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Access to Information and Adoption of New Farming Practices – A Spatial Analysis[1]

Shobhit Kulshreshtha[2]

Abstract

In this study, I delve into the factors shaping the adoption of new farming practices among Indian farmers, with a particular focus on the role of information access and its diverse sources. Leveraging nationally representative data on rural households from the National Sample Survey Office, Government of India for the year 2019, I employ logistic regression to gauge the likelihood of farmers adopting new agricultural techniques based on the information they receive from various channels. Additionally, I undertake spatial linear regression analysis to unravel the dynamics of information spillovers pertaining to new farming practices across districts. The results highlight the significance of the information source in driving adoption decisions, with progressive farmers and input dealers emerging as influential sources. Moreover, the spatial analysis provides compelling evidence of information diffusion across district boundaries, highlighting the varying efficacy of different information channels. These findings offer valuable insights for policymakers aiming to craft targeted interventions aimed at shaping farmers' decision-making processes regarding the adoption of innovative farming practices.

JEL Codes: Q15, Q16, Q54
Keywords: Farming Practices, Information Access, Technology Adoption, Spatial Spillovers

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Introduction

The adoption of new farming practices not only empowers farmers with advanced technology to enhance productivity but also offers the potential for increased profits. Extensive research has demonstrated that, particularly in developing countries in South Asia and Sub-Saharan Africa, access to information plays a pivotal role in influencing farmers' decisions to adopt these innovative techniques (Aryal et al., 2018; Cole & Fernando, 2021). It has also been highlighted in the literature that the source of information can significantly impact farmers' propensity to adopt new farming practices (Aryal et al., 2018). Moreover, it has been observed that farmers who exhibit greater homogeneity in a region, in terms of farm characteristics and household attributes, are more inclined to adopt new farming practices when they observe others in their community doing the same. Conversely, farmers, in a region, who differ significantly in these aspects are less likely to emulate their peers when it comes to adopting new farming practices (Munshi, 2004). This intriguing observation suggests the presence of spatial spillovers in the adoption of new techniques, implying that the behavior of one farmer may influence the decisions of neighboring farmers. This spatial interdependence presents a critical dimension in unraveling the complexities of adoption of new farming practices among farmers. Despite the acknowledged significance of these factors, a comprehensive national-level study on the adoption of new farming practices among Indian farmers, along with an examination of the spatial spillovers related to access to this information, has been absent because of data limitations.

In this study, I aim to bridge this research gap. To achieve this, I pursue two main objectives. Firstly, I estimate the impact of access to information and the source of information on the adoption of new farming practices at the rural household level in India. Secondly, I investigate the spatial spillovers stemming from varying degrees of access to information from diverse sources across different districts in India. By delving into these spatial spillovers, this research explores the intricate dynamics that shape the agricultural landscape regarding information spillovers and technology adoption in the country.

I leverage the most recent national survey data, the “Socio-economic survey” that was conducted by the National Sample Survey Office (NSSO), Government of India during the period January to December 2019, for my analysis. The survey encompasses rural households across India. This dataset is particularly valuable as it provides comprehensive insights into various aspects, including access to information and the sources of such information. I conduct the spatial analysis at the district-level because farmers' adoption decisions can be significantly influenced by the characteristics and practices of neighboring districts. This approach allows me to pinpoint specific regions or clusters where adoption patterns may differ and where targeted interventions and policy efforts can be strategically directed. By uncovering these localized dynamics, I add to the literature on adoption of new farming practices in India, emphasizing the importance of considering the geographical context when studying technology adoption in agriculture. There might be some concerns about the data representativeness at the district level which could be considered a limitation of this study.

In this survey, a total of 58,035 households were covered. However, for the purpose of my analysis, I restricted the sample to 45,690 households, who provided responses to questions regarding their access to information pertaining to innovative farming practices. During the period of survey, the farmers were visited twice. Out of a total of 45,690 households, only 24,551 households had access to information about new farming practices. I am focusing on these 24,551 households who had access to information. At the district level, I aggregated the

binary variable indicating whether a farmer had access to information to compute the proportion of farmers with access to information at the district level. This proportion was then employed as the outcome variable for the district-level analysis, where I estimated the spatial spillovers in access to information among farmers across districts.

For the household analyses, the treatment variable is defined as the share of farmers who had access to information from any source regarding a new farming practice in the district, excluding the concerned farmer. These are the famous leave-one-out instruments that have been used in the literature for instrumental variable analysis. However, in this study, this variable is considered as the main treatment variable because it captures the access to information among the peers of a farmer, which can directly influence a farmer's access to information and hence their adoption decision. In addition, I have also defined this variable for different sources to understand the role of the source in influencing the decision of farmers to adopt new farming practices. Excluding the concerned farmer also addresses the concern of reverse causality. To conduct a robust analysis, I incorporated an extensive array of control variables that can influence farmers' decisions to adopt new farming practices into my study. These control variables were carefully selected based on prior research findings (Chanana-Nag & Aggarwal, 2020; Jha & Gupta, 2021) and encompassed various factors known to influence a farmer's decision to adopt new farming practices. By considering these controls, I aimed to comprehensively account for potential confounding factors and ensure the validity and reliability of the analysis. In addition, I conducted a bias correction test suggested by Oster (2019) to check for omitted variable bias.

The empirical methodology employed in this study consists of two distinct parts. Firstly, I delve into the household-level decision-making process regarding the adoption of new farming practices. In this context, my dependent variable is binary, taking on values of 1 or 0 to indicate whether the farmer adopts a new farming practice, conditional on receiving information from a source. To estimate the probability of a household adopting a new farming practice in response to changes in the share of farmers with access to information within her district, I utilize logistic regression. Additionally, I investigate how residing in districts with farmers having access to information from different sources influences the likelihood of adopting these innovative farming techniques. The main mechanism behind this effect is that a farmer might receive information regarding new farming practices from her peers, which can directly affect their adoption decision. In this first phase, logistic regression serves as a powerful statistical tool that allows us to model the probability of an event occurring, in this case, the adoption of new farming practices, while considering various explanatory variables. The primary focus of my analysis is to assess how the increasing share of farmers with access to information within a district affects the odds of a household adopting new farming practices. Additionally, I aim to understand how the dominance of specific information sources in a district impacts the adoption decisions of farmers residing in that district.

Secondly, I employ spatial econometrics models to explore the spatial spillover effects of access to information and from varying sources of information. Specifically, I utilize a general nesting spatial econometric model to analyze information spillovers across districts. This model considers the spatial dependencies that may exist between neighboring districts and how they affect information access, encompassing spatial dependencies in access to information, observed factors, and unobserved factors. Furthermore, to capture the variation in information access through various sources, I estimate the spatial models for the share of farmers accessing information from different sources. I have conducted specification tests and provide estimates from different model specifications to ensure the validity and robustness of these results.

I find that if a farmer were to relocate to a district with a 10-percentage point higher share of farmers having access to information, their likelihood of adopting a new farming practice would increase by 14 percent compared to if they had remained in their original district. This significant effect highlights the pivotal role of information access in driving the adoption of innovative farming techniques. Furthermore, I find that residing in a district with a higher share of farmers accessing information from progressive farmers, input dealers, or print media enhances the likelihood of farmers adopting new farming practices compared to districts where the primary information source is from other channels. This finding indicates the influence of peer learning and expert guidance in motivating farmers to adopt innovative techniques, in addition to the information being circulated by newspapers and magazines among peers. The presence of progressive farmers and input dealers as information providers likely facilitates the dissemination of practical and relevant knowledge, thus encouraging adoption. Conversely, my analysis also revealed that residing in a district where the share of farmers who access information from electronic media has a dampening effect on the likelihood of farmers adopting new farming practices. This observation suggests that electronic media may not be as effective in conveying necessary information or motivating farmers to adopt new techniques. These findings highlight the influence of information sources on farmers' technology adoption decisions. The share of farmers who have access to information from various sources within a district plays a crucial role in shaping the propensity of farmers to adopt new farming practices, with significant implications for agricultural development and policy considerations. The results are robust when using different model specifications and correcting for omitted variable bias.

Findings from spatial analysis demonstrate that when neighboring districts have a higher proportion of farmers with access to information, this exerts a positive influence on the share of farmers who gain information from any source in a district. This implies that the spread of information and knowledge does not remain confined within district boundaries but transcends them, fostering a culture of innovation and modernization across neighboring regions. The findings highlight that interventions aimed at enhancing information access and dissemination should not be limited to individual districts but should also consider the knowledge-sharing networks that span across district boundaries. However, the inferences drawn from this analysis may be somewhat limited due to concerns regarding the representativeness of the data at the district level.

This study contributes broadly to the body of research investigating technology adoption among farmers (Foster & Rosenzweig, 2010). Specifically, it adds to the literature on the determinants of agricultural mechanization in developing countries (Ali, 2012; Asfaw et al., 2011; Ghimire et al., 2015; Kumar et al., 2020; 2021; Mottaleb et al., 2011; Simtowe et al., 2011; Singh et al., 2015). Previous studies in this area have explored various socio-economic, farm-level, and institutional factors influencing agricultural modernization. This study extends this literature by investigating the role of specific information sources in facilitating technology adoption among farmers. While some studies conducted in various states of India have acknowledged the importance of information sources in influencing farmers' behavior, they often failed to identify which sources were most effective in encouraging the adoption of new techniques and which were less impactful. In this study, various sources potentially influencing adoption decisions are examined, shedding light on those that may play a crucial role. Furthermore, this research provides evidence on the role of broader geographical characteristics in explaining information spillovers related to the adoption of new farming practices. By employing district-level analysis, regional dynamics and spatial interdependencies that significantly influence the dissemination of information regarding new

agricultural technologies are captured. Through this study, a contribution is also made to the existing literature emphasizing the significance of heterogeneity among farmers in shaping technology adoption outcomes (Magnan et al., 2015; Munshi, 2004). It is argued that farmers' decisions to accept new farming practices are often influenced by the actions of their peers. By incorporating spatial analysis into this study, I contribute to the literature by looking at the collective effect of farmers' access to information, within a regional context.

In addition, with this research I contribute to the broader literature on spatial patterns in various aspects of rural development in India. Prior studies have explored spatial patterns in agriculture growth (Hazrana et al., 2019), land use (Sharma, 2016), contract farming (Narayanan, 2015), and irrigation (Blakeslee et al., 2023). By introducing a spatial model to analyze information access across districts in rural India, this study not only expands the understanding of how these spatial patterns evolve but also adds a critical dimension by explaining the spatial spillovers that occur across districts concerning access to information.

This paper proceeds as follows: Section 2 provides the detailed explanation of data and variable definitions used for the analysis. In Section 3, I provide the descriptive statistics and spatial patterns in the data. Section 4 provides the econometric models and the findings of the paper. Section 5 concludes.

Data

In this study, I use data from the "Socio-economic survey" conducted by the National Sample Survey Office (NSSO), Government of India during the period January to December 2019. The aim of the survey was to get information on the rural households regarding their operational holdings, economic well-being, farming practices, and awareness and access to new information practices in agriculture. It is a nationally representative survey where the same rural household was visited twice. The first visit was conducted between January and August 2019 and the second visit was made in September to December 2019. The survey covered whole of rural India[3] surveying 58,035 households in the first visit and 56,894 households in the second visit. For this study, data from both survey visits are incorporated. Farmers were queried twice regarding information received from 16 different sources[4], the corresponding farming practices, and subsequent adoption. The dataset is confined to households reporting access to such information, totaling 24,551 farmer households. Each farmer could receive information from multiple sources, however, for a given source only one farming practice was noted. Therefore, there can be only 16 possible source-technology pairs per farmer per visit. For my final analysis, I focus on these 24,551 farmer households that reported having access to information about new farming practices. Moreover, I keep all their possible choices of adopting new farming practice from multiple sources. In total, I have 58,195 household-source-visit[5] pairs that are derived from these two visits.

[3] The survey excluded a few villages in Andaman and Nicobar Islands that were hard to access.
[4] The sources are Progressive Farmers, Input Dealers, Government Extension Agents, Krishi Vigyan Kendras (KVKs), Agricultural University, Private Commercial Agents, Veterinary Departments, Cooperatives, Farmer Producer Organizations (FPOs), Private Processors, Agri. Clinics and Agri. Business Centres, NGO, Kisan Call Centre, Print Media, Electronic Media, Smart Phones.
[5] It can also be written as household-technology-visit pairs as per source, one technology was reported.

Outcome variable

The survey inquired about whether households had implemented a new farming practice recommended by a source. Given that the primary objective of this paper is to ascertain the factors influencing farmers' adoption of new farming practices in agriculture, this specific question serves as the outcome variable for the analysis. It is imperative to acknowledge that there are various sources of information. Accordingly, I define the outcome variable as $Adopt_{ids}$ which is a binary indicator that takes the value 1 if household i residing in district d of state s has implemented recommendations from any information source for a particular farming practice, and 0 if not. Thus, this variable does not differentiate between the sources of information. It is important to note that this variable is conditional on the fact that these farmers had access to information.

In district-level analysis, the focus shifts from adoption patterns to spatial spillovers in access to information. This shift is crucial because adoption of new farming practices is inherently tied to households' access to relevant information. Essentially, if households do not have access to information, they cannot adopt a new farming practice as that is how the question is asked in the survey. This approach aligns with the idea that a household's decision to adopt is influenced by its access to information within the district and by neighboring districts where most rural households also have access to information from various sources. Thus, at the district level, the outcome variable is defined as the share of surveyed households with access to information regarding new farming practices, denoted as $ShareAccess_{ds}$. This variable aggregates the binary access variable at the district level, indicating the overall proportion of households with access to information. Additionally, $ShareAccess_{ds}^{p}$ is defined for each of the six possible sources of information providers "p". This allows for an examination of spatial spillovers in information access among rural households at the district level, offering insights into how information about new farming practices diffuses across geographic regions through different providers.

Explanatory variables

A significant contribution of this study lies in its examination of the potential impact of spatial information diffusion among rural households in India on their adoption choices regarding new technology. To explore this, I define variable $ShareAccess_{-ids}$ as the main treatment variable. This variable captures the proportion of farmers within a district who have gained access to information, relative to the total number of farmers surveyed in that district, excluding the farmer in question. This proportion serves as a measure of the peer network of farmers who have access to information.

By excluding the farmer under examination from these variables, I address the concern of reverse causality. It can be argued that a farmer's decision to adopt a new farming practice cannot influence the share of farmers in that district who gain access to information, and thus, the adoption decision of one farmer cannot cause changes in this treatment variable. With this approach, I ensure that the adoption behavior of a single farmer does not artificially inflate or deflate the overall adoption patterns observed in the district. This helps to disentangle the influence of peer networks and information diffusion from the individual adoption decisions of specific farmers. By employing this method, I can more accurately assess the impact of spatial information diffusion on adoption behavior, providing insights that are robust to potential biases arising from reverse causality.

Additionally, the adoption of new technology by farmers is intricately linked to their awareness of available information. This awareness can stem from various sources that disseminate knowledge about advancements in agriculture. To quantify the share of farmers who have access to information from these diverse sources at the national level, I identify six prominent sources and rank them as follows: 1. progressive farmers, 2. input dealers, 3. government extension agents, 4. print media, 5. electronic media and 6. all other sources. These rankings provide a hierarchical representation of the prevalence and influence of different information sources among farmers. Using this information, I construct source specific additional variables which are defined for a household i as $ShareAccess_{-ids}^{p}$ indicating the share of farmers in the district who have access to information from source p, excluding the farmer i under examination.

Research in the field has highlighted a range of factors that can influence a farmer's choice to adopt new agricultural technology (Jha & Gupta, 2021). These factors may include farmers' personal characteristics, financial status, attributes of their land, access to irrigation facilities, the types of crops cultivated, and other regional attributes (Aryal et al., 2018; Kumar et al., 2021). Since these variables are likely to affect the farmer's adoption decision, I incorporate these variables as additional covariates within the model. A further explanation of these variables is provided in the next section. At the district level, these variables are aggregated to explore how district characteristics influence information access among these geographic regions.

Descriptive Statistics and Spatial Exploration

Descriptive Statistics

Table 1 offers a comprehensive glimpse into the rural households included in the analysis, categorizing their characteristics into three distinct domains: the attributes of the household head, household-specific factors, and farm-related attributes. This comprehensive examination allows us to delve into the demographic, socioeconomic, and contextual elements that collectively shape the adoption behaviors of rural households.

I start with household head's characteristics. It could be seen that more than 90 percent of the household heads were male, highlighting a prevalent male-dominated leadership within these households. Additionally, the average age of household heads was approximately 52 years, signifying an older demographic leading these rural households. The educational attainment of these household heads was also noteworthy, with nearly 33 percent illiterate and additional 41 percent with only primary education. This underscores the critical role of external information sources in acquiring knowledge about new farming practices. An important thing to note is that almost 98 percent of these farmers had not received any formal agricultural training, highlighting their reliance on external information providers for insights into innovative farming techniques.

Next, I turn to household-specific attributes. There was considerable variation in monthly per capita expenditure among these rural households, indicating a range of economic well-being, with some households enjoying relative affluence. 98 percent of households had a bank

account. However, only 55 percent of them have taken loans, suggesting that, despite financial access, a significant portion of households did not rely on credit for their agricultural activities. The religious and caste composition of these households is diverse, with the majority being Hindu. The caste composition showed that 47 percent belonged to other backward castes (except scheduled caste and tribes), while only 27 percent belonged to general caste category. Some of the state agricultural policies provided differential treatment to farmers belonging from different social background. Therefore, including these variables becomes important to control for such targeted policies prevalent in different states.

The section on farm-related attributes provides valuable insights. Access to irrigation stood out, with only 67 percent of farmers having this crucial resource at their disposal. This access could significantly influence crop choices and the adoption of new farming practices. Moreover, only 14 percent of households possessed insurance against crop loss, indicating potential vulnerabilities when facing agricultural risks. Land ownership patterns indicated that most farmers owned their land entirely, while only 5 percent had joint ownership. Joint ownership might introduce complexities in decision-making related to the adoption of new farming practices. Crop cultivation patterns revealed that, on average, farmers grew more than one crop on their farms, with cereals being the most cultivated crop. Paddy emerged as the predominant crop among these farms. Studies have shown that farmers growing paddy and wheat rely more on fellow farmers while those who grow maize are rely more on input dealers for information (Kumar et al., 2021). Therefore, it is essential to control for the crop that these farmers mainly produce in the analysis to avoid such biases.

Table 2 presents descriptive statistics detailing the adoption rates among farmers who received information from various sources during the two visits. Notably, each farmer may receive information from multiple sources, but for the computation of the share of farmers with access to information from a specific source, each farmer appears once per visit. The table indicates striking similarity in adoption patterns across the two visits, suggesting that the timing of the visit did not significantly impact the estimates. Furthermore, it is evident that farmers were more likely to adopt new farming practices when receiving information from progressive farmers or input dealers, whereas adoption rates were comparatively lower when the information originated from print or electronic media sources.

These findings provide a comprehensive understanding of the rural households under analysis and the contextual factors that may impact their adoption of new farming practices. This nuanced exploration sets the stage for further in-depth analysis and investigation.

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min	Max	Sample
Household Head's Characteristics					
Gender (1: Male, 0: Female)	0.92	0.27	0	1	24,551
Age	50.39	13.21	18	105	24,551
Agriculture Training (1: Yes, 0: No)	0.02	0.14	0	1	24,551
Education					
Illiterate	0.33	0.47	0	1	24,551
Primary to Medium	0.41	0.49	0	1	24,551
Medium to Higher	0.20	0.40	0	1	24,551
Graduate and above	0.06	0.24	0	1	24,551
Household's Characteristics					
Log (MPCE)	8.97	0.51	6.48	11.85	24,551
Bank Account Holder (1: Yes, 0: No)	0.98	0.13	0	1	24,551
Loan Taken (1: Yes, 0: No)	0.55	0.50	0	1	24,551
Log (Household Size)	1.49	0.48	0	3.53	24,551
Religion					
Hindu	0.88	0.32	0	1	24,551
Muslim	0.08	0.27	0	1	24,551
Christian	0.02	0.13	0	1	24,551
Others	0.02	0.14	0	1	24,551
Caste					
Scheduled Tribe	0.12	0.32	0	1	24,551
Scheduled Caste	0.14	0.35	0	1	24,551
Other Backward Caste	0.47	0.50	0	1	24,551
General Caste	0.27	0.45	0	1	24,551
Farm Related Characteristics					
Irrigation (1: Yes, 0: No)	0.67	0.47	0	1	24,209
Crop Insurance (1: Yes, 0: No)	0.14	0.34	0	1	23,712
Number of Crops	1.60	1.06	1	10	23,686
Log (Land Size)	0.57	1.01	-4.61	4.61	24,302
Major Crop Grown					
Cereals	0.68	0.47	0	1	24,079
Pulses	0.03	0.17	0	1	24,079
Sugar & Spices	0.04	0.20	0	1	24,079
Fruits & Vegetables	0.04	0.19	0	1	24,079
Oil Seeds	0.11	0.31	0	1	24,079
Other Crops	0.08	0.27	0	1	24,079
Animal Farm	0.02	0.14	0	1	24,079
Jointly Operated (1: Yes, 0: No)	0.05	0.22	0	1	24,300
Ownership of Land					
Entirely Owned	0.82	0.39	0	1	24,300
Entirely Leased	0.01	0.12	0	1	24,300
Both Owned and Leased	0.16	0.37	0	1	24,300
Entirely Otherwise Possessed	0.01	0.04	0	1	24,300

Note: MPCE stands for monthly per capita expenditure of the households and is in INR. Land size is measured in hectares. Sampling weights are used to compute the average and standard errors. Source: Author's calculation from NSSO, 2019 data.

Table 2: Adoption rates from various sources of information providers

Source of Information	Visit 1		Visit 2	
	Adopted	Not Adopted	Adopted	Not Adopted
Progressive Farmers	0.92	0.08	0.91	0.09
Input Dealers	0.94	0.06	0.93	0.07
Government Extension Agents	0.86	0.14	0.83	0.17
Print Media	0.71	0.29	0.68	0.32
Electronic Media	0.70	0.30	0.65	0.35
Other Sources	0.83	0.17	0.83	0.17

Note: Number of observations for visit 1 is 33,188 and for visit 2 is 25,023. Number of observations for progressive farmers is 18,049, for input dealers is 15,773, for government extension agents is 2,340, for print media is 4,064, for electronic media is 9,570 and for other sources is 8,415. No distinction is made on the type of information accessed by households from these sources. A household can be repeated more than once if it has received information from more than one sources during a visit. Other sources include NGOs, smart phones, cooperatives, agricultural universities, etc. Source: Author's calculation from NSSO, 2019 data.

Spatial Exploration

Moran's I is a commonly used measure to detect spatial autocorrelation in a data series. It provides information on whether distribution of a variable is clustered, dispersed, or random. The global form of Moran's I can be written as:

$$Moran's\ I_{Global} = \frac{N}{\sum_i \sum_j w_{ij}} \left(\frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \right)$$

Where, w_{ij} is an element of spatially weighting matrix **W** corresponding to districts *i* and *j*; $\bar{y}$ is the mean on the variable of interest, and N is the number of districts. Moran's I can be interpreted as a measure of covariance of observations in the neighboring districts relative to the variance of the observations across districts. A value of Moran's I closer to unity indicates clustering of spatial units.

Moran's I is a valuable tool for assessing global spatial autocorrelation, but it may not capture the potential presence of spatial clustering around specific districts. To address this, I calculate local Moran's I:

$$Moran's\ I_{Local} = \frac{(y_j - \bar{y}) \sum_{j=1}^{n} w_{ij}(y_j - \bar{y})}{\sum_{i=1}^{n}(y_j - \bar{y})^2 / n}$$

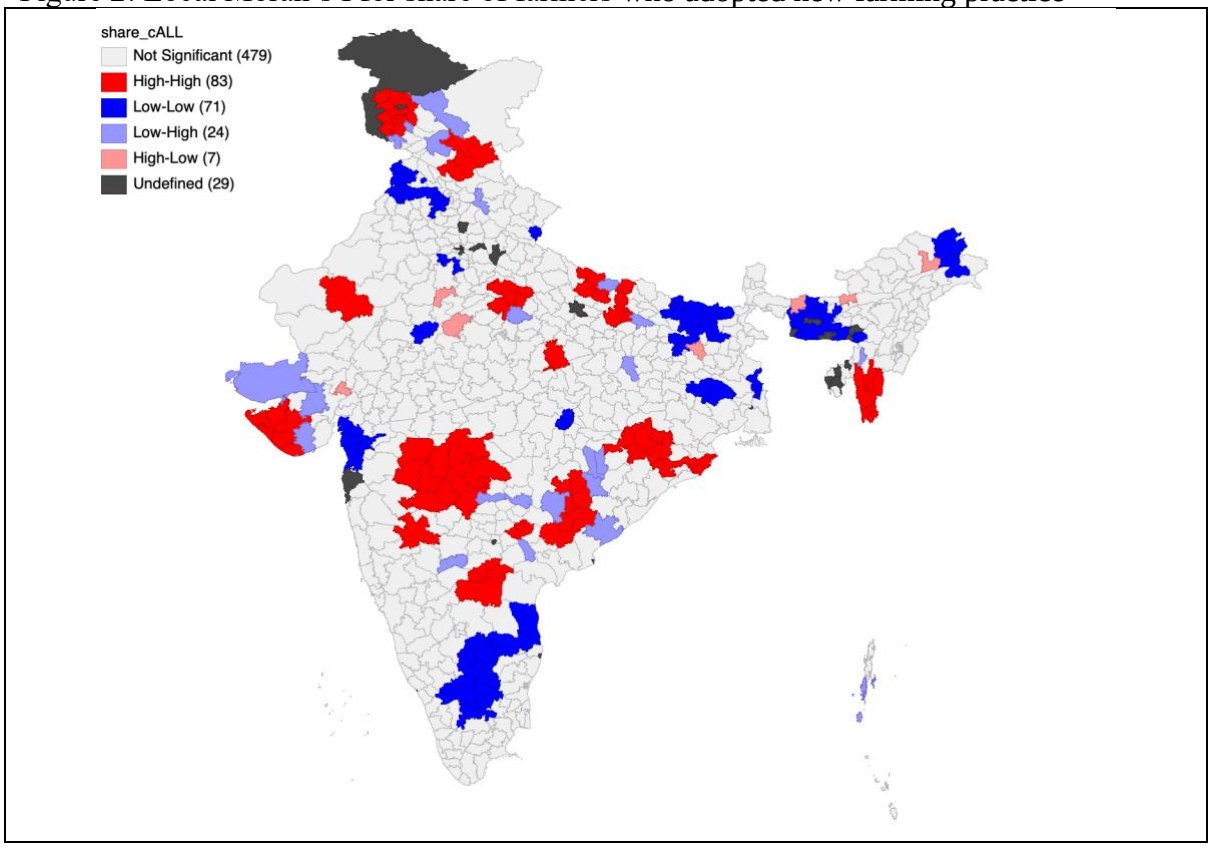
In the absence of global spatial autocorrelation, local Moran's I identify districts that exhibit significant deviations from spatial randomness. Conversely, in the presence of global spatial autocorrelation, it identifies districts that contribute most to the overall pattern of spatial clustering. The global Moran's I value is 0.339 for access to information regarding new farming practices, estimated using a row-standardized inverse distance spatial weight matrix. This positive and highly significant value indicates spatial dependence in access to information. Districts with a higher share of farmers who have access to information tend to be located nearer to districts with similarly high shares, while districts with lower access rates are situated nearer to other districts with lower access rates.

However, global Moran's I ignore the potential instability of local units. Therefore, a more granular investigation is conducted to determine if access to information exhibits spatial concentration and, if so, in which districts this concentration is most pronounced. Local Moran's I, computed for each observation, allows for the assessment of the degree of spatial clustering of similar values around specific locations, aiding in the identification of statistically significant patterns of spatial association. Figure 1 shows local Moran's I for the share of farmers who have access to information regarding new farming practices across districts in India.

There are four types of local spatial associations identified: (i) districts with a high share of farmers who have access to information and are surrounded by neighbors with similarly high access rates (HH); (ii) a district that has a low share of farmers having access to such information but is surrounded by neighbors with high access to information (LH); (iii) districts that have a low share of farmers having access to information and are situated among neighbors with similarly low access rates (LL); (iv) districts that exhibit a high share of farmers with access to information but are surrounded by neighbors with low access rates (HL). Utilizing an inverse distance weight matrix, it was identified that 83 districts fall into the High-High (HH)

category, while 71 districts belong to the Low-Low (LL) category, both of which are significant. This observation highlights the presence of positive local spatial autocorrelation, leading to the formation of distinct spatial clusters. Additionally, there are 479 districts where no significant local Moran's I values were found. Findings from this analysis provide evidence of spatial clustering of access to information regarding new farming practices across districts in India. This suggests a need to examine the spatial patterns of access to information regarding new farming practices using spatial econometric models and to understand the role of information access in the formation of such clusters.

Figure 2: Local Moran's I for share of farmers who adopted new farming practice



Note: The districts that are undefined include districts for which the data is not available for there was no access to information among farmers in these districts. Total number of districts are 693, out of which data is available only for 664 districts.
Source: Author's calculation from NSSO, 2019 data. Software used: GeoDa

Methodology and Results

Household Level Analysis

Baseline Regression

The importance of access to information and its provider in adoption decisions of rural households has been argued by various studies (Aryal et al., 2018; Birthal et al., 2015; Sapkota et al., 2018). To investigate whether information access at the district level can influence farmer's decision, I test the hypothesis that households residing in districts with higher access to information among their peers are more likely to adopt these practices. I use the adoption decision of the farmer as the dependent variable. The estimation equation is as follows:

$$Adopt_{ids} = \begin{cases} 1 \; if \; Adopt^*_{ids} > 0 \\ 0 \; if \; Adopt^*_{ids} \leq 0 \end{cases} \quad (1)$$

$$Adopt^*_{ids} = \alpha + \theta ShareAccess_{-ids} + \beta HHead_{ids} + \gamma HH_{ids} + \delta Farm_{ids} + \lambda_s + \varepsilon_{ids} \quad (2)$$

Where, $Adopt_{ids}$ is the binary indicator taking value 1 if the household i living in district d of state s had adopted any farming practice coming from any source of information. $Adopt^*_{ids}$ is the latent variable that explains whether a farmer will adopt a new farming practice or not. The variable of interest in this equation is $ShareAccess_{-ids}$ which is the share of farmers in the district d of state s who have access to information from any possible source leaving the household i out. I control for an extensive list of variables that might also influence the decision of adopting the new technology, these are included in the household head's characteristics ($HHead_{ids}$), household characteristics (HH_{ids}) and farm characteristics ($Farm_{ids}$) as detailed in previous section. λ_s are the state fixed effects[6] and ε_{ids} is the error term and is assumed to be independent of all the covariates. The parameter of primary interest is θ, which quantifies the effect of the proportion of farmers with access to information in the district on the probability of a farmer adopting a new farming practice. I hypothesize that higher access to information in a district corresponds to an increased likelihood of adopting new farming practices by the farmers. Excluding the farmer i in constructing the variable $ShareAccess_{-ids}$ solves the problem of reverse causality as it is highly unlikely that an individual farmer's adoption decision can influence the number of farmers in the district who have access to information from various sources.

There might be a concern that the error term ε_{ids} is still correlated with $ShareAccess_{-ids}$ and might bias the estimates because of omitted variable bias. To address this concern, I have conducted bias correction tests as suggested by Oster (2019). The methodology is explained in more detail in the next sub-section.

Table 3 presents the estimated effects of the share of peers who have access to information in a district on the likelihood of a farmer adopting a new farming practice. In Column (1), the estimates from the logit model, represented as odds ratios from logistic regression, are presented. The coefficient in this column suggests a significant and substantial impact: if a farmer were to relocate to a district with a 10-percentage point higher share of farmers having access to information, excluding the farmer, then that farmer would have a 14 percent higher

[6] I have controlled for state fixed effects and not district fixed effects because the treatment variable is defined at the district level and hence district fixed effects should essentially include the treatment variable. Therefore, to avoid this perfect multicollinearity, I exclude district fixed effects.

chance of adopting new farming practices compared to those who remain in their original district. This effect is highly significant, as indicated by the 1% level of significance. Furthermore, similar positive and statistically significant effects are observed in Columns (2) and (3) of the table for the other two specifications. These consistent findings emphasize the pivotal role of access to information within a district in shaping a farmer's decision to adopt new farming practices, as proposed by various information providers.

Access to information can originate from various sources, and significant variation exists across districts in terms of the prominence of these information providers. A farmer's decision to adopt a new farming practice may depend on the source of information. For instance, farmers might place trust in fellow farmers who have already adopted these practices or in input providers who maintain regular contact with them. To account for this variation, I exploit the differences in share of farmers who have access to information from various sources across districts by excluding the concerned farmer. I estimate these effects using the following equation:

$$Adopt^{*}_{ids} = \alpha + \sum_{p=1}^{6} \phi^{p} ShareAccess^{p}_{-ids} + \beta HHead_{ids} + \gamma HH_{ids} + \delta Farm_{ids} + \lambda_{s} + \varepsilon_{ids} \quad (3)$$

Where, $ShareAccess^{p}_{-ids}$ as defined in the Data section, indicated the share of farmers in the district who have access to information from source "*p*", excluding the farmer "*i*" under examination. Other variables are defined similarly to those in Equation (2). Parameter ϕ^{p} quantifies the effect of the share of farmers having access to information from source provider p in a district on the likelihood of farmers adopting new farming practices.

Table 3: Baseline results

Variables	Logit (OR) (1)	OLS (2)	Probit (ME) (3)
Dependent Variable: Adopted Technology (1: Yes, 0: No)			
Share of Peers with Access to Information	1.14***	0.02***	0.07***
	(0.03)	(0.00)	(0.01)
Household Head Characteristics	Y	Y	Y
Household Characteristics	Y	Y	Y
Farm Characteristics	Y	Y	Y
State Fixed Effects	Y	Y	Y
Observations	55,864	55,881	55,864
R-squared		0.04	

Note: For the logit model in column (1), I present estimated odds ratio. Odds ratio is defined as probability of adopting technology divided by probability of not adopting the technology. For other two models, Columns (2) and (3), I have shown the estimated coefficient θ. Standard errors are robust and clustered at state. Level of significance *** p<0.01, ** p<0.05, * p<0.1

Table 4 presents the estimated coefficients for share of farmers who have access to information from various providers. Notably, the findings reveal distinct impacts of different information sources on the likelihood of farmers adopting new farming practices. Specifically, the results indicate that if the peers are receiving information from progressive farmers, input dealers, or print media then the farmer is more likely to adopt new farming practices compared to those

who primarily receive information from other sources. Conversely, if the peers in a district rely on electronic media for information, then the farmer's chance of adopting new farming practices decrease in comparison to those obtaining information from alternative sources.

Considering the odds ratio presented in column (1) of the table, if a farmer is relocated from one district to another where the share of peers who have access to information from progressive farmers is 10 percentage points higher, then the farmer would be 11 percent more likely to adopt a new farming practice compared to those who are not relocated. Similarly, this effect would be 10 and 19 percent for input dealers and print media, respectively. However, the effect for print media and input dealers is only significant at the 10 percent level of significance. On the other hand, if a farmer is relocated to a district with a 10-percentage point higher share of peers having access to information from electronic media, then the farmer's likelihood of adopting a new farming practice reduces by 17 percent. Additionally, I present the estimated coefficients for the covariates used in Equation (3) in Table A1 in the Appendix. The sign and magnitude of estimated coefficients are intuitive and in line with the findings of other studies in this literature (Birthal et al., 2015; Kumar et al., 2021).

Table 4: Effect of source of information on adoption decision of farmers

Variables	Logit (OR)	OLS	Probit (ME)
	(1)	(2)	(3)
Dependent Variable: Adopted Technology (1: Yes, 0: No)			
Share of Peers with Access to Information (Base: Other Sources)			
Progressive Farmers	1.11**	0.01**	0.06**
	(0.05)	(0.01)	(0.02)
Input Dealers	1.10*	0.01*	0.05*
	(0.07)	(0.01)	(0.03)
Government Extension Agent	1.08	0.01	0.05
	(0.13)	(0.02)	(0.07)
Print Media	1.19*	0.03*	0.09*
	(0.11)	(0.01)	(0.05)
Electronic Media	0.83***	-0.03***	-0.11***
	(0.04)	(0.01)	(0.03)
Household Head Characteristics	Y	Y	Y
Household Characteristics	Y	Y	Y
Farm Characteristics	Y	Y	Y
State Fixed Effects	Y	Y	Y
Observations	55,864	55,881	55,864
R-squared		0.05	

Note: For the logit model in column (1), I present estimated odds ratio. Odds ratio is defined as probability of adopting technology divided by probability of not adopting the technology. For other two models, Columns (2) and (3), I have shown the estimated coefficient ϕ^p. Estimated coefficients for the covariates are presented in Table A1. Errors are clustered at state. *** p<0.01, ** p<0.05, * p<0.1

Robustness Checks

To address omitted variable bias, I adopt the approach introduced by Altonji et al. (2005) and extended by Oster (2019) to assess its magnitude and correct for it. In this methodology, the treatment variable, denoted as X (in our case, the share of farmers with access to information in the district excluding the focal farmer), is assumed to have a coefficient θ in the regression equation. Additionally, Z represents a vector of observable covariates, while V encompasses all unobservable components. The equation is expressed as:

$$Y = \theta X + \rho Z + V$$

A fundamental assumption of this approach is that the selection of observable variables is proportional to the selection of unobservable factors. I denote this proportionality factor as δ, which is derived from the relationship:

$$\frac{Cov(X,V)}{Var(V)} = \delta \frac{Cov(X,\rho Z)}{Var(\rho Z)}$$

Oster (2019) proposed an alternative method to gauge bias by examining the changes in θ and R-squared when additional controls are incorporated into the regression model. This enables the estimation of a consistent estimator for the share of farmers with access to information in a district, excluding the focal farmer, based on two parameters: the coefficient of proportionality (δ) and R-max. Here, R-max signifies the maximum achievable R-squared when all potential control variables, including unobserved ones, are included in the regression. The methodology assumes that observable factors are at least as influential as unobservable ones. The value of δ can range from 1 to -1, indicating the relative importance and direction of effects of unobservable factors compared to observable ones.

A value of 1 signifies that unobservable factors have an effect similar in magnitude and direction to observable ones, while -1 indicates an effect in the opposite direction. If the point estimate of θ falls within the 95% confidence interval from the original model, it suggests minimal omitted variable bias. However, δ may exceed absolute unity, implying greater influence of omitted variables compared to control variables on θ. In extreme cases, δ could render θ insignificantly different from zero, suggesting no significant effect of the treatment variable on farmers' adoption decisions. To address this, we identify the δ value where θ equals zero. Moreover, this approach is only applicable from linear regression models and hence I apply the approach for the linear probability model presented in Column (2) of Table 3.

The treatment variable in the model represents the proportion of farmers with access to information in a district, excluding the focal farmer. The concern of endogeneity arises because this variable might be correlated with unobserved factors at various levels, such as household, district, or state. To estimate R-max, Oster (2019) recommended using a value of 1.3 times the R-squared obtained from the regression including all control variables. The results, presented in Table 5, reveal that the bias-adjusted θ consistently falls within the 95% confidence interval of the original regression from Table 3. This suggests that even after accounting for all other factors, the estimated coefficient of the treatment variable significantly influences farmers' adoption decisions. Additionally, the estimated value of δ is -7.99, indicating that the influence of unobserved factors must outweigh that of observable factors for the effect of access to information within the district to be nullified. However, this scenario seems unlikely given the inclusion of a comprehensive set of control variables, as suggested in the literature, in the

regression specification. Therefore, these findings suggest that the observed relationship between the treatment variable and adoption decisions remains significant even after addressing potential endogeneity concerns and controlling for relevant factors.

Table 5: Assessment of potential omitted variable bias

	Uncontrolled R^2	Controlled R^2	Identified Estimation Bias	
			θ for $\delta = 1$ or $\delta = -1$	δ for $\theta = 0$
Coefficient of the share of farmers having access to information (θ)				
Adoption	0.01	0.02	[0.01, 0.02]	-7.99
	(0.005)	(0.003)		

Note: The uncontrolled coefficient is obtained by excluding all other covariates from the model. Controlled coefficient is the estimate of parameter θ that is presented in Table 3. The result is obtained using the command 'psacalc' in STATA following Oster (2019).

I conducted several robustness checks to assess the stability of the estimated effects presented in Table 3 and Table 4. The results of these checks are detailed in Table A2 in the appendix. In the first two columns of Table A2 (columns 1 and 2), I estimated Equations (2) and (3) while controlling for NSS region fixed effects but not state fixed effects. The estimates obtained are consistent with those in the main analysis, showing similar directions and nearly identical magnitudes. Moving to the next two columns (columns 3 and 4), I re-estimated Equations (2) and (3) while clustering the standard errors at the district level. Although the magnitude of the estimates remains unchanged, they now exhibit an even stronger statistical significance at the 1 percent level. In the last two columns (columns 5 and 6), I presented the estimates of the treatment variables while clustering the standard errors at the household level. Remarkably, the magnitude of the estimates remains consistent and, notably, they are significant even at the 1 percent level. These findings indicate that altering the model specifications does not substantially affect the results. Despite variations in clustering at different levels and controlling for different fixed effects, the estimates of the treatment variables remain robust in terms of both magnitude and statistical significance.

In addition, I carried out the analysis at the level of NSS region. Where, NSS regions are geographic units which are formed by combining multiple districts. I carry out this analysis to account for the data representativeness. To account for this, I modified Equations (2) and (3) as follows:

$$Adopt^{*}_{ins} = \alpha + \theta ShareAccess_{-ins} + \beta HHead_{ins} + \gamma HH_{ins} + \delta Farm_{ins} + \lambda_s + \varepsilon_{ins} \quad (4)$$

$$Adopt^{*}_{ins} = \alpha + \sum_{p=1}^{6} \phi^{p} ShareAccess^{p}_{-ins} + \beta HHead_{ins} + \gamma HH_{ins} + \delta Farm_{ins} + \lambda_s + \varepsilon_{ins} \quad (5)$$

Here, the treatment variables are defined at NSS region level rather than at the district level. Table A3 in the appendix presents the estimates of θ in Equation (4). The estimate suggests that if a farmer is relocated to an NSS region with a 10-percentage point higher share of farmers who have access to information, excluding the focal farmer, from any source, then her probability to adopt a new farming practice will increase by 18 percent. This finding is intriguing, as it implies that peer effects operate not only at the district level but also at the broader NSS region level.

However, upon closer examination of the specific sources of information providers, this effect

diminishes. As shown in Table A4 in the appendix, the estimates are not statistically significant at the 5% level. This suggests that while peer effects may play a role in influencing adoption decisions at the NSS region level, they do not seem to be driven by specific sources of information providers at this level.

Heterogeneity Analysis

The analysis in the previous sub-sections has yielded valuable insights into the influence of information access and information providers on the adoption of new farming practices among rural households. However, it is important to note that these effects are aggregated across different groups of farmers. Existing research has consistently highlighted the significance of farm size as a pivotal factor in explaining the likelihood of adopting new farming practices (Aryal et al., 2018; Kumar et al., 2021; Pal et al., 2022). It is worth noting that the impact of access to information on adoption decisions may vary between farmers with larger farms and those with smaller ones, even after considering various covariates. This underscores the importance of dissecting the data to understand these nuances. In addition, empirical evidence, as seen in Table A1, underscores that farmers cultivating different crops exhibit varying tendencies in adopting new farming techniques. This aligns with the broader literature highlighting that farmers involved in the cultivation of wheat and other cereals tend to be more inclined to adopt new practices compared to those primarily engaged in paddy cultivation in India (Munshi, 2004).

Recognizing the significance of these two factors in influencing the adoption of new farming practices among rural households in India, I conduct separate estimations of Equation (3) for distinct farmer groups. I evaluate the effect of prominent information sources on the adoption of new farming practices for farmers with small, medium, and large-sized farms[7]. Furthermore, I estimate Equation (3) independently for farmers engaged in paddy cultivation, maize cultivation, and other cereal crops. This approach allows me to gain a more nuanced understanding of how information dissemination and the choice of information source impact technology adoption among different segments of the rural households. Moreover, the source of information might play an important role in determining the adoption decision based on the type of information that is accessed by the farmer. To account for this, I estimate Equation (3) separately for six types of information categories: improved seed variety, fertilizer application, plant protection, farm machinery, harvesting and marketing and any other advice.

Table 6 provides insights into the influence of different sources of information on the adoption decisions of farmers across three distinct categories of farm sizes: small, medium, and large. The results are somewhat surprising, revealing that the share of peers who have access to information from various sources, other than electronic media, does not significantly impact the decision to adopt new farming practices for farmers with large farms. This is surprising because large farmers might have the possible resources to implement these new farming practices. However, for the farmers with medium and small land holdings the results are similar to the ones that were observed in Table 4. Access to information among the peers through progressive farmers or input dealers have a positive influence on adoption decision of the farmers while electronic media has a negative influence on adoption decisions. For farmers with medium land size (ranging from 1 to 4 hectares), access to information among peers through print media can increase the chances of adopting new farming practices. These findings

[7] Small farm size includes farm sizes that are less than 1 hectare in land area. Farms falling within the range of 1 to 4 hectares are classified as medium-sized farms and farms with a land area exceeding 4 hectares are considered large-sized farms.

underscore a nuanced relationship between farm size and the influence of the share of farmers who have access to information from different sources. This emphasizes the importance of tailoring agricultural extension and information dissemination strategies to the specific needs and characteristics of different farm size categories.

Table 7 presents estimated odds ratios related to the share of peers who have access to information from various sources in districts for farmers cultivating three major crops: paddy, maize, and other cereals. Surprisingly, these findings reveal that farmers cultivating different crops are influenced by different sources of information within their districts, highlighting the nuanced dynamics at play. Farmers engaged in paddy cultivation exhibit a greater propensity to adopt new farming practices when they reside in districts where the peers have access to information from input dealers and print media. This trend does not necessarily hold true for farmers cultivating maize and other cereals. Maize cultivators are influenced primarily by the progressive farmers and government extension agents. However, farmers involved in cultivating other cereals are influenced by government extension agents as their dominant source of information. In fact, these farmers are 4 times more likely to adopt new farming practices when residing in districts where government extension agents are the primary information providers, compared to those residing in districts where most farmers receive information from other sources.

Table 8 presents the estimated odds ratios associated with the share of peers who have access to information from various sources in districts, concerning farmers seeking advice for different types of new farming practices. It is evident that the impact of different information sources varies depending on the type of advice sought for new farming practices. Access to information from progressive farmers in a district significantly influences farmers' decisions to adopt new varieties of seeds, fertilizers, farm machinery, and other farming practices belonging to that district. Input dealers also play a significant role in influencing adoption decisions, particularly regarding fertilizers and pesticides. Government extension agents are important for encouraging farmers to adopt new farming practices related to farm machinery and other practices, while access to information through electronic media surprisingly has a negative effect on the adoption of new practices related to seeds, fertilizers, pesticides, and other farming practices.

It is possible that socio-economic factors, farm size, and the type of crop grown by farmers interact with the share of farmers who have access to information on new farming practices in the district. To capture these interaction effects, I estimate Equation (3) by interacting the share of access to farmers from various sources with the type of crop grown by the farmer, their farm size, their caste, and their log monthly per capita consumption expenditure. Table A5 presents the estimated odds ratios for these interaction terms. Each value in the table corresponds to the estimated odds ratio for the interaction term between the variable in the column and the variable in the row.

In the first panel of the table, the estimates highlight that farmer growing maize, other cereals, or any other crop are more likely to adopt new farming practices if the information comes from progressive farmers compared to paddy growers. However, the opposite is true if the information is from input dealers, where paddy growers are more likely to adopt the new farming practice compared to any other crop grower. In panel 2 of the table, it is observed that farmers with large or medium-sized farms are more likely to adopt new farming practices if they receive information from electronic media compared to farmers with small land size. Moreover, compared to the scheduled tribe caste group, all other caste groups have a higher

chance of adopting a new farming practice if the share of access to information among peers from government extension agents is higher. For other sources, caste does not seem to play a significant role in adoption decisions. Finally, the log monthly per capita expenditure of the farmers, when interacted with the share of farmers who have access to information from various sources, does not yield significant estimates. This suggests that affluent farmers are as likely to adopt new farming practices from any of these sources as a less affluent farmer.

The analysis delves into the complex dynamics surrounding the adoption of new farming practices among rural households, considering factors such as farm size, crop type, and socio-economic status. Findings reveal nuanced relationships between information access, information sources, and adoption decisions. While progressive farmers and input dealers significantly influence adoption across different farm sizes, crop cultivators, and types of farming practices, the impact of electronic media varies. Surprisingly, electronic media has a negative effect on adoption in certain contexts. Moreover, interaction effects highlight the differential influence of information sources based on farm size and caste groups. These insights underscore the importance of tailored agricultural extension strategies that account for the diverse needs and characteristics of rural communities to promote sustainable agricultural practices effectively.

Table 6: Logit results for different size of farms

Variables	Small Farms	Medium Farms	Large Farms
	(1)	(2)	(3)
Dependent Variable: Adopted Technology (1: Yes, 0: No)			
Share of Peers with Access to Information (Base: Other Sources)			
Progressive Farmers	1.21***	1.08*	1.13*
	(0.04)	(0.05)	(0.08)
Input Dealers	1.14**	1.12*	1.07
	(0.07)	(0.07)	(0.07)
Government Extension Agent	1.14	1.03	1.13
	(0.16)	(0.12)	(0.17)
Print Media	1.12	1.25**	1.10
	(0.10)	(0.13)	(0.12)
Electronic Media	0.73***	0.84***	0.87***
	(0.05)	(0.05)	(0.04)
Household Head Characteristics	Y	Y	Y
Household Characteristics	Y	Y	Y
Farm Characteristics	Y	Y	Y
State Fixed Effects	Y	Y	Y
Observations	10,986	26,903	17,931

Note: In all three columns I have presented the estimated odds ratio from logit specification of the model. Errors are robust and clustered at state. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Logit results for different crops

Variables	Paddy	Maize	Other Cereals
	(1)	(2)	(3)
Dependent Variable: Adopted Technology (1: Yes, 0: No)			
Share of Peers with Access to Information (Base: Other Sources)			
Progressive Farmers	1.05	1.35***	1.17
	(0.04)	(0.10)	(0.11)
Input Dealers	1.22***	0.97	1.02
	(0.06)	(0.09)	(0.12)
Government Extension Agent	1.06	1.60**	4.11**
	(0.10)	(0.35)	(2.85)
Print Media	1.35***	1.06	0.82
	(0.12)	(0.23)	(0.21)
Electronic Media	0.77***	0.88	0.81***
	(0.05)	(0.11)	(0.05)
Household Head Characteristics	Y	Y	Y
Household Characteristics	Y	Y	Y
Farm Characteristics	Y	Y	Y
State Fixed Effects	Y	Y	Y
Observations	30,227	3,220	3,598

Note: In all three columns I have presented the estimated odds ratio from logit specification of the model. Errors are robust and clustered at state. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Logit results for different type of information accessed.

Variables	Seed Variety	Fertilizer Application	Plant Protection	Farm Machinery	Harvesting & Marketing	Others
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Adopted Technology (1: Yes, 0: No)						
Share of Peers with Access to Information (Base: Other Sources)						
Pr. Farmers	1.11*	1.16***	1.02	1.54***	1.16	1.34***
	(0.07)	(0.06)	(0.07)	(0.22)	(0.20)	(0.11)
Input Dealers	1.12	1.16**	1.21***	0.89	0.95	0.88
	(0.08)	(0.07)	(0.09)	(0.14)	(0.13)	(0.14)
Gov. Ext. Agents	1.09	1.02	1.09	1.49***	1.25	2.14***
	(0.19)	(0.11)	(0.15)	(0.18)	(0.25)	(0.57)
Print Media	1.30***	1.06	1.04	0.97	1.18	1.40
	(0.12)	(0.17)	(0.17)	(0.19)	(0.27)	(0.31)
Electronic Media	0.77***	0.84***	0.87**	0.87	0.98	0.67**
	(0.04)	(0.05)	(0.06)	(0.15)	(0.15)	(0.11)
HH Char.	Y	Y	Y	Y	Y	Y
Household Char.	Y	Y	Y	Y	Y	Y
Farm Char.	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
Observations	24,829	14,940	9,905	769	2,988	2,002

Note: In all three columns I have presented the estimated odds ratio from logit specification of the model. Pr. Farmers is short for Progressive Farmers, Gov. Ext. Agents is short for Government Extension Agents, HH Char. is Household Head Characteristics, Household Char. is Household Characteristics, Farm Char. is farm characteristics and State FE is State Fixed Effects. Errors are robust and clustered at state. *** p<0.01, ** p<0.05, * p<0.1

District Level Analysis

An insightful observation from Figure 2 is the discernible presence of distinct clusters in the distribution of access to information regarding new farming practices across districts in India. These clusters highlight regions where the majority of farmers have access to information about these practices, contrasting with other clusters where such access is limited. This underscores the significance of recognizing local spatial patterns and disparities in information access among districts. It is evident that certain regions exhibit concentrated patterns with higher access to information, likely influenced by local factors or shared characteristics among neighboring districts. To model this spatial dependence of information access across districts, I employ a general nesting spatial (GNS) econometric approach. An advantage of starting with a general nesting model is that I can account for local spatial dependence by means of an endogenous spatial lag, exogenous spatial lags, and a spatial lag in the error term. I represent this spatial model as follows:

$$y = \alpha + X\beta + \rho Wy + WX\theta + u$$
$$u = \lambda Wu + \varepsilon \qquad (6)$$

Where, y represents the share of farmers in a district who have access to information regarding new farming techniques, while X encompasses various district characteristics that could potentially influence information access among farmers within the same district. Wy is the spatial lag of the dependent variable, where W is the spatial weight matrix. Similarly, WX is the spatial lag of the explanatory variables. Moreover, it is assumed that error u follows a spatial autoregressive process with a spatial autocorrelation coefficient λ. This assumption is reasonable because access to information among farmers regarding new farming practices within a district can be influenced not only by internal factors but also by random shocks that propagate within the district and spill over from neighboring districts, constituting information spillovers across districts. For instance, if a workshop on new farming practices is held in a district and farmers from neighboring districts attend, it can influence the access to information about these practices among farmers in both the host district and the districts from which the attendees originated. However, it is important to note that in this scenario, the spatial lag of the dependent variable might be correlated with the random shock, leading to biased OLS estimates. To mitigate this issue, maximum likelihood estimation is employed to estimate Equation (6). With this model specification, I aim to capture potential local spatial dependence and consider the interplay of various factors influencing information access among farmers across districts in India. This comprehensive approach accounts for both the internal dynamics within districts and the external influences from neighboring areas, providing a robust framework for analyzing the spatial aspects of information dissemination in agriculture. To ensure the validity of this model, several specification tests were conducted which are presented in Table A6 in the appendix.

Table 9 presents the results for this model. Column (1) represents a simple linear model without spatial components, while Columns (2) and (3) correspond to the spatial model as presented in Equation (6). In Column (2), estimates for the district characteristics (β) are presented, while in Column (3), estimates for the spatially weighted district characteristics (θ) are provided. A positive and statistically significant value of ρ in this model suggests that the share of farmers with information access tends to be higher in districts where neighboring districts also have a higher share of farmers with access to information. Furthermore, a positive and statistically significant value of λ indicates that random shocks increasing the share of farmers' access to information in neighboring districts also contribute to an increase in the share of farmers with

access to information within the district. These findings strongly indicate the presence of information spillovers regarding new farming practices across districts in India[8]. Additionally, other variables such as the share of farmers with small or medium-sized farms, the share of Hindu population, the share of farmers experiencing crop loss, and the share of farmers producing fruits and vegetables might also play a role in explaining access to information. While being surrounded by districts primarily with small or medium-sized farms can diminish access to information, other variables exhibit a positive spatial spillover in accessing information from various sources across districts in India.

As a robustness check, I also run different specifications of the model presented in Equation (6). Table A7 in the appendix presents the estimates for spatial Durbin model (SDM), spatial autoregressive combined model (SAC) and spatial Durbin error model (SDEM). Findings from these models suggests that the estimates presented in Table 9 are robust to different model specifications. Hence, there exists spatial spillovers in access to information across districts in India. It is important to note here, however, that because the data might not be representative at the district level and only at the NSS region level the inference of these estimates is only limited. To address this concern, I also conducted the analysis at the level of NSS regions. However, the findings do not show information spillovers over these geographic units. This is intuitive as these regions comprise of many districts and information might not spillover to that extent. The study, as mentioned in the introduction, acknowledges that using district level estimates is a limitation of this study.

The previous section has highlighted the pivotal role of information providers in influencing the adoption of new farming practices. Nonetheless, it is plausible that farmers are not solely influenced by the source of information provider within their own district but also by neighboring districts. To investigate this, I separately estimate Equation (6) for access to information from different sources. This approach enables me to gauge the varying effectiveness of diverse information sources and the impact of other district-level characteristics on access to information from these sources. The findings for different sources of information are presented in Table A8 in the appendix. Interestingly, the information spillover varies across different sources. Positive information spillovers are observed when information is provided by input dealers, government extension agents, and electronic media. Conversely, negative information spillovers are evident when the source is print media. This suggests that farmers have less access to information from print media in a district if they are surrounded by districts with a higher share of farmers who have access to information from print media. Notably, there is no statistically significant evidence for information spillovers through progressive farmers or any other sources. The coefficient on the spatial error term λ is positive and significant for all the sources of information providers, except other sources. This suggests that there exists a positive spatial autocorrelation. This finding strengthens the argument that access to information from different sources cluster together spatially.

[8] These results remain robust to using different weighting matrix.

Table 9: OLS and GNS model results

Variables	OLS	Spatial Model	
		Non-Weighted ($\hat{\beta}$)	Weighted ($\hat{\theta}$)
Dependent Variable: Share of farmers with access to information			
Share of farmers with small farms	-0.245***	-0.237***	-2.596***
	(0.052)	(0.053)	(0.579)
Share of farmers with medium farms	-0.166**	-0.159**	-3.386***
	(0.073)	(0.064)	(1.135)
Share of farmers trained in agriculture	0.589*	0.581**	3.247
	(0.321)	(0.229)	(6.947)
Share of non-General category	-0.090**	-0.038	0.804
	(0.038)	(0.036)	(0.583)
Share of Hindu	0.024	0.045	0.788*
	(0.030)	(0.033)	(0.415)
Share of households who took loan	0.251***	0.214***	-1.140
	(0.057)	(0.050)	(0.798)
Share of farms which are irrigated	0.043*	0.023	0.623
	(0.025)	(0.025)	(0.389)
Share of farms that faced crop loss	0.034	0.010	1.076**
	(0.026)	(0.024)	(0.539)
Share of farmers producing cereals	0.252***	0.211***	0.400
	(0.035)	(0.039)	(0.464)
Share of farmers producing pulses	-0.205**	-0.250**	-1.625
	(0.102)	(0.115)	(2.168)
Share of farmers producing sugar/spice	0.108	0.133	1.377
	(0.113)	(0.110)	(1.751)
Share of farmers producing fruits/vegetables	0.504***	0.201**	8.939***
	(0.091)	(0.087)	(1.618)
Share of farmers producing other crops	0.190**	0.196**	-1.138
	(0.079)	(0.078)	(1.370)
Share of farmers producing oil seeds	0.197***	0.236***	0.331
	(0.073)	(0.083)	(1.012)
Rho			0.797***
			(0.188)
Lambda			0.854***
			(0.160)
Constant	0.223***	0.156*	
	(0.057)	(0.080)	
Observations	663	663	663
R-squared	0.233		
Mean of the dependent variable ($\bar{Y}$)	0.26	0.26	0.26

Note: The non-weighted column represents the estimates for the independent variables (X). The weighted column, on the other hand, represents the estimates of spatially weighted independent variables (WX). $\bar{Y}$ is the mean of the dependent variable: share of farmers who have access to information from any source. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Conclusion

This study addresses a significant research gap in understanding the dynamics of access to information from various sources and the decision to adopt new farming practices among Indian farmers. It highlights the role of the share of farmers who have access to information and the major source in influencing farmers' decisions to adopt new farming practices. Additionally, it explores the presence of information spillovers across districts, shedding light on how farmer can learn about new farming practices from not only the peers in their district but also from their peers in districts surrounding them.

Using data from the National Sample Survey Office for the year 2019, encompassing a substantial number of rural households across India, I exploit spatial regression models to estimate spatial spillovers across districts in access to information. At the household level I find that farmers who have access to information regarding new farming practices are significantly more likely to adopt them, with specific sources such as progressive farmers, input dealers and print media playing a particularly influential role. The dominance of electronic media as an information source, on the other hand, is associated with lower adoption rates. The results remain robust to different model specifications and correcting for omitted variable bias.

A significant limitation of this paper is the potential lack of representativeness of the data at the district level, thus limiting the inferences drawn from spatial analysis. Additionally, there may still be endogeneity concerns at the household level. However, bias correction tests and the use of leave-one-out treatment variables provide some evidence that these endogeneity concerns are not major challenges. While a panel data setting could have addressed these concerns, unfortunately, such data is not currently available. Future research could explore these issues more thoroughly using panel data or instrumental variables methods. Moreover, small area estimation techniques as suggested by Chandra (2013, 2021) could be employed to address the concern of data representativeness at the district level, offering a promising avenue for future investigation.

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Appendix

Table A1: Estimated parameters for the covariates of Table 4.

Variables	Logit (OR)	OLS	Probit
	(1)	(2)	(3)
Dependent Variable: Adopted Technology (1: Yes, 0: No)			
Male	0.91	-0.01	-0.05
	(0.06)	(0.01)	(0.04)
Log (Age)	0.98	-0.00	-0.01
	(0.08)	(0.01)	(0.04)
Education (Base: Illiterate)			
Primary to Secondary	0.88**	-0.02**	-0.06**
	(0.05)	(0.01)	(0.03)
Secondary to Graduate	0.89*	-0.01**	-0.06**
	(0.05)	(0.01)	(0.03)
Graduate and above	0.91	-0.01	-0.05
	(0.07)	(0.01)	(0.04)
Agricultural Training	1.06	0.01	0.04
	(0.12)	(0.01)	(0.06)
Bank Account	0.97	-0.01	-0.03
	(0.15)	(0.02)	(0.09)
Log (Household Size)	0.98	-0.00	-0.01
	(0.04)	(0.00)	(0.02)
Religion (Base: Hindu)			
Muslim	0.87	-0.01	-0.07
	(0.10)	(0.01)	(0.06)
Christian	1.11	0.02	0.06
	(0.10)	(0.01)	(0.05)
Others	1.31*	0.03**	0.17**
	(0.19)	(0.01)	(0.07)
Caste (Base: Schedule Tribe)			
Scheduled Caste	1.28*	0.04*	0.15*
	(0.19)	(0.02)	(0.08)
Other Backward Caste	1.38***	0.04***	0.18***
	(0.14)	(0.01)	(0.06)
General	1.33**	0.04**	0.16***
	(0.15)	(0.01)	(0.06)
Loan Taken	1.04	0.01	0.02
	(0.06)	(0.01)	(0.03)
Irrigation	1.24**	0.03*	0.12**
	(0.13)	(0.02)	(0.06)
Jointly Operate	0.96	-0.00	-0.02
	(0.13)	(0.02)	(0.07)
Holding (Base: Entirely Owned)			
Entirely Leased	1.23	0.02	0.11
	(0.18)	(0.02)	(0.08)
Both Owned and Leased	1.15	0.02	0.07
	(0.10)	(0.01)	(0.05)

Entirely Otherwise Possessed	0.91	-0.01	-0.05
	(0.39)	(0.06)	(0.25)
Number of Crops Grown	1.03	0.00	0.02
	(0.06)	(0.01)	(0.03)
Log (Land Size)	1.01	0.00	0.00
	(0.03)	(0.00)	(0.02)
Crop Insurance	1.17	0.02	0.08
	(0.14)	(0.01)	(0.06)
Major Crop Grown (Base: Pulses)			
Cereals	1.31*	0.03	0.15*
	(0.20)	(0.02)	(0.08)
Sugar & Spices	1.24	0.03	0.11
	(0.22)	(0.03)	(0.10)
Fruits & Vegetables	1.60*	0.06	0.24
	(0.45)	(0.04)	(0.15)
Other Crops	1.26	0.03	0.13
	(0.26)	(0.03)	(0.11)
Oil Seeds	1.19	0.02	0.09
	(0.29)	(0.03)	(0.14)
Animal Farm	1.23	0.03	0.12
	(0.27)	(0.02)	(0.11)
Observations	55,864	55,881	55,864

Note: For the logit model in column (1), I present estimated Odds ratio. Odds ratio is defined as probability of adopting technology divided by probability of not adopting the technology. For other two models, Columns (2) and (3), I have shown the estimated coefficients. Errors are clustered at state. *** p<0.01, ** p<0.05, * p<0.1

Table A2: Robustness checks

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Adopted Technology (1: Yes, 0: No)						
Access to Information	1.14***		1.14***		1.14***	
	(0.02)		(0.03)		(0.01)	
Share of Peers with Access to Information (Base: Other Sources)						
Progressive Farmers		1.08**		1.11***		1.11***
		(0.04)		(0.04)		(0.01)
Input Dealers		1.16***		1.10**		1.10***
		(0.07)		(0.04)		(0.02)
Government Extension Agent		1.03		1.08		1.08**
		(0.10)		(0.09)		(0.03)
Print Media		1.28***		1.19**		1.19***
		(0.10)		(0.08)		(0.03)
Electronic Media		0.80***		0.83***		0.83***
		(0.04)		(0.04)		(0.01)
HH Char.	Y	Y	Y	Y	Y	Y
Household Char.	Y	Y	Y	Y	Y	Y
Farm Characteristics	Y	Y	Y	Y	Y	Y
State Fixed Effects	N	N	Y	Y	Y	Y
NSS Region Fixed Effects	Y	Y	N	N	N	N
Std. Err. Clustered at State	Y	Y	N	N	N	N
Std. Err. Clustered at District	N	N	Y	Y	N	N
Std. Err. Clustered at Household	N	N	N	N	Y	Y
Observations	55,828	55,828	55,864	55,864	55,864	55,864

Note: I present estimated Odds ratio. Odds ratio is defined as probability of adopting technology divided by probability of not adopting the technology. HH Char. is Household Head Characteristics and Household Char. is Household Characteristics, *** p<0.01, ** p<0.05, * p<0.1

Table A3: Baseline results with treatment variable defined at NSS region.

Variables	Logit (OR)	OLS	Probit (ME)
	(1)	(2)	(3)
Dependent Variable: Adopted Technology (1: Yes, 0: No)			
Share of Peers with Access to Information (NSS Regions)	1.18**	0.02**	0.09**
	(0.09)	(0.01)	(0.04)
Household Head Characteristics	Y	Y	Y
Household Characteristics	Y	Y	Y
Farm Characteristics	Y	Y	Y
State Fixed Effects	Y	Y	Y
Observations	55,864	55,881	55,864
R-squared		0.04	

Note: For the logit model in column (1), I present estimated odds ratio. Odds ratio is defined as probability of adopting technology divided by probability of not adopting the technology. For other two models, Columns (2) and (3), I have shown the estimated coefficient. Standard errors are robust and clustered at state. Level of significance *** p<0.01, ** p<0.05, * p<0.1

Table A4: Effect of source of information at NSS region level

Variables	Logit (OR)	OLS	Probit (ME)
	(1)	(2)	(3)
Dependent Variable: Adopted Technology (1: Yes, 0: No)			
Share of Peers with Access to Information at NSS Regions (Base: Other Sources)			
Progressive Farmers	1.30*	0.03*	0.15**
	(0.20)	(0.02)	(0.08)
Input Dealers	1.00	-0.00	-0.01
	(0.13)	(0.01)	(0.07)
Government Extension Agent	1.81*	0.08**	0.33*
	(0.61)	(0.04)	(0.18)
Print Media	1.06	0.01	0.03
	(0.17)	(0.02)	(0.09)
Electronic Media	0.85	-0.02	-0.09
	(0.10)	(0.01)	(0.07)
Household Head Characteristics	Y	Y	Y
Household Characteristics	Y	Y	Y
Farm Characteristics	Y	Y	Y
State Fixed Effects	Y	Y	Y
Observations	55,864	55,881	55,864
R-squared		0.05	

Note: For the logit model in column (1), I present estimated odds ratio. Odds ratio is defined as probability of adopting technology divided by probability of not adopting the technology. For other two models, Columns (2) and (3), I have shown the estimated coefficient ϕ^p. Estimated coefficients for the covariates are presented in Table A1. Errors are clustered at state. *** p<0.01, ** p<0.05, * p<0.1

Table A5: Logit results for different interaction terms.

Variables	Progressive Farmers	Input Dealers	Government Extension Agents	Print Media	Electronic Media
	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Adopted Technology (1: Yes, 0: No)					
Crop Type (Base: Paddy)					
Maize	1.23**	0.82**	1.42	0.76	1.22
	(0.11)	(0.07)	(0.35)	(0.16)	(0.17)
Other Cereals	1.22**	0.79**	2.47*	0.72	1.07
	(0.11)	(0.08)	(1.17)	(0.19)	(0.09)
Other Crops	1.17**	0.78***	1.27**	0.70**	1.31**
	(0.09)	(0.05)	(0.15)	(0.11)	(0.15)
Farm Size (Base: Small)					
Medium	0.94*	1.01	0.90**	1.08	1.09**
	(0.03)	(0.04)	(0.05)	(0.12)	(0.04)
Large	0.98	0.93	1.01	0.95	1.14***
	(0.06)	(0.05)	(0.06)	(0.10)	(0.05)
Caste (Base: ST)					
SC	1.11	0.90	1.59**	0.81	0.93
	(0.12)	(0.09)	(0.35)	(0.13)	(0.08)
OBC	1.11	0.83*	1.27*	0.81	0.92
	(0.09)	(0.08)	(0.19)	(0.13)	(0.07)
General	1.17	0.83*	1.44**	0.77	0.90**
	(0.12)	(0.08)	(0.21)	(0.13)	(0.04)
Log(MPCE)	1.01	0.97	1.05	0.86**	1.21**
	(0.06)	(0.06)	(0.10)	(0.06)	(0.09)

Note: The table presents the interaction terms between the share of farmers who have access to information from various sources (mentioned as column titles) and various independent variables (mentioned as row names). For instance, value 1.23 in column 1 for Maize must be read as the interaction term between the share of farmers who have access to information from progressive farmers and the maize growers, with paddy growers as the base category. I have presented the estimated odds ratio from logit specification of the model. In each specification Household Head Characteristics, Household Characteristics, Farm characteristics and State Fixed Effects are included as other covariates. Errors clustered at state. *** p<0.01, ** p<0.05, * p<0.1

Table A6: Specification Tests

Specification	Test Statistic (p-value)
Wald test for inclusion of spatial terms	122.02 (0.00)
Wald test: GNS v/s SDM ($\lambda = 0$ & $\rho \neq 0$)	8.67 (0.00)
Wald test: GNS v/s SDEM ($\lambda \neq 0$ & $\rho = 0$)	6.90 (0.01)
Wald test: GNS v/s SLX ($\lambda = 0$ & $\rho = 0$)	19.53 (0.00)

Note:

Table A7: Robustness to different spatial model specifications

Variables	Spatial Durbin Model		Spatial Autoregressive Model		Spatial Durbin Error Model	
	Non-Weighted	Weighted	Non-Weighted	Weighted	Non-Weighted	Weighted
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Share of farmers with access to information						
Small Farms	-0.219***	-2.720***	-0.221***		-0.241***	-2.905***
	(0.052)	(0.528)	(0.049)		(0.054)	(0.588)
Medium Farms	-0.144**	-3.721***	-0.153**		-0.165**	-3.641***
	(0.063)	(1.079)	(0.062)		(0.064)	(1.151)
Trained	0.575**	3.387	0.597**		0.584**	4.287
	(0.231)	(6.463)	(0.234)		(0.231)	(7.030)
Non-General	-0.037	0.943*	-0.077**		-0.038	0.826
	(0.036)	(0.544)	(0.033)		(0.036)	(0.593)
Hindu	0.042	0.927**	0.010		0.044	0.929**
	(0.033)	(0.385)	(0.029)		(0.033)	(0.418)
Loan	0.224***	-1.269*	0.216***		0.214***	-0.805
	(0.050)	(0.732)	(0.048)		(0.050)	(0.809)
Irrigated Land	0.028	0.527	0.028		0.024	0.721*
	(0.025)	(0.361)	(0.024)		(0.025)	(0.400)
Crop Loss	0.011	0.968**	0.022		0.009	1.122**
	(0.024)	(0.494)	(0.023)		(0.024)	(0.546)
Cereals	0.211***	0.499	0.234***		0.211***	0.639
	(0.039)	(0.428)	(0.036)		(0.039)	(0.469)
Pulses	-0.264**	-0.974	-0.211**		-0.258**	-1.686
	(0.116)	(2.051)	(0.103)		(0.116)	(2.190)
Sugar/spice	0.134	1.558	0.140		0.134	1.226
	(0.110)	(1.587)	(0.104)		(0.110)	(1.778)
Fruits/vegetables	0.208**	9.036***	0.387***		0.204**	10.16***
	(0.088)	(1.503)	(0.080)		(0.088)	(1.614)
Other crops	0.202**	-1.318	0.192**		0.196**	-1.118
	(0.078)	(1.271)	(0.076)		(0.078)	(1.387)
Oil Seeds	0.229***	0.371	0.199***		0.236***	0.279
	(0.083)	(0.916)	(0.071)		(0.084)	(1.027)
Rho		0.855***		0.890***		
		(0.138)		(0.107)		
Lambda				1.048***		0.906***
				(0.0347)		(0.142)
Constant	0.284***		0.188***		0.294***	
	(0.081)		(0.067)		(0.086)	
Observations	663	663	663	663	663	663
$\bar{Y}$	0.26	0.26	0.26	0.26	0.26	0.26

Note: The non-weighted column represents the estimates for the independent variables (X). The weighted column, on the other hand, represents the estimates of spatially weighted independent variables (WX). Robust Standard Errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table A8: Estimates from GNS model for different sources of information

Variables	Progressive Farmers		Input Dealers		Government Agents	
	Non-Weighted	Weighted	Non-Weighted	Weighted	Non-Weighted	Weighted
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Share of farmers with access to information						
Small Farms	-0.187***	-1.096*	-0.054	-0.640	-0.050***	-0.261
	(0.046)	(0.606)	(0.038)	(0.411)	(0.019)	(0.200)
Medium Farms	-0.135**	-2.404**	-0.045	-1.097	-0.051**	-0.209
	(0.053)	(1.055)	(0.046)	(0.814)	(0.023)	(0.396)
Trained	-0.160	-6.689	-0.170	-9.676*	0.179**	2.119
	(0.190)	(6.600)	(0.165)	(4.963)	(0.081)	(2.432)
Non-General	-0.040	0.794	-0.0001	0.361	-0.004	0.0473
	(0.029)	(0.606)	(0.026)	(0.417)	(0.013)	(0.203)
Hindu	0.037	0.582	-0.019	0.265	-0.002	0.115
	(0.028)	(0.489)	(0.024)	(0.295)	(0.011)	(0.144)
Loan	0.137***	0.413	0.177***	0.213	0.056***	-0.0002
	(0.041)	(0.879)	(0.036)	(0.567)	(0.017)	(0.278)
Irrigated Land	-0.004	0.212	0.055***	-0.158	0.009	-0.056
	(0.021)	(0.407)	(0.018)	(0.275)	(0.008)	(0.136)
Crop Loss	-0.018	-0.507	0.045***	0.312	0.006	-0.158
	(0.019)	(0.577)	(0.017)	(0.382)	(0.008)	(0.189)
Cereals	0.048	0.486	0.037	0.317	0.0237*	0.230
	(0.032)	(0.537)	(0.028)	(0.328)	(0.014)	(0.162)
Pulses	-0.153	0.335	-0.143*	-1.059	-0.027	-0.803
	(0.094)	(2.019)	(0.083)	(1.547)	(0.041)	(0.760)
Sugar/spice	0.034	0.684	-0.059	1.904	-0.001	-0.399
	(0.089)	(1.926)	(0.079)	(1.238)	(0.039)	(0.607)
Fruits/vegetables	0.025	6.015***	0.058	2.409**	-0.014	0.0202
	(0.072)	(1.548)	(0.063)	(1.141)	(0.031)	(0.556)
Other crops	0.011	-1.143	0.112**	0.0357	-0.005	-0.172
	(0.064)	(1.371)	(0.056)	(0.973)	(0.027)	(0.478)
Oil Seeds	0.089	-0.312	-0.004	-0.267	0.015	-0.223
	(0.069)	(1.099)	(0.059)	(0.716)	(0.029)	(0.352)
Rho		0.542		0.718***		0.690**
		(0.359)		(0.251)		(0.271)
Lambda		2.235***		0.726***		0.660**
		(0.128)		(0.265)		(0.300)
Constant	0.249***		-0.007		0.0975***	
	(0.077)		(0.061)		(0.030)	
Observations	663	663	663	663	663	663
$\bar{Y}$	0.12	0.12	0.09	0.09	0.02	0.02

Note: The non-weighted column represents the estimates for the independent variables (X). The weighted column, on the other hand, represents the estimates of spatially weighted independent variables (WX). $\bar{Y}$ is the mean of the dependent variable. Robust Standard Errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table A8: Estimates from GNS model for different sources of information (Contd.)

Variables	Print Media		Electronic Media		Other Sources	
	Non-Weighted	Weighted	Non-Weighted	Weighted	Non-Weighted	Weighted
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Share of farmers with access to information						
Small Farms	-0.049**	-1.113***	-0.052	-1.355***	-0.095***	-0.744**
	(0.022)	(0.349)	(0.035)	(0.385)	(0.029)	(0.307)
Medium Farms	-0.039	-0.946	0.019	-0.224	-0.120***	-0.869
	(0.025)	(0.583)	(0.042)	(0.754)	(0.035)	(0.613)
Trained	0.154	4.779	0.661***	6.693	0.620***	2.906
	(0.095)	(4.089)	(0.152)	(4.650)	(0.129)	(3.749)
Non-General	-0.043***	0.429	-0.041*	-0.267	-0.051**	0.0578
	(0.014)	(0.322)	(0.024)	(0.389)	(0.020)	(0.314)
Hindu	0.023*	-0.046	-0.005	0.336	0.007	0.452**
	(0.014)	(0.257)	(0.022)	(0.277)	(0.018)	(0.224)
Loan	0.013	-0.677	0.064*	-1.132**	0.052*	-0.351
	(0.019)	(0.436)	(0.033)	(0.532)	(0.028)	(0.431)
Irrigated Land	0.019**	0.605**	0.013	0.547**	0.004	0.033
	(0.009)	(0.253)	(0.016)	(0.260)	(0.014)	(0.210)
Crop Loss	0.018*	0.707**	0.021	1.167***	-0.008	0.344
	(0.009)	(0.312)	(0.016)	(0.362)	(0.013)	(0.291)
Cereals	0.037**	-0.060	0.023	-0.321	0.056**	0.064
	(0.015)	(0.240)	(0.026)	(0.311)	(0.022)	(0.246)
Pulses	-0.021	-1.723	-0.072	-3.742***	-0.131**	-0.094
	(0.043)	(1.193)	(0.076)	(1.446)	(0.064)	(1.181)
Sugar/spice	0.082**	-0.142	0.134*	-1.749	0.131**	-0.929
	(0.041)	(1.238)	(0.072)	(1.177)	(0.061)	(0.934)
Fruits/vegetables	0.079**	3.309***	0.170***	4.895***	0.011	3.484***
	(0.033)	(0.940)	(0.058)	(1.068)	(0.049)	(0.896)
Other crops	0.054*	0.731	0.047	-0.994	0.070	-0.688
	(0.029)	(0.928)	(0.052)	(0.916)	(0.044)	(0.732)
Oil Seeds	0.143***	0.713	0.133**	0.716	0.060	-0.043
	(0.032)	(0.586)	(0.055)	(0.679)	(0.046)	(0.541)
Rho		-1.910**		0.905***		0.228
		(0.821)		(0.0936)		(0.492)
Lambda		5.918***		0.924***		0.352
		(0.114)		(0.0780)		(0.498)
Constant	-0.001		0.046		0.187***	
	(0.043)		(0.056)		(0.047)	
Observations	663	663	663	663	663	663
$\bar{Y}$	0.03	0.03	0.08	0.08	0.07	0.07

Note: The non-weighted column represents the estimates for the independent variables (X). The weighted column, on the other hand, represents the estimates of spatially weighted independent variables (WX). $\bar{Y}$ is the mean of the dependent variable. Robust Standard Errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1