A longitudinal analysis of the Mahatma Gandhi National Employment Guarantee Act using a Multidimensional Poverty Index

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The data used come from Young Lives, a longitudinal study of childhood poverty that is tracking the lives of 12,000 children in Ethiopia, India (in the states of Andhra Pradesh and Telangana), Peru and Vietnam over a 15-year period. **www.younglives.org.uk**

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“Numbers have life; they are not just symbols on paper.”

\- Shakuntala Devi

Abstract

The Mahatma Gandhi National Rural Employment Guarantee Act (MNREGA) has been championed as one of the most successful attempts to provide a universal employment guarantee scheme in the form of a public work program. Institutionalized in 2005, it is now the largest public work program in the World, providing employment for more than 55 million rural households across the Indian state. However, despite its scale and political success, its impact on poverty and destitution has not been well studied. This paper attempts to study the longitudinal effects of the program using a Multidimensional Poverty Index (MPI) based on the Alkire-Foster's methodology. The dataset used was provided by the Young Lives Longitudinal Study which has been collecting information on child wellbeing in the area of Andhra Pradesh since 2002. The Young Lives study, which covers individuals from 2002 until 2014, focuses its attention on two different cohorts of children: The Older cohort and the Younger cohort which will be studied separately. In addition, due to data limitations, we decided to focus our analysis only between the years 2006 and 2014. In order to assess the level of multidimensional deprivation in our population we used the Alkire-Foster's methodology to construct a Multidimensional Poverty Index which comprises of three equally weighted dimensions divided in ten equally weighted indicators. For the purpose of our study we will use the following indicators: Education, Health and Living Standards. The MPI shows clearly how households participating in the program tend to have a decrease in Living Standard destitution of 12.8% for the Older cohort and of 8.4% for the Younger cohort. Thirdly, in order to assess, the treatment effect of the MGNREGA we perform a Difference-in-Difference for both cohorts. The analysis resulted in a cumulative treatment effect of 8.7% for the Older cohort and 2.4% for the Younger cohort. Finally, some policy recommendations will be given in order to better estimate the impact of public work programs on a multidimensional level in the future.

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Introduction

In recent times, views on poverty have started to become more multifaceted, extending beyond the mere notion of inadequacy of income, they have been including various aspect of life such as social inclusion, good health, access to opportunities and the achievement basic living standards (ILO 2014). Many studies, proved how income and expenditure are now incapable to portray the underlying reasons leading to transgenerational poverty (Alkire et al. 2011).

Sen's (1979) "Capability Approach" (CA) redefines poverty as depriving people of living a life they value and they have a reason to value. The deprivation is explained in the lack of "capabilities" which is a vector of those functionings and freedoms the individual seeks or needs in order to live the life he/she values. As a normative framework, the CA distinguish itself from others by focusing on the difference between means and ends for the evaluation of individual well-being, and proposals about social change in the society (Herguner 2012). In this context, the CA suggest that economic growth is necessary for development, however, it also states that mere economic growth is not always sufficient as it doesn't necessarily lead to an expansions of human capabilities. In fact, the CA primary characteristic is to focus on what people are effectively able to do and to be, which differs from simply concentrating on income, expenditures, consumption or basic needs. A focus on people's capabilities in the choice of development policies signifies a deep theoretical difference, and leads to different policies compared to utilitarian policy prescription (Herguner 2012).

This theoretical difference is important when we, as policy analyst, select the type of intervention we want to use to help poor populations. This paper focuses on Public Work Programs (PWPs) and their impact on fostering people capabilities. So far, the literature has been assessing the ability of PWPs, in smoothing consumption when an adverse shock, such as a drought or the loss of employment occurs, or as a way for women and other socially excluded parts of the population to actively participate in society. This assessment has, so far, been carried out only in terms of "quantifying" the impact of PWPs without looking into the effects that these programs could have had in terms of increased capabilities. In order to assess the long terms effects of the PWPs in increasing individual capabilities, we need a dual approach: the first part will unfold a quantitative assessment of the impact of the PWP in our sampled population. The second part, will try to assess the ex-post effect of the PWP after the individual has completed the program. In this scenario we look at a specific question: "was the participation instrumental in increasing the individual skills, knowledge or social inclusion?" To be able to carry out such an assessment, however, we would need studies that continue to monitor the participating population after they completed the program. Such studies, however, at the moment do not exist, or if they do, they lack the time-span necessary to conduct a meaningful assessment.

In this study we will conduct the first part of the aforementioned approach using one of the most prominent PWP: The Indian Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA). In this paper we will assess its effects on deprivation using a Multidimensional Poverty Index (MPI) crated using the Alkire-Foster's methodology. This approach, which stems out the Human Development Index, takes into account three equally weighted dimensions (Health, Education and Living standards) which are meant to proxy not only for income-related variables but also for the wide array of capabilities an individual need in order to live the life he/she wants to live. Unfortunately, we cannot, due to data limitations, endeavor in the second part of our analysis, however, we consider this paper the corner-stone toward a long term assessment of PWPs as tools for capabilities development.

We decided to focus on the MGNREGA because Public Works Programs have been part of India's policy agenda for millennia. The "Arthashastra", written during the 4th century B.C. by the Indian teacher, philosopher and royal advisor Chanakya, suggested workfare measures to cope with high unemployment and to combat poverty in time of famine and duress (Uppal 2009). More recently, the 1880 Code of Famine advocated for work camps where only those most in need would access. After the independence, many attempts have been put in place to ensure a minimum level of security against hunger and other adverse shocks. The most successful of these was the Maharashtra Employment Guarantee Scheme (MEGS) which we could consider the grandfather of the Mahatma Gandhi Rural Employment Guarantee Act which was launched in 2005 and has, so far, been seen as a revolutionary step in creating a safety net for poor people.

The MGNREGA is a public work program in India whose aim is to correct for cyclical unemployment, by providing rural households with employment and income opportunities. Registered households are offered up to 100 days of work per year which should protect them from income shocks and enhance their capability to smooth income and consumption when necessary. The MGNREGA is one of the most prominent, active public work program which ensure universality and gender equality. Amartya Sen himself has praised the program as being worldwide unique in its pro-poor strategy, as no country in the World has ever given, by constitution, the right to work to such a large amount of population (Deka and Panda 2015). So far it has reportedly provided employment to 55 million households with a total amount of provided employment of over 2.04 billion person-days and over 2.5 million works taken up (Uppal 2009).

Despite having generated considerable debate in the policy forums it has not been adequately analyzed from a quantitative multidimensional point of view. At present, few study exists that present a longitudinal and multidimensional analysis of the MGNREGA. Henceforth, the underlying research question of this paper is to present a longitudinal assessment of the Mahatma Gandhi National Rural Employment Guarantee Act using a Multidimensional Poverty Index (MPI). This MPI, despite being constructed using the Alkire-Foster's methodology has to be considered as a new index, specifically tailored to assess the impact of the MGNREGA.

Secondly, as mentioned, we want to take the first step toward a study of public work programs not only from a mere safety-net point of view but as tools to promote, foster and enhance the capabilities of those who decide to partake in the program. We will conduct our assessment using the Young Lives Longitudinal dataset, that offers a survey that spans from 2006 (one year after the implementation of the program) until 2014 covering a variety of household and individual specific information.

The paper is organized as follow: chapter one will briefly present the MGNREGA program, followed by chapter two were we will have an excursus on the literature concerning the impact of the program and how it has been pivotal in helping the Indian population so far. Chapter three will focus on the dataset we use for our analysis: The Young Lives Study, a longitudinal analysis based in the region of Andhra Pradesh. There we will also talk about the limitation of this dataset. Chapter four will discuss the methodology behind the creation of our multidimensional poverty index. As we said, we are using the Alkire-Foster methodology which, however, we customize to better represent our sampled population. Here, we also perform a series of robustness checks to validate the choice of our indicators. Chapter five is the heart of this paper. Here we present our findings in terms of multidimensional poverty as well as another series of robustness checks. As the dataset we are using takes the form of a longitudinal study in chapter six we perform an analysis using a difference-in-difference methodology which will grant us the assessment of the impact of the MGNREGA within our population between the year 2006 and the year 2014. To conclude we will briefly talk about the policy implication of our study.

Chapter 1 – The Mahatma Gandhi Rural Employment Guarantee Act

The National Rural Employment Guarantee Scheme (NREGS), was initially implemented in September 2005 in all states in India with the exception of the states of Jammu and Kashmir that where included in December 2007. The program was renamed on the 2nd of October 2009 to Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA). From the theoretical point of view, the MGNREGA serves the outcome of realizing the right of work and the enhancement of livelihoods through the construction and development of economic and social infrastructures.

In brief, the MGNREGA can be described as a universal public work program, which guarantees 100 days of unskilled wage employment to any individual, aged 18 or older, living in rural areas. Given its universality, there's no criteria that prevents an individual to join the program provided is willingness to work at the minimum wage. Moreover, the program allocates a specific quota for women: it is prescribed that at least one-third of all beneficiaries must be women; in addition, it sets a 60:40 wage-to-material ratios in projects to ensure parsimony in material expenditure. During its first year the MGNREGA[1] involved an expenditure of $4.5 billion with was also excepted to create 2 billions days of wage work. By providing increased employment opportunities to a total of 55 million households, the MGNREGA has brought important changes in the socio-economic framework in India (Rao 2014).

As mentioned, the MGNREGA emphasis is on the construction of community and nation-wide infrastructures targeted to improve or increase local and national assets. For instance, we can see project focused on water conservation and/or rain water collection, rural connectivity, irrigation canals, drought management, land development and flood control. Individuals seeking unskilled labour and willing to partake in the program have to submit their application to the *Gram Panchayat*, the village council. The application is then sent to the *Mandal Computer Centre* (MCC) which creates a distinct job card. This job card is the used by the individual to apply for the unskilled wage work. According to the Act manual, the entire process should take no more than 15 working days and if employment is not provided in the following 15 days he/she has to be compensated by the State with an unemployment allowance.

[1] In 2005 the MGNREGA was named NREGS: National Rural Employment Guarantee Scheme, the name was changed later on.

Historically, the MGNREGA was implemented in three phase. In phase 1, between September 2005 and February 2006, the scheme targeted 200 among the poorest districts in India. The second phase was rolled out in May 2007 and covered and additional 130 districts. Finally, by April 2008, the program included all the remaining rural districts in India. The Ministry of Rural Development in the 2006-2007 annual report showed that more than 200 million poor households, of which more than 10% were based in the state of Andhra Pradesh, were employed in the NREGS[2] in those years.

Given it specific characteristics and the large-scale nature of this public work program, the MGNREGA has generated a distinctive interest among policy makers and social scientists, especially in understanding its effectiveness as poverty-reduction program. By giving the households the right to work and new employment opportunities, the MGNREGA has highly influenced the ability of households to smooth income in case of adverse shocks (Rao 2014). Moreover, studies have shown that the increased capability to cope with shocks, induced by the new job opportunities, can lead to an increase in general wealth but can also influence household's ability to access credit, willingness to take risks to an overall ability to control changes (Khanna and Zimmermann 2016).

However, the MGNREGA's ability to have an incidence on household wellbeing depends on a variety of factors, such as: outreach of the programme, poor's take-up ratio and correct administration. On the agricultural side, the MGNREGA intervention would be considered positive only if the individual work undertaken under the scheme would help enhance land productivity. Moreover, a 100 days of work will certainly help those on the poverty line, or those that might fall under it given a shock (the transient poor), but for the severely poor such a small amount of working days can only reduce the intensity of their deprivation briefly, but their situation won't change in the long run. In fact, a right-based intervention such as the MGNREGA cannot, per se, resolve the multiple socio-economic deprivation that poor in rural communities have been facing over a long time as a consequence of denied justice and constant neglection.

From the implementation point of view, quality has been shown to greatly vary across India (Gehrke 2014). In many state the provision of work under the MGNREGA is too unpredictable and faulty administration has hindered the program capacity to offset shocks, hence, losing its ability to build capacity at the household level. However, Andhra Pradesh is

[2] As mentioned, the program changed name from NREGS to MGNREGA in 2009.

one of the states where takeover is the highest as well as the provision of working days generated par rural household (Gehrke 2014).

Nevertheless, after 10 years from its implementation, it is now time to focus once more on the MGNREGA to see if a continuous participation has had any long-lasting effect on households. So far, studies have forgone an adequate long-term rigorous empirical evaluation. Existing studies have tended to primary focus on the administrative side and operational aspects such as: worksite selection, creation of physical assets, social audits, transparency and anti-corruption measures. In conclusion, given the its characteristics, the ability to increase household wellbeing and capacity building its paramount to conduct an effective assessment of the impacts that the MGNREGA might have had on those individuals that have been consistently participating in the program since its implementation.

Chapter 2 – Literature Review

The international community, throughout the last 10 years has being consistently involved in the fight against poverty. Conditional and unconditional cash transfers, along with public work programs, are among the most used policies to tackle deprivation in developing countries (de Hoop and Rosati 2014). However, whether cash transfer have been already deeply studied and evaluated by the academic community, less attention has been given to public work programs (UCW 2010; de Hoop and Rosati 2013). Studies have shown that public work programs have historically played an important role in countering short-term and seasonal unemployment (Subbarao 1997). Globalization, in tandem with the economic crisis, increased the poor exposure to risks and vulnerabilities especially in developing countries. Public work programs, thus had to expand their scope, by providing flexible and cost-effective ways to help poor households to cope with these new challenges (Subbarao 1997).

As we mentioned in the previous chapter, researchers and policy analysts have been interested in finding out the welfare effects that the MGNREGA has on participating households. The underlying social benefit of the program is to help and protect poor rural households from destitution and deprivation by providing work in case of covariate shocks. An employment guarantee scheme's benefit is twofold: a transfer benefit, which is to increase the worker's income, and a stabilization benefit, which is to provide an income smoothing characteristic helpful during the agricultural off-peak season where employment opportunities are lower, or when the market faces negative fluctuations (Ravallion 1990).

The MGNREGA program was introduced in India with the aim of improving households' purchasing power, especially in those rural area with a majority of unskilled, unemployed individual that were struggling to access the labour market. By providing a social safety-net the program aimed to enhance resilience among vulnerable groups, increase labour participation and create durable and productive assets in the most deprived area (A. Dasgupta 2012). The 2011 evaluation reform from the Ministry of Rural Development (2011), shows that the program had a positive effect in an increase of food a non-food items, as well as a positive effect in reduced labour migration, which can be strongly correlated with a general increase in well-being. Moreover, a number of studies have been showing positives effects in terms of shock resilience, agricultural productivity, labour market outcomes and women empowerment (Behrman 2014; Gehrke 2014; Klonner and Oldiges 2012; Rao 2014; Uppal 2009).

By providing additional employment opportunities, an employment guarantee scheme can help household to better cope with income shocks in case, for instance of adverse weather conditions or the loss of family member. The insurance effect that these schemes may provide is particularly important for those households which are highly exposed to covariate risks such as droughts, floods, or crop disease. In rural areas, where households are highly dependent on agricultural outcomes, wages were shown to fall according to covariate shocks (Gehrke 2014). Income fluctuation are particularly detrimental for poor households as they limit or reduce their decision making capacity. Transient poverty is, in fact, often correlated with uninsured risk. From an ex ante point of view, it effects activities, assets and investment choice, whilst from an ex post point of view it reduced asset's availability. In this context, the MGNREGA offers households the opportunity to work independently of shocks, hence, influencing the household's ability to smooth income when the shock subsists.

From the agricultural productivity point of view, given the higher capacity to offsets shocks provided by public work program, Gehrke (2014), demonstrated how households are able to shift their agricultural production toward high-risk and high-profit crops. The study showed how this enhance in productivity is highly dependent on intra-household decision, exogenous factors and, most importantly on the size and typology of crops. Previous studies (Imbert and Papp 2011; Jha et al. 2011), demonstrated that benefits, despite not being generally large, are larger for poorer households and for those with small land-holdings with a consistent redistributive effect from those household with large-owned land to those with smaller ones.

According to Bhattacharyya et. Al (2012), between 2004-05 and 2007-08 the MGNREGA has had an increasing effect in rural wages between 3 and 5 percent, where female workers and marginalized groups where those benefitting the most.[3] In addition, Imbert and Papp (2013), showed how the MGNREGA had raised the wage levels in private sector, in fact, wages paid under the MGNREGA are often higher than those paid for casual work, hence, households shift their labour supply from the private sector to the program. What these studies have emphasized is that demand for labour is highly dependent on season and that the MGNREGA satisfies its role of a safety-net during the off-peak agricultural season where working opportunity are relatively scarce.

As we said, among the group benefitting the most from the program we find female labourers. According to Zimmermann (2012), the MGNREGA is particularly attractive to women as it increases their private sector wages. However, the research shows that this effect is localized during the agricultural main season and less during the off-peak season. More studies (Arora, Kulshreshtha, and Upadhyay 2013), have further discussed the effects of the program on women empowerment. As we mentioned in the previous chapter, the MGNREGA enshrines specific entitlements for women to facilitate their full participation, such as equal wage between man and women and a minimum statutory requirement of 33% female enrolment among the total participating workforce. According to the study, the empowerment effect is perceived by 95.5% of the surveyed female population whilst enhancing their capabilities not only inside the household but also enabling them to be participate effectively in society.

As we can see, the MGNREGA, have a positive effect in more than one single issues. Increase in rural household consumption, gender empowerment, technology innovation and risk management are among the indicator of the multidimensionality of poverty. As a matter of, the MGNREGA can actively be consider an anti-poverty instrument to counter multidimensional poverty. Despite, the literature presents a number of multidimensional poverty study concerning the MGNREGA, so far a study based on longitudinal data is missing. Henceforth, this study aims to close this gab by providing a multidimensional study of the welfare effect of the MGNREGA program. In order to fulfil this task we will make use of the Young Lives Longitudinal study, a panel data that spans across 14 years in the region of Andhra Pradesh. [4]

[3] With marginalized group we refer to scheduled castes (SC) and scheduled tribes (ST).
[4] We will talk more about the YL study and about multidimensional poverty analysis in the next chapters.

Chapter 3 – Data: The Young Lives Longitudinal Study

For our research, we are using data coming from the Young Lives Longitudinal Study, a survey that collects information on 3000 children in the state of Andhra Pradesh in Southern India. This longitudinal study tracked 1008 children born in 1994-95, defined as Older Cohort, and 2011 children born in 2001-02, defined as Younger Cohort in four rounds. Round one took place in 2002, Round two between 2006 and 2007, Round three in 2009 and Round 4 in 2014. Studies have demonstrated a low rate of attrition up until round three (Outes-leon and Dercon 2008). Moreover, to estimate the poverty reduction effect in the long term we need to focus our study in those areas where implementation has been constant and methodical and where demand for employment has been sufficiently met (Gehrke 2014).

During the four rounds, data have been collected at the child, household and community level. The information collected are multiple such as health, schooling, illness, literacy and cognition, as well as parents' human capital, household assets, household per capita consumption and expenditure and shocks' incidence. Regarding the MGNREGA, households were asked a number of questions, for instance: if any member had registered for the program, the extent of the employment within the program itself, the wage received and if they received unemployment allowance before applying. Moreover, in order to ensure the representability of the data in respect of whole India, information were collected in six different districts of Andhra Pradesh covering different regions, income level and geographical characteristic.[5]

Andhra Pradesh is the 5th largest state in India, with a total population of 84.5 million and the fastest growing in terms of GPD growth rate despite being predominantly a rural state (Government of India, Ministry of Home Affairs 2011). As mentioned, the MGNREGA was enacted in 2005, hence during Round two. At this stage, the sample was selected among 20 different sentinel sites (at the community level) in which 100 households with 1-year-old child and 50 households with 8-year-old child where randomly selected. By the second round 70% of the eligible households were registered in the program which suggests a satisfactory coverage. Finally, by the third round the program was implemented in all remaining districts. By this time, we can see that approximately 81% of the eligible households residing in the

[5] It is important to mention that only four out of six surveyed districts were covered by the MGNREGA by its implementation: Cuddapah, Anantapur, Mahbubnagar, Karimnagar. West Godavari and Srikakulam became part of the program on a later stage.

early-stage districts and 75% of those residing in the later-stage where registered in the program. Finally, by the fourth round the program reached all areas of Andhra Pradesh. This longitudinal study despite not being collected for a specific analysis of the MGNREGA program has several strength and suits quite well the purpose of our analysis: it spans from the very early stage of its implementation till its maturity; it breath of the survey encompasses several variables useful for providing controls in estimation and, finally; at present there is no other longitudinal study that covers such length in years making these data extremely important.

As we mentioned, the YL study revolves mostly around child-related variables. Children are, as a matter of fact, a group that have been largely ignored in the literature, very few study exists on a child basis (Uppal 2009). At the same time, a growing consensus exists suggesting that childhood health, education and general wellbeing is strongly correlated with later economic success and in general with an increase access to opportunity, hence, breaking the intergenerational link with poverty (Uppal 2009).

While at the individual level, this focus on children is surely a major strength of the YL longitudinal study, from the household perspective it is, instead, a limitation. Household related characteristics are provided but related to the individual child-id without providing further information on the household structure.

Intra-household characteristics are of paramount importance to assess the impact at the intra-household level of any social program. It exists, in fact, the possibility of sample bias in a manner relevant for the evaluation of the MGNREGA if the households taking up the program have systematically different characteristics than those how did not. Intra-household information, such as household structure, number of children, number of elderly and dependency ratio could affect labour decision as well as the decision to participate or not to the MGNREGA. Given the survey methodology, we can only partially control for these characteristics.

In addition, another possible limitation of panel studies on child poverty is the inevitable change in type and structure of relevant variables as the individual grows up. The determinants of welfare, or poverty, at age 5 or under are mostly related to household characteristics such as the level of parental care. As the child grows up, other variables become more relevant such as education and child work. It is important to notice this trade-off in the selection of comparable indicators across time in order to be able to capture a correct picture of a child wellbeing at each point in time.

However, this would mean only that our analysis cannot be generalized to the entire population but is meant to provide an overlook of the longitudinal effect of one of the biggest and most important universal public work programs. The analysis remains valid to the extent of the individual level and especially on the basis of our population; in addition, given the breath of the longitudinal study this is the first time a study tries to assess the long term effect of the MGNREGA, hence, the use of the Young Lives data is justified.

Chapter 4 – Methodology

For the purpose of this study income, by itself, loses its ability to correctly portray the situation of an individual o household facing poverty. As a matter of fact, income can be described as one of the many lack in capabilities that an individual may face. According to Amartya Sen's (1979) "Capability Approach", poverty is define as being deprived of capabilities, which can be describe as the lack of freedoms people value and have a reason to value. Capabilities are formulated in two main parts: functionings and freedom. With functionings we define those activities or beings that people value or have a reason to value. For instance, being healthy, educated or respected. The concept of value is paramount; in fact, we can consider a function to be relevant only if transpose what the individual actually value for his life. This passage is important especially because it opens up to a participatory approach where research takes a bottom-up approach firstly toward the understanding of the necessity of the individual. Moreover, Sen's defines a second concept: to have a reason to value. Some people value activities which are by definition harmful, hence, a certain degree of social choice has to be made in order to prevent the fostering of such harmful behaviors.

According to Sen (1976), the measurement of poverty involves two steps: *identification* (who are the poor) and *construction of an index* (to create an aggregate measure combining different relevant characteristics). Therefore, to be able to correctly portray the multifaceted characteristics of poverty, as well as the long lasting effect of the MGNREGA in terms of improvements in living standard, this study proposes an analysis using a multidimensional poverty index following the Alkire-Foster methodology. Capabilities are the freedom to enjoy valuable functionings (Alkire et al. 2011). In fact, the individual must be able to choose among all the capabilities he values and has a reason to value to be able to pursue the life paths he finds fit for himself. For our research, we use a modified version of the Alkire-Foster "Global

MPI" which uses information from 10 indicators organized in three equally weighted dimensions: Health, Education and Living Standards. These dimensions are meant to provide a proxy of Sen's capabilities and the within-dimensions indicators should reflect individual's functionings and freedoms.

As a matter of fact, the academia offers a plethora of options, which reflect different ways of understanding the nature of poverty. Some authors derive their lists from agreed development goals such as the World Summit on Social Development or the Millennium Development Goals (Biggeri, Trani, and Mauro 2010; Roche 2010). In order to ensure transparency and replicability we decided to use the same indicators present in the Human Development Index (HDI) as well as the same number of within-dimensions indicators. The Alkire-Foster methodology to construct a Multidimensional Poverty Index suggest two dimensions for health, two for education and six for living standard (Alkire et al. 2011; Alkire and Foster 2009).

Despite being data constraint, the choice of dimensions is of vital importance. In fact, all of them have intrinsic and instrumental value: both health and education are valuable themselves as are instrumental to the achievement of other vital outcomes. Similarly, although living standards consist of resources they can provide a useful proxies of the basic amenities of housing and services, as well as assets, which are identified as important in the MDGs (Alkire and Foster 2013). As we mentioned, this study presents a modified version of the Alkire-Foster's MPI the reasons behind the use of a modified version of the Global MPI are mostly due to data constraints. Some of the indicators where not collected during the surveys, hence, we had to proxy those missing with others that were present in the dataset. Moreover, round one, lacked most of the variables needed hence, for this study we decided to drop it.

Table 1, below, show the list of dimension and indicators we decided to use to construct our MPI. Given the limitation we talked about in chapter three, we decided use child-specific indicators that could be used also as proxy for the general level of wellbeing of the entire household. Unfortunately, we cannot control for intra-household characteristics such as number of elderly or number of members in each household.

Table 1 - Multidimensional Poverty Index dimensions and indicators

Dimension	Indicators of Deprivation	Cut of Point
Education	Household maximum level of education	Deprived if the household head as an education below 8th grade (Primary School)
	Distance from school in minutes	Deprived if the distance is more than 20 minutes
Health	Nutrition	Deprived if there was no consumption of any fruit and vegetables in the last 24h
	Thinness	Deprived is the child BMI-for-age z score is < than 2 standard deviations
Living Standards	Access to electricity	Deprived if no access to electricity
	Access to safe drinking water	Deprived if no access to running water/tap water
	Access to sanitation	Deprived if no access to proper sanitation (no flush or septic tank)
	Access to safe cooking fuel	Deprived if fuel is different than kerosene, gas and electricity
	Housing quality	Deprived if the score is below .05 (on a scale from 0 to 1)
	Assets Owned	Deprived if the score is below the mean (on a scale from 0 to 1)

The choice of indicators should reflect and focus on the relevant characteristics that lead to deprivation. Poverty is manifested not only by material deficiencies but also susceptibility to risks due to social discrimination and/or contrast within the social networks as well as constraints on choice and opportunity at household and individual level (Porter and Dornan 2010).

Table 1 shows the indicators we have chosen based on the literature. For the Health dimension we look at *nutrition* in terms of fruits and vegetables consumption in the last 24 hours, as an indicator of being able to have a balanced diet and children BMI, or *thinness*, which is meant to proxy the health level of the household as children malnutrition is a sign of underlying general poverty. Multiple studies have, in fact, demonstrated the relation between malnutrition, development and poverty traps. Research into childhood nutrition have revealed that the lack of macronutrients has an influence on mental development and other aspects of poverty exacerbate this effects leading to poverty traps (Brown and Pollitt 1996; P. Dasgupta 1997; Jha, Gaiha, and Sharma 2009).

Additionally, we derive information on educational deprivation by using two indicators: *maximum years of schooling achieved by the household head* and *access to school in terms of distance in minutes*. Given the longitudinal aspect of our study we decided to inspect for household level of education instead of the individual one in terms of highest educational level attained by the household head. Moreover, we control for access to education in terms of distance from school in minutes. Literature have shown that the further the individual is from school the more it is prone to drop-out (Chaudhry and Rahman 2009; Jensen and Nielsen 1997; Paruzzolo 2009).

Finally, to account for living standard we have a set of indexes measuring household environment that inform us on the *availability of electricity*, *safe drinking water*, *adequate cooking fuel* and on the *quality of the house* (in terms of roofing and flooring) and on the number of *assets owned*. The last one, number of assets owned, was constructed by accounting only for those assets that were consistently present throughout the surveys in all the rounds, which are: radio, television, bicycle, motorbike, automobile, landline phone, mobile phone, refrigerator and fan. These indicators are meant to provide a picture of the material deprivation present in the household.

4.1 – Variable Robustness Check

Although multidimensional poverty analysis has been considered to be an improved alternative to monetary measures of poverty, the literature presents a number of poverty indices that have been constructed without a careful consideration of the effects that each variable, defined as poverty indicator might have on poverty itself. Are the chosen variables complements or substitute? Are them statistically important to assess the desired outcome? We try to answer these type of question to provide a possible way to check the robustness of the variables we will later use to create our dimensions.

Using a simple logit regression, we assess the significance of each variable before constructing the multidimensional poverty index as follow:

$$(1)\ NREGSp = \beta_0 + \beta_1 Round + \beta_2 Fruveg + \beta_3 Stunt + \beta_4 Elec + \beta_5 Toiletq + \beta_6 Drwaterq + \beta_7 Cookingq + \beta_8 EduNone + \beta_9 EduPrimary + \beta_{10} EduSecondary + \beta_{11} EduTertiary + \beta_{12} Timesch + \beta_{13} HQ + \beta_{14} CD$$

Before proceeding with the analysis of the result yielded by our econometric model we decided to assess if our model could be used to control for the unobserved time invariant characteristics of our dataset. Fixed-effects models are used to overcome a potential endogeneity bias in the estimations of parameters in model (1). However, we decided to perform a Housman test on our model to control if a random-effect could better in explaining the characteristics of our sample.[6] In contrast with fixed-effects, random-effects while still controlling for unobservable heterogeneity, allows this heterogeneity to be constant over time and correlated with the independent variables.

The Hausman test performs a specification test using two specification of the same model, one using a fixed-effect estimation and the second using a random-effect estimation. It later performs a hypothesis test where the hypothesis is that the individual-level effects are adequately modelled by a random-effects model.

The following table present the result of our final hypothesis testing:

[6] Wooldridge (2001) shows that the fixed-effects estimators are more consistent and more robust compared with those of a random-effects estimation. This is why the Hausman test compares the random-effects model to the fixed-effects model, which is known to be more consistent.

Table 2 - Results of the Hausman Test performed on model (1)

Hausman Test

	b	B	$b-B$	$(V_b - V_B)$
	Fixed-effects	Random-effects	Difference	S.E
Fruit and Vegetables	0.3085053	0.2228011	0.0857042	0.1284187
Presence of a stunted children	-0.3061616	-0.3234602	0.0172986	0.2231017
Access to electricity	0.872526	1.582596	-0.7100703	0.2869042
Access to sanitation	-0.8854108	-2.477686	1.592275	0.1889409
Access to drinking water	0.0891253	0.5594819	-0.4703566	0.3759084
Access to safe cooking fuel	0.080275	-1733412	1.813687	0.1896092
No education	1.462751	1.221258	0.2414928	1.512639
Primary education	2.134869	1.299021	0.8358479	1.516016
Secondary education	0.6375565	0.7371589	-0.0996025	1.469955
Travel time to school (in minutes)	0.0044379	0.0055157	-0.0010778	0.0035614
Housing quality index	-0.5345263	-0.8658776	0.3313513	0.3111526
Consumer durable index	-1.506534	-3.027928	1.521395	0.6022352

$$Test: H_0: difference\ in\ coefficent\ is\ not\ sytematic$$

$$chi2(12) = (b-B)'[(V_b - V_B)^{-1}](b-B)$$
$$= \quad \mathbf{234.84}$$
$$Prob > chi2 = \mathbf{0.000}$$

As we can see the initial hypothesis that the fixed-effects are correctly modelled by a random-effects specification is resoundingly rejected.

Having controlled which specification is better suited to analyse our model we can now proceed to assess the effects on poverty of the MGNREGA program. As the model specifies our dependant variable is $NREGSp$[7] which is a dummy variable that takes the value of 1 if somebody inside the household participate to the program and 0 otherwise. The coefficient

[7] In the dataset the treatment variables concerning the participation to the MGNREGA program was coded using the old name of the program.

estimator β_1 captures the effect of each new round on the program participation. The coefficient estimator β_2 is a dummy variable that controls for the effect of having a proper nutrition and will later be used to create the *nutrition* indicator; it takes the value of 1 whenever we have consumption of both fruits and vegetables in the last 24 hours and 0 otherwise. The coefficient estimator β_3, controls for the presence of a stunted children in the household; it will be later used for the *thinness* indicator and takes the value of 1 when a stunted children is present and 0 otherwise. The coefficient estimator β_4, controls for access to electricity; it is a dummy that takes the value of 1 when the household receive electricity and 0 when not and it will be used to create the *access to electricity indicator*. The coefficient estimator β_5, is a dummy variable that controls for proper sanitation in the household; it take the value of 1 when the household has a flush toilet or a septic tank and 0 otherwise. It will be used to create the *access to sanitation* indicator. The coefficient estimator β_6, is a dummy that takes the value of 1 if the household receives piped water in the house or has access to a public well and 0 otherwise. It will be used to factor the *access to drinking water variable* later on. The coefficient estimator β_7, is a dummy variable that takes the value of 1 if the house cooks using electricity, gas or kerosene and 0 otherwise. It will be used later to create the *access to safe cooking fuel* indicator. The coefficient estimators β_8, β_9, β_{10}, and β_{11}, are all dummy variable which control separately for the effect of each level of education attained: none, primary and secondary. Later on, the will be factored in the construction of the *level of education* indicator. The coefficient estimator β_{12}, is a dummy that controls for the effect of living in an area with no or limited access to an educational facility. It takes the value of 1 if the walking distance is less than 20 minutes and 0 otherwise and it will be used to create the *access to education* indicator. The coefficient estimator β_{13}, controls for the effect of an increasing housing quality; is a continuous variable that runs from 0 to 1 where 0 is the minimum level and 1 is the maximum. Finally, the coefficient estimator β_{14}, is a continuous variable that controls for the effect of an increasing amount of assets owned as described before; it take the value of 0 when none of the selected assets are present and 1 when all of the are present in the household.

Table 3 - Logit Analysis of MGNREGA participation

	Coefficient	*Standard Error*
Round 3	2.958***	(0.144)
Round 4	4.099***	(0.186)
Fruit and Vegetables		
Yes	0.317**	(0.103)
Presence of stunted children		
No	-0.370**	(0.117)
Access to electricity		
Yes	1.529***	(0.207)
Access to sanitation		
Yes	-2.479***	(0.142)
Access to safe drinking water		
Yes	0.609**	(0.252)
Access to safe cooking fuel		
Yes	-1.638***	(0.140)
No education	1.391***	(0.341)
Primary education	1.419***	(0.334)
Secondary education	0.791**	(0.325)
Tertiary education	Omitted due to collinearity	
Travel time to school (in minutes)	0.008***	(0.002)
Housing Quality	-0.782***	(0.211)
Consumer durables	-3.597***	(0.385)
Constant	-2.484***	(0.461)
Observations	6928	

Note: Standard errors in parentheses, * p<.1, ** p<.05, *** p<.001 - **Source**: Young Lives Longitudinal Study

As we can see from Table 3, all the variables are statistically significant between the 99 and 95 percent confidence level, hence we can infer that they are useful predictors of participation to the MGNREGA program. As we are regressing using a logit model the coefficient can be interpreted in terms of odds ratio or log-odds keeping all the other variables constant. Odds ratios can be described as the ration between the probability of success over the probability of failure. As we can see the odds ratios increase each round because in each round the program was implemented in more areas of Andhra Pradesh reaching more people. The odds ratio of *Fruit and Vegetables* shows us how being able to provide a proper nutrition is a sign of wellbeing among the sampled population. Same goes for *Presence of a stunted children*; if children are well nourished there is less need for the household to take-up the program. The negative odd ratio shows us, in fact, that the probability of taking up the program decreases if kids in the family are well nourished. *Access to sanitation* and *Access to safe cooking fuel* shows the same pattern with a negative odd ratio. *Access to safe drinking water* on the other hand shows a peculiar likelihood and the same goes for *Access to electricity*. Despite being a rural state, in the last couple of years, Andhra Pradesh has been subject of intense development. Probably electricity and running water are by now widespread in the State. When we look at the three education variable we can see how the more educated an individual is the more he/she has need of the program justifiable by the increase amount of opportunity education provide to individual. While *Time travel to school* doesn't give us much information it is important to look at the last two variables in depth: the odd ratios of *Housing Quality* and *Consumer durables* are negative, showing how the necessity to take-up the program decreases when those two indexes increase. The academia proved that the MGNREGA program has a positive impact in case of covariate shocks (Gehrke 2014). Households have been found to cope with these events by selling their assets which then leads them to fall into a poverty trap. This negative odd ratio can be a step to further proof this relation.

Having controlled for the robustness of our indicators, we can now safely proceed to analyse destitution in our sampled population. Given the peculiarity of the YL dataset the analysis will be conducted differing between Younger and Older cohort.

Chapter 5 – Alkire-Foster's Multidimensional Poverty Index

In the previous section we discussed the reasoning behind using a multidimensional poverty index instead of relying only on an income-based analysis. Following the Alkire and Foster's methodology (2011), we proceed firstly by explaining the methodology for the identification of the poor (cutoff point), the measuring the headcount ratio (H), the proportion of maximum possible multidimensional deprivations for poor children, or intensity of poverty (A), and the adjusted headcount ratio (M).

5.1 – The poverty cutoff

The literature presents multiple ways to deal with the choice of a specific cutoff point. Bourguignon and Chakravarty (2003), make a distinction between "intersection" and "union" definition of poverty. According to their study, a person can be considered multidimensionally poor using an "union" approach whenever he/she is deprived in more than one dimension. Alternatively, if we follow an "intersection" approach to multidimensional poverty, the same individual is considered poor only if he/she is deprived in all the dimensions at the same time. Ultimately, choosing a cutoff point is a normative decision made by the researcher according to specific assumptions.

In order to correct for this limitations, Alkire and Foster (2009) introduced an approach that melds Bourguignon and Chakravarty methodologies by introducing a way to count the poor using two forms of cutoffs. The first form defines a specific line or cutoff whether a person is deprived or not deprived with respect of that dimension. The second form delineates how deeply that person must be to be considered poor. This procedure uses a counting methodology in which the second cutoff is a minimum number of dimensions of deprivations (Alkire and Foster 2009). This "dual cutoff" method focuses more to those suffering from multiple deprivations but also works well in situation with many dimensions.

The counting system proceed as follow: at first to each individual is assigned a deprivation score which is calculated by taking a weighted sum of the deprivations experience so that it lies between 0 and 1 for each individual. The score takes the value of 0 when the person doesn't experience any deprivation and 1 when he/she faces all the possible deprivations. This counting vector is explained as follow:

$$c_i = w_1 I_1 + w_2 I_2 + \cdots + w_n I_n$$

where $I_i = 1$ if the individual is deprived in indicator i and $I_i = 0$ otherwise, and w_i is the weight attached to indicator i with $\sum_{i=1}^{n} w_i = 1$. The second cutoff point is meant to identify who is multidimensionally poor and it calculates the share of weighted deprivations an individual must experience in order to be considered poor, and it is usually denoted as k. The person is considered poor if his/her deprivation score is equal to or greater than the poverty cutoff, as follow: $c_i \geq k$.

For our research we have defined a cutoff point k of 0.5, which means that a person's deprivation score should be at least half of the total weighted indicators to be considered multidimensionally poor. It is important to mention that, in this methodology, those individuals with a deprivation score that lies below the defined poverty cutoff, even when non-zero, have their score replaced by a "0" and the existing deprivations are not considered in the "censored headcounts" which, to differentiate from the original deprivation score is denoted as $c_i(k)$.

5.2 – Calculating the Multidimensional Poverty Index (aggregation)

After having identified who is poor we can start measuring poverty in our sample. The first and most common way is to calculate the percentage of poor people. The headcount ratio H is defined by:

$$H = \frac{q}{n}$$

where q is the amount of people identified using the dual cutoff approach and n is the total sampled population. The headcount ratio provides a simple way to assess the percentage of poverty in our sample but unfortunately do not have the desired property of monotonicity, which requires that if the amount of deprivation experienced by an individual increases the headcount ratio should decrease.

The second component we analyze is called intensity (or breadth) of poverty (A), and it calculates the average deprivation score of multidimensionally poor people and it is expressed as:

$$A = \frac{\sum_{i=1}^{n} c_i(k)}{q}$$

where $c_i(k)$ is the censored deprivation score of an individual i and q is the total amount of people who are multidimensionally poor in the surveyed sample.

Finally, the multidimensional poverty index, as adjusted headcount ratio, is calculated as the product of both:

$$M = H \times A$$

and is therefore expressed as the average number of deprivations experienced by the deprived individuals as a proportion of the total number of deprivation experienced by the total sampled population.

5.3 – Multidimensional Poverty Analysis

We start by looking at the general poverty aggregates we mentioned before. Table 4 and table 5 show respectively: the poverty headcount (H), the poverty sensitivity score (A) and the multidimensional poverty index or adjusted headcount (M) for both our Older and Younger cohort. From the one hand, children from the Younger cohort where, at the time of the survey, aged between 4 and 5 years old, in Round Two and between 11 and 12 in Round Four. From the other hand, children from the Older cohort where aged between 11 and 12 in Round Two and between 18 and 19 in Round Four. For the purpose of our analyses we decided for a cutoff point of 0.5.

Table 4 - Multidimensional Poverty Aggregates, Older cohort

Multidimensional Poverty Aggregates – cutoff point at 0.5				
Index	Estimation	S.E.	95% Conf. Interval	
H	42.50%	0.015	0.396	0.454
A	63.60%	0.005	0.626	0.645
M(0)	27.00%	0.010	0.251	0.289

Table 5 - Multidimensional Poverty Aggregates, Younger cohort

Multidimensional Poverty Aggregates – cutoff point at 0.5				
Index	Estimation	S.E.	95% Conf. Interval	
H	35.50%	0.008	0.339	0.371
A	62.40%	0.003	0.619	0.63
M(0)	22.20%	0.005	0.212	0.232

This first, general analysis tells us that the Older cohort is consistently more deprived in all aggregates compare to the younger cohort. The headcount ratio shows that 42.50% of our population is deprived, however, as we said this figure does not satisfy the monotonicity principle, thus we will use is only as an illustrative figure. The average deprivation score of those defined as multidimensionally poor is 62.40%. Finally, the adjusted headcount, which is the figure we will use so far to analyze poverty in our sample, tells us that 27% of children in the Older cohort is multidimensionally poor.

Now, we will dwell deeper in our study be looking at the change between rounds in multidimensional poverty. Table 6 and Table 7 show the different multidimensional poverty aggregates discussed above for children in the Older and Younger cohort in two different rounds broken down by single deprivation. In both case the cutoff point was maintained at 0.5.

Table 6 - Adjusted Headcount Ratio (M): Older cohort, by Round

Adjusted Multidimensional Headcount (M)					
Dimension	**Indicators**	**M(0) with cutoff at 0.5**			
		Round Two (2006)	Round Four (2014)	Difference	Total
Health	Nutrition	23.00%	23.80%	-0.80%	23.20%
	Thinness	14.50%	11.20%	3.30%	13.80%
	Total	**37.50%**	**35.00%**	**2.50%**	**37.00%**
Education	Years of Schooling	23.50%	24.40%	-0.90%	23.70%
	Access to Education	14.30%	26.10%	-11.80%	16.60%
	Total	**37.80%**	**50.50%**	**-12.70%**	**40.30%**
Living Standards	Access to Electricity	1.50%	0.02%	1.48%	1.20%
	Sanitation	7.20%	5.70%	1.50%	6.90%
	Safe Drinking Water	0.70%	0.60%	0.10%	0.60%
	Housing Quality	4.30%	1.80%	2.50%	3.80%
	Safe Cooking Fuel	7.80%	5.30%	2.50%	7.30%
	Assets Owned	3.40%	1.20%	2.20%	3.00%
	Total	**24.70%**	**14.50%**	**10.20%**	**22.70%**

Table 7 - Adjusted Headcount Ratio (M): Younger cohort, by Round

Adjusted Multidimensional Headcount (M)					
Dimension	**Indicators**	**M(0) with cutoff at 0.5**			
		Round Two (2006)	Round Four (2014)	Difference	Total
Health	Nutrition	23.00%	22.30%	0.70%	22.70%
	Thinness	17.30%	15.90%	1.40%	16.70%
	Total	**40.30%**	**38.20%**	**2.10%**	**39.40%**
Education	Years of Schooling	25.10%	23.90%	1.20%	24.60%
	Access to Education	4.80%	18.20%	-13.40%	10.60%
	Total	**29.90%**	**42.10%**	**-12.20%**	**35.20%**
Living Standards	Access to Electricity	2.10%	0.40%	1.70%	1.30%
	Sanitation	7.90%	7.20%	0.70%	7.60%
	Safe Drinking Water	0.90%	0.20%	0.70%	0.60%
	Housing Quality	5.80%	3.20%	2.60%	4.70%
	Safe Cooking Fuel	8.30%	6.80%	1.50%	7.60%
	Assets Owned	4.80%	2.00%	2.80%	3.60%
	Total	**29.80%**	**19.70%**	**10.10%**	**25.40%**

As we can see from Table 6, the dimensions where individuals are more prone to be poor are Health and Education, where Living Standards is similar for both cohorts. The Older cohort tends to be more deprived in terms of Education with a total of 40.3%. This is an interesting finding as children in the Older cohort tend to have older parents compared to those in the Younger cohort, and it tells us something about the importance of education as a way to escape poverty and possible poverty traps. Looking at the total amount par each dimensions and their changes between Round Two and Four we can see that, despite an overall decrease we have some staggering increase within single indicator. Nutrition for instance increased by 0.8% where Thinness decreased by 3.3%. These changes can be associated with covariate shocks, especially in terms of drought or catastrophic rainfall that happened between the two rounds. In 2013 an intense drought hit Andhra Pradesh destroyed 119 mandals[8] of arable land (Ahmed 2015); we can assume this as one of the reasons behind the increase in the Nutrition variable. At the same time, the good weather condition registered on average in the past 10 years could be the cause of the decrease in Thinness. Years of Schooling tends to remain the same since its calculated over the completed years of education attained by the household head. The registered decrease of 1.2% could be associated to changes within the household structure.[9] Access to Education, however, shows a staggering increase of 13.4%; at present we cannot explain such an increase without making assumption that requires further research. A possible explanation could be migration to a further area or given that we are looking at teenagers between 18 and 19 years old, the possibility that they have to commute further to be able to attend secondary school or the University. Looking at the Living Standard dimension we can see that all the indicators have faced a decrease which can be explained by the general development Andhra Pradesh is realizing in the past years. Especially, access public assets such as electricity and safe drinkable water are a sing of this generalized development.

Table 7 shows the same pattern across dimensions and indicators but here the dimension where people are most deprived is Health. The Younger cohort, as we mentioned is comprised of children that where 4 or 5 during Round Two and reached the age of 11 and 12 in Round Four. Many studies show that at this early stages having a proper nutrition is paramount to have a proper cognitive development (Brown and Pollitt 1996). As we can see, in fact, Thinness is the biggest deprivation children face when they are young. The assumption

[8] A "mandal" is an administrative measure of land mostly used in the states of Andhra Pradesh and Telangana. It is the same as the "tehsil".

[9] As we mentioned in Chapter 3, a limitation of the Young Lives Study is that is not possible to account for intra-household variables.

we made about the possibility of covariate shocks such as drought or intense rainfall could still be applied. Moving to the Education dimension, we can see that the indicator Access to school still reports an increase in percentage of about 13.4%. Children at age 4 and 5 do not go to school, hence the low degree of deprivation in Round Two, however when they grow older being able to freely go to school seems to be a challenge also for children in primary education. From the policy perspective such an indicator can be used to assess how school are dislocated in the territory and see if Andhra Pradesh needs more school or simply better infrastructures.[10]

Table 8 and 9 lend us a temporal analysis of multidimensional poverty in Andhra Pradesh; as we can see, from 2006 to 2014 living standard have increased as well as health. Education is the only component that needs further analysis being the only one that increased in 8 years. However, this could be the effect of household decision (Younger cohort individuals commuting further to go to the University) or other intra-household decision which, unfortunately we cannot study given the limitation of the dataset we are using.

We switch our focus now and look at the potential multidimensional effect of the MGNREGA program in both cohorts. Table 8 and 9 presents the results.

[10] We consider access to school in terms of walking distance between the house and the educational structure where 20 or more minutes, walking distance are considered to be too much.

Table 8 – Adjusted Headcount Ratio (M): Older Cohort, by MGNREGA participation

Adjusted Multidimensional Headcount (M)									
Dimension	**Indicator**	**Round Two (2006)**				**Round Four (2014)**			
		Non Participating	**Participating**	**Difference**	**Total**	**Non Participating**	**Participating**	**Difference**	**Total**
Health	Nutrition	24.10%	21.70%	2.40%	23.00%	27.80%	22.30%	5.50%	23.80%
	Thinness	14.80%	14.10%	0.70%	14.50%	12.40%	10.80%	1.60%	11.20%
	Total	**38.90%**	**35.80%**	**3.10%**	**37.50%**	**40.20%**	**33.10%**	**7.10%**	**35.00%**
Education	Years of Schooling	23.90%	23.10%	0.80%	23.50%	24.70%	24.30%	0.40%	24.40%
	Access to Education	13.50%	15.10%	-1.60%	14.10%	29.90%	24.60%	5.30%	26.10%
	Total	**37.40%**	**38.20%**	**-0.80%**	**37.80%**	**54.60%**	**48.90%**	**5.70%**	**50.50%**
Living Standards	Access to Electricity	1.60%	1.30%	0.30%	1.50%	0.00%	0.30%	-0.30%	0.20%
	Sanitation	6.90%	7.50%	-0.60%	7.20%	0.70%	7.60%	-6.90%	5.70%
	Safe Drinking Water	1.00%	0.30%	0.70%	0.70%	0.00%	0.40%	-0.40%	0.30%
	Housing Quality	3.90%	4.70%	-0.80%	4.30%	1.40%	1.90%	-0.50%	1.80%
	Safe Cooking Fuel	7.20%	8.40%	-1.20%	7.80%	2.40%	6.40%	-4.00%	5.30%
	Assets Owned	3.10%	3.80%	-0.70%	3.40%	0.70%	1.40%	-0.70%	1.20%
	Total	**23.70%**	**26.00%**	**-2.30%**	**24.70%**	**5.20%**	**18.00%**	**-12.80%**	**14.50%**

Table 9 – Adjusted Headcount Ratio (M): Younger Cohort, by MGNREGA participation

Adjusted Multidimensional Headcount (M)									
Dimension	**Indicator**	**Round Two (2006)**				**Round Four (2014)**			
		Non Participating	**Participating**	**Difference**	**Total**	**Non Participating**	**Participating**	**Difference**	**Total**
Health	Nutrition	24.00%	21.60%	2.40%	23.00%	25.10%	21.70%	3.40%	22.30%
	Thinness	17.10%	17.70%	-0.60%	17.30%	18.10%	15.40%	2.70%	15.90%
	Total	**41.10%**	**39.30%**	**1.80%**	**40.40%**	**43.20%**	**37.00%**	**6.20%**	**38.20%**
Education	Years of Schooling	25.10%	25.10%	0.00%	25.10%	25.40%	23.50%	1.90%	23.90%
	Access to Education	4.70%	4.90%	-0.20%	4.80%	18.60%	18.10%	0.50%	18.20%
	Total	**29.70%**	**30.10%**	-0.40%	**29.90%**	**44.00%**	**41.60%**	**2.40%**	**42.10%**
Living Standards	Access to Electricity	2.70%	1.20%	**1.50%**	2.10%	0.30%	0.40%	-0.10%	0.40%
	Sanitation	7.40%	8.60%	-1.20%	7.90%	3.90%	7.90%	-4.00%	7.20%
	Safe Drinking Water	1.20%	0.60%	0.60%	0.90%	0.00%	0.30%	-0.30%	0.30%
	Housing Quality	5.40%	6.30%	-0.90%	5.80%	2.50%	3.30%	-0.80%	3.20%
	Safe Cooking Fuel	7.90%	8.80%	-0.90%	8.30%	4.10%	7.30%	-3.20%	6.80%
	Assets Owned	4.60%	5.10%	-0.50%	4.80%	2.00%	2.00%	0.00%	2.00%
	Total	**29.20%**	**30.60%**	**-1.40%**	**29.80%**	**12.80%**	**21.30%**	**-8.50%**	**19.80%**

Both cohorts show similar results and patterns in terms of general deprivations with the Older cohort being more deprived in educational terms and the Younger one more on health terms. If we look more closely to the Health dimension, we can see how total deprivation tends to reduce between rounds for participating individuals where it tends to increase for those who do not take up the program. This reduction could be associated with the treatment effect but it could also be due to reverse causality; later on we will try to assess this using the difference-in-difference technique that measures the longitudinal effect of a treatment between participating and non-participating individuals. In terms of Education, deprivation tends to be high in both dimensions for both cohorts and across rounds which is consistent with the results presented in the Table 1 and 2. Living Standard shows us a peculiar pattern: both cohorts display a general reduction in terms of deprivation across rounds but those who participate in the MGNREGA are consistently more deprived in Round Four compared to Round Two. A possible reason could be the following: people that participate into the public work program are, by definition, in need of help, and as the literature has shown workfare programs are mostly taken up to offsets income-related shocks. Hence, the table portrays the situation at point in time of those taking up the program, which, as assumed, should be more deprived in terms of living standards than those that have not necessity of it.

In order to support the findings produced by the modified version of the Alkire-Foster's Multidimensional Poverty Index we constructed, we will now proceed with a number of statistical health checks meant to control for robustness within our index.

5.4 – Multidimensional Poverty Index Robustness Analysis

Multidimensional poverty estimation has been growing in number in recent years (Apablaza and Yalonetzky 2013). However, significant challenges as well as disagreement remain over whether the chosen dimension of wellbeing should be analyzed separately or jointly, using a composite index. The literature (Maasoumi and Yalonetzky 2013) suggests the use of indices as better tools to monitor change when we have multiple indicators. In addition, even when few indicators are present, we could be more interest in computing multidimensional analysis that take into account the joint distribution of indicators in the population.

Nevertheless, despite being a useful tool, composite indices are subject to a number of limitations (J. Foster, McGillivray, and Seth 2009). In fact, a question about the reliability of the assessment they provide often arise. One of the major concern comes with the choice of weights which inherits the relative significance given to each component in the index. Weights can be decided using a number of approaches, such as normative approaches, statistical methods, and rules of thumb (Decancq and Lugo 2013). The literature, however, have demonstrated that despite the selection of the weighting system when it is consistent with the underlying principles or methods employed in the poverty analysis, their final selection is, by a matter of fact, arbitrary (J. E. Foster, McGillivray, and Seth 2013). In the context of a MPI, the selection of equal weights is, as we said, justified in terms of comparability and replicability as well as expert opinion and participatory analysis.

The possibility of arbitrary weights, creates the need for an evaluation of robustness since a most prominent problem is that the poverty evaluation can be eventually altered when choosing a different methodology.[11] Hence, more and more studies are, nowadays, focusing on the development of theoretical and statistical tools to perform robustness assessments of multidimensional poverty analysis (Alkire et al. 2010; J. E. Foster, McGillivray, and Seth 2013; J. Foster, McGillivray, and Seth 2009; Maasoumi and Yalonetzky 2013; Permanyer 2011).

Firstly, we start our robustness analysis by checking the correlation between each deprivation by performing a Cramer's V test which performs an association test between two nominal variables giving a score that ranges between 0 and 1, where 0 is "no association" and 1 is "perfect association".[12] Performing this test across the selected deprivation indictors is a tool to check for overlap/redundancy across indicators. Low level of association will testify that each of our indicators measure deprivation independently from each other (Alkire et al. 2015b).

Table 10 below, shows the result of the Cramer's V test performed across the deprivation we used to construct our Multidimensional Poverty Index

[11] One can found completely different results using a different weighting system which will invalidate the results as well as possible policy recommendations.
[12] In a Cramer's test 1 can be only reached when the two variables are the exact same.

Table 10 – Cramer's Test of Association across deprivation indicators

Cramer's V test										
Deprivation	**Nutrition**	**Thinness**	**Years of School**	**Access to School**	**Electricity**	**Sanitation**	**Drinking Water**	**Housing Quality**	**Cooking Fuel**	**Assets**
Nutrition		0.0711	0.0949	0.0108	0.0736	0.0149	0.0202	0.0474	0.121	0.0454
Thinness	0.0711		0.119	0.0205	0.0681	0.1505	0.0547	0.1153	0.1518	0.1044
Years of Schooling	0.0949	0.119		0.0249	0.1343	0.361	0.0611	0.213	0.3998	0.2029
Access to School	0.0108	0.0205	0.0249		0.0428	0.0065	0.0005	0.0408	0.0512	0.0583
Electricity	0.0736	0.0681	0.1343	0.0428		0.1624	0.1111	0.2439	0.1564	0.2439
Sanitation	0.1491	0.1505	0.361	0.0065	0.1624		0.1001	0.2976	0.638	0.264
Drinking Water	0.0202	0.0547	0.0611	0.0005	0.1111	0.1001		0.1681	0.0949	0.1809
Housing Quality	0.0474	0.1153	0.213	0.0408	0.2439	0.2976	0.1681		0.3109	0.8206
Cooking Fuel	0.121	0.1518	0.3998	0.0512	0.1564	0.638	0.0949	0.3109		0.2814
Assets	0.0454	0.1044	0.2029	0.0583	0.2439	0.264	0.1809	0.8206	0.2814	

As we can see, association amongst indicators is consistently weak across most indicators confirming their independency from each other.

After testing association across indicators we need to test if the MPI is robust to a set of different weights. To test this, we estimated the same MPI using a different weighting structure: we decided to equally weight only the indicators, thus changing the weighting structure to: 20% to Health, 20% to Education and 60% to Living Standards.[13] Then we verify if the adjusted headcount ratio (M) remains stable using three correlation approaches: (i) Pearson's correlation coefficient, (ii) Spearman's rank correlation coefficient and (iii) Kendall's rank correlation coefficient (Tau-b). We use three different correlation coefficient as Pearson measures the linear relationship between a pair of ranking, Spearman is based on the change in M rank between a pair of scores and Kendall is calculated by comparing each pair of scores in a pair of rankings.[14] Table 11, shows the different correlation results:

[13] For readability we will define these newly created MPI as Test MPI

[14] According to Conover (1999, 323), "Spearman's ρ tend to be larger than Kendall's τ in absolute terms. However, as a test of significance, there is no strong reason to prefer one over the other because both will produe nearly identical results in most cases." Moreover, the ordering can refer to the poverty ordering of two aggregate entities or scores but it could also refer to an order of more than two entities or scores; in this case we refer to as a ranking. Clearly, the robustness of a ranking depends on the robustness of all possible pairwise comparisons (Alkire et al. 2015a).

Table 11 – Correlation among Adjusted Headcount Ratio

		Pearson's Coefficient	Spearman's Coefficient	Kendall's Coefficient (Tau-b)
Original MPI	*M(1)*	0.9291	0.9255	0.8280
Test MPI	*M(1)*			
Original MPI	*M(2)*	0.9384	0.9260	0.8305
Test MPI	*M(2)*			
Original MPI	*M(3)*	0.8452	0.8921	0.7865
Test MPI	*M(3)*			
Original MPI	*M(4)*	0.8803	0.8812	0.8146
Test MPI	*M(4)*			
Original MPI	*M(5)*	0.8451	0.8550	0.7938
Test MPI	*M(5)*			
Original MPI	*M(6)*	0.6330	0.6394	0.6060
Test MPI	*M(6)*			
Original MPI	*M(7)*	0.7809	0.7797	0.7698
Test MPI	*M(7)*			
Original MPI	*M(8)*	0.5177	0.4906	0.4884
Test MPI	*M(8)*			
Original MPI	*M(9)*	0.7843	0.7786	0.7786
Test MPI	*M(9)*			
Original MPI	*M(10)*	1.0000	1.0000	1.0000
Test MPI	*M(10)*			

As we can see the correlation among all M remain consistent across all three correlation methodology confirming the robustness of our MPI methodology.

Having confirmed that our analysis is robust we can now proceed to assess the impact of the MGNREGA in longitudinal terms.

Chapter 6 – Effect of the MGNREGA on multidimensional poverty

So far we have been able to assess a temporal change in multidimensional deprivation in Andhra Pradesh and the difference between participating and non-participating household in terms of multidimensional poverty. As we seen, the results of our MPI showed a substantial deprivation in terms of living standards faced by those participating in the MGNREGA.

Given the structure and limitation of the Young Lives study the unit of observation will be the child whom household is participating in the program. We assume in fact that the effect of the participation will trickle down to child in terms of diminishing deprivation. Another characteristic of out longitudinal study is the possibility to correct for those time-invariant unobservable characteristics.[15] The DiD method assumes that unobserved heterogeneity in participation is present but that these factors are time invariant (Khandker, B. Koolwal, and Samad 2009).[16]

In order to assess the temporal effect on multidimensional deprivation derived by participating in the public work program we are going to use a difference-in-difference (DiD) analysis including a fixed-effects regression. A DiD analysis estimates the difference in difference of average outcomes of two groups over time by comparing the difference in average outcomes of households that applied and received employment under the MGNREGA with the average outcomes of households that applied and did not receive employment in either or both time period.

The average program impact is estimate by the DiD as explained by the following specification:

$$DiD = [E(Y_4^R) - E(Y_2^R)] - [E(Y_4^N) - E(Y_2^N)]$$

where Y_t identifies the outcome in the period of interest $t = \{2, 4\}^{17}$, R and N respectively denotes "Receiving" household (those that applied and received employment) and "Nom-receiving" (those that not applied or that applied but do not received employment under the MGNREGA).

[15] We partially controlled for endogeneity before the creation of the MPI, while choosing which variables where best suited to create the index.
[16] By a matter of fact, the DiD allows for unobserved heterogeneity that may lead to selection bias by defining them as being time invariant.
[17] Where 2 denotes Round 2 and 4 denotes Round 4

As mentioned, the outcome we want to assess with our double-difference estimation is the change in adjusted headcount (M) between participating and non-participating household across rounds. We calculate so within a regression framework, which is specified as follow:

$$Y_{it} = \beta_0 + \beta_1 Round + \beta_2 Treatment + \beta_3 Did + \varphi_{4-15} + \omega_{16-18} + \varepsilon_{it}$$

where Y_{it}, the dependent variable is the multidimensional adjusted headcount ratio (M) with a cutoff point of 0.5, $\beta_3 Did$ is an interaction term between the post-program treatment variable $\beta_2 Treatment$ and time, or program participation $\beta_1 Round$. In order to control for omitted variable bias we decided to include the sets of control variables: φ_{4-15} stand for the set of deprivation variables we used to create our MPI and ω_{16-18} stands for a set of household-related characteristics.[18] Finally, ε_{it} is the panel data fixed-effects error term.

We analyzed the treatment effect for both the Older and the Younger cohort, below we can find the results:

[18] In φ_{4-15} we find the following ten deprivation: nutrition, having a stunted children in the household, maximum years of schooling completed by the household head, access to school, access to electricity, access to sanitation, access to safe drinking water, housing quality index, safe cooking fuel, assets. Where, ω_{16-18} includes: child ages in years, having faced a drought in the past year (shock variable), sex of the household head, household size and region of residence (urban or rural).

Table 12 – Difference-in-Difference analysis for the Older cohort

Panel Logit Analysis of MGNREGA participation		
	M(0) with cutoff set at 0.5	Standard Errors
Adjusted Round for DiD	0.009	(0.176)
MGNREGA Participation	Omitted due to collinearity	
DiD interaction Term	**0.087****	**(0.031)**
Deprivation - Nutrition	0.200***	(0.022)
Deprivation - Stunting	0.244***	(0.023)
Deprivation - Years of Schooling	0.166***	(0.046)
Deprivation - Access to School	0.254***	(0.023)
Deprivation - Access to Electricity	0.235***	(0.071)
Deprivation - Access to Sanitation	0.027	(0.030)
Deprivation - Access to Drinking Water	0.111	(0.079)
Deprivation - Housing Quality	0.087**	(0.044)
Deprivation - Type of Cooking Fuel	0.066**	(0.033)
Deprivation - Assets	0.104**	(0.046)
Child's age - in years	-0.015	(0.026)
shock-drought	-0.080**	(0.028)
Sex of household head	-0.088*	(0.047)
household size	-0.008	(0.007)
Region of residence	0.010	(0.033)
Constant	-0.145	(0.748)
Observations	1111	

Source: Young Lives Longitudinal Study – * p<.1, ** p<.05, *** p<.001

Table 13 – Difference-in-Difference analysis for Younger cohort

Panel Logit Analysis of MGNREGA participation		
	M(0) with cutoff set at 0.5	Standard Errors
Adjusted Round for DiD	-0.059	(0.078)
MGNREGA Participation	Omitted due to collinearity	
DiD interaction Term	**0.024****	**(0.012)**
Deprivation - Nutrition	0.191***	(0.009)
Deprivation - Stunting	0.235***	(0.014)
Deprivation - Years of Schooling	0.172***	(0.018)
Deprivation - Access to School	0.216***	(0.010)
Deprivation - Access to Electricity	0.115***	(0.017)
Deprivation - Access to Sanitation	0.022	(0.015)
Deprivation - Access to Drinking Water	0.080**	(0.025)
Deprivation - Housing Quality	0.156***	(0.018)
Deprivation - Type of Cooking Fuel	0.016	(0.012)
Deprivation - Assets	0.063**	(0.020)
Child's age - in years	0.007	(0.012)
shock-drought	0.002	(0.012)
Sex of household head	-0.001	(0.023)
household size	0.001	(0.003)
Region of residence	0.002	(0.002)
Constant	-0.294***	(0.075)
Observations	3505	

Source: Young Lives Longitudinal Study – * p<.1, ** p<.05, *** p<.001

Did the MGNREGA had an impact on household wellbeing in terms of change in multidimensional censored headcount ratio?

Given the results portrayed in Table 12 and Table 13, we can positively infer that the MGNREGA, between 2006 and 2014 had, a positive effect for the Older cohort of 8.7% significant at the 95% level and of 2.4% for the Younger cohort also significant at the 95% level. Given the premises of the program, its universality, and the 8 years that passed between the surveys one could be disappointed with such a low degree of treatment effect. Nevertheless, considering the robustness check we performed before and after the creation of the multidimensional poverty index we consider these results highly valuable from a policy perspective.

A possible limitation of our analysis could be that we cannot control for selection bias, or self-selection. The first source of self-selection occurs from a design point of view: participating in the program is not a random decision but households self-select themselves into the program. However, we can consider this a time-invariant characteristic of our assessment and we hope it was captured by our fixed effects-estimation. As we showed in our multidimensional analysis deprived household have a similar characteristic in term of living standard deprivation. In addition, as other studies demonstrated, the MGNREGA is mostly used during the off-peak season by small farmers which take-up the program repeatedly each year when farming doesn't allow them to sustain their livelihood. The second potential bias is omitted variable which we tried to restricted by included variables that should control for various household and individual characteristics as well as specific cause of deprivation. Finally, another possible limitation could be the likelihood of heterogeneity in impacts that could occur if the program had different impacts according to different household characteristics. Unfortunately, we cannot control specifically for these effects as our dataset is not structured to analyze intra-household characteristics.

Chapter 7 – Policy Implications and Conclusion

As the largest public work program in the World, the Mahatma Gandhi Rural Employment Guarantee Act has been championed as being the most effective policy for decreasing unemployment rates, facilitating consumption smoothing, creating assets and alleviating multidimensional poverty. As we saw from chapter two, the literature has proven these claims in a variety of fields: from income smoothing to shock aversion, the MGNREGA has proven its capacity to better people lives and increase their resilience against shocks.

However, until now the literature have been concentrating on specific characteristic of the program disregarding well-rounded, holistic analysis on poverty and destitution. This paper tried, with all its limitations, to close this gap by presenting a multidimensional poverty analysis using the Young Lives Longitudinal study, the only set of data offering enough information to perform such type of analysis with a time span running from 2006 (right after the implementation of the program) till 2014. Given the limitations we mentioned throughout the paper, which are inherited in the specific nature of our dataset, we cannot generalize our findings outside the context of Andhra Pradesh.

We decided to create a new multidimensional poverty index, specifically tailored to analyze the MGNREGA following the Alkire-Foster methodology. We created an index which is comprised of three equally weighted dimensions with ten, equally weighted, indicators. All the indicators have been controlled, using a robustness check, to prove their ability to correctly represent destitution in our sampled population. The multidimensional poverty assessment we conducted focused on two different cohort of children, the Younger cohort and the Older cohort which differ only in terms of age years. In terms of descriptive analysis, we focused on two different part: we firstly analyzed the differences between cohorts from 2006 to 2014; secondly we look for differences within cohort but between household participating and non-participating in the MGNREGA.

In terms of longitudinal analysis, we can see how the Older cohort experiences a decrease in health deprivation of 2.5 percent points, an increase in educational deprivation of 12.7 percent points and a decrease in living standards deprivations of 10.2 percent points across 8 years.[19] On the other hand, the Younger cohort, in the same time span, experienced a decrease in health deprivation of 2.1 percent points, an increase in educational deprivation of 12.2 percent points and a decrease in living standards deprivation of 10.1 percent points.

In terms of multidimensional effect of participating in the MGNREGA program we saw how in 2006 households from the Older cohort participating in the program were 3.1 percent points less deprived in health than those non participating. The same individuals in round four, experienced a drop of 7.1 percent points in health deprivation. Educational deprivation was higher by 0.7 percent points in household participating in the public work program compared with those non-participating in round two. However, in round four, the situation changed showing a difference in percent points of 5.7 between those participating and those non-participating. Finally, in terms of living standard deprivation, in round two we see those participating more deprived by 2.3 percent points, and, in round two, the same individuals faced a staggering increase of 12.8 percent points. What is important to notice, however, is the change in percentage point between the two round of those households participating in the MGNREGA: health-related deprivations decreased by 2.7 percent pints, educational deprivations increased by 10.7 percent points, and the living standards dimension decreased by

[19] From 2006, when the second round of surveys were taken to 2014 when the fourth round of surveys were taken.

8% points. The Young cohort followed the same pattern with participating household being more deprived in the health dimension in round two but less in round two. In terms of education, the numbers keep being consistent with the older cohort with non-participating households being more deprived than the participating ones. Finally, consistency is also found in terms of living standards. Here, as well, what is important to notice is that between the two rounds, household that took-up the program faced, overall, a decrease in their deprivations which clearly demonstrated that the MGNREGA has an impact on the multidimensional level.

To assess the degree of treatment effect we conduct a difference-in-difference analysis for both cohorts that resulted in treatment effect of 8.7% for the older cohort and 2.4% for the younger one both significant at the 95% level. Despite, not being a substantial result from the quantitative point of view, we consider this cumulative 11.1% a positive outcome give that numerous robustness check we conducted before its assessment. Both cohorts faced the same degree of deprivation and, longitudinally, experienced the same pattern of decrease and increase in all dimensions, which is quite interesting.

From the policy perspective the MGNREGA seems to have a small, yet important effect in decreasing multidimensional deprivation in Andhra Pradesh. This sheds an important light on the impacts that public work programs can have on poor households: the universal characteristic of the MGNREGA, its people driven demand and its gender equality characteristics could have important spillover effects in the near future fostering and contributing even more in the development of rural India as well as all those countries which decided to implement such an important, yet often disregarded, policy tool. Moreover, these effects might be proven fundamental when considering the enhancing aspect in terms of capabilities. As we have seen, during the years stunting has been decreasing among children in participating household and living standards have been increasing; these are all sign of an improved well-being among the population. Well-being that might have had an impact in terms of new access to opportunities and, overall, in terms of increasing freedoms and capabilities. Moreover, both cohorts faced the same degree of deprivation and, longitudinally, experienced the same pattern of decrease and increase in all dimensions, which is quite interesting as it demonstrates how differences in age between cohorts was not a factor in defining poverty. Education, on the other hand, showed consisted differences between rounds. The Education dimension was created using two indicators: maximum level of education achieved by the household head and access to school in terms of walking distance from the facility. Most of the increase in deprivation is associated with the second indicator. A child that cannot go to school because it is too far away and has no means to go to class in a safe manner is curbed in its freedom to be educated. From the capability approach stand point we are in front of a clear disregard toward child wellbeing and future development which policy makers could address using policy tools such as public work programs. This issue needs further study in order to grasp its multidimensional characteristics, however, if the deprivation is due to lack in road transportation, the MGNREGA could, if implemented correctly, for instance, foster road reconstruction or renovation in the area.

Nevertheless, to be able to assess these long terms effects, we need data that take into account intra-household characteristics such as household composition and power balances between family members. Intra-household characteristics are of paramount importance in a multidimensional assessment especially if these characteristics have a direct impact on the household decision making. The MGNREGA is considered to be the best and most successful public work program so far, we believe it is time to conduct a serious research on its effect on the Indian population by collecting specific data on those that partook in the program so far.

To conclude, public work programs have been considerably important in the fight against poverty, this paper, with all its limitations, has tried to demonstrate this by undergoing a multidimensional analysis, however, we believe that is time for a shift in focus in the academia: we need to start looking at public work programs not only as mere safety-nets but also as frameworks for a consistent human development, which means that we need to consider public work programs as a more holistic approach in the fight against destitution and thus ex-ante and ex-post data collection are now needed.

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