How well targeted are social assistance programs in India- a case study of Indira Gandhi National Old Age Pension Scheme

Contents

Abstract:

Targeting is a key hurdle faced in the implementation of social assistance programs. The inclusion of non-eligible beneficiaries leads to type-2 errors; while the exclusion of eligible leads to type 1 error in the program. In this context the following study aims to study about targeting errors in the Indira Gandhi National Old Age Pension Scheme (IGNOAPS) - an unconditional cash transfer program focussed on the elderly in India. Using the Panel data released by the IHDS we investigate the role of political connections and other social networks in targeting error incidence of the program. The results suggest that political network increases the probability of non-eligible receiving the program (type-2 error) which clearly signals favouritism. This has policy implications as local political factors are considered to be exogenous in designing social policies.

INTRODUCTION

Vulnerabilities are present in all stages of human life, but they are most sharply felt during the old age (Gupta, 2013). Constant deprivation of the poor prevents them from making any safety arrangements for their old age. Drifting away from traditional joint families and rise in migration further increases the dependence of poor on the government in India. It is in this context a government sponsored pension scheme like Indira Gandhi National Old Age Pension Scheme (IGNOAPS) play a vital role in providing safety net for the vulnerable section of the society.

Targeting is a key hurdle faced in implementing social assistance programs. It is often seen that social assistance programs that are implemented in large scale usually fails to reach the intended beneficiaries. Indira Gandhi National Old Age Pension Scheme program had been in place from 1995, but there is very little information available on the public domain about the program. At present in order to be eligible for this program an individual should belong to a below poverty household and should be greater or equal to 60 years of age. This eligibility criterion is prescribed by the central government and is used for providing assistance to the state government. The estimates from the nationally representative data collected by IHDS shows that the per cent of non-eligible among the total beneficiaries in this program was 60% in 2005-06 and this has come down to 38.5% in 2011-12. This indicates that the targeting incidence has come down, but it also highlights that there is evidence of targeting error in the scheme. One potential reason for targeting error could be that besides the eligibility criteria stated by the government there are other possible determinants for receiving this scheme. The role of networks in providing access to social assistance program is well documented. Given this background the following paper unpacks the role networks in this scheme.

The question on targeting is important for two reasons. First, the purpose behind any targeting scheme is scarcity of economic resources which is more acute in a developing country like India. Therefore, given that we have limited economic resources it is important to identify the deserving recipients. Second, this would further deepen our understanding on the scheme given that there is limited secondary information available on this scheme. The existing literature on the scheme focuses on the aspects of consumption, poverty (Garroway,2013), compliance (Gupta (2013), Duta (et al) (2010) and Chopra and Puddussery (2014)), wellbeing of the elderly, living arrangements, employment and expenditure (kasuhal,2014) and the role of networks in targeting error is yet to be explored.

The paper is divided in four sections. The first section focuses on targeting incidence in the scheme, program implementation and the literature on networks and IGNOAPS, in section 2, we have discussed about the data and section three focuses on methodology and in the last section we have discussed about the findings of the paper.

1. Targeting incidence- program implementation & networks

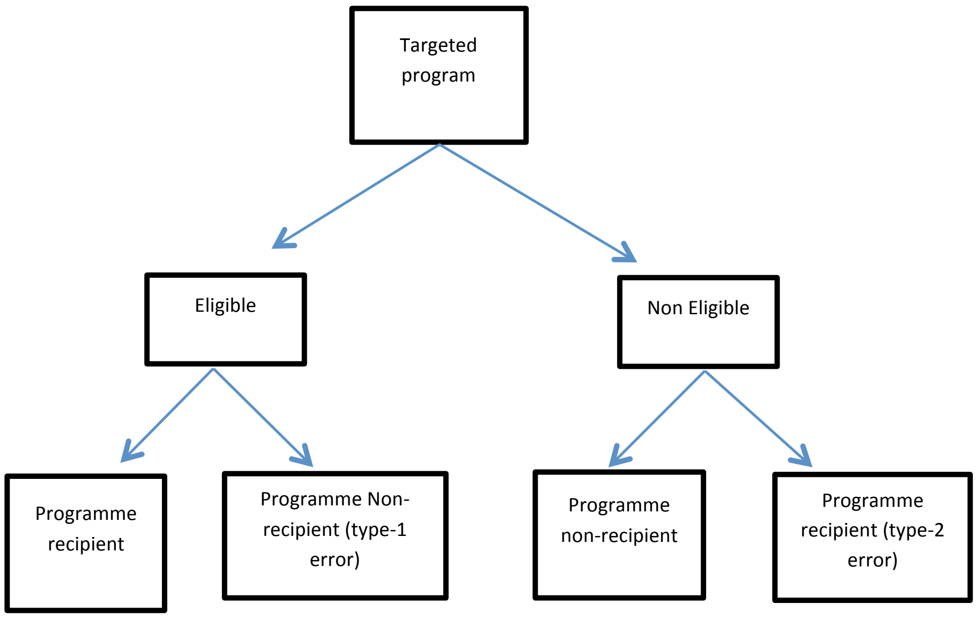
As the title suggest this section has discussion on three interrelated components. The first component of targeting incidence in the program is connected with the aspect of program implementation mechanism. The component on program implementation leads to the final part on the role of networks; this provides an assertion on why we suspect the role of networks in this scheme.

1.1 Targeting incidence

Targeted program usually focuses on a fixed set of eligibility criteria. There are different targeting mechanisms which include: individual assessment, self-selection and categorical targeting. Individual assessment is done at the household or individual level and is based on the assessment unit's income or education attainment. Conditional cash transfers given to the poor based on their children's school attendance or merit scholarship programs is an example of individual assessment. The second targeting mechanism of self-selection is a choice variable; this mechanism provides poor an option to participate or not to participate in the program. An example for this is the Below Poverty Line welfare program implemented in India that provides subsidised food materials for the poor; the poor can choose to buy or not to buy from these subsidised shops. Categorical and Geographical targeting is when targeting takes place based on ethnicity, family status, gender or a particular geographical location (World Bank,2007). IGNOAPS can be classified as a mean tested, self-selected and categorical targeted program.

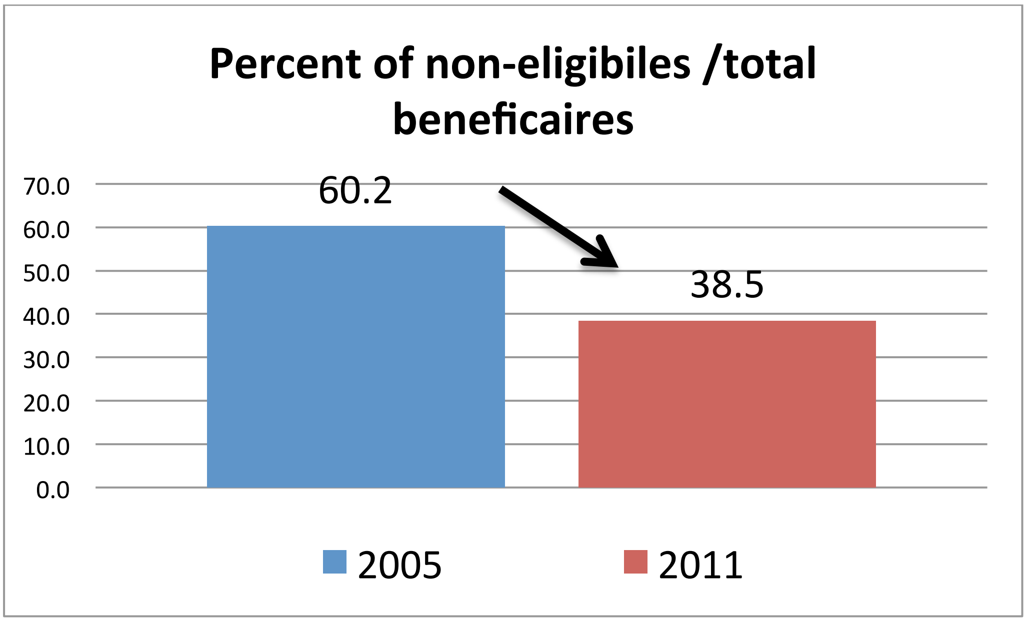
In any targeted program there are two groups of individuals/households; one is a set of eligible and the other group consist of non-eligible (figure 1). When programs are targeted based on some eligibility criteria then all the eligible should constitute the group of program recipients. If the eligible individuals or households do not receive the program then this leads to type 1 error. The non-eligible individuals /households should ideally constitute the group of program non-recipients, but if the non-eligible receives the program then it leads to type 2 errors.

Figure 1: Targeting error



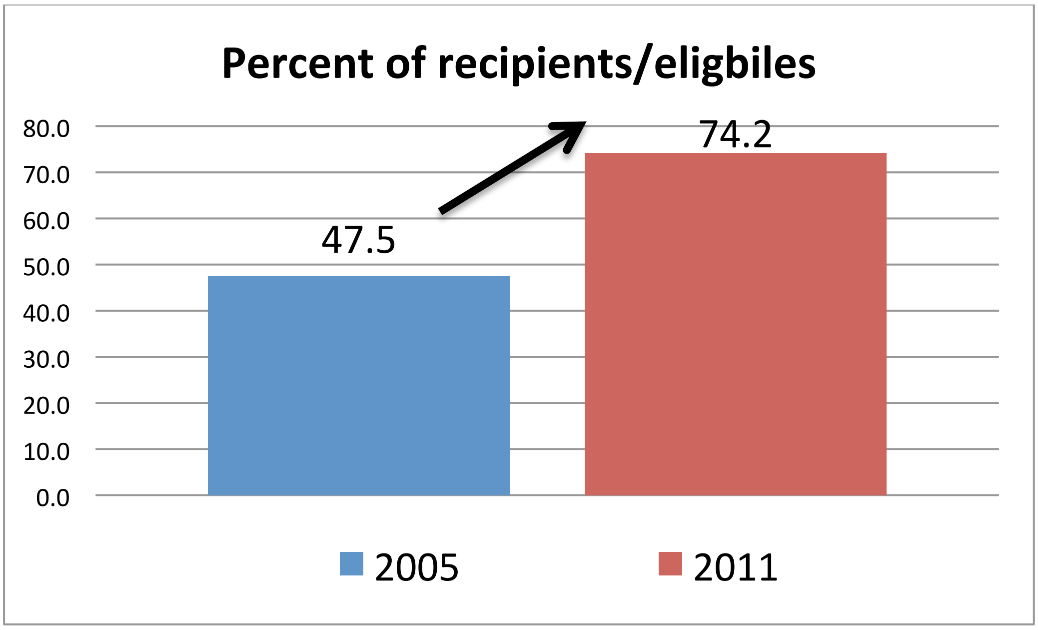
In the context of IGNOAPS in 2005 the per cent of non-eligible to total beneficiaries was 60.2% in 2005 and this has come down to 38.5% in 2011 (figure 2). The per cent of recipients among the eligible was 47.5% in 2005 and this has increased to 74.2% in 2011 (figure 3). This clearly indicates that there has been a decline in targeting incidence. In 2005 the eligibility criteria used by the central government was that the person should be or greater than 65 years of age and also be a destitute. There was no formal mechanism that was used to identify a destitute. Hence, the government in 2007 changed the criteria of being a destitute to someone belonging to a Below Poverty Line household. The use of an observable criterion over the time has reduced the per cent of non-eligible receiving the program (figure 2). In 2011 the program underwent the second round of change when the eligible age criterion was reduced from 65 to 60 years. This has led to inclusion of more persons in the scheme (figure 3).

Figure 2: Non-eligible in IGNOAPS



Source: IHDS data (2005-06 and 2011-12)

Figure 3: Eligible recipients in IGNOAPS



Source: IHDS data (2005-06 and 2011-12)

In table 1 and table 2 the incidence of targeting is further sub-classified for the years 2005 and 2011. In both the tables we have listed out the number of right targets, which is the set of individuals who have met the eligibility criteria and are receiving the program and also the non-eligible who do not receive the program. The numbers of eligible individuals who are not receiving the program constitutes type 1 error. As mentioned earlier, the number of non-eligible individuals who do not receive the program also constitutes under the right targeting group. But the number of non-eligible individuals receiving the program constitutes type-2 errors in the program. We are usually not concerned about the right targets and it is only the type-1 and type 2 targeting errors that are worrisome. Therefore, the analysis in this paper focuses on the non-eligible individuals receiving the program (type 2) and eligible individuals who do not receive the program (type 1).

We have not used the conventional mechanism from the literature to measure the targeting errors. Type 2 targeting error in the literature is measured as the number of non-eligible individuals receiving the program in the whole sample. This way of calculation is more relevant if the data is collected only to study about that particular program. But the IHDS dataset used in this paper is not collected for the purpose of studying about IGNOAPS. Therefore when I estimate type 2 errors (number of non-eligible/ (number of non-eligible + non recipient of IGNOAPS)) my denominator becomes larger and the type 2 errors in the program become insignificant. The idea behind highlighting the targeting incidence is to shed light on the issue of targeting in the program, but the use of conventional method undermines the error in the program. Therefore in table 1 & and table 2 we have only provided the actual numbers on targeting errors. The Pearson chi2 statistic in both the tables is significant and this indicates that in both years being eligible for the program is essential for receiving the program. This shows that eligibility and being a recipient of the program are dependent on each other.

Table 1: Targeting errors in 2005

	2005	Recipient	Non-recipient	Total
Eligibility	Yes	Right target (540)	Type-1 error (3,199)	3,739
	No	Type-2 errors (915)	Right target (209,882)	210,797
	Total	1,455	213,081	214,536

Pearson chi2 (1) = 1.4e+04***

Table 2: Targeting errors in 2011

	2011	Recipient	Non-recipient	Total
Eligibility	Yes	Right target (2,650)	Type-1 error (6,032)	8682
	No	Type-2 errors (1,723)	Right target (200,412)	202,135
	Total	4,373	206,444	210,817

Pearson chi2 (1) = 3.2e+04***

In the subsequent section we have discussed about the program and also about the implementation mechanism.

1.2 Background of the scheme

National Social Assistance Program (NSAP) was introduced by the central government of India in 1995 with the aim to provide safety net to the vulnerable section in the society. The three major components of the scheme include: National Old Age Pension Scheme (NOAPS), National Family Benefit Scheme (NFBS) and National Maternity Benefit Scheme (NMBS). NOAPS was provided to a destitute applicant with no means to live and who are and above 65 years of age. Central government provided an assistance of Rs.75 to eligible beneficiary. In 2002-03 this central government initiative was converted into a state plan; from when on all the financial assistance provided by the central government were in the form of 'Additional Central Assistance'. And over the years there have been iterations in the scheme. In 2007 the scheme was renamed as Indira Gandhi National Old Age Pension Scheme and the eligibility criteria for the scheme changed from being a destitute to any person who have attained 65 years or higher and should belong to a below poverty household. And the scheme was formally launched in 2007. The central assistance to the beneficiaries was also increased from Rs. 75 to Rs.200 was provided to the beneficiaries in the same time. In an memorandum released by the Ministry of Rural Development in 2011, the age eligibility criteria for the program was lowered from 65 to 60 years and the cash entitlements for recipients who are above 80 years of age increased from Rs.200 to Rs.500. In a recent initiative the central government of India has released revised guidelines for NSAP and have proposed to re-convert NSAP back to a central government plan.

Figure 4: Time scale

23rd September 2007

- Renamed as IGNOAPS
- People who are above 65 years old and belonging to a BPL household is eligible under the scheme
- The scheme was formally launched on 19-11-2007
- Central assistance was increased from Rs.75 to Rs.200

30th June 2011

- Age eligibility criteria were lowered from 65 to 60 years for both male and female.
- The central rate of assistance provided to beneficiaries who are above 80 years of age was increased from Rs.200 to Rs.500
- The revised norms will be implemented from 1.4.2011

Source: NSAP website

The central government had requested the state governments to make an equal or greater contribution under the scheme. But there are states that haven't made any contributions besides the central government assistance and there are states that have made lesser contribution to the scheme. The central government provides state government the independence to modify the implementation of the scheme. The table 1a in the appendix section enumerates the amount of pension, state contribution and eligibility criteria used by states to identify IGNOAPS beneficiaries. The secondary information has been collected from various state government portals on eligibility criteria, but there isn't any secondary information available for some states. Based on the information available it can be observed that apart from Delhi and Haryana that uses income criteria, other states still use BPL as the eligibility criteria for the scheme. The number of beneficiaries in the program was more than 17 million in 2010-11 and this has increased to more than 22 million in 2012-13[i]; the increase in the number of beneficiaries indicates the scale of operation in the program.

1.2.1 Implementation of the scheme

National Social Assistance Program (NSAP) was introduced by the central government of India in 1995 with the aim to provide safety net to the vulnerable population of the society. The three major components of the scheme include: National Old Age Pension Scheme (NOAPS), National Family Benefit Scheme (NFBS) and National Maternity Benefit Scheme (NMBS). There are various stages involved in working of the NSAP schemes which includes identification of the beneficiaries, verification, getting inputs at the local level from the Gram Sabha / Ward Sabha /Area Sabha (figure 5 below). The program implementation at the district level is done by the Zila Parishad or its equivalent. At the local level, the Gram Panchayat /Municipality implement the program. The mechanism in which the program works may vary across each state. But as per the NSAP guidelines issued the following steps are to be followed in the program implementation process

Figure 5: Implementation process

Source: NSAP website

- ***Identification***

The first step is to identify the beneficiaries. Identification of beneficiaries is based on the BPL census conducted in 2002. At the local level Gram Panchayats / Municipalities play a pivotal role in identifying beneficiaries. Beneficiaries are primarily identified based on the BPL census. Identification of new beneficiaries is done based on: application filed by the citizens, the beneficiaries can also be identified by the gram panchayat /municipality or any other competent authority. In all the cases completion of application is mandatory.

- ***Verification of applications***

The state appoints a verification officer or a team who under the supervision of an authorized officer verifies all the applications and provides reasons for sanction or rejection.

- ***Discussion - Gram Sabha /Ward Sabha /Area Sabha.***

The verification authority needs to discuss about the list of recommended applications with the Gram Sabha in rural areas or Ward Sabha / Area Sabha in urban areas. The suggestions of these bodies need to be reported by the verification officer to the sanctioning authority.

- ***Sanction***

The sanctioning authority at the Municipality / Block level will approve applications that are verified and recommended by the Gram Sabha / Ward Committee / Area Sabha. The sanctioning authority will issue orders of the approved application to the Gram Panchayat /Municipality.

In an ideal situation the sanctioning process should increase the chances of deserving recipients to receive benefits. But given there are many non-deserving recipients receiving benefits, the role of networks can't be undermined. Given that there is incidence of targeting error in the program, the paper further explores the role of networks in helping individuals to receive the program. In the next section the literature on networks is discussed.

1.3 Networks

Networks play an important role in providing information to people. And given the important role played by information people often tend to believe information from their own personal sources (Granovetter, 2005). Information asymmetry and higher level of illiteracy in the developing countries further perpetuates the significance of information from their reliable counterparts. Apart from providing information networks are also as a source of dependence in times of crisis. Banerjee &Duflo (2007) found that poorer households tend to depend on villagers, friends and other relatives for financial help.

The role of networks in the lives of poor is well documented by Williams, Glynn et.al (2003). Based on their study in the states of West Bengal and Bihar in India the authors found that the in rural areas networks with panchayat members are important for them to access loans. Panchayat member also emerged as a key focal point of contact, helping the villagers to gain admission to hospitals or school.

Putnam (1993) in his famous work on "Making Democracy work" has distinguished between two types of networks, horizontal and vertical networks. A horizontal network refers to relationship with agents of equal status. While vertical network refers to relating agents of unequal status or rather the relationship is hierarchical. Putnam has cited networks of civic engagement as an example of horizontal networks. Parton-client relationship as an example of vertical network because the relationship is hierarchical and is characterised by dependence rather than on solidarity. Networks of civic engagements, like neighbourhood associations, choral services, cooperatives, sports club represents horizontal interactions; high membership density of these organisations is indicative of higher level of co-operation for mutual benefit. The key difference between a horizontal and vertical network is the former is a "web like" network and the latter is a "may pole like" networks (Putnam, page number 173)

Some studies don't formally use the terminology of vertical relationship; rather they name it as elite connectedness or political association which implies a vertical relationship as the nature of such relationships are hierarchical. Panda (2015) found that household proximity with panchayat/nagarpalika/ward committee brightens their chances of getting a BPL card. Using the IHDS-phase 1 data the authors found that political connections of the household play an important role enabling households to get the BPL card at the national, rural and the urban level. The concept of political capture of public goods is widely seen in India and this plays an important role in determining an individual's access to the scheme. Hiraway (2003) has highlighted the same issue by pointing out that in the presence unequal power structure which is more prevalent in the Indian context, the problem with targeted schemes are to identify poor persons with specific characteristics. Galasso and Ravallion (2005) studied about the Bangladesh's Food-for-Education Program and their results confirmed that villages with high levels of land inequality are not efficient at targeting the poor through the program.

Using the horizontal and vertical framework developed by Putnam, Caeyers and Dercon (2012) found that a household that has close relations with persons holding official positions has higher probability of receiving food aid in Ethiopia. These households have 12% percentage higher probability of receiving the food aid compared with households with no official tie ups. The authors divided the household networks into horizontal, vertical and informal networks. Horizontal refers to networks with equal powers; vertical refers to network with a local political power and informal networks are those whom poor can depend in times of crisis. Horizontal network aids information flow to households. And vertical network help individuals to gain favouritism or it can signal the need for support. In order to measure horizontal networks the authors used the size of the largest iddir (funeral society) to which the household belongs. Vertical network refers to close association of the household with political elites. It is measured as the number of household's close associates who holds any official position in the peasant association. Informal social networks is measured based on the number of households or individuals that the household can depend during times of crisis.

The authors found that vertical networks play an important role in helping people to access food in the aftermath of a drought situation. And even at the later period vertical networks play an important role in deciding upon the amount of transfers received. Households with higher level of informal social network have a lower probability of receiving food aid. Newman and Zhang (2015) found that in Vietnam that households which have proximity with local government are more likely to be classified as poor, a key determinant factor for whether the households receive public benefits program. Markussen and Tarp (2011) found that in the case of Vietnam having a relative in political and bureaucratic position increases the household's agricultural investment. Connections are important as they strengthen property rights, access to loans and off-farm employment.

Alatas et.al (2013) in their work on Indonesia measured elite connectedness; in order to measure elite connectedness the author used two household measures: a household member holds a formal or informal leadership role, if someone is connected to these households with formal and informal leadership by marriage or by blood. Das (2015) measured political connections by political strength. Political affiliation is measured if the household supports the local party in power; political strength is measured using if the household participates in political meetings. Vertical ties may not always be relationship with elected representatives. It can also be ties shared between poor and a person of in formal organisations like bank, police and agricultural extension officer. Although residents and tenant associations is an example for horizontal networks, but for residents in these associations this could also be a vertical tie as it links them with an influential above them who control over their daily lives (Middleton et.al (2005)).

Aida et.al (2009) studied about the role of horizontal and vertical social capital on health. With the help of principal component analysis they categorised groups of high principal scores into horizontal social capital and low scores into vertical social capital. The groups included in the category of vertical social capital are political organizations and associations, industrial and professional groups, religious groups and associations, local community associations, old age clubs, and volunteer fire-fighting groups. And horizontal social capital includes volunteer groups, citizens' and consumer action groups, sports groups and clubs, and hobby clubs. The idea of using principal component analysis factor loadings to decide between horizontal and vertical groups may not be the most appropriate measure. By not looking at the nature of these associations and relying only on principal component analysis to group them as horizontal and vertical social capital is logically inconclusive.

There are multiple lenses to view horizontal and vertical networks; horizontal networks are usually measured as group membership in civic engagement groups and vertical networks are measured as political connection/affiliation of the household. There are other microscopic aspects of these networks, for example: a horizontal church group can still have a hierarchical social structure, a predominant characteristic found in vertical networks (Grootaert, 1999). Putnam defined a civic community as one where there is co-operation, solidarity and public spiritedness which could equally been seen in a church group.

Group memberships are commonly used as a measure of horizontal networks, but one need to use this with caution in the context of developing countries as the formal organizations are relatively scarce. And as pointed in the literature (Krishna, (2004)) formal associations in Indian villages are formed by state governments and formations of these organisations reflect the organizational skill of the state governments, but these organisations can be redundant with its functioning. We need to take into account the feature of informal networks as well in the developing countries; informal network can still be horizontal in nature. There are various mechanisms used to measure networks which indicate that there isn't any standard way to measure both horizontal and vertical networks. The measurement of networks transcends across boundaries.

In this paper we are keen to know about the role of networks in aiding individuals to receive the program. A horizontal network is synonymous to solidarity framework, which is a sense of acting together with a public spirit, and this network help individuals with information flow thereby it increases the probability of someone receiving the scheme. While vertical networks which signify political connection of an individual can help non-eligible individuals to gain access to the program. The research question here is to study the role of networks in the context of targeting errors in the program; and having a horizontal or vertical network can have different implications on the probability of receiving the program. Although networks play an important role in helping individuals to receive the program their role is not explored in the existing studies on IGNOAPS. In the next section we have discussed about the existing literature on IGNOAPS.

1.4 Literature on IGNOAPS

Garroway (2013) evaluated the impact of the scheme on the aspects of consumption and household income. The author has evaluated both old age pension scheme and widow pension scheme from the NSAP program. Since the program has selection bias as the eligibility is based on the BPL status and Antodya ration card, the author has used the propensity score estimator to evaluate the impact of the program on the household's incomes, consumption and poverty status of the beneficiaries. The results suggest that the recipients of old age pension scheme have lower consumption and incomes and higher poverty rates than their counterfactual control group.

Kaushal (2014) investigated the impact of the Indira Gandhi National Old Age Pension Scheme on the wellbeing of the elderly, living arrangements, employment and expenditure pattern in India. The author has combined the data on employment and unemployment schedule from the 61st (2004-05) and the 64th (2007-08) round of National Sample Survey. The study found that any increase in pension also lead to higher family expenditure, it was also found that in 2007-08 after the increase in pension amount there has been a higher allocation of expenditure towards Medicare and Education. On studying the impact of the pension on living arrangements it was found that pension increase the probability of elderly living in the household, but the results were statistically insignificant.

Gupta (2013) has reported the findings of a survey conducted in March 2011 in a district each in states of Jharkhand and Chhattisgarh. The study aimed to evaluate the impact of the National Old Age Pension Scheme; the evaluation was done on the aspects of delivery mechanism, corruption and the impact on reducing the vulnerabilities of the beneficiaries. This paper reported their findings based on a survey conducted in March 2011 in a single district in Jharkhand and Chhattisgarh to evaluate the functioning of the IGNOAPS. The result was based on the findings of the field work conducted in Latehar district of Jharkhand and Sarguja district of Chhattisgarh on 2011. Both these districts have a large tribal population and are considered backward regions. Based on the responses collected from 60 persons at the block level it was found that respondents found it difficult in accessing banks and they were delay in delivery mechanisms. The delay in cash delivery is due to administrative mechanisms that delay the flow of funds at various levels of administration. The finding also includes the need to index amount transferred with the inflation level. It was also found that the scheme works with very less corruption levels.

Dutta (et al) (2010) evaluated the impact of the National Old age Pensions to the elderly and the widows based on IDHS data and the special purpose household survey data conducted in Karnataka and Rajasthan. The study found that these pensions work well with low level of leakages and targeting the elderly in the poor households. The study has used two datasets to analyse the targeting and coverage aspects of the scheme they have used the IHDS conducted in 2004-05; in order to gauge about leakages they have used a special-purpose household surveys that was conducted in Karnataka (in 2005) and Rajasthan (in 2006). The study has primarily evaluated the social pension scheme from the aspects of coverage, compliance and targeting. The authors found that pension schemes perform better than public distribution system; despite its low coverage pension schemes have relatively low level of leakage.

There has been evaluation of the scheme with respect to consumption, poverty, targeting, compliance, wellbeing of the elderly, living arrangements, employment and expenditure. However, the role of networks is yet to be explored, which will be the contribution of this study. Although Dutta et al has looked at the issue of targeting the study was done at a micro scale, the study will use an all India survey and will explore the role of networks in the context of targeting error in the scheme.

2 Data

We have used the survey data released by IHDS; the survey has information on social capital, labour, education, health and expenditure information both at the household and individual level. The survey was conducted in 1995, 2004-05 and 2011-12. But the 1995 survey was conducted not keeping in mind the possible future rounds; hence there is incomplete documentation for that round. The 2005 data is a nationally representative data collected across 41,554 households, 1503 villages and 971 urban neighbourhoods. The total sample comprises of 41,554 households and this can be divided into two major categories: re-interview households (N=13,900) of the 1993-94 data and new households (N=27,654).

IHDS-2 has re-interviewed 83% of the original households from IHDS-1 round and an additional new sample of 2134 households. The sample size for second round survey is 42,152 households, spread across 33 states and union territories, 384 districts, 1420 villages and 1042 urban blocks located in 276 towns and cities.

IHDS has provided a link file with details on individual person id for 2005 and 2011 rounds, the 2011 household id, 2011 household split id, state id, HH waves (to know if the household has been tracked in both time periods, PWAVES (to know if the person has been tracked in both time periods). There are 150,988 individuals who have been tracked in both time periods[ii].

The descriptive statistics for the panel data is in the appendix section (table A3).In the panel data close to 2% of the sample receives IGNOAPS, 33% of the panel has a BPL card, 18% of them have political connection, 65% of them solve local problems acting along with their community, 52% of them are women, 40% belong to OBC and 20% of them belong to scheduled caste. On an average the individuals in the panel have 5 years of education, 14% of them are part of a self-help group and women have higher exposure to television than newspaper and radio. The t – statistics that basically compares the mean difference here between the IGNOAPS beneficiaries and non-beneficiaries in both time periods and are statistically significant indicating that the sample means of beneficiaries groups are different from the non-beneficiaries group and they are comparable.

2.1 Variables in the dataset

IHDS dataset has very rich information on social networks. The dataset has covered information on various aspects of social networks: memberships and political activity, local trust, local crime, confidence in institutions and other types of networks. The study utilizes the panel data structure of IHDS; therefore, we have focussed on questions present in both the rounds. The questions on local crime and confidence in institutions are more relevant to construct social capital index. Therefore, we have focussed on questions related to memberships & political activity, local trust and other types of informal networks. In table 3 we have enumerated the questions pertaining to other type's networks in both time periods. In table 4 we have listed out the questions on memberships and political activity asked in both rounds. The questions on household's acquaintance (table 3) with officials working in health, education and other government service are more useful to measure the strength and weakness of ties; for example, the question on acquaintance with doctors isn't indicative of any horizontal alignment. They are mere acquaintances which don't reflect on the aspects of coordination or solidarity that forms the crux of the horizontal network. Similarly, the question on acquaintance with government officers is open ended which makes the interpretation difficult .For example, the category of government officer can include a wide range of designations. This category can also include an army officer; in that case the relationship between the officer and the household is no longer a vertical relationship.

Table 3: Questions on Social Network

Do you or any members of your household have personal acquaintance with someone who works in any of the following occupation?		
	Among your relatives/caste/community	Outside the community/caste
Health		
Doctors		
Other health workers		
Education		
Teachers/Principal		
Other school workers		
Government service (other than doctors and teachers above)		
Officers and above		
Other govt. employees		

Source: IHDS data set

The question on memberships (table 4) focuses on formal memberships in organisations; the caveat here as discussed in the literature is that formal memberships are more relevant in the context of developed countries than a developing country like India. The 2005 IHDS village level data set shows that mahila mandal was present only in 46% of the villages, youth clubs in 42%, trade unions in less than 15%, self-help groups are the highest as they are present in more than 60% of villages, credit savings group are in 37%, religious groups are in 50%, caste group in 36%, development groups in 14% and agriculture & other cooperatives in 35% of villages (table 4). This was exactly the concern raised by Krishna; formal memberships are a rare phenomenon in Indian villages as they are rarely present. Non-participation in these associations can be attributed due to the non-existence of such institutes. The individual level participation in any of these networks also looks very small.

Table 4: Formal membership networks in India

Formal memberships organisations	Village level presence (2005) (%)	Participation (2005) (%)	Participation (2011)
Mahila mandal	46.04	7.36	8.9
Youth/sports/reading club	42.57	5.22	2.88
Union/business	14.26	5.06	5.24
Self-help groups	60.76	9.51	18.65
Credit savings group	37.18	6.85	10.67
Religious group (includes social group as well in 2005, while social group is an independent group in 2011, so average is taken for the year 2011)	50.3	14.16	9.62
Caste group	35.98	13.3	8.48
Development group/NGO	14.19	1.88	1.28
Agriculture, milk or other cooperatives	34.64	3.48	3.38

Source: IHDS dataset

Therefore, we needed to look at some other indicator besides memberships in formal organisations that reflects collectivism among people. This led me to the question on local trust; the survey has asked questions on how they resolve water supply issues at the community level (table 5). This question emphasis if families act in isolation or if they act as a community together to resolve the issues. The question on how community act reflects the spirit of horizontal association which is solidarity, civic engagement and co-operation; therefore, the question on how communities act can be a proxy for horizontal network. Similarly, vertical networks measures hierarchical relationships. The most direct question that capture vertical network is that if someone close to the household is a member of village panchayat, nagarpalika or ward committee.

Table 5: Questions on social capital in both 2005-06 and 2011-12 survey

Vertical network	**Coding of the data**
Is there someone close to the household, who is village / neighbourhood a member?	Nobody close to household is a member = 0
	Somebody close to household is a member = 1
Horizontal network	
In some communities, when there is a water supply people bond together to solve the problem. In other communities people take care of their own families individually. What is your community like?	Bond together to solve problem = 1
	Each family solves individually = 0

Source: IHDs questionnaire (2005-06 and 2011-12)

As discussed earlier the two targeting errors that we are concerned here are about non-eligible individuals receiving the scheme (type 2) and eligible individuals not receiving the scheme (type 1) errors in the program. The empirical work will focus on these two groups and in table 6 and 7 we have provided the descriptive statistics of these two groups. The percentage individuals with political connections in the type 2 error group in 2005 were 10% and this has increased to 28% in 2011. The test statistic signifies that the means of these two groups are different. And the variable on solving local problems indicates that 68% of individuals in type-2 error group had horizontal networks and this has increased to 75% in 2011. The percentage of women's composition in the type 2 error group has come down from 2005 to 2011. There has been a marginal change in the caste composition of this group. The average years of age of individuals in this group has slightly reduced in 2011. There has been an increase in the percentage of people who live in the urban area in 2011. There has been an increase in the participation in self-help group among this category. There has been an increase in the media exposure of women over the years in this group.

In Table 7 We have enumerated the descriptive of the type 1 group (eligible non-recipient). Similar to the type 2 error group, the number of individuals with political connections has increased in 2011. The percentage of individuals in this sample reporting to have horizontal network which is measured as solving local problems has increased from 56% in 2005 to 73% in 2011. There has been increase in the per cent of women's composition in this group compared to 2005. There has been a substantial increase in the percentage composition of other backward communities and schedule caste in the type 1 error group. There has been increase in participation in the self -help groups and per cent of people with agriculture land holdings.

Table 6: No-Yes (type 2)

Variables	2005		2011		Test statistic : difference in means between two groups
	Mean	Std. Dev.	Mean	Std. Dev.	
Someone close to household has got political connections	0.101	0.301	0.280	0.449	t =20.06***
Solve local problems	.682	.465	.746	.435	t =16.52***
Gender	.581	.493	.532	.499	t = 5.13***
If the individual belongs to Other backward caste	0.459	0.498	0.435	0.495	t = 2.253**
If the individual belongs to scheduled caste	0.225	0.418	0.246	0.431	t =2.23**
If the individual belongs to scheduled tribe	0.092	0.289	0.113	0.316	t =3.12**
Education of the individual	1.503	2.809	1.870	3.290	t =5.29***
Age	71.120	6.590	67.311	7.250	t =24.77***
Lives in an urban area	0.199	0.399	0.241	0.428	t =4.67***
Agriculture land owned	0.526	0.499	0.520	0.499	t = 0.61
Membership in self-help groups	0.154	0.361	0.234	0.423	t = 9.09***
If the women in the household reads newspaper	0.190	0.393	1.265	0.575	t =93.18***
If the women in the household watches T.V	0.580	0.493	2.130	0.8606	t = 92.57***

Table 7: Yes-No (type 1)

Variables	2005		2011		Test statistic : difference in means between two groups
	Mean	Std. Dev.	Mean	Std. Dev.	
Someone close to household has got political connections	0.081	0.273	0.297	0.457	t =12.98***
Solve local problems	.564	.564	.731	.731	t = 3.49***
Gender	.502	.500	.558	.496	t = 2.391**
If the individual belongs to Other backward caste	0.325	0.468	0.421	0.494	t = 4.84***
If the individual belongs to scheduled caste	0.310	0.462	0.217	0.412	t = 5.29***
If the individual belongs to scheduled tribe	0.039	0.194	0.054	0.227	t = 1.71*
Education of the individual	1.090	2.695	1.986	3.426	t =6.80***
Age	66.908	8.578	66.814	11.493	t =0.215
Lives in an urban area	0.154	0.361	0.218	0.413	t = 3.95***
Agriculture land owned	0.454	0.498	0.562	0.49	t = 5.32***
Membership in self-help groups	0.073	0.260	0.142	0.349	t = 5.24***
If the women in the household reads newspaper	0.200	0.400	1.408	0.685	t = 48.5***
If the women in the household watches T.V	0.625	0.484	2.357	0.828	t =57.61***
Membership in self-help groups	0.073	0.260	0.142	0.349	t = 5.24***
If the women in the household reads newspaper	0.200	0.400	1.408	0.685	t = 48.52***
If the women in the household watches T.V	0.625	0.484	2.357	0.828	t =57.61***

3 Methodology

3.1 Empirical specifications and results

$$\boldsymbol{P_{it} = F(Horizontal\ networks_{it},\ Vertical\ networks_{it,} Age_{it}, BPL_{it}, Antodya_{it}, hh\ specific\ characterstics_{it}, Z_{\ i}) - - - 3}$$

The basic empirical framework is the probability of receiving IGNOAPS is conditioned on horizontal networks, vertical networks; the eligibility criteria and We have controlled for household specific time varying characteristics and time invariant individual specific characteristics (Z_i), t refers to time periods 2005 and 2011 and the unit of study is individual level (i).Equation 3 can be re-written as a specification below (equation 3.1).

$$P\ (Recieving\ IGNOPAS = 1|x, k, a) = \Phi(\alpha_0 + \beta x_{it} + \gamma k_{it} + a_i) - - - - - 3.1$$

The dependent variable is if someone is receiving IGNOAPS which is conditioned on all other variables included in the model. The β coefficients are the variables of interest, Υ denotes the time varying control variables to be included in the model and given that it is not a fixed effect model we need to also control for time invariant characteristics in the model which is denoted by a_i. We have run several regression models (Appendix, table A4), in the first specification we have only introduced the two important criteria's for receiving IGNOAPS which is the person has to be sixty years old and have a BPL card or Antodya card (ultra-poor). In the first model we have examined effects of these two eligible determinants. In model 2, along with the eligibility criteria followed by the government we have introduced horizontal and vertical network variables. In model 3 we have also controlled for the effects of gender, caste (OBC, SC and ST), age, place of residence, household composition, if the person holds any unit of agriculture land- an indicator of wealth, women's access to mass mediums (newspaper, radio and television), membership in self-help groups. In model 4 we have estimated the full model by further controlling for state fixed factors interacted with time.

In model 1, the marginal effect shows that these two eligible criteria increase the probability of receiving IGNOAPS. And in model 2 we further introduce the horizontal and vertical network variables, the marginal effects of these two variables are positive and significant. In model 3, we have introduced a set of control variables that are both household and individual specific. The result shows that household wealth (agriculture land owned) decreases the probability of receiving the scheme, living in urban area reduces the probability of receiving the scheme, and higher household composition also reduces the probability of receiving the scheme. There is more number of beneficiaries of the program in the rural area than the urban area. The implementing authority in the Indian state of Tamil Nadu informed me that people in urban area are richer than rural area. Also, the amount provided in the scheme will not help to suffice urban living standards. Higher household composition is indicative the less likelihood of the older person in the family being a destitute; therefore, the variable is negatively correlated with the probability of receiving IGNOAPS. And belonging to a scheduled caste or other backward caste increases the probability of receiving IGNOAPS. In model 3, we have further controlled for membership in other voluntary organisations. Voluntary organisations are not uniformly present all over India; therefore we have only included membership in self-help groups which is widely present in India. We have also controlled for information from other sources which includes television, radio and newspaper. And by controlling these variables we try to isolate the effect of horizontal network in providing information flow and thereby increasing the probability of receiving IGNOAPS. But variables on mass mediums are correlated (radio and newspaper) with the household wealth and reduce the probability of receiving IGNOAPS. After controlling for the household and individual specific variables the effect of both horizontal and vertical network variables are positive and significant.

In model 4 we have further controlled for state fixed effects interacted with time, this interaction between the state fixed effects and time effects captures if the person received the program because of the action taken by a particular state government in 2011. As stated above mass mediums including TV, radio and newspaper is correlated with the household wealth and reduces the probability of receiving IGNOAPS. After controlling for state effects interacted with time along with a host of household and individual specific variables, vertical and horizontal network is still significant and they increases the probability of receiving IGNOAPS. The explanatory power of model 4 is 52%.

3.2 Eligible versus non-eligible individuals

As discussed from the beginning the study focuses on the type 1 and the type 2 error categories of receiving IGNOAPS. The type 2 error group comprises of non-eligible individuals receiving the scheme and type I group consist of eligible individuals not receiving the scheme. As Micklewright et.al (2004) discusses that any cash transfer program is conditioned on three events. An individual needs to be aware of the program, and then he/she should claim it. And finally the government or other implementation agency will decide on awarding or not awarding the scheme.

$$Pr(reciept) = Pr(award|claim \,\&\, knowledge).\Pr(claim|knowledge)\,.Pr(knowledge) ----4$$

This holds good true even for IGNOAPS. For an individual to receive the benefit they should have the knowledge about the scheme in the first place and they should have claimed for the program. In the final stage the authorities might have accepted or rejected his /her claim. Type 1 error occurs when the eligible have not been accepted in the scheme. However, the data set only gives information on whether someone receives the scheme or don't, but not on if the person has filed a claim for this scheme. It could be possible that many eligible were left from the scheme because they did not make a claim for the program in the first place which is also a case of self-selection. This makes it impossible for us to make any assertion on the effect of networks on this group. However, one can possibly correct for type 1 error in the sample and still look at the role of networks.

We can nest the decision to participate in the program on two conditions which is all the eligible individuals applying for the program and in the next stage they all receive the program. In the first stage we have an eligibility equation which determines an eligible individual applying for the program (equation 5). In the second stage we model the recipient equation whereby we have modelled the determinants of an individual receiving the program (equation 6). This is similar to the heckman probit model where in the first stage we model the determinants that will enable an eligible individual to apply for the program and in the next stage we model the determinants of being a recipient of the program.

$$Pr\ (Eligibility = 1|x) = \ \alpha_0 + \ \gamma x_{it} + +u_{it} ------5$$

$$\Pr(recipient = 1|x) = \ \alpha_1 + \ \beta_1 x_{1it} + IMR + \beta_2 x_{2it} + \delta x_{it} + a_i + v_{it} ----6$$

In equation 5, we have estimated the probability of an eligible individual applying for the program conditioned on certain explanatory variables. The dependent variable here is an eligible individual. The explanatory variable is sensitization of information, as this helps the eligible individuals to apply for the program. The other independent variable used here is the state fixed factors, as states that are proactive towards the development needs of the people ensures that all the eligible individuals apply for the scheme . With the help of equation 5 helps we have predicted the inverse mills ratio (IMR), a probability score for all the eligible individuals if they have all chose to apply for the program. The predicted IMR helps in addressing type 1 error (eligible not receiving the program) and self-selection in the model, as we now predict a probability score for all the eligible individuals in the sample. In equation 6, we have incorporated these probability score and we have run equation 6 for all the eligible individuals and all the non-eligible individuals in order to isolate the effects of networks on eligible (type 1) and non-eligible individuals (type 2) receiving the program.

The next question ahead is on how to define the dependent variable on eligible individual in equation 5. The set of eligibility rules have changed in 2007 and 2011. In 2007 the eligibility criteria has changed from being a destitute to a more observable characteristic of belonging to a BPL household; as there was no formal mechanism to identify a destitute. In 2011 the age eligibility was further reduced from 65 to 60 years. Since the 2005 criterion of someone being a destitute is unobservable we have used the latest (2011) eligibility criterion. Therefore, we have defined the dependent variable of eligible individual eligibility (in the equation 5) as one who is 60 years or older and belongs to a BPL or Antodya (ultra-poor) household. The probability of an eligible individual applying for the scheme increases with the knowledge about the scheme. Sensitization is an important factor that enables the eligible individuals to apply for the scheme. Based on my interaction with some recipients in the rural Rajasthan; the recipients reported that attending public meeting generated awareness about the scheme. Therefore, we have included the variable on attending public meeting in equation 5 and we have also used state fixed effects in the model. The use of state fixed effects reflects the effectiveness of state institutions as this is also a determinant for eligible to apply for the scheme. The estimation equation 5 helps in predicting inverse mills ratio (IMR).

The predicted inverse mills ratio is then incorporated in equation 6. Being a recipient of IGNOAPS is conditioned on the network variables (β_1) and (β_2). The coefficient on δ is the list of all time varying the control variables used in the model. We have also controlled for time invariant characteristics in the model. The use of IMR from equation 5 helps in correcting for type 1 targeting error. This helps in accounting whereby all the eligible individuals participate in the program. We then ran the regression on the eligible and non-eligible individuals. The result from equation 6 for the eligible individuals' indicates that after accounting for self-selection, does being a part of horizontal and vertical network increases the probability of eligible individual to receive the program. Similarly, the result for the non-eligible individual shows that does being a part of horizontal and vertical network increases the probability of non-eligible individual to receive the program. The result on equation 6 is in the appendix section (table A5).

The result shows that on average for the eligible individual's category having a horizontal network increases the probability of receiving IGNOAPS by 2 On an average for the non-eligible group, meeting the eligibility criteria increases the probability of receiving the scheme, but besides being eligible having a political connection also increases the probability of the non-eligible individuals to receive the program. Being part of horizontal networks helps the non-eligible group to receive the program. The control variable displays the usual sign.

3.3 Robustness check

We have controlled for omitted variable bias by using control regressors. The high pseudo R-square of the included model is reflective that the omitted variable bias problem is been taken care off. The Pseudo R-square is higher compared to other studies in the literature; in Cayers and Dercon their probit model explained about 18% of variation; in Panda's work the explanatory power of the variable included was about 15% of the variation. But there is a possibility of unobservable determinants correlating with the political connection variable and also and receiving the social assistance program.

We need to first check if there is an unobservable determinant that is effecting simultaneously both equation (7) and equation 8. The possible correlation of the unobservable determinants with equation 7 and 8 will violate exogenity assumption of the independent variables. We have used a recursive bivariate probit model to correct for this.

$$IGNOAPS\ Recipient_{it} = f\ (\alpha_0 + \beta_{1it} Political\ network\ + \beta_{2it} solve\ local\ problems + \gamma x_{it} + a_i + u_{it})\text{---}7$$

$$Political\ network\ _{it} = f\left(\gamma x_{it} + a_i + \emptyset\ instrument + v_{it}\right)\text{-----}8$$

In a recursive bivariate probit (RBP) model we estimate the main equation (7) and the endogenous equation (8) simultaneously. The two error terms u_{it} and v_{it} are bivariate normal distributed and the correlation $(u_{it}, v_{it}) = \rho$. The possibility of a joint determination of errors (ρ) is dependent on the functional form of the error terms. Monfardini & Radice (2006) found that by including an exclusion restriction, an instrument variable for the endogenous regressor that is not present in the main equation 7, we can relax the assumption on the functional form of the errors and can still test for exogenous assumption of the model. The inference of the exogeneity assumption using the likelihood ratio test will be then based on the exclusion restriction imposed in the model. Here we impose the exclusion restriction with the help of instrument (Φ) (equation 8).

The condition for the instrumental variable is that the proposed instrument should be correlated with the endogenous explanatory variable, but uncorrelated with the dependent variable in the main equation (exclusion restriction). The instrument should be uncorrelated with u_{it}, else we will come back to the original problem on endogeneity.

$$cov(z, x) \neq 0 \text{ (First stage exist)}$$

$$cov\ (z, u) = 0 \text{ (Exclusion restriction)}$$

The challenge ahead is to find a suitable instrument that is correlated with the political network variable, but uncorrelated with receiving IGNOAPS. Political network in India is based on social identity variables. The problem in choosing social identity based on caste and other networks variables is that they are correlated with the dependent variable and the error variable in equation 7. This violates the exclusion restriction of the instrumental variable.

State domicile status is an important criterion that needs to be satisfied by households in order to apply for state sponsored scholarship or for jobs with the state government. In order to be a domicile of a state a person has to be a continuous permanent resident of the state for a fixed duration of time. The duration of residency changes for each state, in the state of Tamil Nadu a person has to reside for six years; while in the neighbour state of Kerala the person should live for at least fifteen years to apply for the domicile status. The duration of stay criteria followed in Kerala is similar to other Indian states like Uttarkhand and Haryana. It is widely followed that a person has to live for a period of fifteen years in the same state to be eligible for the state domicile status. Households who have been living for a short time have little interest to make political connections than households who have been living longer. It is common that most households tend to forge political connections when they have met the eligibility criteria. Political connections help individuals to overcome bureaucratic hurdle and to expedite the process for getting the domicile status. Therefore, we have used the variable on the length of living in the same state; this variable is constructed for individuals whose origin state is different from the resident state and who have been living for fifteen years or. Based on the secondary information available on the domicile criterion followed in some Indian states number of years living in a state for at least fifteen years is a widely followed criterion lesser (table A6 in Appendix). The turning point from where households tend to make political connection is difficult to establish with different domicile criterions followed by states. But the likelihood of someone having a political connection is lower for someone living in the same state for less than fifteen years away from their origin state than a naturalised resident of that state. The variable on length of living in the same state is an exogenous variable as this is not the eligibility criterion set for being an IGNOAPS beneficiary. The household with the length of living less than fifteen years whose origin state is different is negatively correlated with the political connection variable.

As mentioned by Nicholas (2011) an easier way to estimate the binary dependent and binary endogenous model is to use instrumental variable. The instrumental variable method disregards the binary nature of the data, but it has the advantage of easy interpretable probability coefficients. This also helps in capturing the average effect on the treated, but the drawback is that the estimates are biased, and their performance on small sample can be inferior to a correctly specified maximum likelihood model. Therefore, recursive biprobit model is better suited.

The results on biprobit coefficients with instrument on individual living less than 15 years in the state (table A7) with negative rho indicates that unobservable determining the likelihood of someone receiving IGNOAPS is negatively correlated with the unobservable determining household political connections. The null hypothesis of ($\rho = 0$) that the political connection variable is exogenous is rejected for the complete sample and the non-eligible group (table A7). For the estimation on the full sample the unobserved determining receiving IGNOAPS are negatively correlated with the unobservable on political connection, but is not highly significant. The value of rho is non-zero and is statistically significant (at 10% only). For the eligible household sample the correlation of the errors is almost zero, thereby accepting the null hypothesis of the political connection variable being exogenous. For the sample on non-eligible individuals the correlation coefficient is similar, but it is statistically significant.

The marginal effects of equation 7 which is the direct effect of independent variables on dependent variables; and equation 8 which is the indirect effect of dependent variables on political connections is estimated using a single equation in table A8. The direct and the indirect effects are computed for the whole sample and for the non-eligible individuals. The results in table (A8) reinforces the same finding that the probability of receiving IGNOAPS increases with meeting the eligibility requirements, having higher level of horizontal network and belonging to a lower caste. The instrument on length of living in the place for less than fifteen years is highly significant for both the direct and indirect effect equation for both complete and non-eligible sample. After correcting for the possible endogeneity, the variable on having political connections is still significant and positive for the complete data and non-eligible individuals to receive the program. Household wealth, household composition and higher education reduce the probability to receive the program.

We have tested for a possible endogeneity for the political connection variable, as there could be unobservable determinants that could determine both political connection and receiving IGNOAPS. We rule out the possibility of unobservable determinants which simultaneously determine someone being a recipient of IGNOAPS and solving local water supply problems; ability of the household to resolve the local water supply problem acting along with the community is dependent on the nature of the household member and is not correlated with someone being a recipient of IGNOAPS.

4 Conclusion

The study aims to unpack the role of networks in receiving Indira Gandhi National Old Age Pension Scheme in India. The paper in particular looks at the role of both horizontal and vertical networks in receiving the social assistance program. Horizontal network aids information flow, while vertical networks indicate local political connection. The paper finds that besides the eligibility criteria stated by the government, both horizontal and vertical network plays an important role in helping individuals to access this scheme. On further classifying the sample into eligible and non-eligible individual's receiving the scheme; the paper examines the role of network in type 1 and type 2 errors in the program. Political connections are significant for the ineligible individuals to receive the scheme than for eligible individuals. This clearly indicates that political connection is a determinant for type-2 errors in the scheme. We have corrected for the possible endogeneity in the political connection variable by using the recursive bivariate probit model. We have used the instrument on length of living in the state for less than fifteen years; the variable on length of stay is an important factor that determines if the individual receives a state domicile certificate. This certificate is important for the resident as it enables him to apply for state government jobs and other state sponsored scholarships. After taking into account of endogeneity, the variable on political connections is important for non-eligible individuals to receive the program.

The role of networks is important because the question on who gets the pension is important because policies are designed keeping in view certain eligibility criteria's, but considering the role of local politics as exogenous factors. But in reality local political network play an important in determining the beneficiaries. Political connections help people in gaining favouritism. In the present case on IGNOAPS there are high instances of APL card holders receiving the program, one possible explanation could be the political connections of the household.

This is not an isolated case, but it has been found in the studies of Cayers and Darcon in the case of Ethiopia and Panda in the case of BPL cards in India that political connections helps gaining access to social welfare programs. Evaluations of the IGNOAPS program conducted in the Union District of Pondicherry shows that the application forms were distributed collected and submitted with recommendations by the elected MLA (Member of Legislative Assembly). In the Indian state of Jammu & Kashmir the final list of beneficiaries needs to be approved by elected MLA's, which reinforce our finding on political connections. Given that political connection is a significant determinant for non-eligible to receive the program which can further perpetuate the type-2 targeting error in the scheme.

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Appendix

Table A1: Amount of pension, state contribution and eligibility criteria used

	States/UTs	Amount of pension provided as Central Assistance under IGNOAPS (Rs,2011)	Contribution of State Govt. per beneficiary per month under IGNOAPS (Rs) IGNOAPS (Rs) (Rs,2011)	Eligibility criteria used *	Number of beneficiaries (2011)
1	Andhra Pradesh		200		1011153
2	Bihar	200	Nil	BPL card holders with an annual income of less than Rs. 30,000	2369656
3	Chhattisgarh	200	100	n/a	533665
4	Goa	200	800	n/a	2734
5	Gujarat	200	200	n/a	279834
6	Haryana	200	300 for 70 years and 500 for above 70 years	Age, Income < Rs. 50000 per annum	130306
7	Himachal Pradesh	200	130	Age, BPL	91440
8	J&K	200	125	Age proof (Date of birth / Age certificate).Income certificate / BPL certificate / BPL ration card	129000
9	Jharkhand	200	200	n/a	676003
10	Karnataka	200	200	n/a	797862
11	Kerala	200	50	n/a	176064
12	Madhya Pradesh	200	75	n/a	1061033
13	Maharashtra	200	400	Age, BPL	1057510
14	Orissa	200	Nil	n/a	1193176
15	Punjab	200	250	n/a	159792
16	Rajasthan	200	300 for 70 years or below and 550 for above 70 years	n/a	527636
17	Tamil Nadu	200	800	Age, BPL	995237
18	Uttar Pradesh	200	100	Age, For rural: BPL; For urban: BPL/AAY card holder/name appears on survey list of District Urban Development Authority or on MoUD BPL list	3274780

19	Uttarakhand	200	200	Age	183501
20	West Bengal	200	200	n/a	1679381
	NE				
21	Arunachal Pradesh	200	Nil	Age, BPL	14500
22	Assam	200	50		596965
23	Manipur	200	Nil	Age, BPL	72514
24	Meghalaya	200	50	Age, BPL	48112
25	Mizoram	200	50	Age, BPL	23747
26	Nagaland	200	100	Age, BPL	40462
27	Sikkim	200	200	n/a	18806
28	Tripura	200	200	Age, BPL criteria or the destitute criteria	136592
	Union Territories				
29	NCT Delhi	200	800	Age, Income <Rs. 60000 per annum	196446
30	Puducherry	200	400	n/a	20757
31	A&N Islands	200	800 up to 79 years and 500 above 80 years	n/a	1063
32	Chandigarh		500	n/a	4216
33	D&N Haveli	200	300	n/a	944
34	Daman & Diu	200	300	n/a	130
35	Lakshadweep	200	100	n/a	36
	Total				17505053

Source: http://socialjustice.nic.in/pdf/ar12eng.pdf
*Identity criteria has been taken from numerous sources. Government websites,
https://ifrogs.org/EVENTS/PRESENTATIONS/sl_Rinku20150224_pensionworkshop.pdf,
http://www.helpageindiaprogramme.org/other/Destitute_Resources_10_dec/General%20Reference%20MaterialWrite-ups/5%20Senior_Citizens_Guide_%202009.pdf
http://crmindia.org/files/KaIGNOAPS.pdf
https://www.helpageindia.org/images/pdf/state-elderly-india-2014.pdf

A2: Panel attrition

IHDS has re-interviewed only 83% of the households from the earlier 2005 survey. The 17% of households who were missed in the second round of survey could be random or non-random. In order to check for the randomness of attrition I did the probit attrition test. To illustrate, in the attrition probit test we first estimate a unrestricted probit model in equation 1. Here the dependent variable "a" takes the value 1 if the individual has attrited after the first round, else takes the value zero. Xi denotes the independent variable that affects the outcome variable and the attrition variables. The variable (ai) denotes the auxiliary variables that effect both the attrition and the outcome variables.

$$A = x_{i1}\gamma + a_{i1}\delta + v_i - - - 1$$

Before we proceed to equation 2 we need to confirm if attrition is random. Therefore, after estimating equation1 I ran the Wald test to check if all these coefficients are jointly equal to zero. But on testing for other variables it was found that null hypothesis on Joint coefficients equivalent to zero could be rejected. Therefore we can conclude these variables are joint predictors of attrition. In equation 2, I estimated a restricted model with no auxiliary variables. And subsequently I calculated the inverse probability weight which is the ratio between the restricted and the unrestricted model. The idea behind this exercise that it provides more weights to individuals of similar characteristics, but tend to attrite in the second round.

$$A = x_{i1}\gamma + \emptyset_i - - - - - 2$$

$$W_i = p^r/p^u$$

The attrition probit test result on the restricted and the unrestricted model is given below. The unrestricted model below includes all the key variables that affect both attrition and the outcome variable in this question. The dependent variable in both the model is individual who were interviewed in 2005, but attrited in the 2011 round. The explanatory variables included are individual specific variables (age, living in urban area), household specific variables are (BPL card, gender, education completed), household wealth (agriculture land owned), treatment dummies (individual receiving IGNOAPS), interview specific characteristics (interview time), horizontal and vertical networks, location variables (state fixed effects). In the unrestricted model living in urban area, higher age group, gender, treatment dummy of receiving IGNOAPS and higher education increases the probability of attrition. While household having a BPL card, vertical network and agriculture land owned reduces attrition. Vertical network indicates political connectivity with elected official living in that locality, higher agriculture land owned is an indication of wealth they decreases the probability of attrition. In the restricted model the auxiliary variables from the unrestricted models are removed.

Although the pseudo r-square in both the model is very low which indicates that the variable included explains only 4% of variation in the unrestricted model and 2% variation in the restricted model (table A1 in appendix). But many variables included in model are statistically significant. The Wald test reported in table rejects the null hypothesis of attrition being random. Therefore, we have calculated the inverse probability weight which is ratio of probabilities of restricted to unrestricted models.

Most stata commands allows the user to use four types of weights: frequency weights, pweights, aweights and iweights. Frequency weights are weights indicate the number of duplicated observations, pweights are the inverse probability weights, aweights are weights that are inversely proportional to the variance of the observation, iweights doesn't have any statistical interpretation and is mostly used by programmers for certain computation. The command on pweights is more suitable here as it helps me to assign the inverse probability weight, but the xtprobit command doesn’t allow using pweight option, therefore I can’t assign the attrition weights. But if we control for all the variables that are exogenous to the dependent variable, but that determine attrition then the results will be asymptotically equivalent to estimator that takes into account attrition. The table A2.1 gives information on individual level attrition in the data; the characteristics on age, place of residence, sex and wealth are also control variables used in my study.

Table A2.1: Panel attrition model

Variables	Unrestricted model	Restricted model
Living in urban area	0.145***	0.171***
	(0.007)	(0.007)
Individual greater than 60 years of age	0.422***	
	(0.010)	
Household has a BPL card	-0.0543***	
	(0.00693)	
Household composition	-0.0101***	-0.0158***
	(0.001)	(0.00099)
Gender	0.179***	0.168***
	(0.005)	(0.005)
Dummy variable If the individual is an IGNOAPS recipient	0.352***	
	(0.035)	
Solving local problems	0.00567	
	(0.006)	
Education completed years	0.0356***	0.031***
	(0.0006)	(0.0006)
Vertical network	-0.0116**	
	(0.005)	
Agriculture land owned	-0.114***	-0.122***
	(0.007)	(0.006)
Interview time	0.00973	0.005
	(0.006)	(0.005)
Jammu & Kashmir	0.0468	
	(0.068)	
Himachal Pradesh	0.202***	
	(0.066)	
Chandigarh	0.387***	
	(0.097)	
Punjab	0.080	
	(0.066)	
Uttarakhand	0.172**	
	(0.070)	
Haryana	0.100	
	(0.066)	
Delhi	0.815***	
	(0.067)	
Rajasthan	0.222***	
	(0.065)	
Uttar Pradesh	0.205***	
	(0.065)	
Bihar	0.307***	
	(0.066)	
Sikkim	0.244***	
	(0.087)	
Arunachal Pradesh	0.526***	
	(0.078)	
Nagaland	1.058***	
	(0.084)	
Manipur	0.265***	
	(0.085)	
Mizoram	0.535***	
	(0.086)	
Tripura	0.745***	
	(0.077)	
Meghalaya	0.183**	
	(0.081)	
Assam	0.731***	
	(0.067)	
West Bengal	0.0331	

	(0.0660)	
Jharkhand	0.438***	
	(0.0672)	
Orissa	0.158**	
	(0.0660)	
Chhattisgarh	0.161**	
	(0.0671)	
Madhya Pradesh	0.268***	
	(0.0655)	
Gujarat	0.336***	
	(0.0659)	
Daman & Diu	0.0877	
	(0.107)	
Maharashtra	0.00754	
	(0.0655)	
Dadra+Nagar Haveli	0.470***	
	(0.0998)	
Andhra Pradesh	0.517***	
	(0.0658)	
Karnataka	0.423***	
	(0.0653)	
Goa	-0.437***	
	(0.0858)	
Kerala	0.202***	
	(0.0663)	
Tamil Nadu	0.149**	
	(0.0662)	
Constant	-1.202***	-0.843***
	(0.0675)	(0.0158)
Observations	211,815	213,437
Pseudo-R square	0.04	0.02

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2.2: Individual attrition model

	Still alive	Dead	Lost to re-interview	Total
Age				
Less than 15	91.2	0.8	8.0	68,462
15-29 years	89.8	1.2	8.9	59,795
30-44 year	88.6	2.2	9.2	42,423
45-59 year	84.7	6.4	8.9	27,170
60 years or more	64.3	26.4	9.3	17,904
Sex				
Male	86.8	4.4	8.7	1,09,805
Female	87.8	3.6	8.7	1,05,949
Place of Residence				
Rural	88.8	4.3	6.9	1,43,374
Urban	83.0	3.3	13.6	72,380
Asset Groups				
Poorest	87.8	4.9	7.3	39,472
2nd Quintile	88.7	4.1	7.1	38,792
Middle	87.6	3.9	8.5	36,475
4th Quintile	87.3	3.7	9.1	54,226
Richest	84.5	3.4	12.1	46,789
Life-style Diseases				
No	87.9	3.4	8.7	2,03,879
Yes	76.9	13.9	9.2	11,875
Any Difficulty in ADL				
No	86.8	4.3	8.9	1,78,186
Yes	64.9	26.6	8.5	2,533
Total	**87.29**	**4.01**	**8.7**	**100.0**
	1,87,381	**8,532**	**19,841**	**2,15,754**

Source: Adult Mortality in India: The Health-wealth Nexus: Debasis Barik, Sonalde Desai, Reeve Vanneman

Table A3: Descriptive for Panel data

Variables	Mean	Std.dev	Test statistic : difference in means between two groups (beneficiaries/non-beneficiaries)
IGNOAPS recipients	0.015	0.125	
BPL cardholders	0.33	0.470	t = 28.87***
Antodya cardholders	0.04	0.200	t = 22.05***
Someone close to household has got political connections	0.18	0.387	t = 14.55***
Solve local problems	1.657	0.476	t =11.70***
Gender (Male)	0.52	0.499	t = 4.49***
If the individual belongs to Other backward caste (OBC)	0.40	0.491	t = 0.95
If the individual belongs to scheduled caste (SC)	0.20	0.406	t = 12.80***
If the individual belongs to scheduled tribe (ST)	0.08	0.272	t = 1.95*
Education of the individual (Education)	5.08	4.71	t = 53.22***
Age	30.7	19.388	t = 1.4e+02***
Lives in an urban area	0.31	0.462	t = 21.63***
Agriculture land owned	0.49	0.499	t = 4.03***
Household composition	6.14	2.990	t= 22.72***
Membership in self-help groups	0.14	0.351	t = 8.61***
If the women in the household reads newspaper (Women access-newspaper)	0.30	0.459	t = 16.03***
If the women in the household watches T.V (Women access-TV)	0.74	0.437	t = 10.80***
If the women in the household listens to radio (Women access-radio)	0.30	0.461	t = 21.32***
Attends public meeting	0.30	0.460	t = 4.50***

Table A4: Marginal effects

Variables	Model 1	Model 2	Model 3	Model 4
Age60*BPL	0.026***	0.025***	0.011***	0.011***
	(-0.002)	(-0.002)	(-0.0004)	(-0.0004)
Age60*Antodya	0.028***	0.027***	0.014***	0.013***
	(-0.001)	(-0.001)	(-0.0008)	(-0.0008)
Someone close to household has got political connections		0.003***	0.003***	0.0008*
		(-0.0003)	(-0.0004)	(-0.0004)
Solve local problems		0.002***	0.002***	0.002***
		(-0.0002)	(-0.0003)	(-0.0004)
Gender			0.002***	0.002***
			(-0.0003)	(-0.0004)
OBC			0.001**	0.001**
			(-0.0004)	(-0.0005)
SC			0.004***	0.003***
			(-0.0005)	(-0.0005)
ST			-0.0005	0.001
			(-0.0007)	(-0.0008)
Age			0.0009***	0.001***
			(-0.00002)	(-0.00002)
Education			-0.0008***	-0.0008***
			(-0.00006)	(-0.00006)
Urban			-0.005***	-0.004***
			(-0.0005)	(-0.0005)
Household composition			-0.0005***	-0.0004***
			(-0.00006)	(-0.00007)
Agriculture land owned			-0.003***	-0.003***
			(-0.0004)	(-0.0004)
Member in self-help group			0.001**	-0.0006
			(-0.0004)	(-0.0005)
Women access-TV			0.001***	-0.0009*
			(-0.0004)	(-0.0004)
Women access-radio			-0.005***	-0.002***
			(-0.0005)	(-0.0005)
Women access-newspaper			-0.001**	-0.002***
			(-0.0004)	(-0.0005)
State fixed factors below were interacted with time (t=2011)				
Jammu & Kashmir				-0.00003
				(-0.002)
Himachal Pradesh				0.0083***
				(-0.001)
Punjab				0.017***
				(-0.0009)
Chandigarh				0.003
				(-0.007)
Uttranchal				0.008***
				(-0.002)
Haryana				0.0217***
				(-0.0009)
Delhi				0.018***
				(-0.002)
Rajasthan				-0.006*
				(-0.001)
Uttar Pradesh				0.007***
				(-0.0008)
Bihar				0.010***
				(-0.001)
Sikkim				0.003
				(-0.004)
Arunachal Pradesh				0.001
				(-0.006)

Nagaland				
				(.)
Manipur				0.02***
				(-0.003)
Mizoram				0.002
				(-0.007)
Tripura				0.008*
				(-0.003)
Meghalaya				0
				(.)
Assam				0.010***
				(-0.002)
West Bengal				0.003**
				(-0.001)
Jharkhand				0.006***
				(-0.002)
Orissa				0.010***
				(-0.0008)
Chhattisgarh				0.009***
				(-0.001)
Madhya Pradesh				0.005***
				(-0.0008)
Gujarat				-0.007***
				(-0.002)
Daman & Diu				0.002
				(-0.007)
Dadra +nagar haveli				-0.004
				(-0.009)
Maharashtra				-0.005***
				(-0.001)
Andhra Pradesh				0.017***
				(-0.0008)
Karnataka				0.011***
				(-0.0007)
Goa				0.0061
				(-0.0031)
Kerala				0.007***
				(-0.001)
Tamil Nadu				0.003**
				(-0.001)
Pondicherry				0.030***
				(-0.002)
Observations	300037	289915	283431	283032
Pseudo R-square	0.22	0.27	0.48	0.52

Standard errors in parentheses * p<0.05, ** p<0.01, *** p<0.001

Note: Meghalaya and Nagaland got dropped due to collinearity

Table A5: Marginal effects of the eligible and non-eligible individuals

	Eligible individuals	Non-eligible individuals
Inverse mills ratio	0.033	0.003***
	(-0.02)	(-0.0006)
Someone close to household has got political connections	0.009	0.0006*
	(-0.01)	(-0.0003)
Solve local problems	0.024**	0.0008***
	(-0.007)	(-0.0002)
Gender	0.059***	0.0001
	(-0.008)	(-0.0002)
OBC	0.016	0.0009***
	(-0.011)	(-0.0003)
SC	0.047***	0.002***
	(-0.012)	(-0.0003)
ST	0.017	0.001*
	(-0.017)	(-0.0005)
Age	0.009***	0.0005***
	(-0.0005)	(-0.00003)
Education	-0.010***	-0.0004***
	(-0.002)	(-0.00004)
Urban	-0.042***	-0.002***
	(-0.012)	(-0.0003)
Household composition	-0.008***	-0.0002***
	(-0.002)	(-0.00004)
Agriculture land owned	-0.043***	-0.001***
	(-0.009)	(-0.0002)
Member in self-help group	-0.005	-0.00003
	(-0.010)	(-0.0003)
Women access-TV	-0.013	-0.0004
	(-0.009)	(-0.0003)
Women access-radio	-0.028*	-0.0018***
	(-0.011)	(-0.0003)
Women access-newspaper	-0.018	-0.001***
	(-0.012)	(-0.0003)
State fixed factors below were interacted with time (t=2011)		
Jammu & Kashmir	0.027	-0.002
	(-0.057)	(-0.001)
Himachal Pradesh	0.261***	0.001*
	(-0.023)	(-0.0007)
Punjab	0.346***	0.00626***
	(-0.025)	(-0.0006)
Chandigarh	0	-0.005
	(.)	(-0.003)
Uttranchal	0.195***	0.002
	(-0.040)	(-0.001)
Haryana	0.323***	0.00888***
	(-0.027)	(-0.0007)
Delhi	0.293***	0.005***
	(-0.073)	(-0.0013)
Rajasthan	0.048	-0.004***
	(-0.026)	(-0.0008)
Uttar Pradesh	0.128***	0.002***
	(-0.024)	(-0.0005)
Bihar	0.209***	0.003***
	(-0.022)	(-0.0007)
Sikkim	0.143	0
	(-0.074)	(.)
Arunachal Pradesh	0.101	0
	(-0.091)	(.)
Nagaland	0	0
	(.)	(.)
Manipur	0.330***	0.009***
	(-0.069)	(-0.002)

Mizoram	-0.060	0.001
	(-0.142)	(-0.003)
Tripura	0.192*	0.002
	(-0.085)	(-0.002)
Meghalaya	0	0
	(.)	(.)
Assam	0.218***	0.002*
	(-0.041)	(-0.0010)
West Bengal	0.123***	-0.0009
	(-0.028)	(-0.0007)
Jharkhand	0.076	0.001
	(-0.044)	(-0.0009)
Orissa	0.255***	0.003***
	(-0.018)	(-0.0006)
Chhattisgarh	0.199***	0.00404***
	(-0.023)	(-0.0007)
Madhya Pradesh	0.194***	-0.00004
	(-0.018)	(-0.0006)
Gujarat	-0.133**	-0.003**
	(-0.041)	(-0.001)
Daman & Diu	0	0.001
	(.)	-0.003
Dadra +nagar haveli	0.139	0
	(-0.166)	(.)
Maharashtra	-0.038	-0.003***
	(-0.023)	(-0.0007)
Andhra Pradesh	0.343***	0.00851***
	(-0.020)	(-0.0009)
Karnataka	0.241***	0.005***
	(-0.017)	(-0.0006)
Goa	0.103	0.0008
	(-0.149)	(-0.002)
Kerala	0.191***	0.002**
	(-0.024)	(-0.0007)
Tamil Nadu	-0.054	0.005***
	(-0.031)	(-0.00071)
Pondicherry	0	0.012***
	(.)	(-0.001)
Observations	10264	271985

Standard errors in parentheses, * $p<0.05$, ** $p<0.01$, *** $p<0.001$.
Note: certain state fixed factors interacted with time were dropped due to collinearity.

TABLE A6: State domicile criterion

States	Years of residence criteria followed
Arunachal Pradesh	05-10
Chattisgarh	15
Delhi	3
Himachal Pradesh	15
Rajasthan	10 years or more
Tamilnadu	5
Tripura	10
UP	3
Maharashta	15
Kerala	More than 10 years
Bihar	10 years
Uttarakhand	at least 15 years
Gujarat	more than 3 years
Haryana	15 years or more
Karnataka	more than 6 years
Madhya Pradesh	15 years or above.
West Bengal	for at least 15 years
Jammu & Kashmir	minimum 15 years of state residence

Source: State government portals

Table A7: Bi-probit coefficients

	Complete sample		Eligible individuals		Non-eligible individuals	
	IGNOAPS	Political connection	IGNOAPS	Political connection	IGNOAPS	Political connection
Inverse mills ratio	0.193***		0.122		0.377***	
	(-0.054)		(-0.093)		(-0.069)	
Someone close to household has got political connections	0.330*		0.095		0.451*	
	(-0.149)		(-0.3)		(-0.181)	
Solving local problems	0.0936***		0.094**		0.097***	
	(-0.02)		(-0.033)		(-0.026)	
Years of living less than 15years		-0.440***		-4.244***		-0.436***
		(-0.055)		(-0.085)		(-0.055)
Gender	0.104***	0.0008	0.225***	0.017	0.014	0.0002
	(-0.019)	(-0.006)	(-0.032)	(-0.033)	(-0.025)	(-0.006)
Other backward caste	0.128***	0.051***	0.063	-0.017	0.108***	0.052***
	(-0.025)	(-0.008)	(-0.043)	(-0.043)	(-0.031)	(-0.008)
Scheduled caste	0.264***	0.0467***	0.185***	-0.060	0.188***	0.049***
	(-0.028)	(-0.009)	(-0.047)	(-0.048)	(-0.035)	(-0.009)
Scheduled tribe	0.163***	0.0304*	0.065	-0.118	0.120*	0.036**
	(-0.040)	(-0.013)	(-0.064)	(-0.063)	(-0.056)	(-0.013)
Age in years	0.0601***	0.0000193	0.036***	0.002	0.055***	-0.0001
	(-0.0008)	(-0.0002)	(-0.002)	(-0.002)	(-0.001)	(-0.0002)
Education completed	-0.049***	0.004***	-0.038***	0.0003	-0.042***	0.005***
	(-0.003)	-(0.0007)	(-0.006)	(-0.006)	(-0.004)	(-0.0008)
Lives in urban area	-0.242***	-0.387***	-0.157**	-0.312***	-0.249***	-0.389***
	(-0.031)	(-0.009)	(-0.050)	(-0.049)	(-0.039)	(-0.009)
Household composition	-0.023***	0.013***	-0.030***	0.024***	-0.018***	0.013***
	(-0.003)	(-0.001)	(-0.006)	(-0.005)	(-0.004)	(-0.001)
Agriculture land owned	-0.202***	0.203***	-0.170***	0.196***	-0.152***	0.204***
	(-0.022)	(-0.007)	(-0.038)	(-0.035)	(-0.028)	(-0.007)
Membership in self-help group	0.009	0.117***	-0.018	0.033	-0.013	0.120***
	(-0.027)	(-0.009)	(-0.040)	(-0.041)	(-0.039)	(-0.009)
Women access-TV	-0.101***	0.0531***	-0.050	0.001	-0.055	0.057***
	(-0.022)	(-0.008)	(-0.036)	(-0.036)	(-0.030)	(-0.008)
Women access-radio	-0.117***	0.083***	-0.106*	0.027	-0.137***	0.085***
	(-0.024)	(-0.007)	(-0.042)	(-0.041)	(-0.030)	(-0.007)
Women access-newspaper	-0.179***	0.126***	-0.069	0.191***	-0.137***	0.125***
	(-0.027)	(-0.009)	(-0.048)	(-0.046)	(-0.033)	(-0.008)
State fixed factors below were interacted with time (t=2011)						
Jammu & Kashmir	-0.188	0.427***	0.094	0.411*	-0.329*	0.427***
	(-0.12)	(-0.026)	(-0.22)	(-0.164)	(-0.137)	(-0.027)
Himachal Pradesh	0.456***	0.847***	0.974***	1.002***	0.068	0.834***
	(-0.065)	(-0.019)	(-0.131)	(-0.084)	(-0.088)	(-0.02)
Punjab	0.820***	1.081***	1.292***	1.153***	0.625***	1.078***
	(-0.064)	(-0.017)	(-0.146)	(-0.087)	(-0.073)	(-0.018)
Chandigarh	-0.302	-0.0601	0	0	-0.527	-0.056
	(-0.371)	(-0.151)	(.)	(.)	(-0.376)	(-0.151)
Uttranchal	0.394***	0.638***	0.733***	0.466**	0.163	0.645***
	(-0.101)	(-0.034)	(-0.156)	(-0.152)	(-0.14)	(-0.035)
Haryana	1.151***	0.229***	1.240***	0.173	1.092***	0.231***
	(-0.040)	(-0.020)	(-0.106)	(-0.112)	(-0.043)	(-0.020)

Delhi	0.759***	-0.284***	1.118***	-4.362***	0.529***	-0.274***
	(-0.107)	(-0.060)	(-0.279)	(-0.189)	(-0.118)	(-0.06)
Rajasthan	-0.237***	0.0836***	0.183	-0.117	-0.452***	0.0899***
	(-0.064)	(-0.017)	(-0.1)	(-0.101)	(-0.089)	(-0.017)
Uttar Pradesh	0.226***	0.644***	0.469***	0.826***	0.107	0.637***
	(-0.050)	(-0.012)	(-0.113)	(-0.068)	(-0.057)	(-0.012)
Bihar	0.527***	0.744***	0.778***	0.800***	0.324***	0.739***
	(-0.059)	(-0.019)	(-0.109)	(-0.079)	(-0.080)	(-0.019)
Sikkim	0.411	-0.231	0.553	-0.292	-3.754***	-0.231
	(-0.228)	(-0.124)	(-0.285)	(-0.454)	(-0.142)	(-0.129)
Arunachal Pradesh	0.203	1.245***	0.404	1.344***	-3.722***	1.237***
	(-0.296)	(-0.073)	(-0.37)	(-0.28)	(-0.089)	(-0.076)
Nagaland	-4.461***	1.204***	-4.385***	1.027	-3.928***	1.206***
	(-0.176)	(-0.109)	(-0.215)	(-0.681)	(-0.083)	(-0.11)
Manipur	1.159***	1.106***	1.242***	0.345	0.973***	1.144***
	(-0.155)	(-0.066)	(-0.265)	(-0.294)	(-0.2)	(-0.068)
Mizoram	-0.267	3.245***	-0.282	6.610***	-0.219	3.236***
	(-0.37)	(-0.194)	(-0.593)	(-0.105)	(-0.421)	(-0.197)
Tripura	0.339	0.727***	0.712*	1.044***	0.173	0.712***
	(-0.181)	(-0.063)	(-0.342)	(-0.314)	(-0.224)	(-0.065)
Meghalaya	-4.493***	1.274***	-4.525***	1.668***	-3.854***	1.259***
	(-0.108)	(-0.076)	(-0.189)	(-0.445)	(-0.098)	(-0.077)
Assam	0.484***	0.101**	0.820***	0.303	0.259*	0.0894*
	(-0.085)	(-0.036)	(-0.159)	(-0.162)	(-0.112)	(-0.037)
West Bengal	0.0881	-0.403***	0.462***	-0.292*	-0.115	-0.408***
	(-0.060)	(-0.026)	(-0.107)	(-0.138)	(-0.079)	(-0.027)
Jharkhand	0.137	0.892***	0.267	0.847***	0.0352	0.893***
	(-0.096)	(-0.025)	(-0.183)	(-0.135)	(-0.112)	(-0.025)
Orissa	0.702***	-0.827***	0.985***	-1.194***	0.403***	-0.806***
	(-0.045)	(-0.034)	(-0.075)	(-0.158)	(-0.072)	(-0.035)
Chhattisgarh	0.503***	1.338***	0.729***	1.456***	0.318**	1.327***
	(-0.087)	(-0.02)	(-0.17)	(-0.083)	(-0.112)	(-0.021)
Madhya Pradesh	0.205**	1.145***	0.713***	1.175***	-0.139	1.142***
	(-0.067)	(-0.013)	(-0.131)	(-0.063)	(-0.091)	(-0.014)
Gujarat	-0.472***	0.119***	-0.526***	0.161	-0.389**	0.117***
	(-0.109)	(-0.022)	(-0.157)	(-0.11)	(-0.129)	(-0.022)
Daman & Diu	-0.0922	0.451***	-4.834***	0.724	0.072	0.441***
	(-0.382)	(-0.098)	(-0.195)	(-0.555)	(-0.357)	(-0.010)
Dadra +nagar haveli	-0.331	-4.862***	0.535	-4.543***	-4.952***	-4.839***
	(-0.499)	(-0.019)	(-0.635)	(-0.131)	(-0.175)	(-0.019)
Maharashtra	-0.302***	0.180***	-0.155	-0.0675	-0.355***	0.189***
	(-0.061)	(-0.015)	(-0.089)	(-0.082)	(-0.082)	(-0.015)
Andhra Pradesh	1.206***	-0.131***	1.306***	-0.139	0.997***	-0.132***
	(-0.053)	(-0.024)	(-0.079)	(-0.075)	(-0.083)	(-0.026)
Karnataka	0.647***	1.478***	0.882***	1.381***	0.422***	1.485***
	(-0.086)	(-0.013)	(-0.154)	(-0.051)	(-0.107)	(-0.014)
Goa	0.233	-0.684***	0.481	-4.504***	0.171	-0.678***
	(-0.18)	(-0.112)	(-0.603)	(-0.112)	(-0.183)	(-0.113)
Kerala	0.413***	0.026	0.719***	-0.171	0.220*	0.035
	(-0.0604)	(-0.0258)	(-0.092)	(-0.115)	(-0.086)	(-0.027)
Tamil Nadu	0.219**	0.423***	-0.222	-0.189	0.490***	0.449***
	(-0.072)	(-0.022)	(-0.118)	(-0.116)	(-0.083)	(-0.022)
Pondicherry	1.492***	-0.951***	6.722***	-4.358***	1.425***	-0.946***

	(-0.121)	(-0.173)	(-0.146)	(-0.12)	(-0.123)	(-0.174)
Athrho[1]	-0.15		-0.04		-0.22**	
Observations	283417		10286		273131	

Standard errors in parentheses, * p<0.05, ** p<0.01, *** p<0.001.

Note: certain state fixed factors interacted with time were dropped due to collinearity.

[1] Note: Athrho for the complete sample is significant at 10%. So we have computed the marginal effects for it.

TABLE A8: Average marginal effect of the biprobit model

	Marginal effects			
	Complete sample		**Non-eligible individuals**	
Variables	IGNOAPS	Political connection	IGNOAPS	Political connection
Someone close to household has got political connections	0.007**		0.006*	
	(0.003)		(0.003)	
Inverse mills ratio	0.004***		0.005***	
	(0.001)		(0.001)	
Solving local problems	0.002***		0.001***	
	(0.0005)		(0.000)	
Years of living less than 15years		-0.099***		-0.098***
		0.012		(0.012)
Gender	0.002***		0.000***	
	(0.0004)		(0.000)	
Other backward caste	0.003***	0.011***	0.001***	0.012***
	(0.0006)	(0.002)	(0.000)	(0.002)
Scheduled caste	0.006***	0.011***	0.002*	0.011***
	(0.0006)	(0.002)	(0.000)	(0.002)
Scheduled tribe	0.007***	0.007*	0.002**	0.008**
	(0.0009)	(0.003)	(0.001)	(0.003)
Age in years	0.001***	0.000	0.001***	0.000
	(0.00003)	(0.000)	(0.000)	(0.000)
Education completed	-0.001***	0.001***	-0.001***	0.001***
	(0.00007)	(0.000)	(0.000)	(0.000)
Lives in urban area	-0.005***	-0.087***	-0.003***	-0.087***
	(0.0007)	(0.002)	(0.000)	(0.002)
Household composition	-0.0005***	0.003***	0.000***	0.003***
	(0.00008)	(0.000)	(0.000)	(0.000)
Agriculture land owned	-0.005***	0.046***	-0.002***	0.046***
	(0.0005)	(0.002)	(0.000)	(0.002)
Membership in self-help group	0.0002	0.026***	0.000	0.027***
	(0.0006)	(0.002)	(0.001)	(0.002)
Women access-TV	-0.002***	0.012***	-0.001	0.013***
	(0.0005)	(0.002)	(0.000)	(0.002)
Women access-radio	-0.002***	0.019***	-0.002***	0.019***
	(0.0006)	(0.002)	(0.000)	(0.002)
Women access-newspaper	-0.004***	0.028***	-0.002***	0.028***
	(0.0006)	(0.002)	(0.000)	(0.002)
State fixed factors below were interacted with time (t=2011)				
Jammu & Kashmir	-0.004	0.096***	-0.004*	0.096***
	(0.003)	(0.006)	(0.002)	(0.006)
Himachal Pradesh	0.01***	0.190***	0.001	0.187***
	(0.001)	(0.004)	(0.001)	(0.004)
Punjab	0.018***	0.243***	0.008***	0.241***
	(0.001)	(0.004)	(0.001)	(0.004)
Chandigarh	-0.007	-0.014	-0.007	-0.013
	(0.008)	(0.034)	(0.005)	(0.034)
Uttranchal	0.009***	0.143***	0.002	0.144***
	(0.002)	(0.008)	(0.002)	(0.008)
Haryana	0.025***	0.051***	0.014***	0.052***
	(0.0009)	(0.004)	(0.001)	(0.005)
Delhi	0.017***	-0.064***	0.007***	-0.061***

	(0.002)	(0.013)	(0.002)	(0.013)
Rajasthan	-0.005***	0.019***	-0.006***	0.020***
	(0.001)	(0.004)	(0.001)	(0.004)
Uttar Pradesh	0.005***	0.145***	0.001	0.143***
	(0.001)	(0.003)	(0.001)	(0.003)
Bihar	0.012***	0.167***	0.004***	0.165***
	(0.001)	(0.004)	(0.001)	(0.004)
Sikkim	0.009	-0.052	-0.049***	-0.052
	(0.005)	(0.028)	(0.003)	(0.029)
Arunachal Pradesh	0.005	0.280***	-0.048***	0.277***
	(0.007)	(0.016)	(0.003)	(0.017)
Nagaland	-0.1***	0.270***	-0.051***	0.270***
	(0.005)	(0.024)	(0.003)	(0.025)
Manipur	0.026***	0.248***	0.013***	0.256***
	(0.003)	(0.015)	(0.002)	(0.015)
Mizoram	-0.006	0.729***	-0.003	0.724***
	(0.008)	(0.044)	(0.006)	(0.044)
Tripura	0.008	0.163***	0.002	0.159***
	(0.004)	(0.014)	(0.003)	(0.014)
Meghalaya	-0.101***	0.286***	-0.050***	0.282***
	(0.003)	(0.017)	(0.003)	(0.017)
Assam	0.011***	0.023*	0.003*	0.020*
	(0.002)	(0.008)	(0.001)	(0.008)
West Bengal	0.002	-0.091***	-0.001	-0.091***
	(0.001)	(0.006)	(0.001)	(0.006)
Jharkhand	0.003	0.200***	0.000	0.200***
	(0.002)	(0.006)	(0.001)	(0.006)
Orissa	0.016***	-0.186***	0.005***	-0.181***
	(0.001)	(0.008)	(0.001)	(0.008)
Chhattisgarh	0.011***	0.301***	0.004**	0.297***
	(0.002)	(0.004)	(0.001)	(0.005)
Madhya Pradesh	0.005**	0.257***	-0.002	0.256***
	(0.001)	(0.003)	(0.001)	(0.003)
Gujarat	-0.011***	0.027***	-0.005*	0.026***
	(0.003)	(0.005)	(0.002)	(0.005)
Daman & Diu	-0.002	0.101***	0.001	0.099***
	(0.009)	(0.022)	(0.005)	(0.022)
Dadra +nagar haveli	-0.007	-1.092***	-0.064***	-1.083***
	(0.011)	(0.006)	(0.004)	(0.006)
Maharashtra	-0.007***	0.040***	-0.005***	0.042***
	(0.002)	(0.003)	(0.001)	(0.003)
Andhra Pradesh	0.027***	-0.029***	0.013***	-0.030***
	(0.001)	(0.005)	(0.001)	(0.006)
Karnataka	0.015***	0.332***	0.005***	0.332***
	(0.002)	(0.003)	(0.001)	(0.003)
Goa	0.005	-0.154***	0.002***	-0.152***
	(0.004)	(0.025)	(0.002)	(0.025)
Kerala	0.009***	0.006***	0.003*	0.008
	(0.001)	(0.006)	(0.001)	(0.006)
Tamil Nadu	0.005**	0.095***	0.006***	0.101***
	(0.002)	(0.005)	(0.001)	(0.005)
Pondicherry	0.034***	-0.214***	0.018***	-0.212***
	(0.003)	(0.039)	(0.002)	(0.039)

End notes

[i] http://164.100.47.134/lsscommittee/Estimates/15_Estimates_34.pdf (page number 13)

[ii] I created a unique id by combining the state id, district id, primary sampling unit it, household id, person id within the household and a random number. The inclusion of the random number ensures that the individual ids are unique for that person alone and there is no overlap of the id. I merged this id in the 2011 and 2005 individual rounds; thereby generating the unique id in both files. I later appended the 2011 file with the 2005 file.