15	59
Mother’s years of education	72,501	6.737	4.538	0	22
Employment status	88,510	1.482	0.560	0	1
Religion	88,560	1.516	0.745	1	2
Family size	57,022	2.978	2.347	2	40

2.4.2 Balance test

We perform a balance test at the initial stage of projects to see if our control and treatment group are almost similar. From this balance test in table 3, we can perceive that there are not significant differences in most individual characteristics including the nutrition status when they are less likely to be affected (1 year of exposure). However, we notice some differences in terms of residency and distance to urban city. Control group is on average closer to urban city. Even if this test is not that important in DID methodology, it is comforting when it is fulfilled. This test suggests that any significant difference later on may come from more exposure to development projects.

Table 2.3: Balance test of main variables

Variable	0	1	Diff
Z-score	-51.42	-52.04	-0.622
	[0.59]	[0.68]	[0.906]
Family size	2.97	2.98	0.009
	[0.01]	[0.02]	[0.020]
Employment status	1.48	1.48	0.002
	[0.01]	[0.01]	[0.011]
Precipitation	385.77	380.05	-5.725*
	[2.11]	[2.55]	[3.311]
Night light intensity	0.61	0.53	-0.073
	[0.01]	[0.01]	[0.018]
Distance to urban city	5.36	5.13	-0.227***
	[0.00]	[0.00]	[0.004]
Religion	1.51	1.52	0.003
	[0.00]	[0.00]	[0.005]
Residency	1.24	1.4	0.161***
	[0.00]	[0.00]	[0.003]
Gender	0.51	0.5	-0.005
	[0.00]	[0.00]	[0.003]
Mother’s age	37.6	37.45	-0.155
	[0.06]	[0.07]	[0.095]
N	24989	14110	39099

Note: Robust standard errors in parenthesis *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

2.4.3 Main results

Table 4 provides the main results from the estimation of equation1. To consider the fact that individuals belonging to the same cluster may provide similar information which can lead to correlation, we cluster all our standard errors at DHS cluster level. The results of the first column (no controls) show that the kids who are in the vicinity of world bank projects are less likely to suffer from malnutrition compared to others. Indeed, those children show 6.532 percent standard deviation ($P<0.05$) higher HWZ compared to the kids who are living far. To check the robustness of our first result, in column 2 we include a set of child and household characteristics. Since nutrition status depends also on the environment in which people are living, in column 3, we equally include a set of geographic and climatic characteristics. By doing so, we also try to reduce potential omitted variables bias and increase the explanatory power of our specification. Although we have less observations, as not all control variables provide information for all individuals, the results show a similar pattern with the first one. Presence of aid projects significantly improves child's HWZ by 5.761 percent and 4.978 percent standard deviation respectively while controlling for individual and geographic characteristics.

The DID estimator relies on a common trends assumption. This means that the outcomes in treatment and control group would evolve in the same manner without the treatment. To assess this assumption, we compute the falsification estimator in column 4 and in column 5. DIDpl1 in column 4 compares our outcome variable in treatment and control group one year before the implementation of projects and DIDpl2 compares the outcome two years before. As shown in column 4 and column 5, DIDpl1 and DIDpl2 are positive and insignificant even at 10%. Since these coefficients have higher values, the falsification tests may suggest that our DID estimator overestimates the improvement of child's nutrition status, due to a positive pre-trend. However, since they are insignificant and less than half the treatment effect, there might not be a huge concern about the validity of parallel trends. Additionally, the balance test reveals that the treatment and control groups are not that significantly different in the earlier stage of the projects. Therefore, based on these two results, the violation of parallel trends can be ruled out in our case.

Table 2.4: Main results

	DID	DID	DID	DIDpl1	DIDpl2
Estimate	6.532**	5.761**	4.978**	2.137	2.042
Standard Error	(2.647)	(2.865)	(2.059)	(2.196)	(2.936)
Observations	85,752	85,468	74,873	70,947	70,296
Controls	NO	YES (HC)	YES (ALL)	YES(ALL)	YES(ALL)
Cluster FE	YES	YES	YES	YES	YES
Country ×Year FE	YES	YES	YES	YES	YES

Note: Clustered standard errors at cluster level in parenthesis *** p<0.01, ** p<0.05, * p<0.1. Controls included in column 2: child's age, child's gender, mother's age, mother's education, religion, Family size. Controls included in column 3-5: child's age, child's gender, mother's age, mother's education, Family size, religion, precipitation, distance to urban city, area population, duration of the project. Column 4 (DIDpl1) is falsification test result one year before and Column 5 (DIDpl2) falsification test, two years before. The dependent variable is Weight-to-height ratio*100 for children of female respondent under 5 years of age.

2.5 Robustness tests

In this section, we provide a certain number of robustness tests to check the validity of our main findings.

2.5.1 Test of unobservable

Our findings in table 4 are almost similar even with the inclusion of different set of control variables. It may bolter our confidence that the impact is robust to different specifications. Based on that, we may be led to dismiss the possibility of omitted variables bias affecting our results. However, Oster et al.(2016) argue that observing the change in value from the main coefficient is not sufficient to conclude that a coefficient is not influenced by omitted variable bias. The reason is that sometimes the variables we add do not explain a lot of the variance in the dependent variable. Thus, if we incorporate a lot of these variables or controls in the regression, then we should not expect the coefficient of interest to change a lot. In this part of our study, we measure the chance that our coefficients are biased by non-observable variables using two methods. The first method that we use is developed by Altonji et al (2005). According to them, we can make use of selection on observables to evaluate the potential bias from non-observable variables. They develop an indicator that help assess the strength of the likely bias coming from non-observable variables. It is based on the ratio between the coefficient in non-restricted specification and the difference between the restricted and non-restricted coefficients. Mathematically, this ratio is formulated as: $\frac{\gamma^F}{\gamma^R-\gamma^F}$. If the difference between γ^R and γ^F is small, the coefficient of interest will be less likely to be influenced by selection on observables and in this case, the stronger selection on non-observable variables needs to be (relative to observable) to explain away the entire effect (Nunn et al., 2011). In our case, we take two sets of restricted covariates: one with no controls (column 1) and another with a limited set of individual controls (column 2). We also consider an unrestricted set of covariates (column 3). Given our two restricted and one unrestricted specifications, two combinations of restricted and unrestricted controls can be used to calculate the ratios. These ratios are reported in table 5. The ratios are 4.67 and 13.22. Therefore, to assign the entire estimate to selection effects, selection on non-observable variables would have to be at least four times bigger than selection on observables. In our view, these results make it less probable that the coefficient found in table 5 is entirely driven by non-observable variables. For the second method, following the example of (Oster et al., 2016), we calculate delta statistics[4] (δ) from the Olster test which also indicates how much selection on non-observable variables should be to reduce the effect of our main treatment to zero. After calculation with our full control variables, we find a value of 3.154. Oster (2016) suggests

[4] Calculate using psacal command in Stata.

showing a δ greater than 1 as a "robustness reporting standard." Overall, these two methods suggest that selection on unobservables is unlikely to drive our main findings.

Table 2.5: Calculation of ratios and Olster's test 2

	Full controls
Restricted: No control	4.6779
Restricted: Household controls	13.2240
Delta statistics	3.154

Note: each cell from the first two of the table report ratios calculated as: $\frac{\gamma^F}{\gamma^R-\gamma^F}$.

2.5.2 Alternative treatment buffer

Instead of 50 kilometers as in the previous case, we now take as treatment group respondents living within 25 kilometers radius of development projects and those living in 100 kilometers radius. The control being respondents living respectively outside of 25km radius and 100km radius but not exposed to any development project. The results in table 6 stipulate that the more people are close to aid projects the more improvement they experience in their nutrition status. On the contrary, the results in table 7 highlight that when the treatment group is larger (people may be far from aid project in this case), there is not significant improvement in child's nutrition. The falsification tests in columns 4 and 5 of each table even though not significant, produce positive coefficients and may suggest an overestimation of our estimates.

Table 2.6: Results with alternative treatment buffers (25km radius)

	DID	DID	DID	DIDpl1	DIDpl2
Estimate	9.275**	7.932*	6.841**	3.216	2.002
Standard Error	(4.841)	(4.367)	(3.429)	(3.071)	(1.829)
Observations	85,681	85,267	78,995	70,949	70,561
Controls	NO	YES (HC)	YES (ALL)	YES(ALL)	YES(ALL)
Cluster FE	YES	YES	YES	YES	YES
Country ×Year FE	YES	YES	YES	YES	YES

Note: Clustered standard errors at cluster level in parenthesis *** p<0.01, ** p<0.05, * p<0.1. Controls included in column 2: child's age, child's gender, mother's age, mother's education, religion, number of persons in house. Controls included in column 3-5: child's age, child's gender, mother's age, mother's education, Family size, religion, precipitation, distance to urban city, area population, duration of the project. Column 4 (DIDpl1) is falsification test result one year before and Column 5 (DIDpl2) falsification test, two years before. The dependent variable is Weight-to-height ratio*100 for children of female respondent under 5 years of age.

Table 2.7: Results with alternative treatment buffers (100 km radius)

	DID	DID	DID	DIDpl1	DIDpl2
Estimate	2.342	1.932	3.476*	2.412*	1.5422
Standard Error	(4.643)	(3.981)	(2.091)	(1.433)	(2.958)
Observations	84,783	83,921	79,114	69,814	68,745
Controls	NO	YES (HC)	YES (ALL)	YES(ALL)	YES(ALL)
Cluster FE	YES	YES	YES	YES	YES
Country ×Year FE	YES	YES	YES	YES	YES

Note: Clustered standard errors at cluster level in parenthesis *** p<0.01, ** p<0.05, * p<0.1. Controls included in column 2: child's age, child's gender, mother's age, mother's education, religion, number of persons in house. Controls included in column 3-5: child's age, child's gender, mother's age, mother's education, Family size, religion, precipitation, distance to urban city, area population, duration of the project. Column 4 (DIDpl1) is falsification test result one year before and Column 5 (DIDpl2) falsification test, two years before. The dependent variable is Weight-to-height ratio*100 for children of female respondent under 5 years of age.

2.5.3 Alternative treatment variable

Here, instead of using proximity to aid projects as treatment variable as we did in the previous results, we resort to an alternative treatment variable which is monetary value of aid projects. The results in table 8 are in line with the previous ones. When funds allocated to aid projects increase by 1 million USD, child nutrition status (HWZ) increases significantly by 5.34 percent standard deviation (model with all control variables).

Table 2.8: Alternative treatment variable

VARIABLES	(1) No control	(2) Household control	(3) All Controls
Disbursement	6.63***	4.79**	5.34**
	(2.316)	(2.293)	(2.414)
Age		3.17**	2.07***
		(1.517)	(0.641)
Population			-1.038
			(1.391)
Distance			1.375***
			(0.324)
Gender		1.482	1.527
		(1.000)	(1.096)
Region			1.940
			(2.019)
Mother's education		0.781**	0.709**
		(0.351)	(0.323)
Family size		0.725**	-0.704
		(0.330)	(1.675)
Mother's age		0.0101	-0.00357
		(0.0509)	(0.0549)
Duration of the project			-2.353
			(2.519)
Religion		-0.536	-0.858
		(0.670)	(0.719)
Precipitation		-0.790*	-0.582
		(0.428)	(0.460)
Constant	-53.12***	-54.82***	-56.92*
	(4.729)	(5.191)	(29.93)
Observations	69,730	69,310	58,636
R-squared	0.032	0.040	0.035
Cluster FE	YES	YES	YES
Country ×Year FE	YES	YES	YES

Note: Clustered standard errors at cluster level in parenthesis *** p<0.01, ** p<0.05, * p<0.1. In column 1, we do not control for any variable. Column 2 controls for household variables and column 3 controls for all the variables. The dependent variable is Weight-to-height ratio*100 for children of female respondent under 5 years of age.

2.5.4 Exposure to more aid projects

Always with the ambition to further prove the robustness of our findings, we restrict our treatment group only to the individuals exposed at least to 3 aid projects and run our three specifications. Results in table 9 show higher and significant effect of aid on child nutrition.

Table 2.9: Results with number of aid projects

	DID	DID	DID	DIDpl1	DIDpl2
Estimate	10.07**	9.291**	8.187**	4.532*	3.298
Standard Error	(5.063)	(4.163)	(3.456)	(2.785)	(2.643)
Observations	66,651	65,436	57,568	56,734	56,397
Controls	NO	YES (HC)	YES (ALL)	YES (ALL)	YES (ALL)
Cluster FE	YES	YES	YES	YES	YES
Country ×Year FE	YES	YES	YES	YES	YES

Note: Clustered standard errors at cluster level in parenthesis *** p<0.01, ** p<0.05, * p<0.1. Controls included in column 2: child's age, child's gender, mother's age, mother's education, religion, number of persons in house. Controls included in column 3-5: child's age, child's gender, mother's age, mother's education, Family size, religion, precipitation, distance to urban city, area population, duration of the project. Column 4 (DIDpl1) is falsification test result one year before and Column 5 (DIDpl2) falsification test, two years before. The dependent variable is Weight-to-height ratio*100 for children of female respondent under 5 years of age.

2.6 Heterogeneity of the effects

Even though development aid is helpful in improving child's nutrition, the effect may vary based on the age of the child, the area of residency and the type of development aid. This section provides more details about the heterogeneity of the impact already shown.

2.6.1 Heterogeneity based on age

Table 10 displays the impact of aid projects according to the child's age. In column 1, we can perceive that there is no effect on children between 0 and 1 year old whereas there is significant effect on the older age group. The insignificance of the effect on the younger age group can be due to the fact that children of this age are breastfed and therefore are less likely to be affected compared to the older group.

Table 2.10: Results based on age

VARIABLES	(1) age1	(2) age2	(3) age3	(4) age4
Estimate	4.276	7.874**	6.481**	6.904**
Standard Error	(3.309)	(3.377)	(3.241)	(3.157)
Observations	16,773	15,428	14,576	15,153
Controls	YES	YES	YES	YES
Cluster FE	YES	YES	YES	YES
Country ×Year FE	YES	YES	YES	YES

Note: Clustered standard errors at cluster level in parenthesis *** p<0.01, ** p<0.05, * p<0.1. Controls included in column 1-4: age of the kid, gender of the kid, age of the mother, education level of the mother, family size, religion, precipitation, distance to urban city, area population, duration of the project. The dependent variable is Weight-to-height ratio*100 for children of female respondent under 5 years of age.

2.6.2 Heterogeneity based on clusters level of development

Based on our main findings, aid projects impact significantly child's nutrition status. However, this average effect may also mask important heterogeneity that depends on the level of development of the clusters. Poor areas may mostly take advantage and gain more benefit compared to developed areas. To explore this idea, we study the effect depending on cluster level of development. We make use of gross cell production which is a proxy of cluster's GDP to construct cluster's development level index. We code cluster's development level as a binary variable: low developed clusters and developed clusters, where the developed ones are those above the median and low developed clusters are those below the median. The results in table 11 show the effect of aid based on cluster's development index. From this result, we can realize that there is great difference in terms of the effectiveness of aid according to the locality. Aid has a stronger effect in improving child's nutrition in low developed clusters than in developed ones. Also, although the effect is positive in low developed areas, it is significant only at 10%. In other words, the effects appear to be more robust for the underprivileged people. Additionally, the p-value from the test of equality of the effect in rural and urban areas is 0.0214 indicating that we can reject the hypothesis of equality of the effects in these two groups. This finding highlights the fact that aid projects also contribute to decrease group inequalities in child's health.

Table 2.11: Heterogeneity effects based on area of residency

VARIABLES	(1) Low developed areas	(2) Developed areas
Estimates	8.511***	1.512*
Standard Error	(1.276)	(0.903)
Observations	50,764	23,931
Controls	YES(ALL)	YES(ALL)
Cluster FE	YES	YES
Country ×Year FE	YES	YES
p-value: rural= urban: 0.0214		

Note: Clustered standard errors at cluster level in parenthesis *** p<0.01, ** p<0.05, * p<0.1. Controls included in column 1-4: age of the kid, gender of the kid, age of the mother, education level of the mother, Family size, religion, precipitation, distance to urban city, area population, duration of the project. The dependent variable is Weight-to-height ratio*100 for children of female respondent under 5 years of age.

2.6.3 Heterogeneity by aid sector

Contrary to the previous parts where we consider all kinds of aid together, here we analyze sector specific development projects. More specifically, we consider aid in the agriculture sector, health sector and water and sanitation sector. We focus on these three sectors because they are those which are most likely to directly affect child nutrition. The control is composed of people who did not receive any kind of aid projects. The results in table 12 exhibit that agriculture aid contributes more significantly to the improvement of child nutrition compared to the other kinds of aid projects while health aid project is weakly significant. To know which sector policymaker should prioritize when they are facing with resource scarcity, more analyses such as cost-effectiveness analysis are needed. Unfortunately, our data is not rich enough to conduct them.

Table 2.12: Results depending on sectors

	(1)	(2)	(3)
VARIABLES	Agriculture	Health	Water and Sanitation
Estimates	7.280***	5.447*	8.098**
Standard Error	(1.866)	(3.248)	(3.803)
Observations	32,582	20,746	30,434
Controls	YES	YES	YES
Cluster FE	YES	YES	YES
Country ×Year FE	YES	YES	YES

Note: Clustered standard errors at cluster level in parenthesis *** p<0.01, ** p<0.05, * p<0.1. Controls included in column 1-4: age of the kid, gender of the kid, age of the mother, education level of the mother, Family size, religion, precipitation, distance to urban city, area population, duration of the project. The dependent variable is Weight-to-height ratio*100 for children of female respondent under 5 years of age.

2.7 Mechanism of the effect

After studying the impacts of development aid and their heterogeneity effects, it is worthwhile noting potential channels through which those effects are operating. Thus, we explore particularly the effects of development aid on some variables susceptible to influence child nutrition. We distinguish based on our data set three kinds of channels: the development of economic activities measured by light night intensity, local GDP and employment. The reason is that the main cause of hunger and malnutrition in Africa is poverty. Resource-poor people are unable to produce enough food to feed themselves and at the same time are not always able to buy food from markets. Thus, we expect that people living next to development projects may get opportunity to be included as workers and thus get some income which can improve the whole family food consumption or living condition. Moreover, development projects can have some spillover effects in terms of creation of new activities or development of those which were existing before. The results in table 13 highlight that employment status and light night intensity which is a measure of economic activities increase significantly due to development aid projects. On the contrary, the relationship, although positive, does not show a significant improvement in the local GDP proxied by gross cell production.

Table 2.13: Mechanism of the effect

VARIABLES	(1) Local GDP	(2) Light night intensity	(3) Employment
Estimates	0.0103	0.0296**	0.0135**
Standard Error	(0.0183)	(0.0138)	(0.00631)
Observations	75,676	56,936	75,613
Controls	YES	YES	YES
Cluster FE	YES	YES	YES
Country ×Year FE	YES	YES	YES

Note: Clustered standard errors at cluster level in parenthesis *** p<0.01, ** p<0.05, * p<0.1. Controls included in column 1-4: child's age, child's gender, mother's age, mother's education, Family size, religion, precipitation, distance to urban city, area population, duration of the project. The dependent variable in column 1 is local GDP proxied by gross cell production, in column 2 local light night intensity and in column 3 employment status.

2.8 Conclusion and recommendations

This study examines the effects of development aid on child's health particularly its nutrition status in West Africa. Contrary to many previous studies using country level data, our study narrows down the level of analysis by focusing on local areas within countries. Combining geocoded World bank aid projects with several DHS survey data sets and adopting a quasi-experimental analysis, we find that development aid projects significantly increase nutrition status of children living in proximity of aid projects compared to those living far. However, the magnitude of the impact seems very low. To prove the robustness of our finding we conduct a series of analysis by including other control variables, different treatment buffers and alternative treatment variable. The various sensitivity tests run comfort our main findings and provide evidence that our main results are less likely to be influenced by unobservables.

Furthermore, we explore the heterogeneous effects of our analysis which reveals that water-sanitation projects have more effect in terms of improving nutrition compared to health and agriculture projects. Also, the heterogeneity effects depending on the area unveil that the effect is much stronger in low developed clusters than in developed ones.

Moreover, to better understand the mechanism behind, we investigate potential channels through which the effects may transit. The result of this is that respondents living near development projects experience an increase in employment status compared to others. The economic activities proxied by night light intensity increases as well. Those two factors are likely to explain our main results. It seems therefore that aid projects succeed in improving parents' living conditions (proxied by the development of their activities and employment) and this improvement is transmitted to their children. The ineffectiveness of development projects in increasing local GDP is somewhat surprising.

One of the main reasons of this ineffectiveness could be that the funds are not well managed and rather fuel corruption which make it unable to influence positively and significantly local GDP and poverty variables such as health and education. Easterly (2002) provides a certain number of reasons justifying aid ineffectiveness. Unfortunately, our methodology could not accept or reject these hypotheses nor identify clearly how much have the recipient's countries actually received and how much have been taken away by corruption or bureaucracy. Also, our study covers only aid sponsored by the WB, which causes the risk of group contamination. Some individuals in the control or treatment groups may have received development aid projects from other donors. Even if this scenario is less plausible since the WB is the major sponsor of development projects in West Africa, it could attenuate the real effect of development aid provided by this organization. Future studies in that area need to consider this limitation and try to also cover development aid projects financed by other donors.

Overall, even though aid development projects impact significantly child nutrition status, the magnitude of the effect seems very weak and is particularly significantly visible in low developed areas. From a policy perspective, this study points out the need for sponsors of development projects aiming at improving child's nutrition to channel resources toward vulnerable or low developed areas. Also, since distance to aid projects also matters a lot in the perception of the effects, policymakers or donors should make them closer to those who need them the most.

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CHAPTER THREE[5]: Impact of new mining activities on local population's living conditions: Evidence from Agbaou gold mining in Cote d'Ivoire.

ABSTRACT

While many authors have focused their analysis on governance and macroeconomic aggregates, very little attention was paid to the impact of natural resources on local population living conditions. Thus, this study intended to close this gap and assesses the causal effect of gold mining activities on local population living conditions in Cote d'Ivoire more specifically in an area called Agbaou. Moreover, we investigate how it affects differently men and women and the mechanism through which the effect is transmitted. To reach our objective, we use several rounds of Afrobarometer surveys and employ a Difference in Difference methodology in order to reduce bias that may result from possible omitted variables. More precisely, we combine geocode Afrobarometer data with information about the location of the mining and construct our treatment and control group based on the distance from the mining site. After analysis and robustness tests, we find that mining activities in our selected area impact positively and significantly the living condition of the nearer local population compared to those who are far. However, our heterogeneity analysis highlights that the effect is gender specific and most likely to be transmitted through income, employment status and wealth channels.

[5] Co-authored by Professor Taejong Kim

3.1 Introduction

According to the World Bank report (2019), economic activities have significantly increased in Africa since the mid-1990s. Indeed, Gross Domestic Product (GDP) has reached about 4.5 percent a year between 1998-2017, almost doubling the percentage in the previous two decades. Several factors (external and internal) explain this continuous level of growth. The increase of the commodity prices in the extractive sectors since 2000 was one remarkable factor on the external side, and this situation helped the countries endowed with ample natural resources specifically minerals to experience higher GDP compared to those that are not in the same situation. The increase of the commodity prices in extractive sectors has also led to an increase of mine activities and investor interest in countries rich in natural resources. The sharp increase of mining activities has risen its percentage in Africa's total exports. For example, between 2001 and 2014 this part reached about two-thirds of exports in Africa. This situation improved enormously government finance enabling them to invest in building human and physical capital and strengthen their fiscal dependence.

Although natural resources exploitation has buttressed growth in the region richly endowed, an important question remains to be answered and is about whether the wealth generated through their exploitation has significantly increased living conditions of the local population. While some international firms operating in this sector and local administrators have garnered riches from the exports, they have not always been beneficial to local populations in most regions in Africa. For example, after scrutinizing mine contracts in DRC from 2010 to 2012 a report highlights that the country experienced a loss of more than 1.37 billion USD, which represents nearly twice the country's budget allocated to health and education (Africa Progress Panel, 2013). Previous quantitative studies are inconclusive about the relationship between mining activities and benefit from the country in terms of development. While some authors, using cross country data, find a negative nexus (Kim and Lin, 2017; Sachs and Warner, n.d.), other find a positive relationship (Alexeev and Conrad, 2009; Christa Noël Brunnschweiler et al., 2008). Despite these important findings, some skepticisms exist regarding the causality issue. Those skepticisms come from the limitations of using traditional cross-country strategies for drawing proper causality relationships. For example, aggregate data may be plagued by measurement errors and may fail to show the specificities between countries which can happen to be the main cause of an observed phenomenon (Levine et al., 1993). To turn away from that, researchers resort to micro analysis in order to evaluate more closely the effect of the extractive sector on local community well-being. Thus, Chuhan-Pole et al. (n.d.), using geocoded household and localization of gold mining activities in Ghana reveal that men closer to mining sites are more likely to benefit from an improvement of their living condition via an increase of their employment status compared to those who are living far. They also show that women have a higher probability to get a job and increase their earnings. Moreover, Aragón and Rud (2013) reveal evidence of an increase of real income due to mining activities in Northern Peru after using household data from 1997 to 2006.

While many authors have focused their analysis on governance and macroeconomic aggregates, very little attention was paid to the impact on local population close to mining sites. One reason for this limited number of studies is data availability. Generally, African countries don't have comprehensive economic data at subnational level. Therefore, it is often not easy to measure the impact of a given shock at a community level. In line with the previously cited micro studies, we analyze the impact of mining activities on micro basis. More specifically we estimate the causal impact of extractive activities on the living conditions of local population in an area of Cote d Ivoire called Agbaou where gold mining has been operating since 2013. "Agbaou Gold Operations" is the second largest exporter of gold in Cote d'Ivoire and contributes up to 7.60% of the national budget (*EITI, 2017*). Thus, its activities may likely affect the living conditions of local population. As a second objective, we investigate how it affects differently men and women and the mechanism through which the effect is transmitted. The relationship between extractive sector and living conditions is not that straightforward. On the one hand, mining activities can create direct and indirect jobs and provide better market opportunities for the population living next to mining locations but on the other hand, it may also make the population more vulnerable due to large-scale land dispossession, insecurity, pollution or water shortage or by decreasing living standard. Moreover, confounding factors such as trends in the economy make it even more difficult to tease out the effects of extractive activities on any economic outcomes. Whether or not local population has their living conditions improved through mining activities in the case of Cote d'Ivoire is therefore an empirical question which deserves a proper investigation. To reach our objective, we use several rounds of Afrobarometer surveys and employ a Difference in Difference methodology in order to reduce bias that may result from possible omitted variables. More precisely, we combine geocode Afrobarometer data with information about the location of the mining and construct our treatment and control group based on the distance from the mining site. The DID methodology compares the treatment group (respondents in the vicinity of mine) before and after the mine opening while taking away the change occurred in the control group (respondents far away) over time under the parallel trends assumption.

A possible channel through which extractive sector can affects population's well-being is by creating jobs, raising household incomes or contributing to financing social investment (clean water, electricity, hospital, paved roads) and making them more accessible to the population. Due to the low level of education in rural areas, we hypothesize that the mining sector decreases population's living conditions as they may create fewer job opportunities for local population and may be reluctant to invest in human capital building due to profit maximization behavior and weakness of local institutions. Furthermore, we contend that women are more exposed to mining activities compared to men since their traditional roles in rural societies are closely related to farming which may no longer be possible due to land dispossession and they seldom get job opportunities in the extractive sector. In order to check this second hypothesis, after studying potential mechanisms of the effect, we run heterogeneity analysis based on gender.

After analysis and sensitivity tests, we find that mining activities in our selected area impact positively and significantly the living condition of the nearer local population compared to those who are far. However, our heterogeneity analysis highlights that the effect is gender specific. While men experience a significant improvement of their living condition, the effect on women on the contrary is not that significant. Having established that extractive activities significantly increase the overall living conditions of local population, we turn to exploring possible mechanisms that may lie behind this finding. Thus, we find that mining activities in Agbaou significantly increase local community income, employment status and wealth. But the heterogeneity analysis reveals that the effect on each of these variables is also gender specific. The effect on men's income, employment and wealth is positively significant while the effect on women's even though positive, is not significant. Finally, through this paper we find evidence that even though mining activities improve the local population's living conditions, this improvement depends also on the distance. Indeed, those who are too close experience less improvement compared to those who are far. We find evidence that this latter finding can be explained by some adverse effects of development of mining activities which are corruption and insecurity. Closer populations feel more strongly the development of these bad spillover effects which undermine the improvement of their living condition.

Our analysis contributes to expanding the literature about the microeconomic foundations of the resource curse. More specifically, it offers the possibility to prove the veracity of this theory in a new context since from our humble knowledge, our analysis is the first to empirically investigate the effect of extractive sector on local population living conditions using micro data from Cote d'Ivoire. Also, the impacts of extractive industries are more often analyzed only at community level, without considering how they are allocated within the community. Men may gain more benefits, in terms of employment opportunities and revenue, while women and the families they are in charge of are more vulnerable to the risks associated with mining activities. A better understanding of these gender aspects could help formulate better policy recommendations in impacted areas depending on where the disastrous effects are felt more strongly, as well as improving economic and social sustainability of mining activities.

For a better understanding of our topic, we organize our study as follows: In section 2 we review theoretical and empirical literature related to our topic and in section 3, we display the analytical framework of our study. In section 4, we briefly portray the gold mining sector in Cote d'Ivoire and how it has evolved. The session 5 introduces the methodology and data used in our analysis. As section 6, it shows the results and interpretation of our findings. The section 7 gives way to discuss the robustness of our main finding. The heterogeneity and the mechanism underlying the results are shown respectively in session 8 and 9. We conclude our analysis in session 10.

3.2 Literature review

In this session, we will review the theoretical and empirical literature followed by the conceptual framework of our analysis. Finally, we will present the mining sector in Cote d'Ivoire.

3.2.1 Theoretical and empirical literature

On macroeconomic level, it has been observed for some decades that endowment of natural resources is not always conducive to development. For example, countries such as Sudan, Angola and Congo are richly endowed with valuable minerals, and yet their populations are still experiencing low living conditions. (*Mining in Africa*, 2017). Whereas countries such as Japan, Korea, Hong Kong have improved their living standard with virtually no exportable natural resources. This puzzling phenomenon described as "natural resource curse[6]" has first been framed by Auty (2005). Since then, its use spread rapidly and was confirmed by other studies such as Sachs and Warner (1995, 1999), and Gylfason et al. (1999), among others. Many reasons have been advanced to justify this phenomenon. First, prices of natural resources are sometimes subject to secular decline and high fluctuation on the international market, which is a problematic issue when it comes to planification and development plans(van der Ploeg & Poelhekke, 2009). The hypothesis that the prices of natural resources evolve following a downward trend in the long term, relative to the prices of manufactures and other products, is associated with Raul Prebisch (structuralist theories with roots in the 1950s). Rent seeking theory is also used as an argument to explain the resource curse paradox. According to the latter, the focus on natural resources can crowd out the development of other sectors for example education, industries, which might be the ones to impulse greater impacts and spillovers that are good for long term economic development(Gylfason et al., 2001). Third, those countries may be prone to

[6] Observation that countries endowed with abundant natural resources tend to perform badly economically.

armed conflict for the control of riches which can create instability and hinder the development of economic activities, national and international investments(Berman et al., 2017). The forth reason promoted by scholars is that those countries may suffer the so-called "Dutch disease" which is described as a situation in which the export of natural resources increases significantly income and consumer demand. This latter situation translates into higher inflation and an appreciation of the real exchange rate which in turn affects the exports of other industries, making them less competitive with potentially negative impacts on economic activities and industrialization processes(Sachs & Warner, n.d.). Finally, countries with higher natural resources endowment are mostly associated with higher corruption and weaker political and economic institutions which affect the management of their resources (Arezki & Brückner, 2011).

Contrary to "resource curse" proponents, other authors rather talk about ''resource blessings". For them, there is a positive relationship between endowment of natural resources and economic growth. Even if those studies are not many, we can name for example Christa Noël Brunnschweiler et al. (2008) who show evidence that resource abundance positively impacts growth and institutional quality. Moreover, Conrad (2009) claims that the existence of large natural resources in a country has an important impact on long-term economic growth of this country. Furthermore, while affirming that richly endowed countries could gain more from their natural resources, Cavalcanti et al. (2011) reveal that oil abundance significantly and positively impacts both income levels and economic growth. Van der Ploeg and Poelhekke (2009) also do not share the idea of "resource curse". They rather reveal a positive link between the endowment of resources and growth.

However, these macroeconomic studies are plagued by some limitations. For instance, the variable used to measure resource abundance – ratio of primary product export to GDP- by Sachs and Warner (1995) has been criticized by Christa N. Brunnschweiler and Bulte (2008) who said that this variable rather measures resource dependence and not resource abundance. They go on to say that the use of growth models may suffer from important endogeneity issues. Moreover, some authors use only one cross sectional data to prove the hypothesis of "resource curse" and therefore overlook the time dimension(Cavalcanti et al., 2011). In order to include the time dimension, other authors resort to homogeneous panel data with fixed, random effects, generalized method of moment (GMM) approaches. The latter methodology is also limited by its effectiveness to tackle endogeneity. Also, the impact of the extractive sector on well-being is less likely to be homogeneously distributed within a given country. The spillover effects such as environmental issues or the effect of the demand by this sector for local inputs may be stronger in particular for local markets. These local effects cannot be assessed using cross country variation.

Due to all these limitations imposed by macroeconomic data, scholars move their interest from macroeconomic to microeconomic data and make use of local level variation. Contrary to the cross-country analyses, the literature about the impact of extractive sector using within country variation is not that abundant. The economic impacts at the local level may change depending on some context-related factors, such as the degree of economic linkage. Thus, Caselli and Michaels (2013) make use of change in oil output from communities in Brazil to analyze the impact of resource possession. They do not find any significant impact on respondent's well-being. On the contrary, Aragón and Rud (2013), exploiting household level microdata with a DID methodology, reveal a significantly positive effect on living conditions and the benefits created by an increase of local demand extend to the community not directly related to mining activities. However, Caselli and Michaels (2013) reveal that the increase in local revenue and public spending do not lead to higher household income. Coming back to the context of Africa, Kotsadam and Tolonen (2015) match several mine locations to survey data and employ a DID methodology. They show that mining activities not only engender a boom in local economies but also create new employment opportunities outside agriculture. More specifically, women living in a radius of 20 km from mine location shift from jobs in the agriculture sector to jobs in services while men change from agriculture to skilled manual labor. Conversely, Fergusson (2005) taking the example of extractive sector in Nigeria, argues that mining activities develop some enclaves that are sometimes disconnected from other domains in the local economy and therefore are less likely to create job opportunities to improve the living conditions of local population. This idea is challenged by other authors such Lippert (2014). Indeed, the author finds with evidence from Zambian Copper mines a significant improvement in living condition due to proximity to mining activities. Likewise, Benshaul-Tolonen et al. (2019) in their recent study using a geocoded household data merged with data on gold mining location conclude that men in the vicinity of mining activities have a higher probability to get direct employment opportunities compared to those who are farther away and also infant mortality rates is reduced due to the improvement of living condition.

As for gender related effects, it is worth noticing that due to the effects caused sometimes by environmental degradation and land dispossession, women closed to mining activities are most likely to lose their income source. Even worse, during negotiation of land property and compensation for any loss due to mining implantation, they are more often ignored since most of the time men have land title ownership. According to Downing (2002), compared to men, women are most likely to suffer from the negative externalities induced by mining as they deeply depend on their immediate environment which is likely to be altered. For example, their aptitude to fetch clean water for their house may be challenged by water pollution or insufficiency which may generate extra pressure and time burden (Jenkins, 2014; Muchadenyika, 2015).

Moreover, women are less likely to get direct job opportunities from the mining sector compared to men due to their low level of education, their biological characteristics as female (Eftimie et al., 2012). As agriculture or land related activities are women's main livelihood source and given the fact that mining activities may generate fewer opportunities, women's living conditions are most likely to decrease in local areas close to extractive activities.

3.2.2 Conceptual framework

The literature identifies four possible channels through which natural resources can affect the local population's living conditions. First, resource abundance can lead to specialization in this sector at the expense of other sectors such as agriculture -Heckscher-Ohlin model of international trade- which in turn lead to an increase of input prices such as wage and a reallocation of inputs. This situation increases the price of nontraded goods relative to traded ones (local Dutch disease) which can affect the well-being of local population. Second, extractive industries can affect local population well-being through the channel of local fiscal revenue windfall. Indeed, this additional revenue can increase local government budgets and help them finance more social investments. The intensity of this effect depends on whether local institutions are good or not. For example, corruption and bureaucracy may destabilize the positive effect of fiscal revenue on the provision of public goods and local population's well-being by creating rent seeking behavior and conflicts. Figure1 illustrates this mechanism. The second channel identified is via local demand shock. Extractive activities can lead to a rise of local goods and services. This effect is more likely to take place in cases where locally produced inputs such as labor or intermediate materials are used in mining activities. It is important to highlight that, since those activities most of times require skill and capital-intensive inputs, their ability to create employment opportunities may be limited. Nevertheless, backward linkage may be at play. Local small enterprises or individuals offer, for instance inputs for extractive industry. Even if these enterprises or individuals do not have a direct relationship with the mining sector, they may get indirect advantages from it. However, there may be situations where the mining sector creates enclaves that are not connected to other sectors in the local economy. In this particular setting, backward or forward linkages may be weak or inexistent. Figure 2 clearly illustrates this mechanism. The last channel identified is through the effect on local environment such as pollution. Indeed, extractive activities through pollution emitted can directly affect the health of local population or may contribute to environmental degradation-soil, water- which can affect the quality and quantity of their production. Figure 3 explains this mechanism.

Figure 3.1: Channel of local fiscal revenue windfall

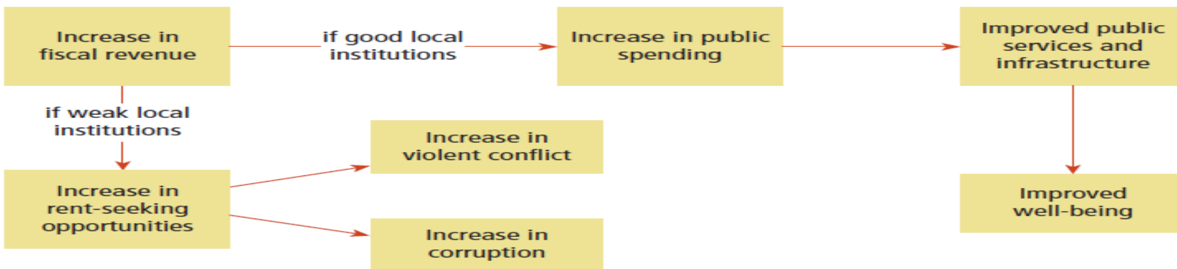


Figure 3.2: Channel of local demand shock

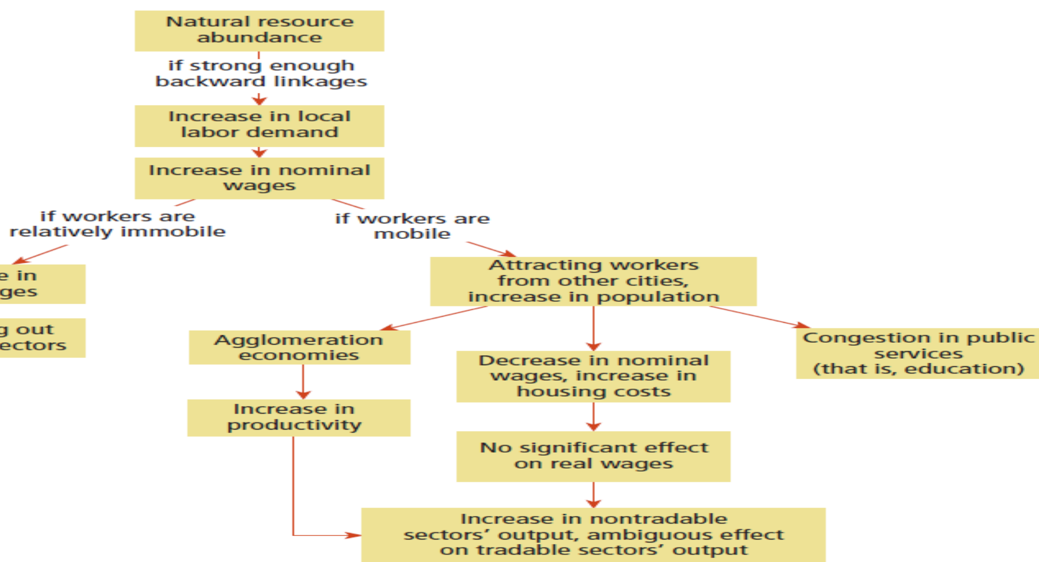
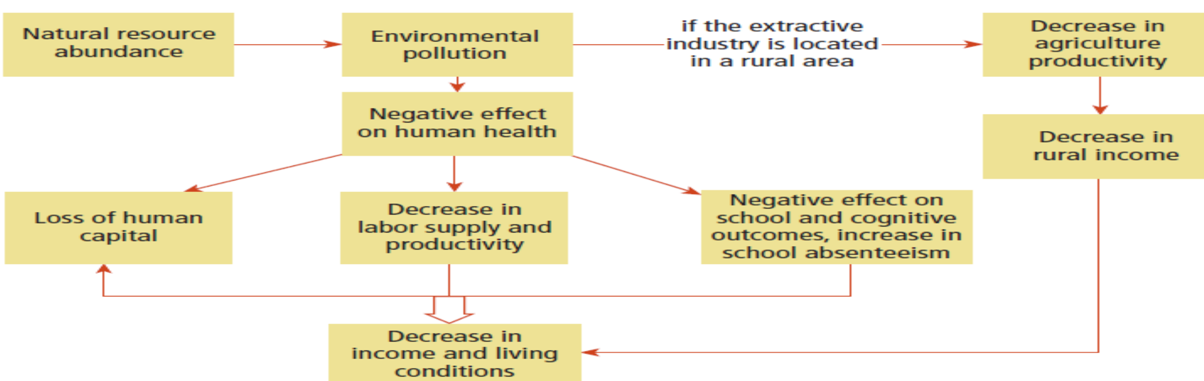


Figure 3.3: local environment channel



Source: Mining in Africa (2017)

3.2.3 Gold Mining in Cote d' Ivoire

In Cote d Ivoire, commercial gold activities started hundreds of years ago with the Baoule community in the central part of the country. However, with French colonization in the 20th century, they began losing hand on huge portion of gold extractive activities for the benefit of the colonizer. Even if informal artisanal mining was prohibited during that time, many families were still making their living by illegally exploiting this precious mineral. In 1984, artisanal and small-scale mining was reapproved under certain conditions (De Jong & Sauerwein, 2021). The first extractive company specialized in gold (Société des Mines d'Ity) started operating in 1991 with a low level of production which kept fluctuating with the development of exploration and drilling techniques and the political situation of the country. Still the amount produced yearly was relatively minor compared to the neighboring countries such as Ghana and Burkina Faso. Thus, in order to attract more foreign investors in this sector and challenge its neighbors, the Ivorian Government implemented some reforms with the development of a new Mining Code in 2014. This new code aims at increasing investments in the mining sector of the country, especially the sector of gold and strengthening its contribution to local development. Among other measures, we have: tax exemption from 3 to 5 years, the elimination of additional profit tax (tax paid by permit holders at the rate of 7 percent of their revenue), greater transparency in the permit allocation and international arbitration to solve disputes which may irrupt (*Dorin*, 2014). All these efforts propelled the country to the 17th place in the world, first among African countries (*Fraser Institute*, 2017). Moreover, these reforms have helped attract many international companies and made them invest millions of dollars. Consequently, the number of explorations has risen from 110 in 2014 to 160 in 2016. Revenue generated from this sector also got improved as a result of these reforms: tax revenue from this field rose by 132% from 2013 to 2015 and has contributed to around 6% of the country's GDP, 12.7% of total export. In 2017, the sector generated 10,524 direct jobs and 31,500 indirect jobs and the turnover declared by the mining sector was 539 billion FCFA (more than one billion USD) against 483 billion FCFA (908 million USD) in 2016, an increase by 10%. The Ivorian mining sector recorded in 2019, a 30% jump in its turnover to reach 761.9 CFA billion against 582.2 billion the previous year. Gold alone represented 622.7 billion CFA francs. More than 100 billion CFA francs were invested in 2019 for a tax revenue of 94.5 billion CFA francs. In 2018, 24.4 tons of gold had been extracted from the Ivorian subsoil(*EITI, 2017*).

If the first priority of these mining companies remains the profit, it is good to highlight that they have also contributed to the development of local communities through their social programs (compulsory and voluntary social spending). Compulsory social payments are defined as compulsory contributions paid by extractive companies as part of local development under contractual agreements or commitments made with local communities (EITI, 2015). Voluntary social payments are defined as voluntary contributions paid by companies within the framework of local development. In 2015, 4.2 billion FCA (or US $ 7.7 million) was paid for compulsory and voluntary social payments by mining and hydrocarbons' companies (EITI, 2015). Like the hydrocarbons sector, Article 131 of the New Mining Code obliges investors to preferably resort to Ivorian companies and expertise for the execution of mining services, in the form of subcontracting, which must be communicated to the Mines Administration. In this context, it is also expected that the mining licensees and their subcontractors must employ as a priority personnel of Ivorian nationality and contribute to the financing of their training program. Likewise, they must also contribute to the financing of capacity building and training of Mining Administration agents, engineers and geologists. In addition, the New Mining Code instituted in its article 124 the obligation for the holder of the operating permit to draw up a community development plan in consultation with local communities and local administrative authorities, with precise objectives and an investment plan and to constitute a fund to be supplied annually. The main objective of this fund is to implement socio-economic development projects for local communities established in the community development plan. This fund is managed jointly by the mining company and the Local Mining Development Committee appointed by joint order of the Minister in charge of Mines and the Minister in charge of Territory Administration. This fund is supplied by mining companies which are called upon to pay 0.5% of their turnover (EITI, 2015).

Concerning Agbaou Gold Operations SA, which is the main subject of our study, the contribution to the local mining development committee (as a voluntary social payment) results in a fixed amount established per ounce of gold produced. The report indicates that Agbaou Gold Operation SA paid 356,445,076 FCFA to the local mining development committee on August 25, 2015(EITI, 2015).

However, concerns remain about the development of mining activities and well-being of local population in Cote d'Ivoire. Among others, there are: the management of the land problem, the compensation of the displaced populations and their resettlement, the dissatisfaction of the local populations and the conflicts between miners and the local population most often due to the land problem and to employment of the local workforce, the distribution of benefits between the municipalities and the central state, the strong pressure due to massive migration around mining sites, the socioeconomic imbalance (early pregnancy, cultural upheaval, high cost of living, development of prostitution), the upsurge in Sexually Transmitted Infections, in particular HIV / AIDS, the impact on health and the environment of the chemicals used, etc.

3.3 Data and methodology

In this session, we present the data used in our study, our empirical strategy and the descriptive statistics.

3.3.1 Data

To study how extractive activities impact the living conditions of local population, we make use of afrobarometer surveys from Cote d'Ivoire and information about the localization of mining activities from Mineral Resources Data System (MRDS). The afrobarometer accurately and precisely measures the attitude of nationally representative samples of African population.

For our study, we make use of afrobarometer grouping of household respondents into geographical clusters, which are a representative selection of Enumeration Area (EA), a statistic unit created as a counting unit for a census. Each cluster has a number and the center of each of them is indicated by geographic coordinates (latitude and longitude). We use three afrobarometer surveys covering the period 2011-2019. Each survey makes available information about individual characteristics including the perception about his living condition. Thus, using different rounds of surveys will help us capture the variation in those characteristics. As for Mineral Resources Database, it provides information about the type of commodity, the geographic coordinates (latitude and longitude), characteristics of the mine and extraction methods. We merge individual information from the Afrobarometer with data from mining activity's location by using QGIS software.

3.3.2 Methodology

To study how extractive industry impacts the living conditions of local population in Cote d'Ivoire, we make use of the difference in difference (DID) method. More specifically, we study the difference in the living conditions before and after the opening of mining in the treatment and use a control group to wash out any contemporaneous change. We define our treatment and control group based on the proximity to mining location. Thus, we analyze whether an individual living in a geographic cluster that is close to Agbaou mine (those who are most likely to be affected) experiences improvements in his living condition compared to an individual not living in the vicinity (those who are less likely to be impacted).

We specify our equation as:

$$\mathbf{Y_{ict} = \alpha + \beta_1 Post_{ct} + \beta_2 Treat_{it} + \beta_3 Post_{ct} * Treat_{it} + \beta_4 X_{ict} + \pi_c + \delta_t + \epsilon_{isct}} \quad \textbf{(1)}$$

Dependent variables

-Living conditions: in the survey, people were asked the following question: ‘’what is your present living condition compared to 12 months ago”. Responses were given on a scale of 1 to 5 as shown in variables description part; 5 representing a very good living conditions. We code the variable ‘’living conditions’’ as a dummy variable equals to 1 if respondent perceive their living conditions as good or very good and 0 otherwise. For robustness test checks, we use other dependent variables reflecting also individual living conditions such as: perception of living conditions compared to others, the frequency at which respondent has access to piped water, cash income, food and the type of shelter respondent is living in.

Independent variables

-Post: since production phase of Agbaou mining started in 2013, we create a dummy variable equals 1 after year 2013 and 0 otherwise.

-Treat: dummy variable equals 1 if individual lives within 25km radius of the mine location. This distance seems comprehensible as extractive activities are generally located in remote areas and people who depend on mining activities most of time travel large distances. However, for robustness checks, we also use other radii.

-Post*treat: represent our treatment variable of interest.

We also include some control variables to increase the explanatory power of our regression and make it less subject to omitted variables bias. Our controls include respondents’ gender, education, age, religion, perception of how fair his ethnic group is treated, his perception of local government performance, the number of persons living in the same house (family size) and area of residency (rural or urban).

One constraint of the probit model is that it does not allow us to use fixed effects estimations to control for unobserved clusters characteristics, possible bias due to omitted variables. We address this by including clusters dummy variables in the probit regression. The effect of mining activities is thus assessed through the comparison between the change in outcomes for individuals that are close to the location in a given year and the change in outcomes for other locations that are considered to be far at the same point in time. The underlying assumption is that locations that are close to and somewhat farther away from the gold mine site were on parallel trends in individual’s living conditions before the beginning of mining activities. We check this assumption by conducting parallel trends test. In all our results, we cluster standard error at cluster level to allow for possible correlation of information provided by individuals from the same cluster.

3.3.3 Descriptive statistics

Table 3.1: descriptive statistics

VARIABLES	N	mean	Sd	min	max
Treat	5,764	0.454	0.498	0	1
Post	5,764	0.379	0.485	0	1
Treat*Post	5,464	0.129	0.335	0	1
Electricity	5,764	0.638	0.480	0	1
Health clinic	5,764	0.584	0.493	0	1
Age	5,364	37.52	15.02	18	106
Family size	5,364	3.783	2.837	1	20
Gender	5,764	0.421	0.400	0	1
Residence	5,764	0.729	0.444	0	1
Present living condition	5,663	2.701	1.232	1	5
Living condition vs others	5,764	2.926	0.948	1	5
Water	5,564	1.254	1.460	0	1
Local corruptions	5,764	1.345	0.887	0	1
Educations	5,747	1.455	1.043	0	3
Local performances	5,764	2.449	0.915	1	4
Income	5,764	2.037	1.348	0	1
Own radios	5,764	0.582	0.493	0	1
Own TV	5,764	0.448	0.497	0	1
Own cars	5,164	0.226	0.418	0	1
Own computers	5,712	0.180	0.385	0	1
Own mobile phones	5,364	0.819	0.385	0	1
Gender	5,764	0.479	0.500	0	1
Shelters	5,264	1.911	1.349	0	1
Religion	5,717	1.513	0.744	1	3
Food	5,764	0.978	1.220	0	1
Employment	5,764	1.182	1.248	0	3

Note: each of these five columns measures respectively: the total number of observations, the mean, the standard deviation, the minimum value and the maximum value.

Table 3.2: Variable description

VARIABLES	Description	Coding
Treat 25km	Treatment group indicator	1 if respondent within 25 km, 0 otherwise
post	Year indicator	1 if after 2013, 0 otherwise
Treat*post	Impact coefficient indicator	Treatment*Post
electricity	Access to electricity	1 if Yes, 0 otherwise
Water	Access to water	1 if Yes, 0 otherwise
Health clinic	Access to health clinic	1 if 1 if Yes, 0 otherwise
Age	Respondent's age	discrete variable
Family size	Number of people in house	discrete variable
Gender	Respondent's gender	1 if Male, 0 otherwise
Residency	Area of residency	1 if rural, 0 if urban
Present living condition	Present living condition indicator	1 very bad, 2 fairly bad, 3 neither good nor bad, 4 fairly good, 5 very good
Living condition compared to others	Living conditions vs. others	1 much worse, 2 worse, 3 same, 4 better, 5 much better.
Local corruptions	Local government corruption perception	0 none, 1 some of them, 2 most of them, 3 all of them
Educations	Respondent's education level	0 no formal education, 1 primary, 2 secondary,3 post-secondary
Local performances	Local government economic performance perception	1 strongly disapprove, 2 disapprove, 3 approve, 4 strongly approve
Incomes	How often have cash income	1 often, 0 not often,
Own radios	Respondent owns radio or not	1 if Yes, 0 otherwise
Own TV	Respondent owns tv or not	1 if Yes, 0 otherwise
Own cars	Respondent owns car or not	1 if Yes, 0 otherwise
Own computers	Respondent owns computer or not	1 if Yes, 0 otherwise
Own mobile phones	Respondent owns mobile phone or not	1 if Yes, 0 otherwise
Gender	Respondent's gender	1 if Male, 0 otherwise
shelters	Type of shelter	1 if good condition, 0 bad condition
Religion	Respondent's religion	1 Christian, 2 Muslims, 3 others
Food	Access to food	1 often, 0 if not often
employment	Employment status	0 No (not looking), 1 no (looking), 2 yes (part time), 3 yes, (full time)

3.4 Benchmark results

Our main results are shown in table 3. We start with the model without covariates (column 1). We can perceive that extractive activities from Agbaou mine impact significantly and positively local population living conditions. In order to show the robustness of our finding and also reduce the bias which may result from omitted variables, we add individual characteristics- age, education, number of Family size, religion, area of residency- to our baseline specification. The effect remains significant and consistent (column 2). To further prove the consistency and strength of our findings, we add individual perception of his ethnic group discrimination by the government, his perception of local government performance. The coefficient of interest in column 3 does not change a lot and remains significant. Moreover, our independent variables display significant coefficients which meet our expectation. Respondent's, age and family size decrease his living condition whereas education, local governance performance increase it (see column 3). Moreover, in order to show whether our results are likely to be influenced by unobservables, following the example of (Oster et al., 2016), we calculate delta statistics (δ) from the Olster test. After calculation with our full control variables, we find a value of 4.583. Oster (2016) suggests showing a δ greater than 1 as a "robustness reporting standard." This result implies that even though unobservables may exist, they are less likely to influence our main finding.

Table 3.3: Benchmark results

VARIABLES	Model 1	Model 2	Model 3	Model 4
Treat*post	0.278***	0.277***	0.289***	0.219***
	(0.0831)	(0.0817)	(0.0788)	(0.0787)
Post	0.0944	0.0945	0.0883	0.0671
	(0.0601)	(0.0593)	(0.0566)	(0.0883)
Treat	0.0694	0.0458	0.0626	0.00835
	(0.0496)	(0.0492)	(0.0479)	(0.0566)
Age		-0.00390***	-0.00471***	-0.00475***
		(0.000847)	(0.000844)	(0.000840)
Educations		0.0821***	0.0801***	-0.0780***
		(0.0132)	(0.0132)	(0.0132)
Family size		0.00432	-0.000391	-7.36e-05
		(0.00491)	(0.00482)	(0.00485)
Religion		-0.0181	-0.0187	-0.0184
		(0.0165)	(0.0163)	(0.0161)
Residence		0.00283	0.0103	-0.0403*
		(0.0406)	(0.0396)	(0.0225)
Ethnic discrimination			-0.00754	-0.0476
			(0.0128)	(0.0492)
Local performance			0.141***	-0.00936

			(0.0142)	(0.0127)
Constant	2.737***	3.024***	2.852***	-0.0990***
	(0.0389)	(0.0664)	(0.0798)	(0.0140)
Observations	5,280	5,242	5,242	4,562
R-squared	0.003	0.011	0.030	0.035
Cluster FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Cluster*Year FE	NO	NO	NO	YES

Note: Dependent variable in each of the three columns is respondent perception of his living condition. Our variable of interest is Treat*Post. Coefficients are reported with standard errors in parentheses clustered at cluster level. *** p<0.01, ** p<0.05, * p<0.1.

3.5 Robustness check

Can these results be interpreted as causal? In this section, we provide a certain number of evidence to strengthen our first findings.

3.5.1 Alternative estimation methods

We take into account the nature of our dependent variable by estimating an ordered probit model. Also, we make use of iteratively reweighted least squares (IRLS) method to mitigate the influence of outlier observations. The results from the two different estimation methods in table 4 are all significant and do not vary at lot from our main result, suggesting possible biases in our estimation method are minimal.

Table 3.4: Alternative estimation methods

VARIABLES	Ordered probit	IRLS
Treat*post	0.253***	0.311***
	(0.0683)	(0.0518)
Post	0.0779	0.0946***
	(0.0493)	(0.0344)
Treat	0.0529	0.0688**
	(0.0412)	(0.0314)
Age	-0.00420***	-0.00528***
	(0.000754)	(0.000827)
Educations	0.0686***	0.0873***
	(0.0115)	(0.0118)
Family size	9.72e-05	-0.00107
	(0.00424)	(0.00438)
Religion	-0.0171	-0.0189
	(0.0144)	(0.0164)
Gender	-0.0349*	-0.0445*
	(0.0198)	(0.0245)

Residence	0.00709	0.0135
	(0.0341)	(0.0287)
Ethnic discrimination	-0.00673	-0.00797
	(0.0113)	(0.0122)
Local performances	0.126***	0.154***
	(0.0127)	(0.0142)
Constant		2.881***
		(0.0745)
Observations	5,242	5,242
Cluster FE	YES	YES
R-squared		0.031

Note: Dependent variable in each of the three columns is respondent perception of his living condition compared to previous year. Our variable of interest is Treat*Post Coefficients are reported with standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

3.5.2 Alternative dependent variable

In our first results our dependent variable was ‘’how respondent perceive his present living condition compared to the previous year’’. To support our first findings, we resort to ‘’how respondent perceives his living condition compared to others’’ as alternative dependent variable in our three specifications. The results in table 5, although different in terms of magnitude are aligned with previous ones. Mining activities significantly increase the living conditions of local community.

Table 3.5: Alternative dependent variable

VARIABLES	Mode 1	Mode 2	Mode 3
Treat*post	0.154***	0.136**	0.142***
	(0.0561)	(0.0543)	(0.0526)
Post	0.0819**	0.0779**	0.0716**
	(0.0382)	(0.0377)	(0.0362)
Treat	-0.0101	-0.00749	0.00470
	(0.0342)	(0.0346)	(0.0338)
Age		-0.00250***	-0.00301***
		(0.000606)	(0.000605)
Educations		0.0344***	0.0326***
		(0.00953)	(0.00947)
Family size		0.000482	-0.00268
		(0.00356)	(0.00346)
Religion		-0.0317***	-0.0320***
		(0.0116)	(0.0115)
Gender		-0.0511***	-0.0570***
		(0.0171)	(0.0169)
Residence		0.0604**	0.0647**
		(0.0289)	(0.0282)

Ethnic discrimination			-0.0134
			(0.00927)
Local performance			0.107***
			(0.0106)
Constant	2.924***	3.092***	2.926***
	(0.0269)	(0.0501)	(0.0596)
Observations	5,280	5,242	5,242
R-squared	0.003	0.008	0.023
Cluster FE	YES	YES	YES
Year FE	YES	YES	YES

Note: Dependent variable in each of the three columns is respondent perception of his living condition compared to others. Our variable of interest is Treat*Post . Coefficients are reported with standard errors in parentheses clustered at cluster level. *** p<0.01, ** p<0.05, * p<0.1.

3.5.3 Alternative treatment buffer

Instead of 25 kilometers as in the previous case, we now take two alternative treatment buffers: a very close (10km radius) and very far distance (70 km radius) from the mining location. The control being those who are not included in the respective radius. The results in table 6 compared to our main findings in table 3 reveal that even if the living condition in local community get improved in all the cases, the magnitude of the effect depends on the distance. Indeed, those who are closer experience less improvement in their living condition compared to those who are a little bit far and this effect becomes insignificant for individuals who are located much further away from mining location.

Table 3.6: Alternative treatment buffer

VARIABLES	Model 10km	Model 70km
Treat*post	0.172**	0.0351
	(0.0460)	(0.0445)
Post	0.0686**	0.0290
	(0.0339)	(0.0325)
Treat	-0.0543*	-0.0428
	(0.0321)	(0.0313)
Age	-0.00253***	-0.00304***
	(0.000606)	(0.000605)
Educations	0.0350***	0.0333***
	(0.00954)	(0.00948)
Family size	0.000672	-0.00246
	(0.00358)	(0.00349)
Religion	-0.0314***	-0.0319***
	(0.0115)	(0.0114)
Gender	-0.0504***	-0.0564***
	(0.0171)	(0.0170)
Residence	0.0381	0.0456
	(0.0307)	(0.0300)
Ethnic discrimination	0.117**	-0.0132
	(0.0469)	(0.00924)
Local performance	0.0693**	0.107***

	(0.0298)	(0.0106)
Constant	3.122***	2.958***
	(0.0481)	(0.0574)
Observations	5,242	5,242
R-squared	0.009	0.024
Cluster FE	YES	YES
Year FE	YES	YES

Note: Dependent variable in each of the three columns is respondent perception of his living condition compared to previous year. Coefficients are reported with standard errors in parentheses clustered at cluster level. *** p<0.01, ** p<0.05, * p<0.1.

3.5.4 Use of other variables reflecting living conditions

To further prove the consistency of our findings, we use alternative dependent variables reflecting how individuals perceive their living condition. These variables measure respondent's accessibility to: health clinic, water, food and shelter. More specifically, the survey asks respondent how often he has access to medical care, piped water, food and the type of shelter he is living in. The results in table 7 highlight the fact that extractive activities significantly increase the access to health clinic, piped water and improve the quality of shelter. However, access to food is not significantly improved. This later result may be problematic in the future for local population.

Table 3.7: Use of other dependent variables

VARIABLES	Access to health clinic	Access to piped water	Access to Food	Type of shelter
Treat*post	0.291***	0.235**	0.0761	0.230***
	(0.0909)	(0.114)	(0.0489)	(0.0550)
Post	0.248***	-0.0631	-0.109	-0.300***
	(0.0655)	(0.102)	(0.0739)	(0.0494)
Treat	-0.0371	-0.0310	-0.00621	-0.140***
	(0.0605)	(0.0731)	(0.0312)	(0.0351)
Age	0.00203**	-0.00217**	0.000753	0.00103
	(0.000945)	(0.00103)	(0.000763)	(0.000859)
Educations	0.0904***	0.0592***	0.0942***	0.137***
	(0.0149)	(0.0180)	(0.0110)	(0.0123)
Family size	-0.00308	-0.0276***	-0.0372***	-0.0441***
	(0.00531)	(0.00609)	(0.00405)	(0.00455)
Religion	0.0219	-0.00606	0.0382**	-0.00168
	(0.0162)	(0.0177)	(0.0151)	(0.0170)
Gender	0.0389	-0.0184	0.0903***	0.00633
	(0.0237)	(0.0257)	(0.0226)	(0.0254)
Residence	-0.0146	0.0308	-0.0577**	-0.0741**
	(0.0498)	(0.0601)	(0.0267)	(0.0300)
Ethnic discrimination	-0.0209	-0.0409***	-0.0220**	0.0337***
	(0.0137)	(0.0154)	(0.0112)	(0.0126)
Local performances	-0.114***	-0.0841***	-0.0883***	0.0136
	(0.0152)	(0.0175)	(0.0132)	(0.0148)
	1.051***	1.769***	1.377***	2.212***

Constant				
	(0.101)	(0.135)	(0.0771)	(0.0867)
Observations	5,242	5,242	5,242	5,242
R-squared	0.032	0.034	0.039	0.031
Cluster FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: Dependent variable in each of the first three columns measure how often respondent has access to medical care, water and food. The dependent variable in the fourth column measures the type of shelter respondent is living in. Our variable of interest is Treat*Post. Coefficients are reported with standard errors in parentheses clustered at cluster level. *** p<0.01, ** p<0.05, * p<0.1.

3.5.5 Parallel trends and anticipation of treatment tests

One of the main assumptions with DID methodology is parallel trends. This assumption assumes that the effect in the treatment and control group would have evolved in the same manner without any intervention. In other words, the living conditions of those close to mining activities and those who are far away would have evolved in the same way without the implantation of gold mining. Even if this assumption is difficult to prove with certitude, we use another afro barometer survey data one-year prior mining company begins their activities and run the regression with all control variables and our treatment group being individuals living within 50km and 25km from the extractive activities. The result in table 8 reveals that before mining activities, there was not any significant difference in terms of living condition between our treatment and control group irrespective of our treatment group definition.

Table 3.8: parallel trends check

VARIABLES	50km	25km
Treat*post	-0.0413	-0.106
	(0.0919)	(0.0769)
Post	0.110*	0.148**
	(0.0657)	(0.0596)
Treat 50km (25km)	-0.116*	-0.0860
	(0.0603)	(0.0567)
Age	0.000660	0.000698
	(0.000873)	(0.000873)
Educations	0.100***	0.102***
	(0.0155)	(0.0155)
Family size	-0.0371***	-0.0373***
	(0.00481)	(0.00480)
Religion	0.0361**	0.0366**
	(0.0154)	(0.0154)
Gender	0.0914***	0.0919***
	(0.0218)	(0.0218)
Residence	-0.0853*	-0.105*
	(0.0508)	(0.0555)
Ethnic discrimination	-0.0240*	-0.0246*

	(0.0127)	(0.0128)
Local performance	-0.0816***	-0.0806***
	(0.0151)	(0.0152)
Constant	1.044***	1.016***
	(0.0885)	(0.0877)
Observations	5,242	5,242
R-squared	0.032	0.031
Cluster FE	YES	YES
Year FE	YES	YES

Note: Dependent variable in each of the three columns is respondent perception of his living condition compared to previous year. Our variable of interest is Treat*Post. Coefficients are reported with standard errors in parentheses clustered at cluster level. *** p<0.01, ** p<0.05, * p<0.1.

3.5.6 Kernel propensity score matching plus DID

To further prove the validity of our analysis we finally use DID plus PSM (Propensity Score Matching). In other words, we create a quasi-experimental design that matches our treatment group and control group based on visible characteristics and assess differences before and after mining activities. As matching algorithms, we make use of kernel matching. The result in table 9 shows that the living conditions of local population living near increases significantly compared to the control group.

Table 3.9: PSM plus DID

VARIABLES	Full
Treat*post	0.271***
	(0.0677)
Post	0.0855
	(0.0552)
Treat	0.0549*
	(0.0320)
Age	-0.000453
	(0.00104)
Educations	-0.135***
	(0.0285)
Family size	0.0422***
	(0.00999)
Religion	-0.00523
	(0.0168)
Gender	0.0118
	(0.0199)
Residence	-0.868***
	(0.107)
Ethnic discrimination	0.0435**
	(0.0207)
Local performance	-0.0803***
	(0.0213)
Constant	0.849***
	(0.136)

Observations	4,194
Cluster FE	YES
Year FE	YES

Note: Dependent variable in each of the three columns is respondent perception of his living condition compared to previous year. Our variable of interest is Treat*Post. Coefficients are reported with standard errors in parentheses clustered at cluster level. *** p<0.01, ** p<0.05, * p<0.1.

3.6 Heterogeneity effect

In order to check our hypothesis relative to the effect by gender, we re-estimate our model with full control variables depending on the gender group. The result in table 10 highlights that the effect of extractive activities on local population's living condition seems to be gender specific. Men and women are differently impacted. Indeed, while men experience a significant increase in their living conditions, the effect for women seems to be weakly significant. Moreover, the p-value from the test of the difference in the coefficients between these two groups (female and male) is 0.0431. This latter result implies that the equality of the effects for these two groups can be rejected. This finding confirms our second hypothesis.

Table 3.10: Heterogeneity effects based on gender

VARIABLES	Full Sample	Female	Male
Treat*post	0.289***	0.171*	0.393***
	(0.0788)	(0.102)	(0.0842)
Post	0.0883	0.0270	0.0977***
	(0.0566)	(0.0680)	(0.0213)
Treat	0.0626	0.0196	0.0548
	(0.0479)	(0.0612)	(0.0515)
Age	-0.00471***	-0.00714***	-0.00315***
	(0.000844)	(0.00126)	(0.00108)
Educations	0.0801***	0.0872***	0.0728***
	(0.0132)	(0.0182)	(0.0160)
Family size	-0.000391	-0.00959	0.00667
	(0.00482)	(0.00665)	(0.00579)
Religion	-0.0187	-0.00441	-0.0310
	(0.0163)	(0.0226)	(0.0221)
Residence	0.0103	0.0393	-0.0148
	(0.0396)	(0.0521)	(0.0439)
Ethnic discrimination	-0.00754	0.00368	-0.0171
	(0.0128)	(0.0176)	(0.0168)
Local performances	0.141***	0.153***	0.129***
	(0.0142)	(0.0210)	(0.0190)
Constant	2.852***	2.867***	2.862***
	(0.0798)	(0.118)	(0.0981)
Observations	5,242	2,359	2,883
R-squared	0.030	0.035	0.029
Cluster FE	YES	YES	YES

Year FE	YES	YES	YES
p-value: Female=Male: 0.0431			

Note: Dependent variable in each of the three columns is respondent perception of his living condition compared to previous year. Our variable of interest is Treat*Post. Coefficients are reported with standard errors in parentheses clustered at cluster level. *** p<0.01, ** p<0.05, * p<0.1.

3.7 Mechanism of the effect

A direct mechanism through which extractive industries may impact local population living conditions is through their effect on job creation, income and wealth. We mainly focus on these channels and analyze how mining activities can affect them.

3.7.1 Income

To measure how extractive activities may influence income, we use as dependent variable the frequency at which respondent has replied having cash income. The result in table 11 with the full sample points out that there is a significant increase in the likelihood to have cash income. However, the heterogeneity analysis reveals that while men experience a significant increase, the effect for women is not significant albeit positive. Additionally, the p-value from the test of equality of the effects between male and female is 0.0358, indicating that we can reject the hypothesis of equality of the effects between these two groups.

Table 3.11: Income mechanism

VARIABLES	Full	Male	Female
Treat*post	0.190***	0.278***	0.0987
	(0.0538)	(0.0747)	(0.0776)
Post	-0.118**	0.0883	-0.150**
	(0.0482)	(0.0670)	(0.0695)
Treat	-0.0189	0.00391	-0.0415
	(0.0343)	(0.0471)	(0.0500)
Age	-0.00158*	-0.000113	-0.00353***
	(0.000839)	(0.00112)	(0.00127)
Educations	0.117***	0.105***	0.127***
	(0.0120)	(0.0167)	(0.0174)
Family size	-0.00173	-0.00317	-0.000482
	(0.00445)	(0.00599)	(0.00664)
Religion	0.00322	-0.0106	0.0190
	(0.0166)	(0.0232)	(0.0238)

Residence	-0.0831***	-0.0828**	-0.0782*
	(0.0293)	(0.0406)	(0.0425)
Ethnic discrimination	-0.0257**	-0.0129	-0.0407**
	(0.0124)	(0.0172)	(0.0178)
Local performance	-0.0577***	-0.0474**	-0.0689***
	(0.0145)	(0.0199)	(0.0211)
Constant	2.294***	2.184***	2.510***
	(0.0847)	(0.115)	(0.121)
Observations	5,242	2,883	2,359
R-squared	0.042	0.038	0.046
Cluster FE	YES	YES	YES
Year FE	YES	YES	YES
p-value: Female=Male: 0.0358			

Note: Dependent variable in each of the three columns how often respondent has cash income. Our variable of interest is Treat*Post. Coefficients are reported with standard errors in parentheses clustered at cluster level. *** p<0.01, ** p<0.05, * p<0.1.

3.7.2 Employment

Since mining activities require most of time high skill and intense capital, their capability to generate direct job opportunities is rather limited. However, as already explained, mining activities may encourage the development of local activities which in turn may raise employment and wage in the local community. To explore this channel, we use as dependent variable the employment status of respondents. The results in table 12 suggest that overall, employment increases significantly in the treatment group relative to the control group. However, the heterogeneity analysis enlightens that the effect in terms of employment is highly significant for men (1 percent) whereas for women the degree of significance is weak (only 10 percent). Moreover, the p-value from the test of equality of the effects between male and female is 0.0179 which means that we can reject the hypothesis of equality of the effects between these two groups. Furthermore, based on the level of education, the results in table 13 highlight that individuals with primary and secondary education are more likely to get employed. On the contrary, for individual with no education and post-secondary education the effect is insignificant. This finding highlights the importance of at least primary education in access to employment.

Table 3.12: Employment mechanism

VARIABLES	Full	Female	Male
Treat*post	0.117***	0.106*	0.123**
	(0.0436)	(0.0642)	(0.0596)
Post	-0.237***	-0.267***	-0.208***
	(0.0450)	(0.0655)	(0.0618)
Treat	0.0416	0.0392	0.0461
	(0.0330)	(0.0486)	(0.0450)
Age	0.000165	-0.000704	0.000836
	(0.000782)	(0.00120)	(0.00103)

Educations	0.132***	0.128***	0.136***
	(0.0112)	(0.0164)	(0.0154)
Family size	0.0117***	0.0165***	0.00760
	(0.00414)	(0.00626)	(0.00553)
Religion	-0.0231	-0.0220	-0.0239
	(0.0155)	(0.0224)	(0.0214)
Residence	-0.0829***	-0.0672	-0.0966**
	(0.0305)	(0.0447)	(0.0418)
Ethnic discrimination	0.0120	-0.00431	0.0272*
	(0.0115)	(0.0168)	(0.0158)
Local performance	-0.0191	-0.0309	-0.00940
	(0.0135)	(0.0199)	(0.0184)
Constant	1.260***	1.376***	1.190***
	(0.0791)	(0.114)	(0.107)
Observations	5,242	2,359	2,883
R-squared	0.021	0.020	0.023
Cluster FE	YES	YES	YES
Year FE	YES	YES	YES
p-value: Female=Male: 0.0179			

Note: Dependent variable in each of the three columns is respondent employment status. Our variable of interest is Treat*Post .Coefficients are reported with standard errors in parentheses clustered at cluster level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.13: Employment based on education level

VARIABLES	No education	Primary education	Secondary education	Post-secondary
Treat*post	0.051	0.254*	0.237**	0.136
	(0.140)	(0.143)	(0.116)	(0.140)
Post	-0.113	-0.147	-0.0357	-0.103
	(0.0991)	(0.102)	(0.0663)	(0.0812)
Treat	-0.147	-0.206**	-0.0707	0.0235
	(0.0896)	(0.0889)	(0.0698)	(0.0863)
Age	0.000718	0.00151	-0.00223*	0.000934
	(0.00183)	(0.00142)	(0.00124)	(0.00195)
Family size	-0.00876	0.0143	0.0140**	-0.00313
	(0.00940)	(0.00992)	(0.00672)	(0.0108)
Religion	0.00612	-0.0135	-0.0476*	-0.0157
	(0.0363)	(0.0286)	(0.0264)	(0.0412)
Gender	0.0876	0.0493	-0.0356	0.0897
	(0.0533)	(0.0425)	(0.0370)	(0.0557)
Residence	-0.147*	-0.0534	-0.102	-0.00500
	(0.0778)	(0.0757)	(0.0641)	(0.0782)
Ethnic discrimination	0.0380	-0.0233	0.00753	-0.0245
	(0.0279)	(0.0254)	(0.0205)	(0.0286)

Local performance	0.0224	0.0178	-0.0695***	0.00405
	(0.0323)	(0.0305)	(0.0226)	(0.0330)
Constant	1.676***	1.383***	1.944***	1.356***
	(0.186)	(0.179)	(0.134)	(0.189)
Observations	1,143	660	446	206
R-squared	0.024	0.049	0.029	0.010
Cluster FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: Dependent variable in each of the four columns is respondent employment status according to his education level. Our variable of interest is Treat*Post. Coefficients are reported with standard errors in parentheses clustered at cluster level. *** p<0.01, ** p<0.05, * p<0.1.

3.7.3 Wealth

Finally, the effect on living conditions may also be transmitted through individual wealth. Since wealth index is not available for each survey round, we use household assets ownership- radio, TV, car, computer, mobile phone- to construct an asset index using principal component analysis (PCA) strategy. The results in table 14 reveal that local population experiences a significant increase in their wealth. The heterogeneity effect however shows that the effect is mostly driven by men's wealth. The p-value from the test of equality of the effects between male and female is 0.0389, implying that we can reject the hypothesis of equality of the effects between these two groups.

Table 3.14: Wealth mechanism

VARIABLES	Full	Male	Female
Treat*post	0.290***	0.443***	0.12013
	(0.0873)	(0.121)	(0.126)
Post	0.123**	0.272***	0.000210
	(0.0625)	(0.0902)	(0.0865)
Treat	-0.0869**	-0.0816	-0.0895
	(0.0433)	(0.0599)	(0.0625)
Age	0.00418***	0.00336**	0.00516***
	(0.00103)	(0.00139)	(0.00153)
Educations	-0.156***	-0.156***	-0.152***
	(0.0149)	(0.0208)	(0.0215)
Family size	-0.0130**	0.00537	-0.0338***
	(0.00547)	(0.00755)	(0.00793)
Religion	0.00604	-0.00579	0.0167
	(0.0205)	(0.0289)	(0.0291)
Residence	0.165***	0.104*	0.232***
	(0.0435)	(0.0604)	(0.0626)
Ethnic discrimination	-0.00926	-0.000770	-0.0185
	(0.0153)	(0.0215)	(0.0218)
Local performance	-0.0602***	-0.0450*	-0.0819***

	(0.0176)	(0.0244)	(0.0255)
Constant	0.173	0.287*	-0.637***
	(0.109)	(0.149)	(0.154)
Observations	2,691	1,550	1,141
R-squared	0.086	0.024	0.046
Cluster FE	YES	YES	YES
Year FE	YES	YES	YES
p-value: Female=Male: 0.0389			

Note: Dependent variable in each of the three columns is respondent wealth index measured with principal component analysis method. Our variable of interest is Treat*Post. Coefficients are reported with standard errors in parentheses clustered at cluster level. *** p<0.01, ** p<0.05, * p<0.1.

3.7.4 Insecurity and corruption

Why do people closer to mining location experience less improvement in their living condition compared to those who are far? Potential explanations may reside in the effect of extractive activities on the local environment such as crime. For example, the influx of strangers into areas experiencing a mining boom may undermine existing community social behavior and create an environment attractive to those with a history of criminal behavior which may affect significantly living condition. Moreover, the presence of natural resources may develop attitudes such as corruption and bureaucracy that may destabilize the positive effect of fiscal revenue on the provision of public goods and local population's well-being by creating rent seeking behavior and conflicts in closer areas. In order to check whether insecurity and corruption significantly impact living conditions, we run our main specification equation while taking them as our outcome variables. For insecurity, we use an indicator variable which measures whether or not respondent has experienced any attack in his area and for corruption, we use individual perception of corruption in his area. The results point out that in closer areas (10km radius) the impact of insecurity and corruption is highly significant compared to further areas. Those two factors may therefore explain the reason why in very close areas the improvement in living conditions is weak.

Table 3.15: Insecurity and corruption

	Insecurity		Corruption	
VARIABLES	Attacked 10km	Attacked 25 km	Corruption10km	Corruption 25km
Post*Treat	0.247**	0.136	0.210**	0.105
	(0.0969)	(0.0828)	(0.0922)	(0.0801)
post	-0.0956	-0.0340	-0.0881	-0.0309
	(0.0582)	(0.0514)	(0.0567)	(0.0500)
Treat	-0.130**	-0.0173	-0.114**	-0.00220
	(0.0614)	(0.0633)	(0.0572)	(0.0594)
Age	4.14e-05	6.50e-05	0.000211	0.000110

	(0.000817)	(0.000822)	(0.000801)	(0.000805)
Educations	0.135***	0.139***	0.115***	0.118***
	(0.0154)	(0.0153)	(0.0147)	(0.0147)
Family size	0.0109**	0.0102**	0.00807*	0.00739
	(0.00499)	(0.00503)	(0.00480)	(0.00483)
Religion	-0.0230	-0.0227	-0.0258	-0.0257
	(0.0166)	(0.0167)	(0.0165)	(0.0165)
Gender	0.0349	0.0343	0.0299	0.0292
	(0.0231)	(0.0231)	(0.0229)	(0.0229)
residence	-0.118**	-0.105*	-0.0947*	-0.0780
	(0.0518)	(0.0578)	(0.0491)	(0.0549)
Ethnic discrimination	0.00747	0.00677	0.00452	0.00383
	(0.0139)	(0.0139)	(0.0134)	(0.0135)
Local performance	-0.0184	-0.0164	-0.0182	-0.0162
	(0.0158)	(0.0157)	(0.0154)	(0.0153)
Constant	1.131***	1.047***	1.490***	1.412***
	(0.0978)	(0.0954)	(0.103)	(0.102)
Observations	3,855	3,255	3,855	3,255
R-squared	0.019	0.017	0.036	0.034
Cluster FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: Dependent variable in each of the last two columns measure respondent perception of corruption. It is a binary variable equals to 1 if respondent thinks that corruption is high 0 otherwise. The dependent variables in the first two columns measure respondent experience with attack. It is a binary variable, equals to 1 if respondent experienced any attack and 0 otherwise. Coefficients are reported with standard errors in parentheses clustered at cluster level. *** p<0.01, ** p<0.05, * p<0.1.

3.8 Conclusion

Our objective in this paper was to study the impact of extractive industries on local community living conditions in Cote d'Ivoire. To reach that, we make use of several rounds of afro barometer data set and data about the precise location of mining activities from Mineral Resources Data System (MRDS). Based on that, we employ a quasi-experimental design (DID) and analyze the difference in living conditions of the nearest population compared to those living far from the mining location before and after mine's production phase. After analysis and several robustness checks- control of individual characteristics, local institution perception, definition of new treatment and control group, use of alternative dependent variables-, our study reveals that mining activities in our selected area impact positively and significantly the living condition of the nearer local population compared to those who are far. We can therefore conclude that so far, instead of resource curse, gold mining is a blessing for local population in the region of Agbaou. This finding is in line with (Lippert, 2014) who also finds that proximity to mining activities lead to an increase of living conditions in Zambia. However, our heterogeneity analysis highlights that the effect is gender specific. While men experience a significant improvement of their living condition, the effect on women on the contrary is not that significant. Furthermore, we explored possible mechanisms that may lie behind this finding. Since a direct channel through which extractive industries may impact local population living condition is through their effect on job creation, income or wealth, we emphasize our explanation on these variables. Thus, we find that mining activities in Agbaou globally significantly increase local community income, employment status and wealth. However, the heterogeneity analysis reveals that the effect on each of these variables is also gender specific. The effect on men's income, employment and wealth is positively significant while the effect on women's even though positive, is not significant. One explanation could be that, when mining activities lead to the displacement of local communities' traditional activities, programs are often conducted to provide new work opportunities or compensate those affected. However, since these programs or compensations only pay attention to formal works displaced or at the owners who have lost their productive assets, they are generally in favor of male employment and ownership at the expense of women. Finally, examining more closely individual living conditions, we got evidence that even if access to water and shelter got significantly improved, there is not a significant improvement in access to food. This situation may be due to land dispossession previously used for agriculture purpose making populations unable to produce enough compared to before. Also, even though we cannot prove it due to the limitation of our data set, there may be a shift of focus from agricultural sector to mining sector where employees can earn monthly income. Consequently, population living near to mining activities may face a serious problem of food insecurity in the future.

Overall, even if living conditions in local community get improved, more attention must be paid to the effect on women, negative spillover effects such as insecurity and corruption induced by the development of mining activities and potential threat to food security. Indeed, as proved above, the development of mining activities is followed by a significant increase in insecurity and corruption behavior in closer areas which may undermine the positive benefits gained. Moreover, improving also gains for women could make the overall gain much better in the short run as well as in the long run. The reason is that, according to some literature, when women have access to employment opportunities or new revenue entry, they tend to invest a large part of this income on their families' health, education and general wellbeing (*United nation*, 2010).

To reach that goal, policies should be oriented at promoting employment opportunities specially for women by mining companies and their suppliers. Also, when land property is granted to mining companies, women are more often excluded from discussions or have their views ignored. Unless the views of all groups are obtained, priorities may not meet the needs of the poorest and most vulnerable in the community. A better policy should therefore go in the direction of allowing both men and women to genuinely express perspectives and concerns, and to understand how activities will impact each one within the community. For example, joint land title to both spouses may be a possible solution. Policies should also be oriented toward tackling the negative spill-over effects such as insecurity and corruption for local population to gain full advantage from mining activities. Finally, government should also consider potential threats to food security and potential mechanisms to tackle it before allowing mining activities.

An extension of this study would be to consider more disaggregated data such as the type of jobs and potential negative externalities variables (degradation of the environment) and social norms in order to better understand why the effect is gender specific. Finally, it will be important to analyze the long sustainability of this economic effect in order to see how the living condition will turn out in the long run.

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