**Do social assistance programs targeted on elderly in India impact household welfare?**

**Abstract**

India’s population has been ageing due to decline in fertility and mortality rates which emphasis the need for anti-poverty reduction policies to focus on elderly. This becomes imperative in a developing economy like India where only 10% of the population receives a pension; this signifies the role played by IGNOAPS a social assistance program targeted on poor elderly in the country. The study evaluates the impact of IGNOAPS on both short and long term household welfare indicators. The study utilizes the 2005-06 and 2011-12 longitudinal data released by the Indian Human Development Survey. We have combined Propensity Score Matching method with the household fixed effects (PSM-FE) to study the impact of the program on the beneficiaries’ welfare and have further used Propensity Score Matching method with fixed effects and an instrumental variable (PSM-FE-IV) to check the robustness of our results. The results show that IGNOAPS reduces household poverty by increasing consumption expenditure, food expenditure, and non-food expenditure. The magnitude of the effect falls drastically when we replace the treatment variable with the amount received as transfers. This signifies that the amount of transfer determines the size of effect. The strongest positive effect of IGNOAPS is on household assets created which highlights that household allocates higher expenditure to reduce long term household poverty. And the program has a small negative on household labour supply. The findings here have policy implications with the projected increase in the elderly population and the likely future expansion of this program.

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# INTRODUCTION

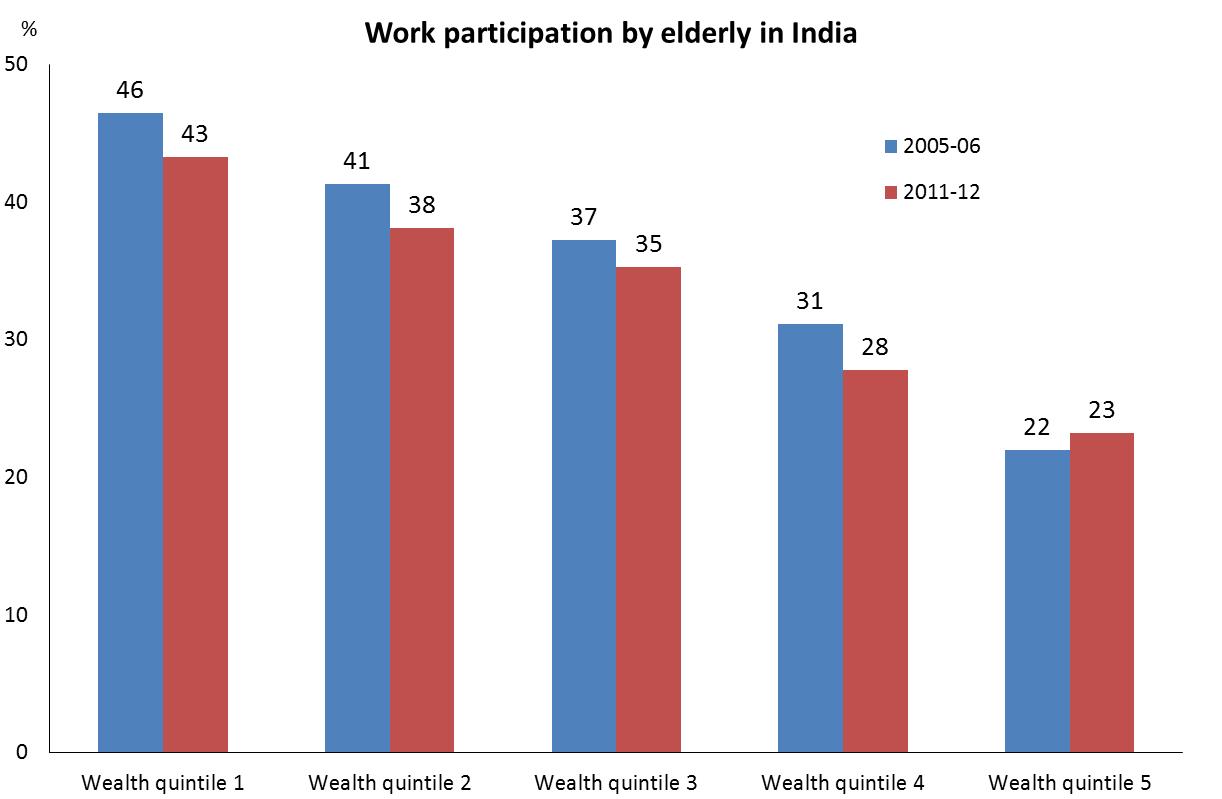
India’s population has been ageing due to decline in fertility and mortality and this has implications on the anti-poverty reduction strategies framed by the country (Pal and Palacios, 2011). Anti- poverty alleviation programs in the form of social assistance needs to focus more on elderly population in order to provide a safety net for them. This becomes imperative in a developing economy like India where only 10% of the population receives a pension; and an estimated 83% of working population in the informal sector is not entitled to receive any pension benefits. Employee’s Provident Fund Organization and the Employee’s State Insurance Corporation are the two major social security plans in India, and both of them covers employees from the formal sector (Uppal and Sarma 2007). Informal sector in India is associated with subsistence economic activity and poor wages and this prevents poor from making any life cycle accumulation of wealth. The lack of an institutionalized social security arrangement for poor signifies the role played by Indira Gandhi National Old Age Pension Scheme (IGNOAPS), a social assistance program targeted on poor elderly in the country. It is in this context the following study evaluates the impact of IGNOAPS on household welfare. The household welfare indicators studied here includes consumption, assets held and household labour supply.

In the past traditional joint family structures in India provided safety net for elderly living in the household, but with the increase in fragmentation of joint family structure and rapid urbanization this informal safety net arrangement provided by families are declining. The average household structure in India declined from 5.5 in 1981 to 5.1 in 2001 (Singh and Das, 2015). This decline in the role of family’s has to be compensated by increasing the role of state as a safety net provider for the poor elderly in the country. The 1948 Universal Declaration of Human rights recognize social security as a basic human right which justifies any state intervention to provide income security to elderly (Holzmann, Robalino and Takayama, 2009).

Research show that two-thirds of elderly in India live in villages and are poor ([Lena et al., 2009](https://www.ncbi.nlm.nih.gov/books/NBK109208/)); half of the elderly are dependents predominantly due to widowhood, divorce, or separation ([Rajan, 2001](https://www.ncbi.nlm.nih.gov/books/NBK109208/)). Older people have a higher probability of being poor in most part of the world (Smeeding and Williamson, 2001). There is an increase in economic compulsion to work by elderly in India (Singh and Das, 2015). The 2005-06 survey from IHDS shows that on 46% of elderly belonging to the poorest wealth[[1]](#footnote-1) quintile worked in India and this has slightly reduced to 43% in 2011-12 (Figure 1). And 37% of elderly belonging to median wealth group worked in 2005-06, compared to 35% in 2011-12. And 22% belonging to the richest wealth quintile worked in 2005-06, compared to 23% in 2011-12. There hasn’t been any substantial change in the percent of elderly working over the years. Elderly who belong to the poorest wealth quintile works twice than those who belong to the richest wealth quintile.

We have used household asset index as a proxy for economic wealth instead of consumption expenditure as consumption expenditure tends to fluctuate more in the short run compared to asset quintiles. Asset accumulation is indicative of a sustained long run economic wealth accumulated by the household (Lahoti, Suchitra and Goutam, 2012). The correlation between elderly working and their economic status signifies the economic compulsion of elderly poor. Although the option of continuing to work helps elderly to lead an active life, but in the case of developing countries elderly engages in informal sector and earns a lower pay than the prime aged workers (Kidd and Whitehouse, 2009).

**Figure 1**



*Source: IHDS 2005-06 and 2011-12*

Therefore, in the case of India we can surmise that a vast majority of elderly live in rural area, they are dependent and are forced to work due to poverty. Unlike developed countries where economic prosperity preceded demographic changes, in India both economic and demographic changes are happening simultaneously and that provides the country with very little time to adjust (Holzmann, Robalino and Takayama, 2009). A report by Ministry of Statistics[[2]](#footnote-2) - India points out that between 2001 and 2011 there has been a 35% increase in the number of persons who are over the age of 60 years of age. This makes it even more important to understand the impact of existing policy levers as these policies are likely to be expanded in future with the increase in elderly population. This study examines the impact of IGNOAPS on household welfare indicators that includes monthly consumption expenditure per capita, monthly consumption per capita food expenditure, monthly consumption per capita non-food expenditure, household assets and the number of persons working in the household.

The study utilizes the 2005-06 and 2011-12 longitudinal data released by Indian Human Development Survey. We have combined Propensity Score Matching (PSM) with household fixed effects (FE) model to estimate the impact of the program. With the help of PSM we have reconstructed the dataset with a valid counterfactual group for both rounds; and we have further used fixed effects model to eliminate the effects of unobservable on the outcome variables. Given that there is self-selection in IGNOAPS as participation in the program is a choice variable in the next stage we have used an instrument to correct for this.

The results show that being a recipient of IGNOAPS increases the average monthly consumption per capita expenditure by 10%, real monthly per capita food expenditure increases by 7%, real monthly per capita non-food expenditure increases by 19%, household assets increases by 16% and the number of persons working in the household declines by 12% for the treatment group. In the second stage we have replaced the dependent variable on household being a recipient of IGNOAPS with the amount received in the scheme in order to understand the impact generated by the transfer amount. And as we replace the treatment variable on being a recipient of IGNOAPS with the amount received in the scheme the magnitude of the treatment effect reduces drastically signifying that size of transfers matter. The result shows that the amount paid in IGNOAPS increases average consumption expenditure per capita by 0.02% for the treatment group; consumption per capita for non-food expenditure increases by 0.004%; assets held by the household increases by 0.006%; and the number of persons worked in the household declined by 0.007%.

To further check the robustness of the results and to correct for self-selection in the treatment variable we have instrumented the dependent variable on the amount received in IGNOAPS with the number of persons at the village/urban local bodies receiving the program. The instrument on the number of beneficiaries receiving the program at the village level denotes the demand for the program; village/urban local bodies with large number of beneficiaries signifies that the amount received in the scheme is greater than the transactional cost involved in applying for the program.

The results from the instrument variable regression shows that a one percent increase in the amount received in IGNOAPS increases monthly per capita expenditure by 0.6% for the treatment group, real monthly per capita food expenditure for this group increases by 0.5%, real monthly per capita non-food expenditure increases by 1.1%, household assets increases by 0.7% and the number of persons working in the household declines by 0.4%. Unconditional cash transfer programs have short term and long term effects; the short term effects of the program is its effect on consumption expenditure and the long term effects include household assets created and labor supply decisions. This research evaluates the short term and long term effects created by IGNOAPS. The empirical evidence here suggests that IGNOAPS generate short term and long term welfare effects and this has policy implications if there is a likely future expansion of this program.

There are very few empirical studies available on India (Garroway, 2013; Kaushal, 2014) and this study differs from the earlier works on the following dimensions: outcome variables measured, data set, and the empirical strategy used. We have estimated the impact of the program on outcomes variables that reflects both the short and long term effects of the program. The study also uses a longitudinal data which helps in eliminating the effects of unobservable compared to a single round of cross section (Garroway, 2013) and pooled cross section (Kaushal, 2014) used in the earlier studies. We have also used Propensity Score Matching with Household Fixed Effects (PSM-FE) to estimate the effects of the program and to check the robustness of the results we have used Propensity Score Matching with Instrumental Variable (PSM-IV) in the second stage. In the earlier works authors have used only PSM (Garroway, 2013) or Pooled OLS regression (Kaushal, 2014) to estimate the effect.

### 1*.***1 SOCIAL SECURITY ARRANGEMENT FOR ELDERLY POOR**

National Social Assistance Program (NSAP) was introduced by the Central government of India in 1995 to provide a social safety net to the vulnerable section of the society. One of the components of NSAP is Indira Gandhi National Old Age Pension Scheme (IGNOAPS) a scheme targeted on poor elderly in India. IGNOAPS provides unconditional cash transfers to elderly belonging to a poor or ultra-poor household in India. In 2002-03 this program covered 6.7 million beneficiaries and by 2014-15 the number of beneficiaries covered under the scheme has more than tripled to 23 million (table 1). The increase in the number of beneficiaries under the scheme indicates the rapid increase in the coverage of the scheme and also the likelihood of a possible future expansion.

**Table 1: Expansion of IGNOAPS**

|  |  |
| --- | --- |
| Year | Number of beneficiaries reported - NOAPS/IGNOAPS (million) |
| 2002-03 | 6.70 |
| 2003-04 | 6.62 |
| 2004-05 | 8.08 |
| 2005-06 | 8.00 |
| 2006-07 | 8.71 |
| 2007-08 | 11.51 |
| 2008-09 | 15.02 |
| 2009-10 | 16.33 |
| 2010-11 | 17.06 |
| 2011-12 | 21.38 |
| 2012-13 | 22.71 |
| 2013-14 | 22.33 |
| 2014-15 | 22.98 |

Source: <https://data.gov.in/catalog/expenditure-and-beneficiaries-under-nsap>

### 1.2 RISE IN ELDERLY POPULATION

Life expectancy at birth in India has increased from 37 years in 1950 to 65 years in 2011 due to improved health services (Arokiasamy et al., 2012; Haub and Gribble 2011). Census of India (2011) has projected the percent of elderly in the total population will be 12% in 2025 and this will rise to 15% in 2035 and to 20% in 2050 (table 2).

**Table 2: Census projections**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Age group | 2025 | 2030 | 2035 | 2040 | 2050 |
| ≥ 60 years | 167 | 195 | 223 | 248 | 308 |
| % of total population | 12.22 | 13.76 | 15.3 | 16.7 | 20.14 |

Source: Ageing population policy responses and challenges, Hemamalini Ramakrishnan (2011)

# LITERATURE REVIEW

Social assistance programs in the form of cash transfers are popular around the world. Cash transfer programs can be both conditional and unconditional. Conditional cash transfers are given only if the beneficiaries attain the specific objective of the program. For e.g., the Brazilian government introduced a cash transfer program Bolsa Familia for poor households, the provisions of cash payments was conditioned on the enrolment of children in school. Similarly, Columbia’s (Familias en Accion[[3]](#footnote-3)), Indonesia’s (Program Keluarga Harapan[[4]](#footnote-4)) and Mexico’s (Oportunidades[[5]](#footnote-5)) are some examples of conditional cash transfer programs. Unlike conditional cash transfers, unconditional cash transfers are not tied with beneficiaries attaining a specific goal. Unconditional cash transfer works when beneficiaries are aware of the choices that needs to be done with the money (Narayanan, 2011). Unconditional cash transfers are also preferred as it involves fewer compliance issues. IGNOAPS can be classified as an unconditional cash transfer program targeted on elderly. Unlike conditional cash transfer program which has explicit outcome goals to track, unconditional cash transfers can affect a large number of outcome variables (Figure 2).

**Figure 2:**

Unconditional cash transfers

Short term

Long term

Household poverty

Investment in productive capacities- health, nutrition, labour supply and migration

The short term impact of unconditional transfer is estimated on household poverty. The long term impacts of unconditional transfers are estimated on the investment on productive capacities which include investment in children’s health, household composition, labour supply and migration (Woolard and Leibbrandt, 2010). In the subsequent paragraphs we have discussed about the welfare effects generated by unconditional cash transfer programs.

Old age pension scheme in South Africa is widely studied in the literature of unconditional cash transfers. South Africa’s old age pension dates back to 1920’s and its impact on the outcome variables on poverty, migration and labour supply are well documented. Case and Deaton (1998) studied about the re-distributive effects of South Africa’s old age pension scheme on the allocation of expenditure towards food, schooling, transfers, and savings. The result shows that both pension and non-pension income have the same effect on food expenditures; and there wasn’t any substantial evidence to claim that elderly favour expenditure on education over other categories of expenditure. It has also been found that pension arrival changes living arrangements; pension received by an elderly grandmother encourages labour market mobility of mothers with grandmothers acting as caretaker for grandchildren (Edmonds, Mammen and Miller, 2005).

Studies have also found that cash transfers promote self-esteem, status and empower the vulnerable group within the household. And the spill over effect of transfers on other household members improves their nutritional status, access to services and creation of household assets thereby creating a wider economic growth (Vincent and Cull, 2009). Based on a focussed group discussion conducted with grandmothers in South Africa it was found that pension increased self-respect for older women and also their credit worthiness (Moller and Sotshongaye, 1996).

Aguero, Carter and Woolard (2006) studied about the impact of South Africa’s child support grant, an unconditional cash transfer targeted on women to improve their children’s nutritional status. The authors found that the child support grant has increased height for age of children and on further extrapolating the estimates with the children’s future wage elasticity it was found that the present discounted value of their future earnings are greater than the cost of providing the grant. This signifies that the long term effects of transfers can break inter-generational poverty. It was also found that both conditional and unconditional cash transfer improves school participation (Baird et.al, 2014).

The effect of unconditional cash transfers on early childhood outcomes is also studied for other regions in Africa. Seidenfeld et.al (2015) studied about the impact of Zambia’s Child Grant on early child outcome indicators; the early child outcomes studied here includes availability of learning materials, adult support for learning, school readiness, non-adult care and preschool attendance. After 24 months of implementing the program it was found that unconditional cash transfer program increases parental support to children and children tends to own more number of books. The result of parental support of children remained consistent irrespective of the different levels of attainment in mother’s education and household composition.

Indonesia implemented the largest unconditional cash transfer program and between October 2005 and September 2006 over 19 million households received 30 USD. Bazzi, Sumarto and Suryahadi (2012) evaluated the impact of this UCT on aggregate expenditure, health care, labour supply and education. It was found that UCT had mixed effect on expenditure; the mixed results are also due to targeting of non-poor households. The findings include households doesn’t change their expenditure to a one time transfer. However, UCT does increase outpatient health service, decrease labour supply of children who are enrolled in school and slightly reduce the labour supply of non- school enrolled children and other household adult members.

The impact of social transfers are studied on various aspects of chronic poverty which includes health, nutrition and schooling outcome, protecting household assets and facilitating asset building. One of the widely studied aspects of social transfer is human capital investment as investment in education prevents intergenerational transmission of poverty. Intergenerational poverty could also be broken by investing in children’s nutrition. Poor nutrition among children results in poor health which curbs their productive capacity and thereby limits their movement out of poverty. In Namibia and South Africa it was found that pension given to grandparents were also used for the payment of grandchildren’s school fees (Devereux, 2001).

Credit inaccessibility faced by poor households in developing countries forces them to forego their current food consumption for future savings; borrowing strategies used by poor households in times of crisis are only effective in short run as the long term consequences of those strategies are devastating. Evidence shows that in Namibia old age pension has increased the access of pensioners to informal credit and in Brazil the non-contributory pension Prevedencia Social Rural has increased the beneficiaries’ access to formal credits (Barrientos and Niño‐Zarazúa, 2011).

Pega et.al (2014) explains four mechanisms through which unconditional cash transfers affects health. The first mechanism is the direct consumption mechanism through which income improves material conditions and that enables individuals to consume nutritious food and thereby improves their health outcomes. The second mechanism is direct status, unconditional cash transfers raises the income of the recipient and therefore it reduces the beneficiaries’ psychological stress and improves their health status. The third mechanism is a combination of direct consumption and direct status mechanisms and in this mechanism UCT can lead to group inclusion and if this group promotes healthy lifestyle then being a part of this group can promote good health for the beneficiaries. The last mechanism through which UCT impacts health is through employment channel. UCT increases the income position and thereby reduces the number of hours worked and if leisure is a normal good then this also improves the health outcome.

In an empirical work in Kenya it was found that transfers targeted on poor households with an orphan or vulnerable child (Cash Transfer for Orphans and Vulnerable Children) reduces depressive symptoms among orphan men who are within the age group of 20-24 years. This finding has major policy implication as this signifies that anti-poverty strategies can be used as a tool to improve the mental outcome of young orphan men in low income countries (Kilburn et.al, 2016).

The impact of unconditional cash transfers on labour supply is also well documented. Abel (2013) highlighted that the availability of pension in South Africa reduces the labour supply of salaried and self -employed household labour supply. Provision of pension increases household income which pushes up reservation wages and reduces labour force participation in households. Given the presence of high level of unemployment and multigenerational household structure in South Africa, the author rejected the hypothesis that female labour supply is constrained due to child care activities. Ardington, Case and Hosegood (2009) have modelled the effect of South Africa’s old age pension on the labour supply response of prime aged household members. The authors quantified the effects of pension on labour supply in two scenarios, when the household gains a pensioner in the first time period and if it loses pension in the second time period. The results shows that the arrival of pension increases the probability of working of other household members and when the household loses pension it reduces the probability of working by other household members. The arrival of pension in the household also facilitates migration of other adult household member and the presence pensioner reduces child care and credit constraints in the household. Sienaert (2008) also studied about the labour supply effects of South Africa’s old age pension scheme. The results confirm that pension is positively correlated with migration. Posel, Fairburn and Lund (2004) confirmed that pension act as a source of income for older woman in the family and facilitate migration of working age women in the family. Thus cash transfers facilitate migration thereby changing household composition.

On evaluating an unconditional cash transfer program in Kenya, Houshofer and Shapiro (2014) found that cash transfers provided on a monthly basis improved household food security and a lump sum payment of transfer improved household expenditure and also the beneficiaries’ psychological wellbeing. Case and Menendez (2007) analysed the impact of the South African Old Age Pension scheme on the lives of pensioners, prime aged individuals and children living with them. The study found that the presence of a pensioner reduces food insecurity in the household and when the pension recipient was a female then it led to a significant improvement in the school enrolment of girls.

Gender is another key dimension through which welfare programs are evaluated. It is commonly believed that cash transfer programs targeting women are more successful in attaining development outcomes. Duflo (2003) studied about the impact of old age pension on intra household allocation. Her results confirmed that the pension received by a woman positively affects the health outcomes of girls in the family. Schady and Rosera (2007) evaluated the impact of Bonode Desarrolo Humano (BDH) an unconditional transfer program implemented in Eucador on household food expenditures. They found that in a mixed adult household with a weaker bargaining power for woman a cash transfer to woman enhances her bargaining position within the household and thereby increases the allocation of food expenditures.

Although the impact of cash transfer programs can be studied on a range of outcome variable we have limited the outcome variable here on account of data limitations. In this study we measure the impact of receiving IGNOAPS on household’s monthly per capita expenditure, monthly per capita food expenditure, monthly per capita non-food expenditure, household assets and number of persons working in the household. There have been prior empirical studies done on IGNOAPS by Garroway (2013) and Kaushal (2014). Kaushal (2014) investigated the impact of IGNOAPS on the wellbeing of the elderly, living arrangements, employment and expenditure pattern in India. Garroway (2013) evaluated the effect of the program on household income, consumption and poverty. Garroway (2013) used the 2005-06 round IHDS data to answer the question; while we have used here panel data. Apart from the consumption variables on household poverty we have also studied here the impact of IGNOAPS on household labour (number of persons working in the household) and the number of household assets held.

# EMPIRICAL FRAMEWORK

The study aims to evaluate if there is a causal link between receiving IGNOAPS and household welfare. The household welfare indicators studied here includes real monthly per capita expenditure, real monthly per capita food expenditure, real monthly per capita non-food expenditure, household assets and number of household members working. All the expenditure variables from the second round are deflated using the IHDS-1 prices (2005-06, base year) in order to make it comparable. All the outcome variables are measured at household level and are converted to logs for easy economic interpretation (log real per capita expenditure, log real per capita food expenditure, log real per capita non-food expenditure, log household assets and log number of household members working).

IHDS-1 has details about 41,554 households and IHDS-2 has information on 42,152 households. And 40,018 households from IHDS-1 have been re-interviewed in IHDS-2. Since we plan to use the panel dataset we focus on households that have been interviewed in both rounds. As we aim to evaluate the causal effect of IGNOAPS we need both treatment and control group. The treatment group here is households that received IGNOAPS and the control group is households that didn’t receive IGNOAPS; and given that we use observational data we only have treatment group. So we use Propensity Score Matching (PSM) to construct a valid counterfactual group.

A household with a member aged 60 years and above are also entitled to receive other benefits program, because the retirement age for government employment in India is 60 years. This norm set by the government sector is also followed by other sectors in the country. If there are other welfare programs employing the same threshold then any jump around the threshold cannot be attributed to the treatment as there are other confounding effects and this rule out the possibility of using Regression Discontinuity Designs (Barrientos and Villa, 2015) and justifies the use of PSM here.

## 3.1 PROPENSITY SCORE MATCHING

The causal effect that we are interested here is the Average Treatment Effect on the Treated (which is the difference in the outcome (Y) when the household ‘i’ receives treatment (t=1) and when the same household (i) doesn’t receive treatment (t=0; c).

The problem in estimating ATT in a non-experimental framework is that we don’t observe the outcome variable for the same household both in the presence and absence of treatment. With the help of a propensity score model we condition the treatment variable on a range of covariates (x); hence, in a propensity score model we replace ‘i’ (same households) with ‘x’ (households with similar characteristics). This method helps in constructing a counterfactual group who are alike to the treatment group, but haven’t received any treatment. However, in order to use a propensity score framework we need to make certain assumptions which include conditional independence, unconfoundedness and overlap.

One of the fundamental assumptions for matching is **conditional independence** which states that

The above assumption implies that the treatment status is random conditional on observable characteristics. This assumption is satisfied when ‘X’ covariates are included in both treatment assignment and potential outcome estimation. The ‘X’ covariates included should be such that it affects treatment assignment and potential outcomes, but not vice versa. This further implies that selection into treatment assignment and potential outcomes are based only on observable characteristics that are included in the model (**Unconfoundedness)**. In order to perform matching we require another assumption which is **overlap or common support** and this states that households with similar characteristics have a positive probability of being in the treatment and control group. This implies that there is a treatment and control variable available for each match on ‘X’.

Since absolute matching is not possible Rosenbaum and Rubin (1984) proposed matching based on a propensity score. The authors proposed that for p(X) equals to the probability that treatment=1 given observable characteristics X,

This implies

In equation 1.1 we estimate the difference between treatment and control group conditioned on covariates (X). And in equation 1.2 we replace the ‘X’ covariates with the probability score p(X) of someone being in treatment or control group.

After constructing the propensity score we need to choose a matching algorithm that helps to match the treatment with control group. There are different matching algorithms available which includes nearest neighbor, caliper and radius, stratification and interval, kernel and local linear and weighting. However, there is a tradeoff between biasedness and variance in selecting each of these matching algorithms. And we have used here Kernel density matching algorithm. In a kernel matching method we use weighted averages of all households in the control group to build the counterfactual group; and the advantage of using a Kernel matching estimator is that we minimize information lost (Caleinedo and Kopeing, 2005). Kernel algorithm generates weights based on the distance of the estimated propensity score between treatment and control group. The weights are then smoothened using standard normal distribution (Handouyahia, Haddad and Eaton, 2013). In the subsequent section we have discussed about the propensity score construction for treatment households.

## 3.2 PROPENSITY SCORE CONSTRUCTION

As discussed in the previous section that in order to evaluate the impact of IGNOAPS we need a treatment and control group and it should be comparable. We constructed propensity score for the treatment variable (households receiving IGNOAPS) based on observable characteristics using a probit model for both the rounds of survey (table 1A). We have used similar covariates to construct propensity score models for both IHDS-1 and IHDS-2 rounds, but in order to attain balancing property we have used interaction terms for the 2011-12 round. Baldwin and Yan (2014) had also used interaction terms to avoid any differences between treatment and control group.

The covariates that are used to construct propensity score model includes if the household has a BPL (poor) card; household has an Antodya (ultra-poor) card; if the household has an elderly member; if the household lives in a rural area and attends public meeting; education level of the household; if the household head belongs to a disadvantaged caste group (Scheduled caste/ Scheduled tribe); women’s access to mass media (newspaper/television). When IGNOAPS was introduced the government used the criterion of an individual being 65 years old and being a destitute to identify beneficiaries; but the program underwent changes in recent times. The age eligibility criterion was reduced from 65 years to 60 years and also the government moved from an unobservable criterion on someone being a destitute to an observable criterion of the person belonging to poor/ultra-poor household. Therefore, we have included the independent variables on household having a BPL card/ Antodya card in the model. We have also used the information on if the household has an elderly (a household member who is or above 60 years) as the program is targeted on individuals who are above 60 years of age. IGNOAPS is largely received in rural India compared to urban parts; the small amount of transfer provided in the scheme is not sufficient enough to meet urban living standards. Household belonging to a BPL household are more likely to receive welfare programs if they attend public meeting (Besley, Rao, & Pande, 2005). Therefore, we have used the interact variable on household living in rural area and attending public meeting to understand this dynamics. We have also used the covariate on household head belonging to a socially disadvantaged caste group to isolate the effects of caste on access to IGNOAPS. We have also included the effects of education and women’s access to mass mediums in our model.

The result from the first stage probit shows that a household having a BPL card has higher probability of receiving the treatment. Similarly, households having an Antodya card also have a higher probability of receiving treatment. Households with an elderly have higher probability of receiving the treatment; and if the household head belongs to a socially disadvantaged caste then it increases the probability of receiving IGNOAPS. Women’s access to mass media reduces the probability of household to receive treatment and this can be due to the correlation between household wealth and access to mass mediums. The results on women’s access to mass mediums are similar to the earlier findings by Garroway (2013). The author pointed out that mass mediums can be a proxy of wealth and this negatively affects the probability of receiving social assistance programs. Although women’s access to mass mediums is considered to effect information dissemination, evidences suggest that this mechanism positively affects the outcome variables on maternal care utilization and health services (Singh, Rai and Singh, 2012; Ajaero, Odimegwu, Ajaero and Nwachukwu, 2016) which are different to the treatment variable used here. If a household lives in a rural area and attends public meeting then it increases the probability of receiving IGNOAPS. And high levels of education reduce the probability of a household receiving IGNOAPS as it also correlated with higher household earnings.

In the second stage, we have used the propensity score derived from the first stage to match treatment household with a control unit. We have used kernel density matching algorithm for matching. Households that were in the common support regions in 2005-06 and 2011-12 are plotted in Figure 3A and Figure 4A. The propensity score for the treatment and control households in 2005-06 and 2011-12 are plotted in Figure 5A and Figure 6A and it can be observed from these figures that there exists a common support zone after matching.

We have performed *Pstest* to assess the matching quality (table 1B). The results from this test signifies that the mean bias in the unmatched sample has come down from 35.5% to 1.6 % after matching for the 2005-06 round; and for the 2011-12 round the mean bias before matching was 48.7% and this has come down to 1.4% after matching. Similarly, median bias has reduced from 19.2% to 1.4% after matching for 2005-06 rounds; and in 2011-12 median bias has reduced from 25.5% to 1.6%. The test statistic from Rubins R[[6]](#footnote-6) and Rubins B[[7]](#footnote-7) is well within the rule of thumb (Rubins B<25; Rubins R [0.5; 2]) which signifies that the quality of matching is good (table 1B).

We repeated the same procedure for both IHDS-1 and IHDS-2 and in both rounds we dropped households that were outside the common support regions. After dropping observations outside the common support region we have 38,320 households in 2005-06 and 40,007 households in 2011-12 rounds. We then constructed a balanced panel dataset with households that are present in common support in both rounds of survey; in the reconstructed panel we dropped households that were present in the common support region for a single round. The balanced panel data has information on 38,309 households that were present in common support regions for both rounds. We then used Propensity Score Matching with Fixed Effects (PSM-FE) method on the balanced panel to evaluate the impact of IGNOAPS. And later we used Propensity Score Matching with Instrumental Variable (PSM-IV) method to address for self-selection of beneficiaries taking place in the scheme.

## 3.3 DATA DESCRIPTIVE

In this section we have provided data descriptive for key variables in the balanced panel (table 2A). In our balanced panel dataset after matching the average monthly real per capita expenditure is INR 978 (table 2A). The monthly expenditure incurred on food is higher than non-food. On average households have at least 12 assets of the maximum 30 assets. And on average two members in the household work; only 6% of the panel receives IGNOAPS; average household composition is five members; average number of years of the highest level of education is 7 years; and on average 28% of them live in urban area; and at means 21% households has members working in the agriculture sector; and on average 53% of them had incurred some debt in the last five years; and 28% of the women in the household has access to newspaper; women’s access to television is higher as at means 72% women has access to TV; and on average the caste composition of scheduled caste is higher than scheduled tribe and the religious composition of Hindus is greater than other groups. And on average 8% of the households receives other welfare programs from the government.

## 3.4 PROPENSITY SCORE MATCHING WITH FIXED EFFETCS[[8]](#footnote-8)

The fixed effect equation that we estimate here is

The outcome variables (Y) estimated here includes log monthly real per capita expenditure, log monthly real per capita food expenditure, log monthly real per capita non-food expenditure, log household assets held and log number of household members working in rounds ‘t’ (2005-06 and 2011-12). The coefficient measures the impact of receiving IGNOAPS on these outcome variables. And we have controlled for the effects of other time varying covariates (X) in the regression model; time invariant unobserved household heterogeneity are controlled by using (). The standard errors are clustered at the household level to avoid any correlation among the outcome variables at the household level. Since this is a fixed effect model and we have two time periods we can eliminate the time invariant unobserved heterogeneity effects by taking first difference. So we can re-write equation 2 as equation 3. And since the program has been present in both time periods we measure the effect of program participation on the average change in the value of outcome variables.

We implemented the fixed effects model on the matched balanced panel data for all the outcome variables. We began with a simple specification with no control variables to evaluate the impact of IGNOAPS recipient households on different outcome variables. For the outcome variable on log monthly real per capita expenditure the result can be interpreted as, if the household receives IGNOAPS then the monthly per capita expenditure of the household will increase by 11% compared with the control group (table 3A); and for the treatment households real monthly per capita food expenditure will increase by 8%; the magnitude of effect is larger for non-food expenditure as this will increase by 22% for the treatment households; and being a recipient of IGNOAPS would increase household’s assets possession by 17%; and it would reduce the number of persons working in the household by 11% for the treatment households.

In table 4A we have reported the second set of results where we have included some additional controls that affects the outcome variables; the controls variables included here are household composition, the highest level of education in the household, place of residence, number of debts held by households and proportion of household members employed for agricultural wages. Higher household composition increases the total expenditure incurred by household, but reduces the per capita expenditure of the household. Higher units of education of the household head increases household earnings thereby it has a positive effect on household expenditure. Also, a large household composition generates more demand for household goods and therefore it positively affects household labor supply. Education is positively correlated with labor supply. Household’s access to credit markets is measured as the number of loans taken by the household in the last five years. Access to credit markets helps in consumption smoothening and we have controlled for this effect. We have also controlled for ratio of household members working as agricultural labors. Agriculture sector is characterized with subsistence wages which can negatively affect the outcome variables on consumption expenditure; this variable also signifies the economic status of the household. Also, the sector of employment can also affect household labor supply decisions.

With the inclusion of additional controls the explanatory power (R-squared) of the model has increased compared to the results from table 4A, but there hasn’t been any drastic change in the outcome variables. For the outcome variable on log real monthly per capita expenditure the result shows that household’s per capita consumption expenditure increases by 10% when they receive IGNOAPS compared with the non-recipients who constitute the control group. And the real monthly food per capita expenditure increases by 7% for households that receive the program and the non-food expenditure increases by 20% for the same group; and access to the program increases the per cent of household assets held by 17% for the treatment group. All the results are statistically significant. As expected the control variables on household composition negatively affects per capita consumption expenditure and the variables on the level of education of the household head positively affects the outcome variables on expenditure and labor supply. And in households with IGNOAPS recipient the number of persons working in the household reduces by 12% and the result is significant. And access to credit market positively affects all the outcome variables. The control on the proportion of household members working in agriculture sector negatively affects all the outcome variables.

In table 5A we have controlled for the effects women’s access to mass mediums, religion of the household head, caste of the household head and the number of other welfare programs received by the household. Socio-economic variables can affect the outcome variables and controlling for them helps us to check the robustness of the results under different specifications. The positive relationship between women’s access to mass media and household assets confirms that mass media acts as a proxy for household wealth. Women’s access to mass mediums positively affects the outcome variables on expenditure and is significant. But it negatively affects the number of persons working in the household and one possible explanation is that mass mediums signify household wealth and this has a negative effect on labor supply. The control on household head belonging to a schedule caste or scheduled tribe displays inconsistent signs and is insignificant for most outcome variables. The control variable on household head being a Hindu (majority religion) is significant and positively affects the outcome variables of expenditure and assets. The number of other welfare programs received by the household also positively affects the outcome variables of expenditure and assets as this increases the income of the household, but negatively affects the outcome variable on household labor supply.

The result remains consistent even with the inclusion of additional controls. The result shows that household receiving IGNOAPS will increase the monthly per capita expenditure by 10%; and monthly per capita food expenditure will increase by 7% for households that receive the program and the monthly per capita non-food expenditure increases by 20%; the household assets increases by 16% and the number of persons working in the household reduces by 12%. We can also interpret the result as following; the monthly real per capita expenditure incurred by the treatment group was INR 864.16 (table 2B) and the results from table 2A shows that when households receives IGNOAPS the monthly per capita expenditure increases by 10% for the treated group, then for the treatment group the new average real monthly per capita expenditure will be INR 950.57; and if the real monthly per capita food expenditure increases by 7% then for the treatment group the average real monthly per capita food expenditure will be INR 392.08; and if the real monthly per capita non-food expenditure increases by 20% the average real monthly per capita non-food expenditure for the treatment group will be INR 277.01 and if the percent of household assets held gets increased by 16% then the average number of assets held by the treatment group will be 14; and if the number of persons working in the household declines by 12% then number of household members working in the treatment group will be approximately equal to 2.

IGNOAPS increases the household income thereby it positively affects the consumption expenditure variables. Consumption is an indicator of household wellbeing; therefore, any positive changes in this indicate the ability of the program to reduce household poverty. Given this program is targeted on poor the effect has to be stronger on food expenditure, but however we observe that there is an increase in allocation towards non-food expenditure and household assets. With the increase in non-labor income it is possible that household now aspires to spend on non-food expenditure that wasn’t possible earlier. However, in this case non-food expenditure also includes outpatient medical services cost. Households that receive IGNOAPS on average spend INR 112.63 (monthly/per capita) for outpatient medical services cost and this constitutes the largest component of expenditure incurred by the treatment household in the non-food category. This signifies the need to improve access to health care facilities in India. Given that in unconditional cash transfers the beneficiaries makes the choice on how to spend the money they choose to invest in productive capacities like household assets so that it will reduce the long term household poverty (Angelucci, Attanasio and Maro, 2011).

Social insurance and social assistance programs can affect labour supply through income and substitution mechanism. Income effect operates when with the arrival of IGNOAPS households decide to reduce the number of hours spent on work or to withdraw from the labour market. Unearned income can reduce liquidity constrains or provide consumption smoothening thereby helping households to reduce their labour supply (Ning et.al, 2016). As Ning argues substitution effect occurs if implicit taxes are imposed on workers who continue to work after the arrival of pension as in the case of some contributory pension system or social earnings test that discourages working.

Although the basic economic theory argues that non-labour income should lead to income effect; it is difficult to disentangle this effect if the program is conditioned on a mean test or labour inactivity test (Barrientos and Sherlock; 2002). Income effect doesn’t create a deadweight loss, but rather it is the intended outcome of the program. The disadvantage of substitution effect is that it creates deadweight loss in the economy; when people work less because of the substitution effect then the economy’s output shrinks and higher tax rates that were originally meant to increase government revenue in real discourages individuals from working and thereby reduce government tax revenue. Kaushal (2014) argues that the change in the eligibility criterion in IGNOAPS from someone with no regular source of income (destitute) to someone belonging to a poor or ultra-poor household reduces the substitution effect for the poor.

## 3.5 DOES SIZE OF THE TRANSFER MATTER?

In the second stage we hypothesized the main explanatory variable of access to IGNOAPS with the amount of money that is been reported to have been received under IGNOAPS (equation 4). The only difference between equation 3 and equation 4 is the replacement of the main explanatory variable of household accessing IGNOAPS with the amount received in the scheme. The amount of money received is deflated to make it comparable with the 2005-06 prices. We have taken the log of the new explanatory variable (amount of money received in IGNOAPS). We have run the specification reported in (table 6A) with the new independent variable on the outcome variables.

The magnitude of the effect of IGNOAPS is reduced as we replace the independent variable with the amount reported to have received under the scheme. If the amount of money received in IGNOAPS increases by one percent (annually) then the monthly per capita expenditure increases by 0.002%; per capita food expenditure increases by 0.0002%; non-food per capita expenditure increases by 0.005%; household assets increases by 0.006% and the number of household members worked reduces by 0.007%.

In equation3 we have estimated the effect of household being a recipient of IGNOAPS on household welfare indicators. And in equation4 we have estimated the effect of the amount received on the same welfare indicators. The magnitude of the effect is stronger when we evaluate the impact of household receiving IGNOAPS than the amount of money reported to have received in the scheme. The results from equation 3 estimate the effect of the program, but we don’t take into account the size of the amount paid. While the results from equation 4 takes into account the size of the transfers; the results still confirm that IGNOAPS amount still positively affect per capita consumption expenditure and negatively affects household labor supply, but the magnitude of the effect is much smaller here compared to the results from equation 3. The results signify that size of the transfer does determine the magnitude of impact. The average amount of money reported to have received from the program at the household level is only INR 2467.56 (annually). Hence, the results obtained here are not surprising.

## 3.6 PROPENSITY SCORE MATCHING WITH FIXED EFFECTS AND INSTRUMENTAL VARIABLE

Although with the help of the fixed effects model we have corrected for time invariant unobserved heterogeneity affecting the outcome variable. Also, with the help of fixed effects we remove the effects of state institutions that are correlated with the amount of transfer given in the scheme as IGNOAPS is a central-state funded program. But the amount received in the scheme can be correlated with the self-selection of beneficiaries taking place in the scheme. Households that have reported to have received an income under IGNOAPS did choose to apply for the program in the first place, compared to similar households that haven’t received any income under IGNOAPS. All the eligible applicants need to complete the application in order to receive this program and submission of the application form is mandatory. Therefore, the independent variable on the amount of money received in the scheme can be endogenous as it is a choice variable and this can be correlated with the self-selection variable present in the error term of the equation. Hence, we have used an instrument to correct for this and this also helps to check the robustness of our estimators. It is also possible that the amount reported to have received under IGNOAPS suffers from measurement error. Given that households were asked to recall the benefit amount received in the last 12 months there is a possibility for measurement error which makes our main explanatory variable endogenous and justifies our use of instrumental variable.

The instrument needs to satisfy two conditions, the instrument (Z) should be correlated with the independent variable (first stage); and the instrument should be uncorrelated with the error term in the model, else the instrument itself can be endogenous. In this case the instrument should be such that it is correlated with amount of money received in IGNOAPS (X), but uncorrelated with the dependent variable (equation 3).

Therefore, we can re-write equation 4 with the help of an instrument in equation 5.

The instrument that we have used here is the number of beneficiaries who have received the program at the village level. The instrument on the number of beneficiaries receiving the program at the village level helps in addressing self-selection taking place in the scheme; ; villages with large number of beneficiaries denotes better information flow and higher rate of acceptance into the program. The instrument signifies a high level of access to the program. Also, a large number of beneficiaries receiving the program also signify the amount received as transfers is greater than the transactional cost involved in obtaining the transfer amount. The transactional cost involved here includes completion of application form, time involved in obtaining age certificate and BPL card (eligibility criteria’s) from the bureaucrats etc. Beneficiaries wouldn’t undergo these hardships unless the amount received from the program is greater than the cost of participating in the program. Therefore, in villages with large number of beneficiaries the incentives (amount) received from IGNOAPS is greater than the cost involved in participating in it which indicates that the instrument (Z) used here is correlated with amount received under IGNOAPS (X). However, there can be spillover effects from the program such that villages with large number of beneficiaries will also have huge influx of IGNOAPS funds and thereby households residing in those villages will have higher units of consumption and assets. But for the spillover effects to happen the amount of money received from the program should be substantially large enough such that it generates spillover effects at the village level. We rule out this possibility here as the highest average amount (annually) reported to have received by the beneficiaries at the village level is INR 3519.458. The amount reported here is very small to create any spillover effect at the village level which justifies our use of this instrument.

We have used this instrument and have estimated equation 5 and the results are reported in table 7A. The standard errors are clustered at the village level. In the first stage we use the instrument (number of beneficiaries receiving the program at the village/ULB level) to estimate the effect of the instrument on the amount of money reported to have received in the scheme. The F- stats result from the first stage regression shows that the instrument is significant in affecting amount received in the scheme (table 7A). In the second stage we use the estimated instrument from the first stage to evaluate the impact on the outcome variables. After instrumenting the amount received under IGNOAPS (log) with the number of beneficiaries receiving the program at the village level we find that IGNOAPS amount positively affects the outcome variables on consumption per capita and household assets and negatively affects labor supply and all the results are statistically significant.

The IV estimates shows that a percentage increase in IGNOAPS amount will now increase the monthly consumption per capita by 0.6%; monthly consumption per capita food expenditure by 0.5%; non-food per capita expenditure 1.1%; and assets held by household will increase to 0.7% and the number of persons working in the household will decline by 0.4% for the treatment group. For example, if the government increases the amount provided under IGNOAPS by 5% then the beneficiaries’ monthly consumption per capita will increase by 3%; monthly food expenditure will increase by 2.5%; monthly non-food expenditure will increase by 5.5%; assets held will increase by 3.5% and household labor supply will reduce by 2%.

The results from the IV estimates are similar to the other findings reported in this paper. IGNOAPS does reduce increase consumption expenditure thereby reducing household poverty. On further disaggregating the data we find household allocates more towards non-food expenditure and household assets. This indicates the household’s increased preference towards non-food expenditure which is mainly driven by the outpatient medical services cost. Although India has made medical strides over the years and has reduced mortality rates and has improved the life expectancy there exist a huge rural-urban divide in the quality of medical services provided; also poor in India don’t have access to health insurance market which further increases their outpatient cost[[9]](#footnote-9). Households also increase their allocation of expenditure towards assets creation which helps in the long term poverty reduction. IGNOAPS has the smallest effect on household labor supply.

The coefficient from the IV regression is upward biased compared to the OLS regression. Although IV estimators are usually upward biased it is still considered to be consistent compared to OLS estimator; as OLS estimators are considered to be inconsistent when the explanatory variables are correlated with the error term. The instrument is significant for all the outcome variables; and the first stage F-stat values are high and Stock-Yogo test statistic is greater than 10 for all the outcome variables which signifies that the instrument is strong.

We have further tested the robustness of our results by replacing the independent variables in the model with covariates used to construct the propensity score. In this model we have only used exogenous variables that affect the outcome variables on consumption, assets and labor supply. This helps us to test the robustness of our results when the treatment and outcome models are affected with the same covariates. The IV estimates shows that a percent increase in IGNOAPS will now increase the monthly consumption per capita by 0.2%; monthly consumption per capita food expenditure by 0.2%; non-food per capita expenditure 0.3%; and assets held by household will increase to 0.1% and the number of persons working in the household will decline by 0.2% (table 8A) for the treatment group. The difference between the IV coefficients reported in table 7A and table 8A is less than 0.5% for the outcome variables on consumption, food expenditure and labor supply and the difference is about 0.8% for non-food expenditure and 0.6% for household assets variable. This signifies that our estimates are consistent.

# DISCUSSION

Unconditional cash transfer programs creates short term and long term effects; the short term effects of the program include its impact on household poverty while its long term impact include investment household assets and labor supply decisions. This paper evaluates the impact of IGNOAPS on the short term and long term household welfare indicators. We have evaluated the impact of the program on per capita consumption expenditure, per capita food consumption expenditure, per capita non-food consumption expenditure, household assets and number of persons working in the household. The welfare indicator on consumption signifies the short term effects of the program; and the indicator on household assets and labor supply signifies the long term effects of the program. In order to measure the impact of the program we have used Propensity Score Matching method to reconstruct the sample with the treatment and control group. And in the reconstructed sample we have used the fixed effects method to evaluate the impact of the program on household welfare indicators. Fixed effects method helps in eliminating time invariant heterogeneity in our model.

The results from the PSM-FE model show that when a household receives IGNOAPS it positively affects their consumption and household assets and negatively affects labor supply. Unconditional cash transfer increases household income thereby it increases consumption expenditure. The positive effect on consumption expenditure signifies the improvement in the short term household welfare; the results show that household tends to allocate more towards non-food expenditure and household assets compared to food expenditure. The increased preference towards non-food expenditure is driven by the outpatient cost paid by the treatment households. Similarly, increase in allocation towards household assets signifies that household aims to reduce their long term poverty.

In the next stage we replace household receiving IGNOAPS with the amount reported to have received under the scheme as this takes into account the size of the transfers. The result shows that as we replace the recipient of the scheme with size of transfers the magnitude of the effect on household welfare indicators reduces drastically. The result highlights that IGNOAPS affects both the short and long term household welfare indicators and the effect is significant. However, the magnitude of coefficient is very small owing to the small size of transfer. This indicates that the amount paid under IGNOAPS needs to be increased. Evidence from Mexico’s Oportunidades, a conditional cash transfer program does highlight that doubling the cash transfers do improve child welfare indicators (Fernald, Gertler and Neufeld, 2008). But that leads to the question on how generous IGNOAPS should be. Social assistance programs in developing countries are lesser than minimum incomes and fails to meet the minimum standard requirements of the ILO Minimum Standards convention (ILO 1952) (Tabor, 2002). This is also true for IGNOAPS and it signifies the need to revise the payment under the scheme, but the policy prescription of increasing the transfer amount needs to be carefully interpreted. Filmer and Schady (2009) cautions that there can be diminishing marginal returns to transfer as they found in the case of Cambodia. Although we don’t have any evidence on this here the policy prescription of large transfers needs to be carefully planned and executed. Filmer and Schady (2009) have emphasized the need for a careful program design such that the program reaches the deserving households.

Given that there is self-selection in the scheme we have used an instrument to correct for this and to check the robustness of our estimate. We instrumented the variable on the amount of money received as transfers with the number of beneficiaries receiving the program at the village level. In villages/ ULBs with large number of beneficiaries the incentives received as transfers is greater than the transactional cost involved in obtaining it. The first stage F-statistic is significant and the Stock Yoger test statistic is greater than 10 which signify the instrument is a strong predictor for amount received in the scheme. The result from the instrument variable regression re-confirms that IGNOAPS positively affects the variables on monthly consumption per capita and household assets and negatively affects household labor supply. We have further tested the robustness of our results by replacing independent variables in the model with the covariates from the propensity score model such that now the treatment and outcome variables are influenced by the same factors. On comparing the IV coefficients it can be found that difference between the results reported from table 8A and table 9A is less than 1% for all the outcome variables. This reiterates that our estimates are consistent.

This research aims to study if there is a causal relationship between IGNOAPS and household welfare indicators. The results confirm that there is a positive effect of household being a recipient of IGNOAPS on the household welfare indicators. But the magnitude of the effect is very small due to the size of transfers. This signifies that there is a greater need for the government to revise the amount paid under IGNOAPS in order to reap higher benefits of the scheme. IGNOAPS is a central-state sponsored scheme where the states have to contribute a similar or higher amount of money in addition to the central assistance given for the scheme. But there are states in India that provide greater amount of money in addition to central assistance and some states fail to make any contribution and some states contribute lesser amount of money compared to the central assistance given in the scheme. For example, in our matched panel dataset the average amount reported to have received in the state of Haryana is 6.8 times greater than Uttaranchal. This further results substantial variation in the amount paid as transfers. But our results shows that even after eliminating for the state level differences the impact of the amount provided under IGNOAPS is very small on household welfare indicators.

Given that the percent of elderly population will continue to rise and there are very little social assistance programs in place targeting poor elderly; IGNOAPS will continue to play an important role in the lives of poor elderly who otherwise don’t have any alternative source of safety net. Our research does confirm that IGNOAPS has a positive impact on many household welfare indicators. Theoretically, non-labor income does affect the labor supply negatively. But the magnitude of the labor supply effect here is very small. The result do signifies that social assistance program does impact the household welfare and any future increase in the amount of transfer with careful program design can increase the household welfare of the beneficiaries.

# APPENDIX

**Table 1A: Propensity score models**

|  |  |  |
| --- | --- | --- |
| **Variables** | **2005-06** | **2011-12** |
|  | Coefficients | Coefficients |
| Household has a BPL card | 0.168\*\*\* |  |
|  | (0.03) |  |
| Household has a Antodya card | 0.347\*\*\* |  |
|  | (0.08) |  |
| If the household has an elderly member (age 60 years or more) | 1.483\*\*\* | 1.619\*\*\* |
|  | (0.04) | (0.027) |
| Household lives in rural area & attends public meeting | 0.079\*\* | 0.125\*\*\* |
|  | (0.03) | (0.023) |
| Highest number of years education in the household | -0.016\*\*\* | -0.025\*\*\* |
|  | (0.00) | (0.002) |
| Head of the household belongs to Scheduled caste | 0.308\*\*\* |  |
|  | (0.03) |  |
| Head of the household belongs to Scheduled tribe | 0.020 |  |
|  | (0.06) |  |
| If women in household has access to newspaper | -0.194\*\*\* |  |
|  | (0.04) |  |
| If the household head belongs to Scheduled caste or Scheduled tribe |  | 0.106\*\*\* |
|  |  | (0.023) |
| If the women in the household has access to T.V |  | -0.041 |
|  |  | (0.025) |
| Household has a BPL or Antodya card |  | 0.584\*\*\* |
|  |  | (0.022) |
| \_cons | -2.84\*\*\* | -2.507\*\*\* |
|  | (0.049) | (0.037) |
| Pseudo R2 | 0.21 | 0.26 |
| Number of observations | 39967 | 40007 |

**Table 1B: Covariates balanced in PSM**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Sample** | **Ps R2** | **LR chi2** | **p>chi2** | **Mean Bias** | **Median Bias** | **Rubin’s-B** | **Rubin’s- R** | **% Variance** |
| **2005-06** | | | | | | | | |
| Unmatched | 0.212 | 2464.1 | 0 | 35.5 | 19.2 | 169.9\* | 0.33\* | 0 |
| Matched | 0 | 1.8 | 0.987 | 1.6 | 1.4 | 5.2 | 1.02 | 0 |
| **2011-12** | | | | | | | | |
| Unmatched | 0.268 | 6638.73 | 0 | 48.7 | 25.5 | 169.2\* | 0.43\* | 0 |
| Matched | 0 | 1.87 | 0.931 | 1.4 | 1.6 | 3.2 | 1.02 | 0 |

**Table 2A: Summary statistics: Panel data**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Variables** |  | **Mean** | **Std.Dev** | **Min** | **Max** | **Observations** |
| Real monthly per capita expenditure | overall | 978.10 | 1100.85 | 4.00 | 69321.78 | N=76536 |
|  | between |  | 861.71 | 98.55 | 35710.39 | n=38309 |
|  | within |  | 685.65 | -32633.30 | 34589.49 | T-bar=1.99786 |
| Real monthly per capita food expenditure[[10]](#footnote-10) | overall | 386.43 | 226.46 | 0.00 | 5157.60 | N=76618 |
|  | between |  | 180.91 | 0.00 | 2965.90 | n=38309 |
|  | within |  | 136.21 | -2003.55 | 2776.41 | T-bar=2 |
| Real monthly per capita non- food expenditure[[11]](#footnote-11) | overall | 250.69 | 339.00 | 0.00 | 17763.62 | N=76618 |
|  | between |  | 263.94 | 6.75 | 10590.06 | n=38309 |
|  | within |  | 212.75 | -7800.89 | 8302.27 | T-bar=2 |
| Assets[[12]](#footnote-12) | overall | 12.86 | 6.10 | 0.00 | 30.00 | N=76601 |
|  | between |  | 5.62 | 0.00 | 29.00 | N=38309 |
|  | within |  | 2.38 | 1.86 | 23.86 | T-bar=1.99956 |
| Number of household members working | overall | 2.21 | 1.46 | 0.00 | 13.00 | N=76618 |
|  | between |  | 1.13 | 0.00 | 12.00 | N=38309 |
|  | within |  | 0.92 | -3.79 | 8.21 | T-bar=2 |
| Household receiving IGNOAPS | overall | 0.06 | 0.25 | 0.00 | 1.00 | N=76618 |
|  | between |  | 0.19 | 0.00 | 1.00 | N=38309 |
|  | within |  | 0.16 | -0.43 | 0.57 | T-bar=2 |
| Household size: Number of persons in the household | overall | 5.39 | 2.77 | 1.00 | 38.00 | N=76618 |
|  | between |  | 2.25 | 1.00 | 27.00 | N=38309 |
|  | within |  | 1.61 | -11.61 | 22.39 | T-bar=2 |
| Highest education in the household | overall | 7.51 | 4.96 | 0.00 | 16.00 | N=76618 |
|  | between |  | 4.51 | 0.00 | 15.50 | N=38309 |
|  | within |  | 2.05 | -0.49 | 15.51 | T-bar=2 |
| If the household lives in an urban area | overall | 0.281 | 0.45 | 0.00 | 1.00 | N=76618 |
|  | between |  | 0.44 | 0.00 | 1.00 | N=38309 |
|  | within |  | 0.08 | -0.22 | 0.78 | T-bar=2 |
| Number of household members working as agriculture labours as a share of total working household members | overall | 0.21 | 0.37 | 0.00 | 1.00 | N=72186 |
|  | between |  | 0.32 | 0.00 | 1.00 | N=37786 |
|  | within |  | 0.19 | -0.29 | 0.71 | T-bar=1.91039 |
| Number of debts in the last 5 years | overall | 1.53 | 2.75 | 0.00 | 60.00 | N=76555 |
|  | between |  | 2.04 | 0.00 | 35.00 | N=38309 |
|  | within |  | 1.84 | -28.47 | 31.53 | T-bar=1.99836 |
| If the women in the household has access to newspaper | overall | 0.28 | 0.45 | 0.00 | 1.00 | N=76618 |
|  | between |  | 0.37 | 0.00 | 1.00 | N=38309 |
|  | within |  | 0.25 | -0.22 | 0.78 | T-bar=2 |
| If the women in the household has access to TV | overall | 0.72 | 0.45 | 0.00 | 1.00 | N=76618 |
|  | between |  | 0.36 | 0.00 | 1.00 | N=38309 |
|  | within |  | 0.27 | 0.22 | 1.22 | T-bar=2 |
| If the household head belongs to Scheduled Caste | overall | 0.22 | 0.42 | 0.00 | 1.00 | N=76618 |
|  | between |  | 0.40 | 0.00 | 1.00 | N=38309 |
|  | within |  | 0.12 | -0.28 | 0.72 | T-bar=2 |
| If the household head belongs to Scheduled Tribe | overall | 0.09 | 0.28 | 0.00 | 1.00 | N=76618 |
|  | between |  | 0.27 | 0.00 | 1.00 | N=38309 |
|  | within |  | 0.08 | -0.41 | 0.59 | T-bar=2 |
| Number of other welfare programs received by household[[13]](#footnote-13) | overall | 0.08 | 0.29 | 0.00 | 4.00 | N=76618 |
|  | between |  | 0.22 | 0.00 | 3.00 | N=38309 |
|  | within |  | 0.19 | -1.42 | 1.58 | T-bar=2 |
| If the household head is a Hindu | overall | 0.81 | 0.39 | 0.00 | 1.00 | N=76618 |
|  | between |  | 0.38 | 0.00 | 1.00 | N=38309 |
|  | within |  | 0.09 | 0.31 | 1.31 | T-bar=2 |

**Table 2B: Summary statistics: Outcome variables (treatment and control group)**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Main explanatory variables** | **Mean** | **Std. dev** | **Mean** | **Std. dev** |
|  | Treatment group | | Control group | |
| Real monthly percapita expenditure | 864.16 | 759.30 | 986.13 | 1120.492 |
| Real monthly percapita food expenditure | 366.43 | 202.81 | 387.84 | 227.96 |
| Real monthly percapita non- food expenditure | 230.84 | 321.881 | 252.1 | 340.13 |
| Assets | 12.35 | 5.86 | 12.89 | 6.11 |
| Number of household members working | 2.149 | 1.52 | 2.2185 | 1.45 |

**Table 3A: Model with no controls**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **Outcome variables** | | | | |
| **Variables** | **Log real monthly percapita expenditure** | **Log real monthly percapita food expenditure** | **Log real monthly percapita non-food expenditure** | **Log assets** | **Log of number of household members working** |
| Household receiving IGNOAPS (Yes/No) | 0.114\*\*\* | 0.0792\*\*\* | 0.224\*\*\* | 0.171\*\*\* | -0.106\*\*\* |
|  | (0.01) | (0.01) | (0.02) | (0.01) | (0.01) |
| **Controls used** | Nil | Nil | Nil | Nil | Nil |
| Constant | 6.609\*\*\* | 5.816\*\*\* | 5.107\*\*\* | 2.402\*\*\* | 0.704\*\*\* |
|  | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| |  | | --- | | Observations | |  | |  | | 76,536 | 76,518 | 76,448 | 76,499 | 72,186 |
| R-squared | 0.002 | 0.002 | 0.004 | 0.01 | 0.02 |
| Number of Households | 38,309 | 38,308 | 38,309 | 38,308 | 37,786 |

Clustered Bootstrapped Standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 4A:**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Variables** | **Log real monthly per capita expenditure** | **Log real monthly per capita food expenditure** | **Log real monthly per capita non -food expenditure** | **Log assets index** | **Log number of household members working** |
| Household receiving IGNOAPS (Yes/No) | 0.105\*\*\* | 0.075\*\*\* | 0.203\*\*\* | 0.170\*\*\* | -0.120\*\*\* |
|  | (0.01) | (0.01) | (0.02) | (0.01) | (0.01) |
| Household size: Number of persons in the household | -0.086\*\*\* | -0.080\*\*\* | -0.120\*\*\* | -0.009\*\*\* | 0.114\*\*\* |
|  | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Highest education in the household | 0.027\*\*\* | 0.019\*\*\* | 0.043\*\*\* | 0.032\*\*\* | 0.006\*\*\* |
|  | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| If the household lives in an urban area | 0.324\*\*\* | 0.214\*\*\* | 0.466\*\*\* | 0.176\*\*\* | -0.031\* |
|  | (0.02) | (0.02) | (0.03) | (0.01) | (0.02) |
| Number of household members working as agriculture labours as a share of total working household members | -0.147\*\*\* | -0.072\*\*\* | -0.207\*\*\* | -0.102\*\*\* | -0.050\*\*\* |
|  | (0.01) | (0.01) | (0.02) | (0.01) | (0.01) |
| Number of debts in the last 5 years | 0.022\*\*\* | 0.008\*\*\* | 0.030\*\*\* | 0.009\*\*\* | 0.003\*\*\* |
|  | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Constant | 6.766\*\*\* | 6.039\*\*\* | 5.289\*\*\* | 2.157\*\*\* | 0.046\*\*\* |
|  | (0.01) | (0.01) | (0.02) | (0.01) | (0.01) |
| |  | | --- | | Observations | |  | |  | | 72,077 | 72,055 | 72,005 | 72,077 | 72,130 |
| Number of Households | 37,781 | 37,772 | 37,772 | 37,781 | 37,784 |
| R-squared | 0.19 | 0.16 | 0.16 | 0.19 | 0.29 |

Clustered Bootstrapped Standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 5A: Model with all the controls included**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Variables** | **Log real monthly per capita expenditure** | **Log real monthly per capita food expenditure** | **Log real monthly per capita non -food expenditure** | **Log assets index** | **Log number of household members working** |
| Household receiving IGNOAPS (Yes/No) | 0.103\*\*\* | 0.073\*\*\* | 0.200\*\*\* | 0.163\*\*\* | -0.122\*\*\* |
|  | (0.01) | (0.01) | (0.02) | (0.01) | (0.01) |
| Household size: Number of persons in the household | -0.086\*\*\* | -0.080\*\*\* | -0.120\*\*\* | -0.007\*\*\* | 0.114\*\*\* |
|  | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Highest level of education in the household | 0.024\*\*\* | 0.017\*\*\* | 0.037\*\*\* | 0.028\*\*\* | 0.007\*\*\* |
|  | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| If the household lives in an urban area | 0.297\*\*\* | 0.195\*\*\* | 0.418\*\*\* | 0.140\*\*\* | -0.024 |
|  | (0.02) | (0.02) | (0.03) | (0.01) | (0.02) |
| Number of household members working as agriculture labours as a share of total working household members | -0.140\*\*\* | -0.067\*\*\* | -0.196\*\*\* | -0.091\*\*\* | -0.050\*\*\* |
|  | (0.01) | (0.01) | (0.02) | (0.01) | (0.01) |
| Number of debts in the last 5 years | 0.021\*\*\* | 0.007\*\*\* | 0.028\*\*\* | 0.007\*\*\* | 0.004\*\*\* |
|  | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| If the women in the household has access to newspaper | 0.066\*\*\* | 0.053\*\*\* | 0.082\*\*\* | 0.011\*\*\* | -0.013\*\* |
|  | (0.01) | (0.01) | (0.01) | (0.00) | (0.01) |
| If the women in the household has access to TV | 0.145\*\*\* | 0.097\*\*\* | 0.265\*\*\* | 0.278\*\*\* | -0.019\*\*\* |
|  | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| If the household head belongs to Scheduled Caste or Scheduled tribe | -0.019 | 0.002 | -0.022 | 0.008 | 0.003 |
|  | (0.02) | (0.01) | (0.02) | (0.01) | (0.01) |
| Number of other welfare programs received by household | 0.069\*\*\* | 0.034\*\*\* | 0.182\*\*\* | 0.092\*\*\* | -0.081\*\*\* |
|  | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| If the household head is a Hindu | 0.082\*\*\* | 0.075\*\*\* | 0.122\*\*\* | 0.053\*\*\* | -0.009 |
|  | (0.02) | (0.02) | (0.03) | (0.01) | (0.01) |
| Constant | 6.607\*\*\* | 5.912\*\*\* | 5.021\*\*\* | 1.941\*\*\* | 0.067\*\*\* |
|  | (0.02) | (0.01) | (0.03) | (0.01) | (0.02) |
| |  | | --- | | Observations | |  | |  | | 72,081 | 72,077 | 72,005 | 72,027 | 72,130 |
| Number of Households | 37,782 | 37,781 | 37,772 | 37,777 | 37,784 |
| R-squared | 0.19 | 0.21 | 0.19 | 0.20 | 0.29 |

Clustered Bootstrapped Standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 6A: Dependent variable: amount of money received in IGNOAPS**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Variables** | **Log real monthly per capita expenditure** | **Log real monthly per capita food expenditure** | **Log real monthly per capita non -food expenditure** | **Log assets index** | **Log number of household members working** |
| Log of amount of money  Received under IGNOAPS | 0.002\*\* | 0.0002 | 0.005\*\*\* | 0.006\*\*\* | -0.006\*\*\* |
|  | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Household size: Number of persons in the household | -0.086\*\*\* | -0.080\*\*\* | -0.120\*\*\* | -0.008\*\*\* | 0.114\*\*\* |
|  | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Highest education in the household | 0.024\*\*\* | 0.017\*\*\* | 0.038\*\*\* | 0.028\*\*\* | 0.006\*\*\* |
|  | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| If the household lives in an urban area | 0.302\*\*\* | 0.199\*\*\* | 0.426\*\*\* | 0.146\*\*\* | -0.028 |
|  | (0.02) | (0.02) | (0.03) | (0.01) | (0.02) |
| Number of household members working as agriculture labours as a share of total working household members | -0.140\*\*\* | -0.067\*\*\* | -0.195\*\*\* | -0.091\*\*\* | -0.050\*\*\* |
|  | (0.01) | (0.01) | (0.02) | (0.01) | (0.01) |
| Number of debts in the last 5 years | 0.021\*\*\* | 0.007\*\*\* | 0.028\*\*\* | 0.007\*\*\* | 0.004\*\*\* |
|  | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| If the women in the household has access to newspaper | 0.066\*\*\* | 0.053\*\*\* | 0.082\*\*\* | 0.011\*\*\* | -0.013\*\* |
|  | (0.01) | (0.01) | (0.01) | (0.00) | (0.01) |
| If the women in the household has access to TV | 0.146\*\*\* | 0.097\*\*\* | 0.268\*\*\* | 0.281\*\*\* | -0.021\*\*\* |
|  | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| If the household head belongs to Scheduled Caste or Scheduled tribe | -0.017 | 0.003 | -0.019 | 0.01 | 0.002 |
|  | (0.02) | (0.01) | (0.02) | (0.01) | (0.01) |
| Number of other welfare programs received by household | 0.067\*\*\* | 0.032\*\*\* | 0.179\*\*\* | 0.091\*\*\* | -0.081\*\*\* |
|  | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| If the household head is a Hindu | 0.084\*\*\* | 0.076\*\*\* | 0.125\*\*\* | 0.055\*\*\* | -0.01 |
|  | (0.02) | (0.02) | (0.03) | (0.01) | (0.02) |
| Constant | 6.616\*\*\* | 5.913\*\*\* | 5.042\*\*\* | 1.967\*\*\* | 0.037\*\* |
|  | (0.02) | (0.02) | (0.03) | (0.02) | (0.02) |
| |  | | --- | | Observations | |  | |  | | 72,085 | 72,081 | 72,009 | 72,031 | 72,134 |
| Number of Households | 37,782 | 37,781 | 37,772 | 37,777 | 37,784 |
| R-squared | 0.19 | 0.20 | 0.18 | 0.19 | 0.29 |

Clustered Bootstrapped[[14]](#footnote-14) Standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 7A: Instrumental variables[[15]](#footnote-15)**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Variables** | **Log real monthly per capita expenditure** | **Log real monthly per capita food expenditure** | **Log real monthly per capita non-food expenditure** | **Log of household assets index** | **Log of number of household members working** |
| Log amount received under IGNOAPS instrumented with (Number of beneficiaries receiving the program ) | 0.576\*\*\* | 0.508\*\*\* | 1.148\*\*\* | 0.733\*\*\* | -0.422\*\*\* |
|  | (0.04) | (0.03) | (0.07) | (0.04) | (0.02) |
| Household size: Number of persons in the household | -0.125\*\*\* | -0.115\*\*\* | -0.199\*\*\* | -0.058\*\*\* | 0.143\*\*\* |
|  | (0.01) | (0.00) | (0.01) | (0.01) | (0.00) |
| Highest education in the household | 0.025\*\*\* | 0.018\*\*\* | 0.039\*\*\* | 0.029\*\*\* | 0.006\*\* |
|  | (0.00) | (0.00) | (0.01) | (0.00) | (0.00) |
| If the household lives in an urban area[[16]](#footnote-16) | 0.148 | 0.063 | 0.121 | -0.039 | 0.083 |
|  | (0.1) | (0.08) | (0.17) | (0.09) | (0.05) |
| Number of household members working as agriculture labours as a share of total working household members | -0.193\*\*\* | -0.114\*\*\* | -0.296\*\*\* | -0.159\*\*\* | -0.011 |
|  | (0.02) | (0.02) | (0.05) | (0.03) | (0.02) |
| Number of debts in the last 5 years | 0.022\*\*\* | 0.008\*\*\* | 0.030\*\*\* | 0.008\*\* | 0.003 |
|  | (0.00) | (0.00) | (0.01) | (0.00) | (0.00) |
| If the women in the household has access to newspaper | 0.104\*\*\* | 0.086\*\*\* | 0.155\*\*\* | 0.059\*\* | -0.040\*\* |
|  | (0.03) | (0.02) | (0.05) | (0.03) | (0.02) |
| If the women in the household has access to TV | 0.145\*\*\* | 0.096\*\*\* | 0.263\*\*\* | 0.278\*\*\* | -0.02 |
|  | (0.03) | (0.02) | (0.06) | (0.03) | (0.02) |
| If the household head belongs to Scheduled Caste or Scheduled tribe[[17]](#footnote-17) | -0.142\*\*\* | -0.107\*\* | -0.262\*\*\* | -0.145\*\* | 0.092\*\* |
|  | (0.05) | (0.04) | (0.1) | (0.06) | (0.04) |
| Number of other welfare programs received by household | 0.374\*\*\* | 0.303\*\*\* | 0.791\*\*\* | 0.475\*\*\* | -0.303\*\*\* |
|  | (0.05) | (0.04) | (0.09) | (0.06) | (0.03) |
| If the household head is a Hindu | 0.027 | 0.026 | 0.011 | -0.034 | 0.031 |
|  | (0.11) | (0.1) | (0.21) | (0.14) | (0.07) |
| Instrument: Number of beneficiaries receiving the program | 0.001\*\*\* | 0.001\*\*\* | 0.001\*\*\* | 0.001\*\*\* | 0.001\*\*\* |
|  | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| First stage F-statistic | 137.52 | 137.45 | 135.36 | 141.34 | 137.22 |
| Kleibergen-Paap Wald rk F statistic | 78.34 | 78.60 | 78.59 | 78.9 | 78.5 |
| Number of observations | 68598 | 68592 | 68466 | 68500 | 68692 |
| **Stock Yogo statistic:** 10% maximal IV size: 16.38  15% maximal IV size : 8.96  20% maximal IV size : 6.66  25% maximal IV size :5.53 | | | | | |

Robust standard errors are clustered at the PSUID level, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 8A: Instrumental variable regression using the variables used in the propensity score construction**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variables | Log real monthly per capita expenditure | Log real monthly per capita food expenditure | Log real monthly per capita non-food expenditure | Log of household assets index | Log of number of household members working |
| Amount received under IGNOAPS instrumented with Number of beneficiaries receiving the program | 0.002\*\*\* | 0.002\*\*\* | 0.003\*\*\* | 0.001\*\*\* | -0.002\*\*\* |
|  | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Household lives in rural area and attends public meeting | 0.042\*\*\* | 0.017\* | 0.032 | 0.019\*\*\* | 0.074\*\*\* |
|  | (0.01) | (0.01) | (0.03) | (0.01) | (0.01) |
| Highest level of education in the household | 0.004\*\*\* | -0.002 | 0.006\*\* | 0.021\*\*\* | 0.033\*\*\* |
|  | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| If the household head belongs to scheduled caste or schedule tribe | -0.079\*\*\* | -0.056\*\* | -0.127\*\* | -0.035 | 0.095\*\*\* |
|  | (0.03) | (0.03) | (0.06) | (0.02) | (0.03) |
| If the women in the household has access to TV | 0.119\*\*\* | 0.069\*\*\* | 0.209\*\*\* | 0.245\*\*\* | 0.002 |
|  | (0.01) | (0.01) | (0.02) | (0.01) | (0.01) |
| If the women in the household has access to newspaper | 0.031 | 0.018 | 0.026 | -0.008 | 0.025 |
|  | (0.03) | (0.02) | (0.04) | (0.02) | (0.02) |
| Number of beneficiaries receiving the program | 0.48\*\*\* | 0.48\*\*\* | 0.48\*\*\* | 0.48\*\*\* | 0.45\*\*\* |
|  | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| First stage F-statistic | 141.56 | 143.71 | 143.97 | 141.43 | 127.84 |
| Kleibergen-Paap Wald rk F statistic | 313.405 | 312.695 | 311.359 | 311.528 | 333.603 |
| Number of observations | 76446 | 76412 | 76270 | 76374 | 68792 |
| cluster | 39 | 39 | 39 | 39 | 39 |
| **Stock Yogo statistic:** 10% maximal IV size: 16.38  15% maximal IV size : 8.96  20% maximal IV size : 6.66  25% maximal IV size :5.53 | | | | | |

Robust standard errors are clustered at the PSUID level, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Figure 3A: Regions in common support 2005-06**



**Figure 4A: Regions in common support 2011-12**



**Figure 5A: PS match in 2005-06**



**Figure 6A: PS match in 2011-12**



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1. Wealth quintiles have been created from the household asset index. We have used the same type asset index for both 2005-06 and 2011-12 and all the assets in the index have equal weights. There are five wealth quintiles and the poorest (least number of assets) households (least number of assets) constitute wealth quintile 1 (figure 1), second poorest constitute wealth quintile 2, the median group constitutes wealth quintile 3, second wealthiest are in wealth quintile 4 and the wealthiest belongs to wealth quintile 5. [↑](#footnote-ref-1)
2. http://www.mospi.gov.in/sites/default/files/publication\_reports/ElderlyinIndia\_2016.pdf [↑](#footnote-ref-2)
3. Cash transfers made to poor families conditional on their children attending school and meeting health care requirements. [↑](#footnote-ref-3)
4. households with children or lactating/pregnant women provided on the condition fulfil a range of health and education-related obligation [↑](#footnote-ref-4)
5. This program provides monetary educational grants to families whose child is enrolled in school between the third grade of primary and the third grade of high school. [↑](#footnote-ref-5)
6. Rubin’s R statistic is the ratio of treated to control variances in the propensity score index [↑](#footnote-ref-6)
7. Rubin’s B statistic is the standardized difference of means of the propensity score [↑](#footnote-ref-7)
8. We have chosen the fixed effects model based on the results from Hausman test. The results are not reported here. We ran fixed effects and random effects model for all the outcome variables to compare outcomes and the initial hypothesis that household effects can be modelled using random effects is rejected, therefore we have used the fixed effects model. [↑](#footnote-ref-8)
9. http://www.who.int/bulletin/volumes/88/7/10-020710/en/ [↑](#footnote-ref-9)
10. Food expenditure includes spending on Rice, Wheat, Sugar, Other cereals, Cereal products, Pulses, Meat, Sweeteners, Edible oil, Eggs, Milk, Milk products, Vegetables, Fruits/nuts, Salt/spices and Other food. [↑](#footnote-ref-10)
11. Non-food expenditure includes Paan/tobacco/intoxicants, Restaurants/Eating out, Entertainment, Telephone/Cable/Internet charges, Toiletries, Transportation, Consumer taxes/fees, Services (domestic servants, barber, laundry, etc.) and Medical (out-patient services). [↑](#footnote-ref-11)
12. The assets index used here remains the same for 2005-06 and 2011-12. The assets include Any vehicle, Sewing machine, Mixer/grinder, Motor vehicle, Any TV, Colour TV, Air cooler/cond, Clock/watch, Electric fan, Chair/table, Cot, Telephone, Cell phone, Refrigerator, Pressure cooker, Car, Air conditioner, Washing machine, Computer, Credit card, 2 clothes, Footwear, Piped indoor water, Separate kitchen, Flush toilet, Electricity, LPG, Pucca wall, Pucca roof and Pucca floor. [↑](#footnote-ref-12)
13. Other welfare programs include Widow benefits, Disability benefits, Annapurna benefits, Other income benefits, NGO benefits and Maternity benefits. [↑](#footnote-ref-13)
14. Note: In table 6A we have bootstrapped for 500 replications. While for the previous tables we have only bootstrapped for 50 replications. [↑](#footnote-ref-14)
15. We have also tried the IV regression controlling for the effects of NREGA. The dependent variable on Number of other welfare programs received by household also included NREGA. But the result’s didn’t substantially change; the coefficient on real monthly per capita expenditure is 0.59%; food expenditure is 0.54%; non-food expenditure is 1.13%; household assets is 0.7% and the number of household members working reduced by 0.4%.All the results are significant at 1%. [↑](#footnote-ref-15)
16. Household living in urban area has a negative effect on the household assets formation and positively effects household labour supply. Urban area have more job opportunities, therefore if the household lives in an urban area then there is a higher likelihood for household members to work than living in rural areas. Similarly, controlling for all other factors living in urban area don’t positively affect household assets formation and place of residence is a non-significant variable. A plausible explanation for this could be that living in urban area alone cannot ensure long term wealth acquirement owing to the high cost of living in urban area. [↑](#footnote-ref-16)
17. As expected if the household head belongs to a socially disadvantaged caste group then this has a negative effect on household’s consumption expenditure and assets. The result is not surprising given that there is correlation between caste and poverty rates. [↑](#footnote-ref-17)