Impact of social protection policy targeted on the disabled: panel data evidence from India.

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Abstract

Social protection policies targeted at the disabled are hardly evaluated in developing countries. In this paper, we assess the impact of the Indira Gandhi National Disability Pension Programme (IGNDPS), a cash transfer programme targeted at the poor disabled in India. *We evaluate the impact on income and multidimensional poverty, annual budget share incurred on in-patient medical needs, monthly budget share incurred on out-patient medical needs, and real household earnings. We have combined the propensity score matching technique and the difference-in-differences method in panel data. Our empirical results suggest that access to IGNDPS has increased the annual share of expenses incurred on in-patient medical services (0.77%), possibly due to the lack of health insurance. Further, programme recipients have reported a decline in household earnings of 8.3%. Sex-based disaggregated results suggest that the female recipients have experienced a higher level of economic (12 percentage points) and multidimensional poverty (11.8 percentage points).*

Keywords: disability, poverty, welfare, social assistance programme

JEL codes: I31, I38, I18

1. Introduction

People with disabilities (PWDs) comprise 15% of the global population, and 80% live in low-middle-income countries (Uzair, Balog-Way and Koistinen, 2021). Disability is associated with higher levels of multidimensional poverty, lower educational attainment, lower empowerment, and higher medical expenditures in developing countries (Mitra, Posarac and Vick, 2013). However, very little is known about the impact of social protection policies targeted at PWDs and their households in developing countries. Although the deprivation of the disabled is a worldwide concern, the problem is more severe in India, where 26.8 million are disabled (Census, 2011).

Social protection policies predominantly take the form of social assistance programmes (cash transfers) in developing countries (Barrientos, 2011). They are targeted at the poor, focusing on poverty reduction and accompanying other development needs (ibid). Access to cash transfer programmes can help households with disabled members to ease economic burdens (e.g., medical expenses) associated with disability (Palmer, 2013). Further, evidence suggests that cash transfer programmes can help recipients to invest in long-term livelihood strategies.[1] Enhancement of livelihood strategies can improve household earnings, thereby promoting the economic participation of households having with PWDs. In the context of PWDs, social assistance programmes play an important role in reducing poverty, building resilience and

[1] Social protection and growth, no date, from https://cdn.odi.org/media/documents/9100.pdf

promoting inclusion and participation.[2] Article 28 of the Convention on the Rights of Persons with Disabilities, suggests social protection policies targeted at PWDs and their households should also provide them with an adequate standard of living in terms of sufficient food, clothing and shelter in addition to economic security (Palmer, 2013).[3]

Evidence suggests that social assistance programmes targeted at the disabled help them meet their basic needs; however, they have no poverty reduction effect (Loyalka et al., 2014). Similarly, in the case of Namibia, compared to non-programme recipients who have a disability, programme recipients of disability grants have reduced their poverty (Levine et al., 2011). Palmer et al. (2012, cited in Banks et al., 2017), that the penury cash transfer given to PWDs in Vietnam was not sufficient to make a significant impact on the lives of the disabled. In the case of Zambia, evidence indicates that households that receive disability benefits have better health outcomes, investment opportunities and increased community participation (Schneider et al., 2011). Semi-structured interviews conducted in Ghana suggest that programme participants in the disability fund face several barriers, including delays with fund disbursement, bureaucratic hurdles, and information asymmetry in accessing the programme (Opoku et al., 2019). However, there is a shortage of empirical literature that evaluates the

[2] How to Design Disability-Inclusive Social Protection, no date, available at https://reliefweb.int/report/world/how-design-disability-inclusive-social-protection

[3] Article 28 – Adequate standard of living and social protection, no date, available at https://www.un.org/development/desa/disabilities/convention-on-the-rights-of-persons-with-disabilities/article-28-adequate-standard-of-living-and-social-protection.html

impact of social assistance of programmes targeted at PWDs in Low-Middle Income countries (Banks et al., 2017).

In India, descriptive analysis suggests that the National Disability Pension Scheme programme is estimated to reduce poverty by 12% (Wapling, Schjoedt and Sibun, 2021). However, the descriptive analysis does not provide causal inference. National Disability Programme, later known as Indira Gandhi National Disability Programme (IGNDPS), was introduced in 2009 as the flagship of the National Social Assistance Programme (NSAP). NSAP also covers other social assistance programmes targeted at widows, pregnant women (maternity benefit), family benefits in case of death of household head and the elderly (social pension). There is empirical evidence on the impact of social pension and widow benefits programmes (see Garroway, 2013; Kaushal, 2014; Unnikrishnan and Imai, 2020; Unnikrishnan, 2022). However, no empirical evidence exists on the impact of the IGNDPS, and this still needs to be examined.

This is the first research that examines the impact of the Indira Gandhi National Disability Benefits Programme (IGNDPS), an unconditional cash transfer programme targeted at the poor- disabled in India on household welfare. We view welfare through Income Poverty (defined by the National Poverty Line), Multidimensional Poverty Index (MPI), Real Annual Household Earnings, the share of Annual Household Expenses incurred on In-Patient medical needs, and the share of Monthly Expenses incurred on Out-Patient medical needs.

We have used the nationally representative household-level panel data released by the India Human Development Survey (IHDS). The first round of the survey was conducted in 2004-05, which was implemented before the IGNDPS was implemented; hence this data constitutes a baseline. The second round of the survey was conducted in 2011-12, approximately two years after the programme was implemented. IGNDPS recipients and non-recipients can be systematically different, leading to selection bias. Therefore, we have used Propensity Score Matching (PSM) to address selection bias issues between participants and non-participants. We have matched based on the baseline characteristics (2004-05 round). Matching ensures that disabled-programme recipients are comparable with non-recipients and that there are no observable differences between the groups. Later, we employ a Difference in Differences (DiD) strategy in the matched panel in fixed effects settings to estimate the Average Treatment effect on the Treated. We have provided weights in the regression estimations. The weights are based on the propensity score, such that it reweights the sample to address any selection bias that could occur due to changes in the programme participation incentive across the rounds.

Four significant findings emerge here. First, the programme has failed to ease the economic burdens of households with PWDs. The programme has increased the share of annual household expenses incurred on in-patient medical needs (0.77%), possibly due to inadequate health insurance coverage. We also observe a decline in household earnings of programme recipient households by 8.3%. The decline in household earnings occurs mainly because programme-recipient households reduce their participation in sectors that involve physically strenuous work. Second, the programme fails to ensure a good standard of living, as we do not see any significant effect on MPI. Third, the sub-sample analysis suggests that the cash transfer programme reduces MPI in the large metro regions (9.9 percentage points (pp)), with no effect seen in the non-metro areas. Metro regions in India have better infrastructural facilities compared to non-metro locations. Such spatial disparities interact with poverty reduction policies, affecting the level of effectiveness of social assistance programmes in different regions. Fourth, we find that households with female recipients have an increased share of expenses incurred on in-patient medical needs (5.97%) and have reduced their share of out-patient medical expenses (2.45%). We also find that female recipients have experienced a higher level of income poverty (12 pp) and multidimensional poverty (11.8 pp). However, to further explore the programme's negative effect on female participants we required additional information on the attitudinal barriers faced by them. Given that we do not have information on social exclusion that female recipients face, it is hard to underpin the channel.

Broadly, the research aims to make three significant contributions.

First, the research employs a quasi-experimental framework to evaluate the impact of the disability benefits, providing rigorous empirical evidence on the programme. Second, given that there is limited empirical evidence on the role of social assistance programmes targeted at the disabled in developing countries, the research contributes to the existing literature on disability-related welfare policies that are scant in developing countries like India. Third, from a policy perspective, the paper provides insights into India's commitment to realise SDG-1 (end poverty) and 10.2 (empowerment of the disabled). It should be noted that India cannot realise its commitment to reach SDG-1 (end poverty) without addressing the economic vulnerabilities of the disabled.

We have discussed the IGNDPS in section 2. The data and the econometric approach adopted are detailed in sections 3 and 4; results and mechanisms are presented in section 5, and section 6 concludes.

2. Indira Gandhi National Disability Pension Scheme (IGNDPS)

NSAP was introduced in 1995, and the Government of India launched a series of social assistance programmes under its umbrella, including the old-age pension programme, maternity benefit, and family benefits scheme. In 2009, the government expanded the programme by introducing Indira Gandhi National Disability Pension Scheme and Indira Gandhi National Widow Benefits programme (National Social Assistance Programme, Government of India, no date). As stated in the government document, the expansion aims to cover other vulnerable groups within society. IGNDPS was targeted at persons with severe or multiple disabilities between 18-64 years from poor households. As per the guidelines provided by the government, the central government intended to contribute INR 200 (2.43 USD monthly) per beneficiary, expecting the state governments to contribute at least the equivalent of the centre's contribution.[4] If the state government matches the centre's assistance, each beneficiary receives INR 400 (4.86 USD monthly). For the programme recipients in 2011, we find that disability benefits (on average) constitute less than 5% of annual household consumption expenditure.

Figure 1 to be inserted here

[4] National Social Assistance Programme, no date, Government of India. Retrieved March 2023, from https://nsap.nic.in/Guidelines/guidelines%20on%20IGNDPS%2030sep09.pdf

The number of beneficiaries has been increasing since its inception, with some fluctuations in recent times (see Figure 1). In 2011-12 the Government of India allocated INR 1.05 billion to IGNDPS (approximately more than 13.3 million USD).[5] Gram panchayats and municipalities are responsible for identifying new beneficiaries. States are expected to organise camps to determine the disability status and to issue a disability certificate on the spot. These certificates are used as an identification strategy to target the disabled. The state is responsible for providing commuting facilities for the disabled to travel to these camps (National Social Assistance Programme, no date; Indira Gandhi National Disability Pension Scheme, no date). The households that fall Below the Poverty Line/BPL are provided with a card that denotes their socioeconomic status, and households deemed as poor/ultra-poor are provided access to the programme. In November 2012, the government revised the eligibility for the IGNDPS to 18-79 years of age and increased the central government contribution to INR 300-equivalent to 3.64 USD (Indira Gandhi National Disability Pension Scheme, no date).

The programme targets persons who have single or multiple disabilities. The government defines a person as disabled if someone has at least forty per cent of a single disability or eighty per cent of multiple disabilities verified by the medical authorities (Indira Gandhi National Disability Pension Scheme, no date). Research highlights a lack of clear guidelines and a higher degree of subjectivity involved in the execution of the programme (Palmer, 2013). Evidence suggests that only 46 per cent of the PWDs possess disability certificates, a mandatory

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[5] Data.gov.in, accessed on March 1st 2023, from https://data.gov.in/catalog/physical-and-financial-progress-nsap-components?filters%5Bfield_catalog_reference%5D=89991&format=json&offset=0&limit=6&sort%5Bcreated%5D=desc

document required to access the programme (Wapling, Schjoedt and Sibun, 2021). The treatment group consists of 0.9% of the matched sample. The relatively small sample size of programme recipients (N: 324) could also be due to the inaccessibility of disability certificates. However, the dataset does not collect information on the decision to apply for the programme. It is possible that households PWDs voluntarily decided not to participate in IGNDPS (given the small value of benefits) or didn't manage to obtain a disability certificate.

3. Dataset and empirical challenges

We have used the panel data from India Human Development Survey (IHDS) to examine the impact of the IGNDPS. We have used the nationally representative household-level panel data available for 2004-05 and 2011-12 (Desai and Vanneman, 2010; 2015). The dataset comprises 40,018 households captured in 2004-05 and 2011-12. The publicly available dataset has extensive information on various outcome variables, which we aim to examine in this research. Further, the IHDS dataset captures both ex-ante (2004-05 rounds) and ex-post (2011-12) of the IGNDPS (implemented in 2009). This provides a setting to perform Differences in Differences (DiD). To apply a DiD, we require information on the outcomes for those who received the IGNDPS (treatment) and those who didn't (control) ex-ante and ex-post policy intervention.[6] DiD compares the differences in the mean value for the outcomes in the treatment (participants) and the control (non-participants) group, ex-ante, and ex-post IGNDPS policy intervention.

We have applied PSM in the first step to address concerns about selection bias with any observable differences in the characteristics of programme participants and non-participants. Post matching, we have applied DiD in the matched panel data to evaluate the programme's impact. We have defined all the variables in Appendix 1, and the summary statistics are in Appendix 2. Most of the outcome variables are directly observable in the dataset. MPI has been constructed following Dehury and Mohanty (2015). MPI covers health, education, economic status, work and employment and household environment dimensions. We have applied the equal weight strategy proposed by Alkire and Foster (2007 and 2011), ensuring that all

[6] https://diff.healthpolicydatascience.org/

dimensions are equally important. The details on MPI construction are detailed in Appendix 3. Subsequently, we have detailed some empirical challenges faced in this research.

3.1. Empirical challenges

There are two econometric challenges. First, IGNDPS is a self-selected programme. In this case, selection bias exists as some households choose to participate in the programme and others do not, making the programme recipients and non-recipients non-comparable. Therefore, we have employed PSM in the first stage to address selection bias. PSM helps identify a comparable counterfactual group from the sample, and PSM ensures that the distribution of the treatment and the counterfactual group look identical based on observable characteristics. This is further detailed in section 4.

Second, the dataset has captured the recipients of the state-level disability programme in 2004-05 round under IGNDPS. It should be noted that although the central government introduced the program in 2009, some progressive state governments implemented disability programmes much earlier (see the Appendix section in Rao, 2004). In the 2004-05 data (prior to matching), we observed 174 disabled pension recipients. This has increased more than 209% in the second round (539 program recipients), coinciding with the national-level implementation of the programme under IGNDPS. In IHDS-2, 97.5% of disability pension program recipients (526 recipients) received the programme only in 2011-12. They did not receive the benefits in 2004-05.

The number of overlaps with participants receiving the programme in both rounds is small (70 recipients) to compare the relative effectiveness of state versus national-level disability assistance programmes. However, to strengthen the identification strategy, we have excluded households who claimed to have received the benefits either in both rounds (70 recipients) or only in the 2004-05 round (89 recipients). The treatment status would take the value one in the sample if the household received the IGNDPS in 2011-12, whose baseline characteristics have been tracked in 2004-05.

4. Econometric approach

4.1 Propensity Score Matching

This method was proposed by Rosenbaum and Rubin in 1983. PSM relies on the assumption of overlap such that the treatment and the control group have similar distributions after matching. In the first step, we estimated a probit model on the probability of receiving the treatment (IGNDPS) conditioned on certain explanatory variables using 2005 data. We matched on a wide range of covariates, ensuring that the treatment and the control group are comparable based on observable characteristics.

We have used the covariate on households attending public meetings. Previous research on the NSAP programme has noted that public meetings provide a valuable podium to disseminate knowledge on the social assistance programme (Unnikrishnan and Imai, 2020). Qualitative evidence suggests such meetings are significant in helping rural beneficiaries to gain knowledge on social assistance programmes (Unnikrishnan, 2019). Therefore, we have interacted the variable on attending the public meeting with the place of residence (rural/urban). Caste acts as a useful predictor of wealth in India. The scheduled caste/tribe, which constitutes a lower caste is accounted for in the specification. We have also accounted for other wealth proxies, including the roof structure, owning a television, and the highest level of education (Garroway, 2013; Unnikrishnan and Imai, 2020). In addition to these covariates, we have included the covariate on the proportion of adult males in the household. It should be noted that India has one of the lowest female labour market participation rates compared to its South Asian neighbours.[7] The variable on the proportion of adult males reflects the earning potential.

Most of the covariates mentioned above are available on the database. however, the challenge has been to identify a measure of disability. Given the ambiguity around what constitutes single or multiple disabilities, the definition used by Wapling, Schjoedt and Sibun (2021) has been applied.

IHDS includes questions related to activities of daily living on five functional domains: seeing, walking, hearing, communicating, and self-care (Wapling, Schjoedt and Sibun, 2021). The dataset records information if someone "can do the task with difficulty" or is "unable to do". A person is moderate disabled if they "can do it with difficulty" in at least one functional domain (ibid). They are classified as severely disabled if they are "unable to do" in at least one functional domain (see Box1-1 in Wapling, Schjoedt and Sibun, 2021). We applied this information at the individual level to identify PWDs. We later collapsed the dataset at the household level to construct a single variable- if the household has someone with moderate/severe disability. Since the programme is targeted at disabled persons belonging to BPL/ultra-poor households, we have interacted the variable on disability with the poverty status criterion.

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[7] Verick, S., no date, Women's labour force participation in India: Why is it so low? *International Labour Organisation*. Available at https://www.ilo.org/wcmsp5/groups/public/---asia/---ro-bangkok/---sro-new_delhi/documents/genericdocument/wcms_342357.pdf

The estimated results from the first-stage probit estimate, for PSM, are reported in Appendix 4. We find that wealth proxied with the household's education level decreases the household's probability of participating in IGNDPS. The larger earning potential of the household captured by the proportion of adult males in the household reduces the probability of receiving the benefits. Participating in public meetings in rural areas increases the likelihood of receiving IGNDPS. We have also attempted alternate models incorporating the household head’s sex, household size (number of adults), and dependents (number of male and female children) in the specification. However, we do not find any significant effect of the additional variables. Therefore, we have used the results from the primary model for matching.

Post-matching, we used the PS test to evaluate the quality of matching. The results from the PS test suggest that after matching, there are no comparable differences observed between the treatment and the control groups (Table 1).

Table 1 to be inserted here.

The overlap graph is presented in Figure (2) suggest that the treatment and control groups have similar distributions in the baseline, implying the treatment and control groups are comparable. After matching, the sample consists of 34,709 units. The treatment group consists of 324 beneficiaries (0.9% of the matched sample), and the control group of 34,385 units. Further, we performed a DiD analysis on the matched sample using the balanced panel data.

Figure 2 to be inserted here

4.2 Difference in Differences (DiD) estimation

$$Y_{ht} = \beta Trmt_{ht} + \delta_{ht} + \lambda postline_t + \mu_{Dist} + \varepsilon_{ht} \quad (1)$$

In equation (1) Y_{ht} is the outcome variable which includes annual share of household expenditure incurred on inpatient medical services. We re-estimated (1) for other outcome variables. The coefficient of interest is the estimated impact of IGNDPS ($\beta Trmt$). The effect of time fixed effects (postline) is captured by λ, and μ captures district fixed effects in the estimation.

It should be noted that in balanced panel data, the estimated treatment coefficient (β) is equivalent to the interacted effect used in the standard DiD framework. This empirical framework has been increasingly used in policy evaluation research (Galiani, Gertler and Schargrodsky, 2005; Unnikrishnan and Imai, 2020; Unnikrishnan, 2022). Following Unnikrishnan and Imai (2020), we provide weights based on the propensity score (PS) such that the treatment group receives a weight of one, and the control group gets a weight of PS/1-PS. The weight will reduce the sample selection bias as the incentive to participate in the programme could change between the rounds (ibid). We have used most of the observables used in the matching process as control variables. However, due to a potential endogeneity issue, we have dropped the variable on BPL card as a control variable in the DiD estimation. Also, we have used the control variables on religion and several other welfare assistance programmes received by the household in the DiD estimation. These variables are more likely to affect outcome variables on poverty and multidimensional poverty. Previous works have applied a similar approach of including a few additional variables in the DiD estimations after matching (Unnikrishnan and Imai, 2020; Unnikrishnan, 2022). As a measure of robustness, we have re-estimated our main specification (results reported in Table 2) only with variables used in the PS specification. The results are discussed in section 5.

DiD estimates rely on the parallel trend assumption assuming that the treatment and the counterfactual groups would be constant over time, without the treatment. However, to examine this assumption, we require three rounds of the survey, but we have only two rounds of the survey (Unnikrishnan, 2022). The key advantage of implementing DiD estimates in the matched sample is that it is least sensitive to the violation of parallel trend assumption (Ryan et al., 2019). We use nationally representative, household-level panel data, implying that the treatment and control groups likely exhibit similar trends (Unnikrishnan and Imai, 2020).

5. Results and Discussion

The estimated results from equation (1) are detailed in Table 2.

Table 2 to be inserted here.

Our empirical findings also suggest IGNDPS programme recipients, compared to similar non-programme recipients, have reported a decline in earnings by 8.3%. We find that access to the disability pension programme increases the share of in-patient medical expenses by 0.77%.

Examining the control variables, we find that education and household male composition (proportion of adult males) are significant determinants of household earnings and poverty reduction. We have mixed evidence on expenses incurred on in-patient/out-patient medical needs. Education reduces the share of allocation to out-patient medical needs, but household male composition increases the share allocated to in-patient medical needs.

Also, given the rural-urban divide in India, residing in a rural area (compared to an urban area) reduces household earnings, increases medical expenses and worsens MPI. The lower-caste group in India continues to experience a higher income poverty and multidimensional poverty, despite an increase in household earnings. Households that belong to the Muslim religion tend to experience higher income poverty. The income effect generated from other social assistance programmes boosts spending on out-patient medical care, with no effect observed on other outcome variables.

As measure of robustness, we re-estimated the specification with only the variables used in the matching specification. The results suggest that IGNDPS recipients compared to non-recipients have significantly reduced earnings (11. 8%).[8]

5.1 Mechanisms

A key finding is that recipients compared to non-recipients have reduced earnings. [9] The standard labour-leisure model argues that with the arrival of a cash transfer programme, beneficiaries trade-off labour for leisure, subsequently reducing household labour supply. The broader notion of reduction in household labour supply masks specific nuances. It is possible that recipient households may reduce their participation in physically demanding tasks rather than non-laborious tasks.

To explore this, we examined the programme's effect on various sectors of employment. We consider the result on the sub-sample of type of disability (moderate/severe). This helps to understand if the type of disability affects the household labour market decision. Our sub-sample results on moderate disability suggest that programme recipients, have reduced labour market participation as agricultural (10.8 pp) and non-agricultural labourers (17 pp) (Appendix 5). In the case of the severe disability sub-sample, recipient households have drastically reduced their participation in agricultural labour (26 pp) and non-agricultural labour by 14 pp.

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[8] Results will be shared on request.

[9] The programme does not enforce any labour market withdrawal condition on the beneficiaries or their household, which can otherwise lead to a drop in earnings.

We do not observe any reduction in participation in other sectors (having a business/salary/farm). Agricultural and non-agricultural sectors (e.g., construction) are physically strenuous, and the decline in household earnings is due to reduced participation in these sectors.

The other main findings suggest that recipients' increase their spending on in-patient medical expenses (0.77%). This can occur for two reasons. First, due to the programme's income effect, which refers to an increase in the disposable income of programme beneficiaries. However, we do not observe any significant effect of the programme on household income.[10]

Alternatively, it is also possible that the cost of in-patient health care is higher, leading to a subsequent larger share of budget allocation on this item. We examined the programme's impact on households accessing the Rashtriya Swasthya Bima Yojana (RSBY). The Government of India introduced RSBY- National health insurance programme in 2008.[11] The programme targets poor households and covers in-patient medical care expenses.[12] We have information on RSBY recipients in the 2011-12 rounds. Therefore, we examined the impact of IGNDPS for households with RSBY in the 2011-12 rounds (Appendix 6). We did not find any effect of the programme on the annual share of expenses incurred on in-patient medical needs.

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[10] We do not find any significant effect of the programme on household income (excluding disability benefits). Results are kept from being shared here to keep up the length of the paper.

[11] India.gov.in, accessed March 2023, from https://www.india.gov.in/spotlight/rashtriya-swasthya-bima-yojana

[12] India.gov.in, accessed March 2023, from https://www.india.gov.in/spotlight/rashtriya-swasthya-bima-yojana#rsby2

However, it led to a reduction in MPI (5.18 pp). The results suggest that health insurance helps IGNDPS recipient households to mitigate health shocks, allowing them to reallocate resources to address multidimensional poverty.

5.2 Other extensions

Table 3 to be inserted here.

Major metropolitan regions in India continue to be drivers of economic growth. Evidence suggests that the quality of basic services is consistently higher in large metropolitan cities which have a higher per-capita income level.[13] The residents enjoy better access to infrastructure than those living in non-metros. We have disintegrated results for metro and non-metro regions to understand how spatial inequality in infrastructure impedes the effectiveness of poverty reduction policies (see Table 3). The sub-sample results suggest that recipients living in the metropolitan areas have reported reduced household earnings (6%). However, these households have reduced multidimensional poverty (9.9 pp). There is no significant impact of the programme in non-metropolitan regions.

[13] Non-metropolitan class 1 cities of India, no date, retrieved from https://smartnet.niua.org/sites/default/files/resources/HUDCO%20Phase%20II.pdf

5.3 Sub-sample estimations

Table 4 to be inserted here.

For the male sub-sample, we do not find any significant effect of the programme on the outcome variables studied (Table 4). However, income and multidimensional poverty have been exacerbated in the case of female recipients. We do not have information on if the female recipient households face any exclusion/stigma associated with accessing the programme. Evidence suggests that in Kenya, women with disabilities did not access health facilities even with free health care (Kabia et al., 2018). They faced additional barriers. For instance, the need for someone to accompany them to such facilities, the negative attitudes of healthcare workers also constrained access to healthcare (ibid). In section 5.1, we identified that not having access to health insurance is the main reason for recipients to incur higher spending on medical needs. However, from the Kenyan example discussed above, we gather that in the case of women with disabilities, we should examine such findings in light of other intersectionalities like social exclusion/perceptions.

In other alternative estimations, in the sub-sample of the scheduled caste or tribe households, we find a decline in the share of outpatient expenses with no significant effect on other outcomes.[14]

[14] Results will be shared on request.

5.4 Endogeneity and other selection issues

The outcomes in 2011/12 (postline) should not affect the treatment assignment in 2004-05 (baseline), ensuring that there is no reverse causality.

We have matched based on observable characteristics. However, if selection into the programme is influenced by other unobservable factors that can also lead to selection bias. Therefore, we have estimated a selection specification model in the baseline, individual-level data. This method is similar to the Heckman selection model.

$$Pr(disabled)_i = \beta\_0 + \gamma\_ht + \delta\_it + \epsilon\_it \qquad (2)$$

First, we have estimated the probability of an individual (i) being disabled based on their individual (δ) and household (h)-specific characteristics (γ).[15] The error term (ϵ) captures all the other unobservable factors affecting disability. Subsequently, the predicted probability has been used in our primary regression matched DiD specification (equation 1). Similar to Heckman's selection, we assume that the error terms in equation (1) and (2) are correlated. The estimated results after incorporating the probability values (from (2)) are consistent with the

[15] We have included the variable on age, sex, place of residence, marital status, number of persons in the household, years of education completed, scheduled caste or tribe, Muslim, asset quintile of the household, number of days lost due to short-term morbidity, number of days lost due to long-term morbidity, highest female education in the household, smoking/drinking behaviour.

main findings (full sample) reported in Table 2. We find a positive effect on share of expenses incurred for in-patient medical expenses (0.8), and a reduction in household earnings (8%).

5.5 Robustness measures

The government changed the age in November 2012 (see section 2), and there is ambiguity if the survey (2011-12 rounds) was done before or post the change. We evaluated the effects by excluding those who failed to meet the age eligibility criterion of 18-79 years of age. The estimated results suggest that access to the disability pension programme negatively affects household earnings.

Alternatively, we have estimated the effect of the programme on the sub-sample of moderate and severe disabled persons. The results remain consistent with reduction in earnings (29%) and increase in MPI (6.7 pp).[16]

[16] Results will be shared on request.

6. Conclusion and policy suggestions

The paper examines the impact of the IGNDPS, a social assistance programme targeted at the disabled poor in India, on poverty and other welfare dimensions. We find that recipients have reported declining earnings, primarily due to reduced household labour market participation in sectors which involve physically strenuous work. Further, recipient households having health insurance have reallocated the benefits to reduce income and multidimensional poverty. The finding suggests the need to link IGNDPS recipients with other complementary health insurance programmes.

Our sub-sample results on the Metro/Non-Metro region highlight spatial disparities in development, as recipients residing in the metro regions, have reduced MPI, with no such effect found in the non-metro areas. There are spatial disparities in infrastructure growth in India, with metro regions having better facilities. This uneven development has implications for effectiveness of poverty reduction policies. The same programme generates different responses depending upon where the recipient resides. However, to address spatial differences in poverty reduction policies, the government needs to have a long-term commitment to increase investment and access to services in non-metro areas.

The household survey does not provide information on attitudes/ perceptions/ structural barriers that women PWDs face. Such insights are necessary to explore why female recipients experience a higher level of poverty, a higher share of in-patient medical expenses, and a lower share of out-patient medical expenses. This research gap can be explored in future. Also, due to data limitations, we did not consider the types of disabilities (physical vs mental) on the outcomes.

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Table 1: PS test results 2004-05 rounds after matching

Variables	Mean values for the treatment group after matching	Mean values for the control group after matching	P>|t|
Household has someone moderately or severely disabled interacted with BPL/ultra-poor household card	0.041	0.029	0.368
Household roof structure	0.198	0.219	0.48
Household lives in rural area interacts with attending public meeting	0.29	0.24	0.16
Ratio of adults male in the household	0.268	0.289	0.06
Highest adult education in the household	6.8	7.46	0.10
If the household has a TV	0.525	0.523	0.972
Household belongs to scheduled caste/tribe	0.31	0.29	0.56

Table 2 -Weighted fixed effects DiD results [main results]

	Annual household earnings (log transformed)	Share of exp-in-patient	Share of exp-out-patient	Income poverty	Multidimensional poverty (MPI)
Main explanatory variable					
Trmt: Household receiving IGNDPS	-0.083*	0.774*	-0.136	0.004	0.002
	(0.04)	(0.38)	(0.31)	(0.01)	(0.01)
Control variables					
Attends public meeting	0.057	-0.66	0.21	-0.007	-0.02*
	(0.04)	(0.39)	(0.29)	(0.01)	(0.01)
Ratio of male adults in the household	0.957***	2.51*	0.15	-0.325***	-0.331***
	(0.1)	(1.27)	(1.06)	(0.04)	(0.04)
Education of the household's head father/husband	0.04***	0.092	-0.08***	-0.010***	-0.012***
	(0.00)	(0.06)	(0.03)	(0.00)	(0.00)
Place of residence: Rural	-0.76***	0.62	1.619***	-0.015	0.124***
	(0.05)	(0.4)	(0.4)	(0.02)	(0.02)
Other welfare programmes received	-0.10	-0.149	1.395*	0.027	0.06
	(0.06)	(0.69)	(0.62)	(0.03)	(0.03)
Muslim	0.08	-0.33	0.10	0.04*	0.0262
	(0.05)	(0.47)	(0.48)	(0.02)	(0.02)
Scheduled caste/tribe	0.126***	-0.16	-0.34	0.071***	0.113***
	(0.04)	(0.37)	(0.35)	(0.01)	(0.01)

District fixed effects	Yes	Yes	Yes	Yes	Yes
Postline (time fixed effects)	Yes	Yes	Yes	Yes	Yes
Number of observations	47677	66474	66468	66488	65518
R-square	0.39	0.136	0.117	0.256	0.31

Note: *p < 0.05, **p < 0.01,***p < 0.001.
Robust standard errors in parenthesis.

Table 3 -Other extensions of weighted fixed effects DiD estimations

	Share of exp-in-patient	Share of exp-out-patient	Annual Household earnings (log transformed)	Income poverty	Multidimensional poverty (MPI)
Metro[17]					
Trmt: Household receiving IGNDPS	6.12	-1.5	-0.60*	-0.013	-0.099***
	(5.4)	(1.3)	(0.3)	(0.05)	(0.02)
Control variables	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes
Postline (time fixed effects)	Yes	Yes	Yes	Yes	Yes
Number of observations	5180	5,179	3950	5,181	5041
R-square	0.24	0.12	0.51	0.19	0.17
Non- metro					
Trmt: Household receiving IGNDPS	0.66	-0.09	-0.07	0.005	0.005
	(0.4)	(0.3)	(0.04)	(0.01)	(0.01)
Control variables	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes
Postline (time fixed effects)	Yes	Yes	Yes	Yes	Yes
Number of observations	61294	61289	43727	61307	60477
R-square	0.13	0.12	0.38	0.26	0.31

Note: *p < 0.05,**p < 0.01,***p < 0.001. Robust standard errors in parenthesis.

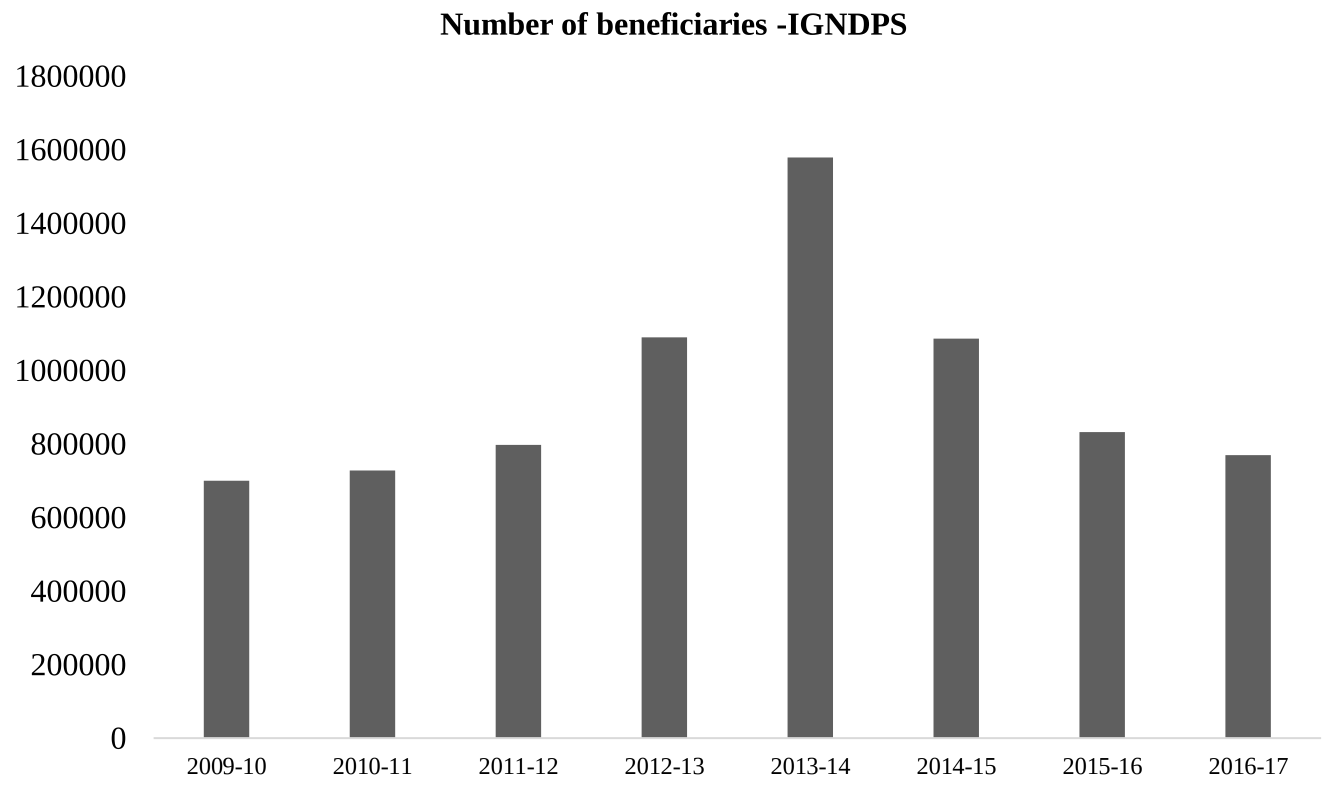
[17] Metro represents Delhi, Mumbai, Kolkata, Chennai, Hyderabad, Bangalore.

Table 4 -Sub-sample estimation

	Share of exp-in-patient	Share of exp-out-patient	Annual Household earnings (log transformed)	Income poverty	Multidimensional poverty (MPI)
Sub-sample: Male					
Trmt: Household receiving IGNDPS	- 1.47	1.10	-0.126	-0.06	-0.05
	(1.69)	(1.08)	(0.1)	(0.04)	(0.04)
Control variables	Yes	Yes	Yes	Yes	Yes
Dist fixed effects	Yes	Yes	Yes	Yes	Yes
Number of observations	1381	1381	938	1381	1356
R-square	0.62	0.70	0.79	0.65	0.77
Sub-sample: Female					
Trmt: Household receiving IGNDPS	5.977***	-2.45**	-0.10	0.12*	0.118*
	(1.6)	(0.84)	(0.1)	(0.05)	(0.05)
Control variables	Yes	Yes	Yes	Yes	Yes
Dist fixed effects	Yes	Yes	Yes	Yes	Yes
Number of observations	1988	1988	1371	1988	1938
R-square	0.62	0.51	0.73	0.67	0.65

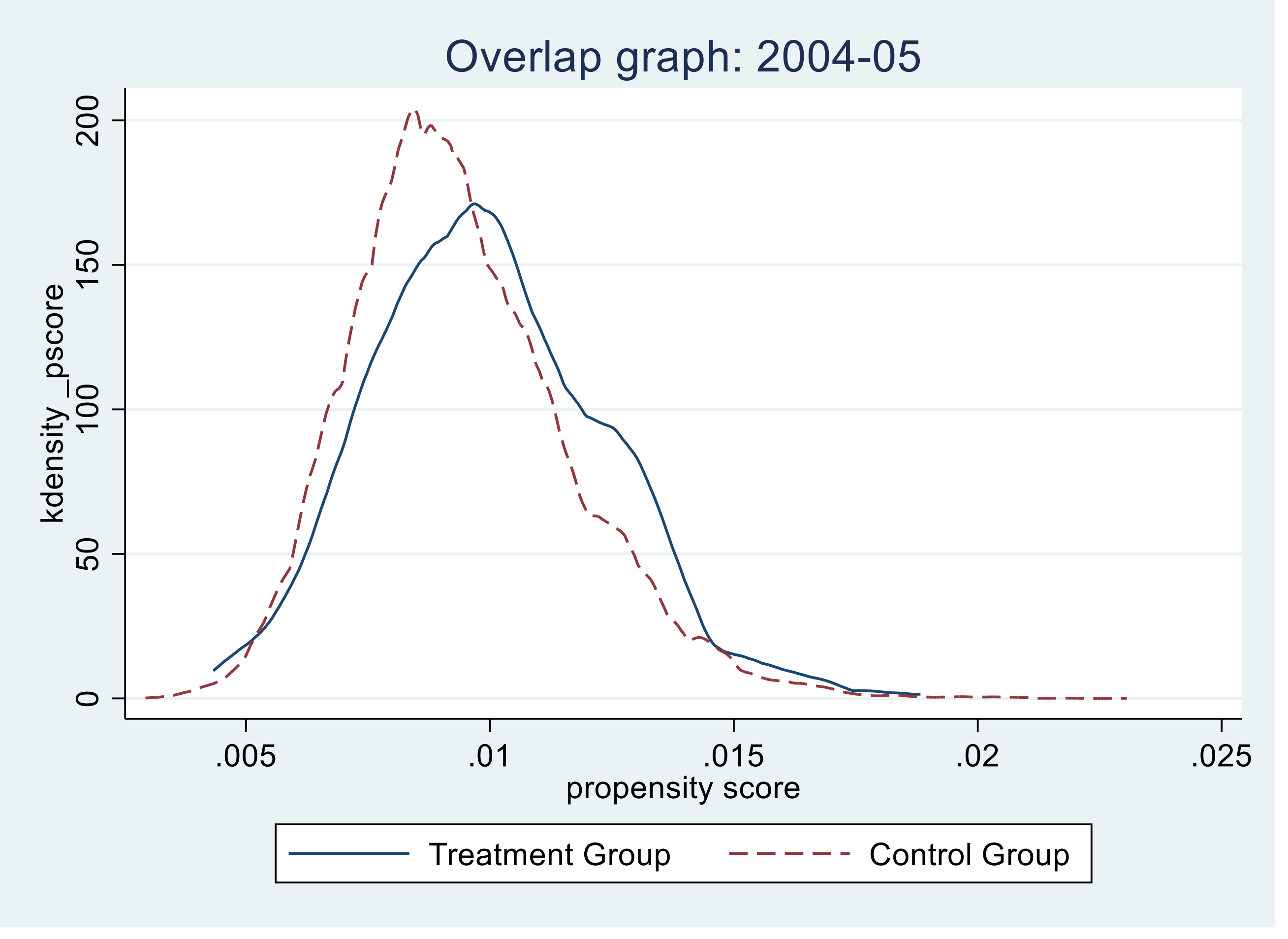
Source: Authors' calculation; *p < 0.05, **p < 0.01, ***p < 0.001. Robust standard error in parenthesis.

Figure 1: Total number of beneficiaries receiving-IGNDPS



Source: https://data.gov.in/resources/all-india-level-expenditure-and-beneficiaries-under-nsap-2002-03-2016-17
Accessed on March 1st, 2023

Figure 2: Distribution of propensity score for baseline



Appendix 1: List of variables

List of variables	Definition	Details
(A) Variables used in the PS specification in the 2011-12 rounds		
Household has someone moderately or severely disabled	If the household has someone moderately or severely disabled, it takes the value one, else zero.	We have used a function-based approach to construct disability status indicator. We have followed the definition given by Wapling, Schjoedt and Sibun, 2021 who have used similar framework in the context of India.
BPL/ultra-poor	The dummy variable on takes the value one if the households belong to Below Poverty Line (BPL)/ ultra-poor categories; else, it takes the value 0.	For the PS specification we have interacted this variable with household has someone moderately or severely disabled.
Household roof structure	The variable takes the value 1 if the household roof is made of grass, mud, thatch, wood, else it takes the value zero	This captures the economic status as roof structures made of grass, mud, thatch, and wood denotes low economic status.

Attends public meeting	The variable takes the value one if someone in the household attends a public meeting, else zero	Public meetings often serve as a place where information on various welfare programmes are disseminated.
Place of residence: Rural	Takes the value one if the household lives in a rural area; otherwise, the variable takes the value zero.	For the PS specification we have interacted this variable with the variable on attends public meeting
Ratio of adult male in the household	Ratio of the of number of male adults to total household members	
Scheduled caste/tribe	The variable takes the value one if the household belongs to either scheduled caste/tribe category; if not, the variable takes the value zero.	
Household owns TV	Takes the value 1 if the household own T.V else it takes the value zero	
Highest adult education in the household	The variable captures the highest level of education of the adult in the household	

(B) Outcome variables		
Expense on in-patient medical services (share of exp-in-patient)	Annual share of in-patient medical expense to total household expenditure.	The medical expense and household expenditure variables are in real terms. Amount spent on in-patient medical expense is only available on annual basis.
Expense on out-patient medical services (share of exp-out-patient)	Share of out-patient medical expense (monthly) to total monthly household expenditure.	The medical expense and household expenditure variables are in real terms. IHDS has recorded monthly details on out-patient medical services, therefore the variable is calculated as a share of monthly household expenditure.
Annual household earnings	The variable captures the annual household earnings with bonuses	The variable is converted to log terms.
Income poverty	The variable takes the value one if the household experiences income poverty; else, it takes the value zero.	The dataset uses Tendulkar poverty threshold to identify someone as economically poor. If the consumption of household is below threshold provided by the Tendulkar Committee the household is considered to be poor, else not.
Multidimensional poverty (MPI)	MPI takes the value one if the household is experiencing multidimensional poverty. Else, it takes the value zero.	MPI was calculated using the standard Alkire-Foster method. Additional details are there in the Appendix 3.
(C) Additional control variables used in the regression specification		

Muslim	If the household head belongs Muslim religion, the variable takes the value one. Else, the variable takes the value zero.
Other welfare programmes received	Total number of other welfare programmes received by the household
Education of the household's head father/husband	This continuous variable captures the education level of the household head's father or husband.

Source: Author's elaboration from the IHDS dataset

Appendix 2- Weighted summary statistics after matching

	Baseline (2004-05)				Postline (2011-12)			
	Mean for the whole sample (N:34709) 1	Mean: Treatment (N:324) 2	Mean: Control (N: 34385) 3	F-stat (reported on 2 and 3)	Mean for the whole sample (N:34709) 4	Mean: Treatment (N:324) 5	Mean: Control (N: 34385) 6	F-stat (reported on 5 and 6)
Outcome variables								
Share of exp-in-patient	3.0	3.84	2.97	2.97	4.03	5.14	3.99	3.63
Share of exp-out-patient	5.3	4.83	5.39	1.62	5.07	5.27	5.10	0.13
Annual household earnings (log transformed)	10.66	10.5	10.61	2.18	10.77	10.65	10.73	1.13
Income poverty	0.22	0.256	0.23	0.82	0.16	0.16	0.17	0.25
Multidimensional poverty (MPI)	0.26	0.284	0.283	0.00	0.187	0.18	0.20	0.64
Control variables								
Attends public meeting	0.29	0.33	0.332	0.00	0.29	0.38	0.30	10.42***
	0.287			0.17	0.306			
Ratio of male adults in the household		0.263	0.27			0.30	0.29	0.32
Education of the household's head	2.48			0.40	2.61			
father/husband		2.2	2.32			2.26	2.44	0.77
Place of residence: Rural	0.66	0.72	0.68	1.95	0.66	0.72	0.68	1.95
Scheduled caste/tribe	0.289	0.302	0.31	0.06	0.29	0.29	0.31	0.29
Muslim	0.119	0.123	0.121	0.01	0.12	0.12	0.122	0.01
Other welfare programmes received	0.036	0.05	0.039	0.61	0.08	0.11	0.08	1.74

Note: *p < 0.05, **p < 0.01, ***p < 0.001

We have presented above the data descriptive of all the key variables after matching. We have provided descriptive for the whole sample 2004-05 (column 1) and 2011-12 rounds (column 4). The mean values presented for the entire sample explore changes across two waves. In addition, we have disaggregated the mean values for the treatment (columns 2 and 4) and the control group (columns 3 and 6) for each round. We have also reported the F-stat to gauge if there are significant differences between the treatment and the control group post-matching. The sample size of the treatment group (N:324) is bigger than the control group (N: 34385).

Outcome variables

On comparing the mean value (whole sample) in baseline and postline, we find that at all India levels, there has been an increase in the share of expenses incurred on in-patient medical purposes and a reduction in both income and multidimensional poverty. At means, the share of expenses allocated for outpatient medical purposes declined in the 2011-12 round. Further, there has been no substantial improvement in annual household earnings in 2011-12 compared to the 2004-05 round. On further disintegrating the data, we find the treatment group at means has spent less than 4% of the annual household budget share to meet in-patient medical needs in the baseline, which has increased to 5.1% in the postline.

Similarly, the monthly household budget allocated for meeting outpatient medical expenses has increased from 4.83% in the baseline to 5.27% in the postline for the treatment group. We do not observe any significant increase in household earnings over time for the treatment group. Income poverty and MPI have dropped for both the treatment and the control group from baseline to postline.

Control variables

We performed matching based on the baseline characteristics. The same set of variables has been used as control variables in the regression specification and some additional variables. All India mean values are reported in columns (1) and (3). Post-matching; we do not find significant differences (F-stat) between the treatment and the control group in baseline and postline. The only exception is the variable on attending the public meeting. Postline, we observe a significant difference in the proportion of beneficiaries attending public meetings in the treatment group (38%) versus the control group (30%).

Appendix 3- MPI construction

Multidimensional Poverty Index has been constructed following Dehury and Mohanty (2015), who has estimated MPI regional estimates using IHDS-(2004-05) rounds. MPI covers various dimensions, including health, education, economic status, work and employment and household environment. Following Dehury and Mohanty (2015), we have used appropriate indicators that best capture these dimensions. However, in some instances, we have applied certain modifications that are also stated in the Table below. The authors constructed the index using the 2004-05 rounds of IHDS. However, keeping in line with the 2011-12 survey, we have modified the indicators measuring per-capita annual income and low-paid employment sector classification used in the work and employment dimension. Further, we used the consumption threshold provided Tendulkar Poverty Line estimation to define the household's economic status. The consumption threshold provided by the Tendulkar committee classifies a household to be economically poor if they are below a nationally determined consumption line. Following Alkire and Foster (2007 and 2011), Dehury and Mohanty (2015) have applied the equal weight strategy. All the dimensions (health, education, economic status, work and employment and household environment) are equally significant.

Sn	Dimensions	Description of indicators used by Dehury and Mohanty	Modifications	Weights
1	**Health**	**Mortality (V1)**: Any child or adult (<60years) death occurred in the household in last one year preceding to the survey date		1/10=0.1
		Nutrition (V2): If the household has any undernourished (BMI <18.5) ever married women (15-49 years)		1/10=0.1
2	**Education**	**School enrolment (V3):** At least one school-age child (6-14 years) in the household currently not enrolled in school		1/10=0.1
		Years of Schooling (V4): No adult member (15 years and above) in the household has completed five years of schooling		1/10=0.1

3	**Economic**	**Consumption expenditure (V5):** If the household falls below the consumption expenditure threshold limit (official poverty line)	Alternatively, we have used the Tendulkar poverty line (classification to define- and 2011-12) poverty.	2/10=0.2
4	**Work and Employment**	**Occupation (V6):** If the per-capita annual income is less than Rs. 5000 and the household belongs to either low paid non-farm business, or labour class households, or low land holdings (<2.5 acre)	We have used the similar description given by the authors (Dehury and Mohanty, 2015). We have retained low-land holdings criteria set by the authors (<2.5 acre). However, we have modified per-capita income criterion. We have used the per-capita income criterion less than Rs. 4538 for the 2004-05 round. However, for the 2011-12 rounds we have used per capita income criterion greater than of Rs. 6288. We define working in low paid non-farm business, if the household engages in Shopkeepers, Other farmers, Plantation labour, Other farming, Forestry ,Hunters, Fishermen, Barbers, Launderers. We also define labour class household if the main source of income is from cultivation, agriculture/non-agriculture wage labour and petty shops.	1/10=0.1

		Employment (V7): No one in the household (15-59 years) has worked more than 240 hours in one activity in the last year preceding to the survey date	1/10=0.1
5	**Household environment**	**Water (V8):** No access to clean drinking water	1/15=0.067
		Sanitation (V9): No access to adequate sanitation	1/15=0.067
		Cooking fuel (V10): No access to clean cooking fuel	1/15=0.067
		Sum of weights	**1**

Source: Dehury and Mohanty (2015) and author (modification column)

Appendix 4: First stage probit results

	Probability of receiving IGNDPS	
	Primary model	Alternate model
Household roof structure	-0.070	-0.06
	(0.05)	(0.05)
Ratio of adult male in the household	-0.33*	-0.385*
	(0.1)	(0.2)
Highest adult education in the household	-0.009*	-0.006
	(0.0)	(0.0)
Lives in rural area and attends public meeting	0.097*	0.108*
	(0.04)	(0.0)
Household has someone moderately or severely disabled	0.128	0.132
	(0.1)	(0.1)
household has a BPL card	0.017	0.02
	(0.0)	(0.0)
Scheduled caste/tribe		
Household owns TV	0.059	0.06

	(0.04)	(0.0)
		-0.034
		(0.01)
Number of adults in the household		
		-0.042
		(0.02)
Number of male children in the household		
		-0.014
		(0.02)
Number of female children in the household		
		0.0035
Sex of the household head (1/0)		(0.01)
Number of observations	38050	38050
PseudoR2	0.005	0.0088

Note: *p < 0.05, **p < 0.01, ***p < 0.001; standard errors in the parentheses.

Appendix 5: Effect of disability pension programme on sectors of employment

	Number of household members participating in various sectors for employment				
	Agriculture labour	Non-agriculture labour	Salary	Business	Farm
Sub-Sample: Moderate disability					
Trmt: Household receiving IGNDPS	-0.108**	-0.17***	0.013	-0.016	0.003
	(0.04)	(0.02)	(0.03)	(0.04)	(0.09)

Control variables[18]	Yes	Yes	Yes	Yes	Yes
Dist fixed effects	Yes	Yes	Yes	Yes	Yes
Number of observations	8740	8740	8740	8740	8740
R-square	0.51	0.44	0.43	0.39	0.46
Sub-Sample: Severe disability					
Trmt: Household receiving IGNDPS	-0.26**	-0.14**	0.03	-0.02	0.06
	(0.08)	(0.05)	(0.06)	(0.09)	(0.14)
Control variables[9]	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes
Postline (time fixed effects)	Yes	Yes	Yes	Yes	Yes
Number of observations	3617	3617	3617	3617	3617
R-square	0.50	0.39	0.42	0.45	0.54

Note: *p < 0.05, **p < 0.01, ***p < 0.001; robust standard errors in the parentheses.

[18] The same control variables as in footnote 12 excluding the variable on religion (Muslim) that was dropped due to collinearity

Appendix 6: Sub-sample analysis on households with health insurance in 2011-12

	Share of exp-in-patient	Share of exp-out-patient	Annual Household earnings (log transformed)	Income poverty	Multidimensional poverty (MPI)
Trmt: Household receiving IGNDPS	0.74	-0.79	-0.05	-0.03	-0.0518*
	(0.9)	(0.5)	(0.06)	(0.02)	(0.02)

Control variables[19]	Yes	Yes	Yes	Yes	Yes
Dist fixed effects	Yes	Yes	Yes	Yes	Yes
Number of observations	4539	4538	3730	4541	4499
R-square	0.38	0.37	0.62	0.43	0.46

Note: *p < 0.05, **p < 0.01, ***p < 0.001; robust standard errors in the parentheses.

[19] The same control variables as in Table 2. We have excluded the variable on religion (Muslim) here, which was dropped due to collinearity.