Access to Information and Agricultural Mechanization– A Spatial Analysis[1]

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Abstract

In this study, I investigate the determinants of agricultural technology adoption among Indian farmers, emphasizing the critical role of information access and its sources. I use nationally representative data on rural households of India, collected by the National Sample Survey Office, Government of India for 2019, to estimate the effect of access to information on technology adoption. Using logistic regression, I estimate the likelihood of whether a farmer will adopt new farming techniques if it receives information from different sources. I also conduct spatial Durbin linear regression analysis to compute spatial spillovers of access to information on farmers' decision to adopt new farming practices across districts. Findings highlight that the source of information matters in adopting new farming practices. Progressive farmers and input dealers emerge as influential sources. Spatial analysis reveals compelling spatial spillovers, indicating that access to information and the dominant source of information provider in neighboring districts can strongly influence a district's adoption patterns. The findings of this study can help in framing targeted policies to influence the decision-making process of farmers to adopt new farming practices.

JEL Codes: Q15, Q16, Q54
Keywords: Agricultural Mechanization, Technology Adoption, Information Access, Spatial Spillovers

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[1] I am grateful for the helpful comments and suggestions provided by Leena Bhattacharya. I would also like to express my gratitude to Ruth Thomas for her valuable research assistance in this project.
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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 technologies 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 agricultural mechanization 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 and their influence on the adoption of new farming practices across different districts in India. By delving into these spatial spillovers, this research explores the intricate dynamics that shape the agricultural landscape regarding 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. Furthermore, the data is representative at the district level, making it well-suited for conducting a district-level spatial analysis to investigate potential spatial spillovers. The district-level analysis is particularly pertinent 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. In this survey, a total of 58,035 households were surveyed. However, for the purpose of my analysis, I focused my attention on a subset of 45,690 households, who provided responses to questions regarding their access to information pertaining to innovative farming practices. For the investigation at the household level, I utilized a binary indicator $Adopt$ as the primary outcome variable. This indicator takes the value 1 if a farmer has adopted a new farming practice, and 0 if they have not. At the district level, I aggregated this binary variable to calculate the proportion of farmers who had adopted new farming practices out of all the surveyed farmers within a given district. This proportion was then employed as the outcome variable at the district level.

For both household and district-level analyses, the treatment variable is the share of farmers who had access to information regarding new farming practices and the sources from which they obtained this information at the district level. Within the survey data, rural households provided valuable insights into whether they had received information about new farming practices, the nature of the information they received, and the channels through which this information was disseminated. A crucial variable that emerged from my analysis was the identification of the dominant information provider within each district. This was determined by identifying the source that supplied information to the highest proportion of farmers within a specific district. This variable proved instrumental in shedding light on the relationship between a farmer's inclination to adopt new farming practices and the predominant source of information within their district. 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.

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 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 its district, I utilize logistic regression. Additionally, I investigate how residing in districts with different dominant sources of information providers influences the likelihood of adopting these innovative farming techniques. In this first phase, logistic regression is 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. I also aim to understand how the dominance of specific information sources in different districts impacts the adoption decision of farmers residing in that district.

Secondly, I employ spatial econometrics models to explore the spatial spillover effects of access to information and the sources of information on the share of farmers adopting new farming practices. Specifically, I employ a general nesting spatial econometric model to analyze how the share of access to information among farmers within a district influences the share of farmers who adopt new farming practices. This model considers the spatial dependencies that may exist between neighboring districts and how they affect adoption patterns, this includes spatial dependencies in adoption, observed factors and unobserved factors. Furthermore, to estimate the impact of the share of farmers accessing information from various sources on the share of farmers adopting new farming practices, I employ the spatial Durbin linear model. This model accounts for the spatial interdependence that can exist only through the explanatory variables, where the behavior of one district can influence the decisions of nearby districts. Throughout the analysis, I have conducted a series of specification tests to ensure the validity and robustness of these models. These tests are essential in assessing whether the chosen model is appropriate for the data and whether the assumptions underlying the models hold true.

I find that if a farmer were to be relocated to a district with just a 1 percentage point higher share of farmers having access to information, their likelihood of adopting a new farming practice would increase by more than five times 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 where the dominant source of information is disseminated by progressive farmers or input dealers substantially enhances the likelihood of farmers adopting new farming practices compared to districts where the primary information source is from other channels[3]. This finding indicates the influence of peer learning and expert guidance in motivating farmers to adopt innovative techniques. 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 dominant source of information is print media has a dampening effect on the likelihood of farmers adopting new farming practices. A plausible explanation of this finding is that these districts coincide with the districts that have on average less access to information and other channels have a strong hold in such districts. This observation suggests that print media may not be as effective in conveying the necessary information or motivating farmers to adopt new techniques. These findings highlight the substantial influence of information sources on farmers' technology adoption decisions. The dominant information provider 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 to using share of farmers getting access to information from these sources.

Findings from spatial analysis demonstrate that when neighboring districts have a higher proportion of farmers with access to information from progressive farmers, input dealers, and electronic media, this exerts a positive influence on the adoption of new farming practices within a given 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. Interestingly, the collective influence generated by the information flow from neighboring districts appears to play a more dominant role in encouraging farmers to adopt new farming practices compared to the information sources present within their own district. 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.

This study, broadly, adds to the body of research that investigates the decision of technology adoption among farmers (Foster & Rosenzweig, 2010). Specifically, it contributes to the literature on 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 strand have explored various socio-economic, farm-level, and institutional factors that influence agricultural modernization. My study extends this literature by exploring the role of specific sources of information that could facilitate technology adoption among farmers. Some studies that were conducted for

[3] Other channels include sources like NGOs, smart phones, cooperatives, agricultural universities, etc.

various states of India have acknowledged the importance of information sources in influencing farmers' behavior. However, they were unable to identify which sources were effective in encouraging the adoption of new techniques and which were less impactful. In this study, I look at various sources that can play a detrimental role in explaining the adoption decisions of farmers. Furthermore, this study provides evidence on the role of broader geographical characteristics in explaining adoption decisions of farmers to adopt new farming practices. I use district-level analysis to capture regional dynamics and spatial interdependencies that can significantly influence the diffusion of new agricultural technologies. Through this study, I also contribute to the existing literature that highlights 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 extend this line of inquiry to capture the collective effect of farmers' adoption decisions 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 the adoption patterns of technology 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 agricultural mechanization.

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" that was conducted by the National Sample Survey Office (NSSO), Government of India during the period January to December 2019. The aim of the survey is to get information on the rural households regarding their operational holdings, economic well-being, farming practices, and awareness and access to various technological developments 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[4] surveying 58,035 households in the first visit and 56,894 households in the second visit. In this study, I have used the data from the first visit of the survey. The reason of focusing on the first visit is that the behavior on access to information and adopting new technology is unlikely to change between the two visits. Excluding households that did not respond to the question regarding their access to information on new agricultural technology and restricting the sample to household heads who are above the age of 18 years, the analysis was conducted on a final sample comprising 45,690 households.

Outcome variable

[4] The survey excluded a few villages in Andaman and Nicobar Islands that were hard to access.

The survey inquiries about whether households have implemented the technological development recommendations provided by different sources. Given that the primary objective of this paper is to ascertain the factors influencing farmers' adoption of new technological developments 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 *Adopt* as a binary indicator. It takes value 1 when household h has implemented the recommendations from any source, and 0 if not. Therefore, there is distinction between the sources of information.

Explanatory variables

A notable contribution of this study is its investigation into the potential impact of spatial information diffusion among rural households in India on their adoption choices regarding new technology. To achieve this, I utilize the proportion of farmers within a district who have gained access to information, relative to the total number of farmers surveyed in that district. This proportion will serve as a metric for calculating spatial clusters among the districts.

Furthermore, the adoption of new technology by farmers is closely tied to their awareness of available information. This awareness can originate from various sources that disseminate knowledge about advancements in agriculture technology. It is worth noting that one source might dominate in one village or district, while a different source could be more prominent in another district. To capture this variation, I construct a categorical variable, $Source \in \{1,2,3, \dots ,6\}$. These values correspond to different major information providers in the district, determined based on the proportion of farmers receiving information from each provider. Progressive farmers correspond to 1, input dealers correspond to 2, government extension agents correspond to 3, print media correspond to 4, electronic media correspond to 5 and all other sources correspond to 6. Detailed explanation of this methodology is explained in the subsequent subsection.

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.

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 four distinct domains: the attributes of the household head, household-specific factors, farm-related attributes, and district-level characteristics. 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, more than 90 percent of the household heads are male, highlighting a prevalent male-dominated leadership within these households. Additionally, the average age of household heads stands at approximately 50 years, signifying an older demographic leading these rural households. The educational attainment of these household heads is also noteworthy, with nearly 36 percent are illiterate and additional 40 percent have 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 have 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. Notably, there is considerable variation in monthly per capita expenditure among these rural households, indicating a range of economic well-being, with some households enjoying relative affluence. Financial inclusion is evident, as 98 percent of households have a bank account. However, only half of them have taken loans, suggesting that, despite financial access, a significant portion of households does not rely on credit for their agricultural activities. The religious and caste composition of these households is diverse, with the majority being Hindu. A noteworthy finding is that 46 percent belong to other backward castes, while only 24 percent fall into the general caste category. Some of the state agricultural policies provide 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 stands out, with only 61 percent of farmers having this crucial resource at their disposal. This access can significantly influence crop choices and the adoption of new farming practices. Moreover, only 11 percent of households possess insurance against crop loss, indicating potential vulnerabilities when facing agricultural risks. Land ownership patterns indicate that most farmers own their land entirely, while only 5 percent have joint ownership. Joint ownership may introduce complexities in decision-making related to the adoption of new farming practices. Crop cultivation patterns reveal that, on average, farmers grow more than one crop on their farms, with cereals being the most cultivated crop. Paddy emerges 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.

The analysis extends to district-level characteristics, focusing on sources of information. At the district level, on average, 45 percent of farmers received information from various sources. Notably, progressive farmers and input dealers emerge as dominant sources of information, with electronic media ranking as the third most prominent source. In contrast, print media and government extension agents dominate only in a few districts but are concentrated geographically in clusters. The map in Figure 1 paints a revealing picture of dominant information sources across districts of India. It highlights spatial clustering, indicating that certain districts exhibit a concentration of dominant information sources. This suggests the possibility of spatial dependence, wherein neighboring districts may influence each other’s access to information and adoption behavior, particularly in clusters where dominant sources are concentrated.

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.

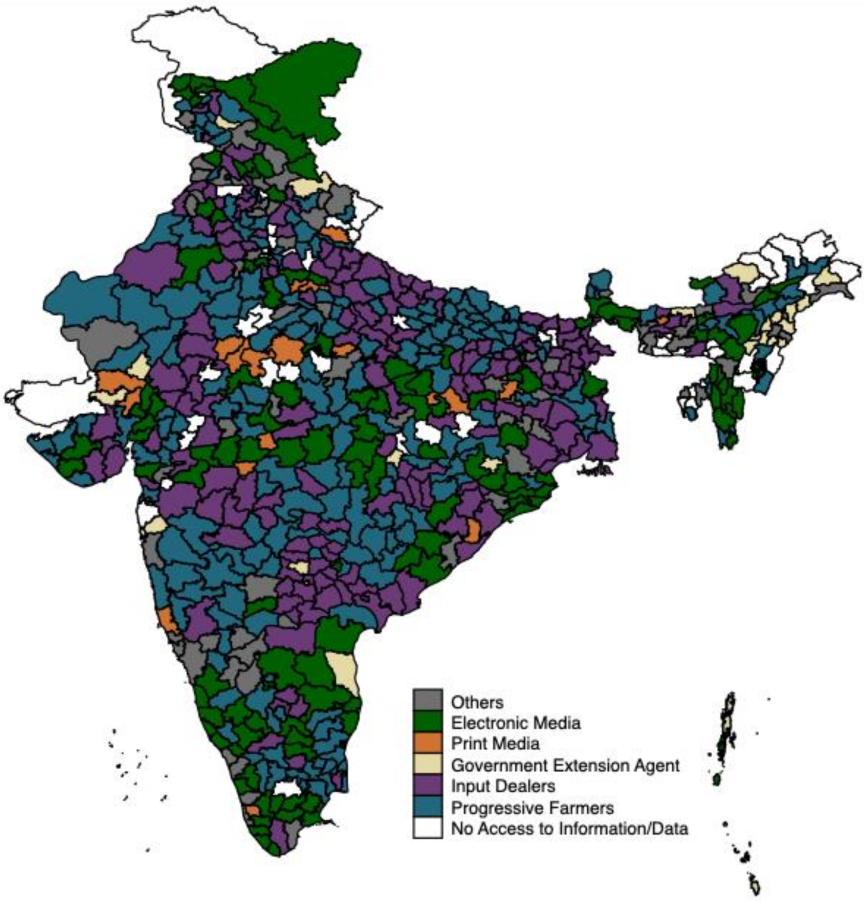
Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max	Sample
Household Head's Characteristics					
Gender (1: Male, 0: Female)	0.91	0.29	0	1	45,690
Age	49.91	13.25	18	110	45,690
Agriculture Training (1: Yes, 0: No)	0.02	0.13	0	1	45,690
Education					
Illiterate	0.36	0.48	0	1	45,690
Primary to Medium	0.40	0.49	0	1	45,690
Medium to Higher	0.19	0.39	0	1	45,690
Graduate and above	0.05	0.22	0	1	45,690
Household's Characteristics					
Log (MPCE)	8.95	0.51	6.22	12.15	45,690
Bank Account Holder (1: Yes, 0: No)	0.98	0.14	0	1	45,690
Loan Taken (1: Yes, 0: No)	0.50	0.50	0	1	45,690
Log (Household Size)	1.49	0.47	0	3.53	45,690
Religion					
Hindu	0.87	0.34	0	1	45,690
Muslim	0.09	0.28	0	1	45,690
Christian	0.02	0.14	0	1	45,690
Others	0.02	0.15	0	1	45,690
Caste					
Scheduled Tribe	0.14	0.35	0	1	45,690
Scheduled Caste	0.16	0.37	0	1	45,690
Other Backward Caste	0.46	0.50	0	1	45,690
General Caste	0.24	0.43	0	1	45,690
Farm Related Characteristics					
Irrigation (1: Yes, 0: No)	0.61	0.49	0	1	44,151
Crop Insurance (1: Yes, 0: No)	0.11	0.31	0	1	41,637
Number of Crops	1.56	1.01	1	10	41,564
Log (Land Size)	0.34	1.17	-4.61	4.61	44,562
Major Crop Grown					
Cereals	0.66	0.47	0	1	45,690
Pulses	0.04	0.19	0	1	45,690
Sugar & Spices	0.05	0.19	0	1	45,690
Fruits & Vegetables	0.03	0.18	0	1	45,690
Oil Seeds	0.07	0.25	0	1	45,690
Other Crops	0.09	0.28	0	1	45,690
Animal Farm	0.06	0.22	0	1	45,690
Jointly Operated (1: Yes, 0: No)	0.05	0.25	0	1	45,690
Ownership of Land					
Entirely Owned	0.81	0.39	0	1	45,690
Entirely Leased	0.03	0.13	0	1	45,690
Both Owned and Leased	0.15	0.36	0	1	45,690
Entirely Otherwise Possessed	0.01	0.06	0	1	45,690

District Characteristics					
Access to Information (Share of farmers)	0.45	0.28	0	1	45,690
Main Source of Information					
Progressive Farmers	0.37	0.48	0	1	43,981
Input Dealers	0.34	0.47	0	1	43,981
Government Extension Agent	0.01	0.12	0	1	43,981
Print Media	0.02	0.16	0	1	43,981
Electronic Media	0.18	0.38	0	1	43,981
Other Sources	0.08	0.26	0	1	43,981

Note: MPCE stands for monthly per capita expenditure of the households and is in INR. Land size is measured in hectares. Other sources of information providers include smart phones, agricultural universities, private commercial agents, cooperatives, NGOs, farmer's call centers, etc. Sampling weights are used to compute the average and standard errors. Source: author's calculation from NSSO, 2019 data.

Figure 1: Main source of information across districts of India



Note: The agency that is able to provide information to the highest share of farmers, receiving information, is considered as the main source of information provider in that district. There are 693 districts for which the map is drawn. For 85 of these districts there is no access to information or the data is not available. 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 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 absence of global spatial autocorrelation, local Moran's I identify districts that exhibit significant deviation from spatial randomness; and in presence of global spatial autocorrelation, it identifies districts that contribute most to overall pattern of spatial clustering. I find that the global Moran's I value is 0.279 for adoption of new farming practices, estimated using row-standardized inverse distance spatial weight matrix[5]. The value is positive and highly significant, indicating spatial dependence in adopting of new farming practice i.e., districts with more share of farmers who adopt new farming techniques are located nearer to the districts with higher share of farmers who have adopted new farming techniques, and the districts with less share of farmers adopting these techniques are located nearer to the districts with other similar districts.

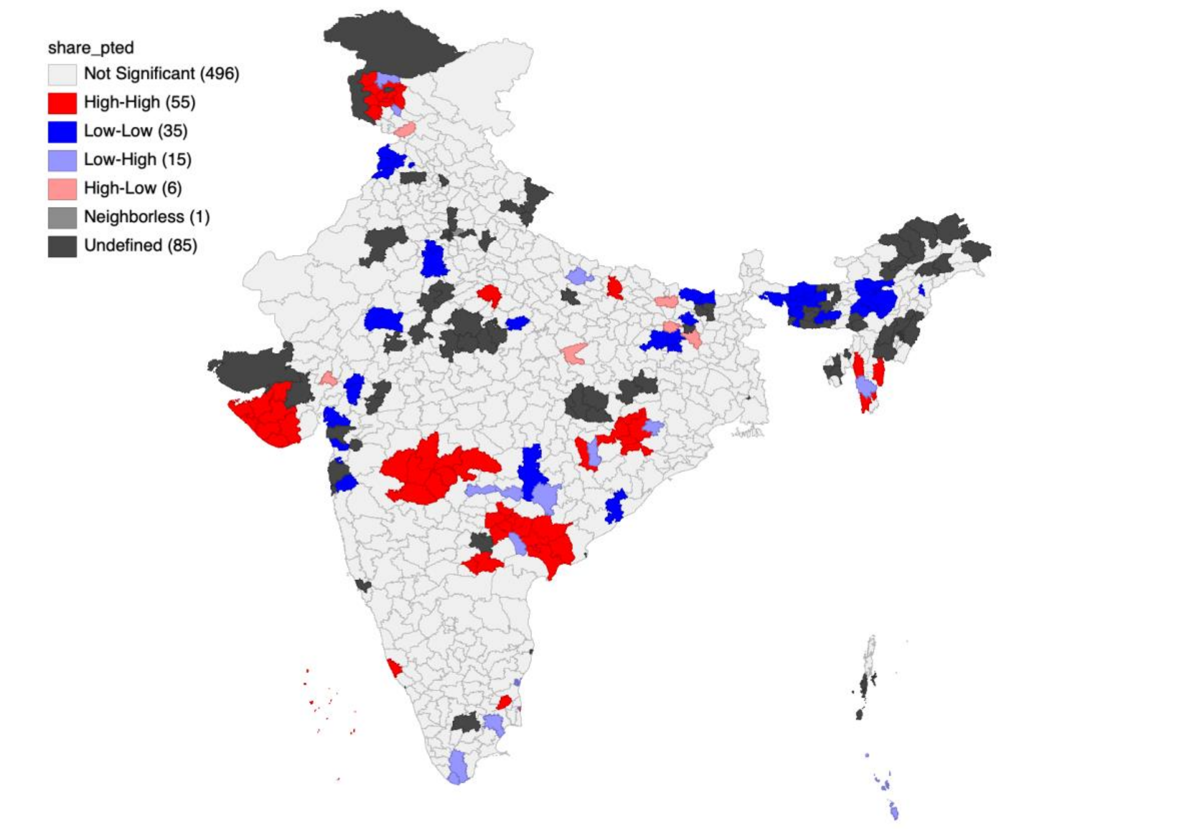
However, global Moran's I ignore potential instability of local units. Therefore, I conduct a more granular investigation to determine if the adoption of new farming practices exhibits spatial concentration and, if so, in which districts this concentration is most pronounced. Local Moran's I, computed for each observation, allows us to assess the degree of spatial clustering of similar values around that specific location, aiding in the identification of statistically significant patterns of spatial association. Figure 2 show local Moran's I for share of farmers who adopted new farming practices across districts in India.

There are four types of local spatial associations: (i) districts with a high share of farmers who have adopted these techniques and are surrounded by neighbors with similarly high adoption rates (HH); (ii) a district that has a low share of farmers adopting these techniques but is surrounded by neighbors with high adoption rates (LH); (iii) districts that have a low share of farmers adopting these techniques and are situated among neighbors with similarly low

[5] I also check whether the results are robust to the specification of spatial matrix. The results remain the same if I use the rook contiguity matrix in place of inverse distance matrix.

adoption rates (LL); (iv) districts that exhibit a high share of farmers adopting these techniques but are surrounded by neighbors with low adoption rates (HL). Utilizing an inverse distance weight matrix, I have identified that 55 districts fall into the High-High (HH) category, while 35 districts belong to the Low-Low (LL) category which are significant. This observation highlights the presence of a positive local spatial autocorrelation, leading to the formation of distinct spatial clusters. Additionally, there are 496 districts where I did not find any significant local Moran's I values. Findings from this analysis provide evidence of spatial clustering of adoption of new farming practices across districts in India. This suggests that there is a need to examine the spatial patterns of adoption of new farming practices using spatial econometric models and understand the role of information access in 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

The importance of information regarding new farming practices 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 are more likely to adopt these practices. I use the adoption decision of the farmer as the dependent variable. Given that the dependent variable is binary, I employ logistic regression to estimate the parameters. The estimation equation is as follows:

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

$$Adopt_{ids}^{*} = \alpha + \theta Access_{ds} + \beta HHead_{ids} + \gamma HH_{ids} + \delta Farm_{ids} + \lambda_s + \varepsilon_{ids} \quad (2)$$

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 $Access_{ds}$ which is the share of farmers in the district d of state s who have access to information from any possible source. 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 and ε_{ids} is the error term following logistic distribution and is 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. I also consider ordinary least squares (OLS) and Probit specifications as alternatives.

Table 2 presents the estimated effects of the share of farmers who have access to information in a district on the likelihood of a farmer adopting a new farming practice. I focus on Column (2) of the table, which presents the odds ratio. The coefficient in this column suggests a significant and substantial impact: if a farmer were to relocate to a district with a 1 percentage point higher share of farmers having access to information, that farmer would have a more than five times higher 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 (1) 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 prominent information sources across districts and estimate their effect using the following equation:

$$Adopt_{ids}^{*} = \alpha + \phi Source_{ds} + \beta HHead_{ids} + \gamma HH_{ids} + \delta Farm_{ids} + \lambda_s + \varepsilon_{ids} \quad (3)$$

Where, $Source_{ds}$ is a categorical variable with ranging from 1 to 6 corresponding to different prominent information providers in the district d of state s. Other variables are defined similarly to those in Equation (2). Parameter ϕ quantifies the effect of the prominent information source provider in a district on the likelihood of farmers adopting new farming practices.

Table 2: Baseline results

Variables	OLS (1)	Logit (OR) (2)	Probit (ME) (3)
Dependent Variable: Adopted Technology (1: Yes, 0: No)			
Share Access to Information (District)	0.97***	5.17***	3.10***
	(0.02)	(0.16)	(0.09)
Household Head Characteristics	Y	Y	Y
Household Characteristics	Y	Y	Y
Farm Characteristics	Y	Y	Y
State Fixed Effects	Y	Y	Y
Observations	39,578	39,578	39,578
R-squared	0.31		

Note: For the logit model in column (2), 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 (1) 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 3 presents the estimated coefficients related to the major source of information providers in the districts. 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 dominant source of information in a district is either progressive farmers or input dealers, farmers are more likely to adopt new farming practices compared to those who primarily receive information from other sources. Conversely, if most farmers in a district rely on print media for information, their chances of adopting new farming technologies decrease in comparison to those obtaining information from alternative sources. The finding is an outcome of the fact that there are only a few districts where the dominant source of information provider is print media and at the same time it coincides with a strong presence of electronic media and other sources. Therefore, districts with print media as the dominant source of information providers rely more on other sources as compared to print media.

I consider the odds ratio presented in column (2) of the table. Comparing two farmers, one residing in a district where most farmers receive information from progressive farmers and the other in a district where the majority rely on various other sources, the former farmer has a 66% higher chance of adopting new farming techniques than the latter. This effect becomes even more pronounced, at 86%, if the dominant source of information in the district is input dealers. Conversely, if a farmer resides in a district where most farmers obtain information through print media, their chances of adopting new farming techniques decrease by 45% compared to a farmer in a district with other information sources. Importantly, all these effects are statistically significant at the 1% level of significance. In contrast, farmers living in districts where the primary source of information comes from government extension agents, electronic media, or other sources exhibit relatively similar chances of adopting new farming practices. I also 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. In addition, as a robustness check, in place of using the categorical variable $Source_{ds}$ in Equation (3), I use the share of farmers who have access to information from the dominant sources in that district. The findings are presented in Table A2 in the Appendix. The results qualitatively remain the same.

Table 3: Effect of source of information on adoption decision of farmers

Variables	OLS	Logit (OR)	Probit
	(1)	(2)	(3)
Dependent Variable: Adopted Technology (1: Yes, 0: No)			
Main Source of Information (Base: Other Sources)			
Progressive Farmers	0.11**	1.66**	0.31**
	(0.05)	(0.36)	(0.13)
Input Dealers	0.14***	1.86***	0.38***
	(0.05)	(0.40)	(0.13)
Government Extension Agent	-0.06	0.76	-0.16
	(0.10)	(0.39)	(0.31)
Print Media	-0.12**	0.55**	-0.35*
	(0.06)	(0.17)	(0.18)
Electronic Media	-0.01	0.95	-0.04
	(0.06)	(0.26)	(0.16)
Household Head Characteristics	Y	Y	Y
Household Characteristics	Y	Y	Y
Farm Characteristics	Y	Y	Y
State Fixed Effects	Y	Y	Y
Observations	39,578	39,578	39,578
R-squared	0.11		

Note: For the logit model in column (2), 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 (1) and (3), I have shown the estimated coefficient θ. Estimated coefficients for different covariates are presented in Table A1. Errors are clustered at state. *** p<0.01, ** p<0.05, * p<0.1

Heterogeneity Analysis

The analysis in the previous sub-section has yielded valuable insights into the influence of information access and prominent information sources 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). This observation aligns with my findings, as indicated in Table A1, where I observe a positive and statistically significant coefficient for land size. Specifically, the estimates suggest that farmers with larger land holdings have, on average, a 21 percent higher chance of adopting new farming practices, even when controlling for all other relevant factors. Furthermore, 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[6]. 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.

Table 4 provides some intriguing 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 dominant source of information does not significantly impact the decision to adopt new farming practices for farmers with small or large farms. For farmers with small land holdings, as well as those with large farms, the influence of the dominant information source within the district appears to be limited. In fact, in the case of large farms, there is a notable exception – if a farmer with a large landholding resides in a district where the primary source of information is print media, their likelihood of accepting the advice of this information source decreases by a significant 68%. This effect is statistically significant at the 1% level. The result is mainly driven by two districts *Banas Kantha* and *Mahesana* in the state of Gujarat, here large farmers get information regarding improved seed/variety through print media. The coefficient is insignificant if I exclude these two districts from the analysis.

Conversely, the findings differ substantially for farmers with medium-sized farms (ranging from 1 to 4 hectares). It appears that for this group, the dominant source of information within the district plays a significant role. Farmers with medium-sized farms are twice as likely to adopt new farming practices if they reside in districts where progressive farmers or input dealers are the primary sources of information, compared to those with similar land sizes but living in districts where information primarily comes from other sources. These findings underscore a nuanced relationship between farm size and the influence of the dominant information source. While the dominant information source appears to be influential for medium-sized farms, it does not significantly impact the adoption decisions of farmers with smaller or larger landholdings. This emphasizes the importance of tailoring agricultural extension and information dissemination strategies to the specific needs and characteristics of different farm size categories.

In Table A3 of the Appendix, I have provided an in-depth analysis of the factors that influence the adoption of new farming techniques among farmers with small, medium, and large landholdings. The results reveal striking disparities in the factors that significantly impact the decision to adopt new farming practices among farmers with different land sizes. Interestingly, household demographics such as the age, caste, and education level of the household head emerge as influential factors specifically for farmers with small landholdings. These demographic characteristics significantly affect their decision to adopt new farming practices. In contrast, for farmers with medium or large landholdings, these demographic variables do not appear to exert a substantial influence on their adoption choices. It must be noted here that almost every state government has year-marked subsidies that are provided to the farmers for introducing new farming practices on their farms. Moreover, these are targeted policies for

[6] 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.

farmers from all backgrounds, especially caste. Medium and large farms can be an indicate that farmers owning this land are well off and hence can reap the benefits of such schemes by the government and therefore caste, or their background does not influence their decision to adopt new farming practices. However, my findings suggest that when it comes to farmers owning small land, their background plays an important role in their adoption decisions and they are unable to benefit from such schemes.

On the other hand, factors like having received agricultural training and whether the household has taken a loan are critical determinants for farmers with medium or large land sizes when it comes to adopting new farming techniques. However, these factors do not seem to be relevant for farmers with small landholdings, suggesting a distinct set of considerations for this group. Furthermore, certain farm-level characteristics, including access to irrigation and having crop insurance, consistently play a role in influencing the decision to adopt new farming practices across all three categories of farmers. These characteristics appear to be universally important factors in shaping adoption behavior.

A noteworthy finding is that the choice of crop being cultivated matters differently for farmers with varying land sizes. For farmers with large landholdings, the specific crop being cultivated does not significantly impact their likelihood of adopting new farming practices. They tend to be more inclined to adopt regardless of the crop type. In contrast, for farmers with small landholdings, they are more likely to adopt new farming techniques when cultivating cereals, sugars and spices, or fruits and vegetables, as compared to when cultivating pulses. These findings provide valuable insights into the unique factors that drive the adoption of new farming practices among farmers with small landholdings. They also highlight the nuanced interplay of demographic, training, loan, and crop-related factors in influencing adoption behavior across different land size categories. Such insights are instrumental in designing targeted interventions and policies aimed at promoting the adoption of innovative agricultural practices among smallholder farmers.

Table 5 presents estimated odds ratios related to the major source of information providers 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 dominant information providers are input dealers and progressive farmers. This trend does not necessarily hold true for farmers cultivating maize and other cereals.

However, farmers involved in cultivating other cereals are influenced by government extension agents as their dominant source of information. In fact, these farmers are 10 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. Conversely, for farmers cultivating maize, residing in districts where the dominant information sources are government extension agents and print media appears to reduce their likelihood of adopting new farming practices. This result compliment the findings by Kumar et al. (2021) where they have shown that paddy farmers rely more on farmers for information while maize farmers rely more on input dealers.

These findings underscore the crop-specific nature of information influence on farmers' decisions to adopt new farming practices. It suggests that the choice of information source can significantly impact the adoption behavior of farmers depending on the type of crop they cultivate. These findings can inform policy makers to promote the adoption of innovative farming techniques in the context of different crops, ultimately contributing to increase agricultural productivity and profitability of such crops.

Table 4: Logit results for different size of farms

Variables	Small Farms (1)	Medium Farms (2)	Large Farms (3)
Dependent Variable: Adopted Technology (1: Yes, 0: No)			
Main Source of Information (Base: Other Sources)			
Progressive Farmers	1.38	1.99***	1.66*
	(0.36)	(0.40)	(0.45)
Input Dealers	1.51*	2.04***	1.80
	(0.36)	(0.38)	(0.64)
Government Extension Agent	1.24	1.02	0.48*
	(0.53)	(0.43)	(0.20)
Print Media	0.56*	0.54	0.32***
	(0.19)	(0.26)	(0.11)
Electronic Media	0.96	1.28	0.85
	(0.42)	(0.30)	(0.32)
Household Head Characteristics	Y	Y	Y
Household Characteristics	Y	Y	Y
Farm Characteristics	Y	Y	Y
State Fixed Effects	Y	Y	Y
Observations	10,210	19,562	9,806

Note: In all three columns I have presented the estimated odds ratio from logit specification of the model. Estimated odds ratio for different covariates are presented in Table A2. Errors clustered at state. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Logit results for different crops

Variables	Paddy (1)	Maize (2)	Other Cereals (3)
Dependent Variable: Adopted Technology (1: Yes, 0: No)			
Main Source of Information (Base: Others)			
Progressive Farmers	1.80*	0.71	0.76
	(0.63)	(0.39)	(0.34)
Input Dealers	2.14**	0.84	0.62
	(0.65)	(0.48)	(0.38)
Government Extension Agent	0.76	0.08***	9.85***
	(0.33)	(0.06)	(5.95)
Print Media	0.97	0.03***	0.41
	(0.48)	(0.04)	(0.28)
Electronic Media	1.18	0.34	0.37
	(0.44)	(0.23)	(0.28)
Household Head Characteristics	Y	Y	Y
Household Characteristics	Y	Y	Y
Farm Characteristics	Y	Y	Y
State Fixed Effects	Y	Y	Y
Observations	22,560	2,710	3,342

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

District Level Analysis

A crucial insight drawn from Figure 2 is the presence of distinct clusters in the distribution of adoption of new farming practices across districts in India. These clusters reveal that there are regions where most farmers have adopted these new techniques, while in other clusters, most farmers have not adopted these new techniques. This underscores the importance of considering local spatial patterns and variations in adoption behavior across districts. It appears that certain regions exhibit concentrated adoption patterns, which may be influenced by local factors or shared characteristics among neighboring districts. To estimate this spatial dependence of adoption of new farming practices across districts, I start with a general nesting spatial (GNS) econometric model. 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:

$$y = \alpha + X\beta + \rho Wy + WX\theta + u$$
$$u = \lambda Wu + \varepsilon \qquad (4)$$

Where, y is the share of farmers in a district who adopted new farming techniques, X are various district characteristics that can influence the adoption decisions of 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 appears reasonable because the adoption of 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. For instance, if a workshop on new farming practices is conducted in a district and farmers from neighboring districts attend, it can influence the adoption of these practices among farmers in both the host district and the districts from which the farmers originated. However, it must be noted that, in this example, the spatial lag of the dependent variable might also be correlated with the random shock and therefore OLS estimates will be biased. To circumvent this problem, I use maximum likelihood estimation method to estimate Equation (4).

With this specification, I can capture potential local spatial dependence and consider the interplay of various factors influencing the adoption of new farming practices among districts in India. This approach considers both the internal dynamics within districts and the external influences stemming from neighboring areas, providing a robust framework for analyzing the spatial aspects of technology adoption in agriculture. To ensure the validity of this model, I have conducted several specification tests[7]. Table A5 in the Appendix presents the results for this model. Column (1) corresponds to a simple linear model without the inclusion of spatial components, while Columns (2) and (3) correspond to the spatial model as presented in Equation (4). The presence of a positive and statistically significant value of ρ in this model suggests that the share of farmers adopting new farming practices tends to be higher in districts where neighboring districts also exhibit a higher share of farmers who have adopted these techniques. Furthermore, a positive and statistically significant value of λ indicates that random shocks that increase the share of farmers adopting technology in neighboring districts also contribute to an increase in the share of farmers adopting new farming techniques within the

[7] Test statistics for these specification tests are provided in Table A4 in the Appendix.

district. These findings strongly indicate the existence of a spatial spillover effect in the adoption of new farming practices across districts in India.

The findings from the previous section have underscored the significant role that the source of information provider plays in the adoption of new farming practices. However, it can be argued that farmers might not only be influenced by information providers within their own district but also by those from neighboring districts. To examine this, I use the share of farmers obtaining information from six possible sources as additional explanatory variables in Equation (4), allowing for an exploration of potential spatial dependencies in terms of information access from various sources. Moreover, when considering the inclusion of access to information from these sources it is important to note that this inherently accounts for the spatial lag of the dependent variable. This is because access to information from various sources is often highly correlated with the share of technology adoption by farmers within the same district.

In essence, by including information access from various sources as explanatory variables, I am indirectly capturing the influence of both local and neighboring sources on the adoption of new farming practices. This approach offers a more holistic perspective on how information dissemination from multiple sources shapes adoption behavior across districts. As a result, it raises the possibility that the spatial lag of the dependent variable may no longer be necessary in the regression analysis. Given these considerations and based on various specification tests, I choose to employ a spatial Durbin linear model (SLX) to estimate the effects of both local and neighboring sources on the adoption of new farming practices. The estimation equation for the spatial Durbin linear model is as follows:

$$y = \alpha + X\beta + WX\theta + u \quad (5)$$

The spatial Durbin linear model allows for a comprehensive assessment of how both local and spatially lagged factors, including information access from various sources, impact the adoption of new farming practices.

Table 6 provides results of the estimated effects of the share of farmers with access to information from various sources within a district on the share of farmers who have adopted new farming techniques in the same district. I have employed both a simple linear regression model (OLS) and a spatial Durbin linear model to unravel the intricate relationships that are driving adoption of new farming practices. In Column 1, I present the estimates from the OLS model. There is a notable positive and statistically significant effect when a higher share of farmers in a district receives information from progressive farmers, input dealers, government extension agents, and electronic media. This suggests that these sources of information are influential in driving the adoption of new farming techniques within a district. Conversely, the share of farmers receiving information from print media does not have a statistically significant effect on the share of farmers adopting new techniques. This finding aligns with expectations, as print media may not have the same impact as more direct and interactive sources of information.

Columns 2 and 3 of Table 6 present the findings from the spatial Durbin linear model, which delves deeper into the spatial aspects of information access and adoption. The direct effect of a higher share of farmers having access to information from various sources on the share of adoption is consistently positive and significant in both models. This implies that, regardless of the source, if there is a higher proportion of farmers with access to information within a district, it positively influences the adoption of new farming practices. The next layer of analysis examines the impact of being in a district where neighboring districts exhibit a higher share of information access from various sources. The findings suggest that when neighboring districts have a greater share of information access from input dealers, progressive farmers, and electronic media, there is an increase in the share of farmers adopting new farming practices. This underscores the notion of spatial spillover effects, where the information dissemination practices of neighboring districts influence adoption behavior. Interestingly, the effect of higher share of information access from government extension agents and print media in neighboring districts does not contribute significantly to an increase in the share of farmers adopting new techniques. This could suggest that certain sources of information, such as government extension services or print media, may not have the same spatial diffusion impact as other sources in driving technology adoption. These results highlight the complex interplay of information sources and spatial dependencies in shaping the adoption of new farming practices. Access to information from specific sources, as well as the influence of neighboring districts, plays a crucial role in driving adoption behavior, emphasizing the importance of considering both the source and spatial context when examining technology adoption in agriculture.

Table 7 presents a detailed breakdown of the estimated marginal effects derived from the spatial linear Durbin model. The analysis dissects the total effect into direct and indirect components for various sources of information, shedding light on the mechanisms through which information access influences the adoption of new farming practices. The results demonstrate a consistent pattern across all sources of information. Whether information is obtained locally within the district or from neighboring districts, an increase in information access positively correlates with a higher share of farmers adopting these new techniques.

The direct effects for almost all sources of information are statistically significant at the 5 percent level, except for print media, which is significant at the 10 percent level. These direct effects highlight that, at the district level, the source from which farmers obtain information regarding new farming practices significantly impacts the adoption behavior. The indirect effects mirror the direct effects, further emphasizing the positive influence of information access. Progressive farmers, input dealers, and electronic media exhibit significant indirect effects at the 1 percent level, signifying that higher access to information from these sources not only drives adoption within a district but also extends its influence to neighboring districts through spatial spillovers. An interesting finding is that the indirect effects dominate the direct effects for all sources of information. This implies that the presence of information clusters, where access to information is higher, leads to increased adoption of new farming practices not only within those districts but also in nearby districts. In essence, these results indicate substantial spatial spillovers of information access from these sources on the adoption of new farming practices.

Overall, this analysis underlines the importance of information access in driving technology adoption, both within districts and across spatially connected regions. It highlights the role of information clusters and spatial diffusion in shaping adoption behavior, offering valuable insights for policymakers and practitioners aiming to promote innovative agricultural practices.

Table 6: OLS and SLX model results

Variables	OLS (1)	Spatial Model (2)
Dependent Variable: Share of farmers who adopted technology		
Share Access to Information (Base: Others)		
Progressive Farmers	0.375***	0.354***
	(0.044)	(0.045)
Input Dealers	0.238***	0.241***
	(0.050)	(0.048)
Government Extension Agent	0.186***	0.180**
	(0.069)	(0.076)
Print Media	0.126	0.167*
	(0.107)	(0.096)
Electronic Media	0.220***	0.128**
	(0.055)	(0.055)
Spatial lag of regressors		
Progressive Farmers		2.988***
		(1.086)
Input Dealers		4.291***
		(1.176)
Government Extension Agent		3.326*
		(1.912)
Print Media		3.873
		(2.615)
Electronic Media		4.821***
		(1.285)
Other Covariates	Y	Y
Observations	664	664

Note: Coefficients of other covariates are presented in Table A6 in the Appendix. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Marginal Effects

Variables	Spatial Model		
	Direct Effect	Indirect Effect	Total Effect
Share Access to Information (Base: Others)			
Progressive Farmers	0.354***	2.858***	3.212***
	(0.045)	(1.039)	(1.038)
Input Dealers	0.241***	4.105***	4.346***
	(0.048)	(1.125)	(1.122)
Government Extension Agent	0.181**	3.182*	3.362*
	(0.076)	(1.829)	(1.825)
Print Media	0.167*	3.705	3.872
	(0.096)	(2.501)	(2.499)
Electronic Media	0.128**	4.612***	4.739***
	(0.055)	(1.229)	(1.223)

Note: 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 agricultural mechanization and technology adoption among Indian farmers. It highlights the pivotal role of information access and source in influencing farmers' decisions to adopt new farming practices. Additionally, it explores the presence of spatial spillovers in the adoption process, shedding light on how the behavior of one farmer can impact the decisions of neighboring farmers.

Using data from the National Sample Survey Office for the year 2019, encompassing a substantial number of rural households across India, I exploit spatial Durbin linear model to estimate spatial spillovers across districts in adopting new farming practices, indicating that farmers are influenced by the adoption decisions of their peers in neighboring districts. 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 and input dealers playing a particularly influential role. The dominance of print media as an information source, on the other hand, is associated with lower adoption rates.

Heterogeneity analysis of the paper suggests that the factors that influence farmers having large land size might not hold for smaller or medium land size. Moreover, sources of information can differently influence farmers cultivating different crops. Findings of this paper can be used by the policy makers to frame targeted policies for the farmers to incentivize them to adopt new farming practices. Various studies have suggested that government needs to intervene to promote agricultural mechanization for sustainable agriculture (Lybbert & Sumner, 2012). Findings of the paper suggests that to promote agricultural mechanization for sustainable agriculture, the government needs to incorporate spatial spill-overs effects while farming their policies.

This study uses a unique dataset that includes data on access to information and whether farmers adopt new farming practices at the national level to explain the relationship between access to information and agricultural mechanization. The study focuses on the cultivation practices but does not distinct between information that these farmers have access to. There is a need to dive deeper into the information that these farmers receive and whether that can influence the adoption decisions of farmers. Future studies could look at this and extend this research.

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Appendix

Table A1: Estimated parameters for the covariates of Table 3.

Variables	OLS (1)	Logit (OR) (2)	Probit (3)
Dependent Variable: Adopted Technology (1: Yes, 0: No)			
Male	0.01	1.07	0.04
	(0.02)	(0.11)	(0.06)
Log (Age)	0.00	1.01	0.01
	(0.02)	(0.08)	(0.05)
Education (Base: Illiterate)			
Primary to Secondary	0.03	1.13	0.07
	(0.02)	(0.08)	(0.05)
Secondary to Graduate	0.03	1.15	0.09
	(0.02)	(0.11)	(0.06)
Graduate and above	0.02	1.11	0.07
	(0.03)	(0.14)	(0.08)
Agricultural Training	0.15***	2.06***	0.43***
	(0.05)	(0.49)	(0.14)
Bank Account	-0.00	0.98	-0.01
	(0.03)	(0.13)	(0.08)
Log (Household Size)	-0.01	0.98	-0.01
	(0.01)	(0.04)	(0.03)
Religion (Base: Hindu)			
Muslim	0.01	1.03	0.02
	(0.02)	(0.11)	(0.07)
Christian	0.05	1.28	0.15
	(0.04)	(0.22)	(0.11)
Others	-0.00	0.98	-0.01
	(0.03)	(0.14)	(0.08)
Caste (Base: Schedule Tribe)			
Scheduled Caste	0.03	1.14	0.08
	(0.03)	(0.16)	(0.08)
Other Backward Caste	0.04	1.22	0.12
	(0.03)	(0.18)	(0.09)
General	0.07**	1.34**	0.18**
	(0.03)	(0.19)	(0.09)
Loan Taken	0.02	1.08	0.04
	(0.01)	(0.05)	(0.03)
Irrigation	0.08***	1.42***	0.21***
	(0.02)	(0.15)	(0.07)
Jointly Operate	0.00	1.00	0.00
	(0.04)	(0.17)	(0.10)
Holding (Base: Entirely Owned)			
Entirely Leased	0.03	1.13	0.08
	(0.04)	(0.22)	(0.12)
Both Owned and Leased	0.04*	1.17*	0.10*
	(0.02)	(0.10)	(0.05)

Entirely Otherwise Possessed	0.06	1.33	0.16
	(0.08)	(0.50)	(0.22)
Number of Crops Grown	0.02**	1.10**	0.06**
	(0.01)	(0.04)	(0.02)
Log (Land Size)	0.04***	1.21***	0.12***
	(0.01)	(0.06)	(0.03)
Crop Insurance	0.12***	1.69***	0.33***
	(0.02)	(0.19)	(0.07)
Major Crop Grown (Base: Pulses)			
Cereals	0.09**	1.50**	0.25**
	(0.04)	(0.29)	(0.12)
Sugar & Spices	0.05	1.26	0.15
	(0.05)	(0.31)	(0.15)
Fruits & Vegetables	0.10*	1.59*	0.29*
	(0.06)	(0.45)	(0.17)
Other Crops	0.13**	1.81**	0.37**
	(0.05)	(0.46)	(0.16)
Oil Seeds	0.07	1.36	0.20
	(0.07)	(0.42)	(0.19)
Animal Farm	0.04	1.18	0.11
	(0.08)	(0.42)	(0.22)
Observations	39,578	39,578	39,578

Note: For the logit model in column (2), 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 (1) and (3), I have shown the estimated coefficient θ. Errors are clustered at state. *** p<0.01, ** p<0.05, * p<0.1

Table A2: Robustness check (Share of access to information from dominant source)

Variables	OLS (1)	Logit (2)	Probit (3)
Dependent Variable: Adopted Technology (1: Yes, 0: No)			
Share Access to Information (Base: Others)			
Progressive Farmers	0.19**	2.47**	0.55**
	(0.08)	(0.92)	(0.22)
Input Dealers	0.14*	1.97*	0.42*
	(0.07)	(0.70)	(0.21)
Government Extension Agent	-0.12	0.53	-0.37
	(0.12)	(0.34)	(0.38)
Print Media	-0.07	0.79	-0.14
	(0.13)	(0.50)	(0.39)
Electronic Media	-0.10	0.60	-0.32
	(0.09)	(0.25)	(0.26)
Household Head Characteristics	Y	Y	Y
Household Characteristics	Y	Y	Y
Farm Characteristics	Y	Y	Y
State Fixed Effects	Y	Y	Y
Observations	39,578	39,578	39,578
R-squared	0.11		

Note: For the logit model in column (2), I present estimated odds ratio. For other two models, Columns (1) and (3), I have shown the estimated coefficient θ. Errors are clustered at state. *** p<0.01, ** p<0.05, * p<0.1

Table A3: Estimated parameters for the covariates of Table 4.

Variables	Small Farms (1)	Medium Farms (2)	Large Farms (3)
Dependent Variable: Adopted Technology (1: Yes, 0: No)			
Male	1.00	0.94	1.25
	(0.17)	(0.13)	(0.24)
Log (Age)	1.28***	1.08	1.12
	(0.12)	(0.08)	(0.13)
Education (Base: Illiterate)			
Primary to Secondary	1.26	1.13	1.10
	(0.21)	(0.10)	(0.11)
Secondary to Graduate	1.32***	1.15	1.16
	(0.13)	(0.12)	(0.10)
Graduate and above	1.63***	1.05	1.13
	(0.28)	(0.18)	(0.16)
Agricultural Training	1.78*	2.08***	3.60***
	(0.55)	(0.56)	(0.93)
Bank Account	0.82	1.29	1.02
	(0.15)	(0.34)	(0.18)
Log (Household Size)	0.90	0.93	0.90
	(0.09)	(0.07)	(0.06)
Religion (Base: Hindu)			
Muslim	1.20	0.82	0.84
	(0.28)	(0.13)	(0.17)
Christian	1.52	1.29	0.93
	(0.47)	(0.39)	(0.30)
Others	0.44	0.81	0.98
	(0.26)	(0.16)	(0.16)
Caste (Base: Schedule Tribe)			
Scheduled Caste	1.71**	1.14	0.52**
	(0.37)	(0.14)	(0.15)
Other Backward Caste	1.83***	1.25	0.82
	(0.34)	(0.20)	(0.21)
General	1.84***	1.29*	1.02
	(0.35)	(0.17)	(0.19)
Loan Taken	1.11*	1.16**	1.06
	(0.07)	(0.08)	(0.11)
Irrigation	1.38**	1.23*	1.63***
	(0.20)	(0.15)	(0.26)
Jointly Operate	0.93	1.03	0.87
	(0.27)	(0.21)	(0.17)
Holding (Base: Entirely Owned)			
Entirely Leased	1.43	1.17	1.23
	(0.36)	(0.29)	(0.28)
Both Owned and Leased	1.04	1.26	1.34**
	(0.16)	(0.20)	(0.18)
Entirely Otherwise Possessed	0.82	1.25	1.86
	(0.66)	(0.49)	(1.84)

Number of Crops Grown	1.16*	1.11*	1.10*
	(0.09)	(0.06)	(0.05)
Crop Insurance	1.60**	1.82***	1.98***
	(0.32)	(0.23)	(0.26)
Major Crop Grown (Base: Pulses)			
Cereals	2.21**	0.95	1.82***
	(0.68)	(0.20)	(0.42)
Sugar & Spices	1.98**	1.13	1.54*
	(0.55)	(0.29)	(0.39)
Fruits & Vegetables	2.25**	1.63*	2.11**
	(0.83)	(0.44)	(0.72)
Other Crops	1.77	1.76**	2.57***
	(0.68)	(0.47)	(0.74)
Oil Seeds	1.32	1.17	2.23*
	(0.29)	(0.37)	(0.92)
Animal Farm	1.39	1.29	1.16
	(0.70)	(0.44)	(0.48)
Observations	10,210	19,562	9,806

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

Table A4: Specification Tests

Specification	Test Statistic (p-value)
Case 1: Without including access to information terms in the model	
Wald test for inclusion of spatial terms	72.99 (0.00)
Wald test: GNS v/s SDM ($\lambda = 0$ & $\rho \neq 0$)	10.40 (0.00)
Wald test: GNS v/s SDEM ($\lambda \neq 0$ & $\rho = 0$)	12.85 (0.00)
Wald test: GNS v/s SLX ($\lambda = 0$ & $\rho = 0$)	26.55 (0.00)
Case 2: Including access to information terms in the model	
Wald test for inclusion of spatial terms	87.49 (0.00)
Wald test: GNS v/s SDM ($\lambda = 0$ & $\rho \neq 0$)	2.73 (0.10)
Wald test: GNS v/s SDEM ($\lambda \neq 0$ & $\rho = 0$)	1.64 (0.20)
Wald test: GNS v/s SLX ($\lambda = 0$ & $\rho = 0$)	5.58 (0.06)

Note:

Table A5: OLS and GNS model results

Variables	OLS	Spatial Model	
		Non-Weighted	Weighted
Dependent Variable: Share of farmers who adopted technology			
Share of farmers with small farms	-0.194***	-0.228***	-3.231***
	(0.0740)	(0.0772)	(0.951)
Share of farmers with medium farms	-0.165*	-0.203**	-2.535
	(0.0962)	(0.0915)	(1.883)
Share of farmers trained in agriculture	0.573**	0.458**	1.486
	(0.222)	(0.212)	(3.190)
Share of non-General category	-0.047	-0.038	0.639
	(0.0455)	(0.0492)	(0.625)
Share of Hindu	-0.004	0.007	0.935*
	(0.040)	(0.050)	(0.542)
Share of households who took loan	0.230***	0.192***	-1.359**
	(0.048)	(0.053)	(0.660)
Share of farms which are irrigated	0.087**	0.098**	1.150*
	(0.038)	(0.040)	(0.685)
Share of farms that faced crop loss	0.106**	0.083**	1.463*
	(0.042)	(0.039)	(0.780)
Share of farmers producing cereals	0.176**	0.147*	-0.312
	(0.077)	(0.086)	(1.144)
Share of farmers producing pulses	-0.149	-0.138	-3.978
	(0.134)	(0.146)	(2.664)
Share of farmers producing sugar/spice	0.138	0.149	-0.750
	(0.120)	(0.139)	(2.000)
Share of farmers producing fruits/vegetables	0.381***	0.100	8.684***
	(0.115)	(0.124)	(2.217)
Share of farmers producing other crops	0.242**	0.192*	-0.894
	(0.0980)	(0.101)	(1.370)
Share of farmers producing oil seeds	0.190*	0.214**	-0.634
	(0.101)	(0.109)	(1.418)
Rho			0.766***
			(0.214)
Lambda			0.749***
			(0.232)
Constant	0.200**	0.403***	
	(0.0898)	(0.133)	
Observations	664	664	664
R-squared	0.122		

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

Table A6: OLS and SLX model results for other covariates in Table 6

Variables	OLS	Spatial Model	
		Non-Weighted	Weighted
Dependent Variable: Share of farmers who adopted technology			
Share of farmers with small farms	-0.217***	-0.237***	-3.943***
	(0.072)	(0.073)	(0.856)
Share of farmers with medium farms	-0.188**	-0.213**	-2.471
	(0.092)	(0.087)	(1.681)
Share of farmers trained in agriculture	0.632***	0.550***	-0.072
	(0.242)	(0.203)	(3.174)
Share of non-General category	-0.058	-0.011	-0.394
	(0.042)	(0.047)	(0.629)
Share of Hindus	-0.042	-0.015	0.768
	(0.038)	(0.048)	(0.508)
Share of households who took loan	0.188***	0.136***	-1.356**
	(0.045)	(0.051)	(0.612)
Share of farms which are irrigated	0.065*	0.092**	0.678
	(0.035)	(0.039)	(0.666)
Share of farms that faced crop loss	0.115***	0.095**	0.921
	(0.042)	(0.038)	(0.736)
Share of farmers producing cereals	0.175**	0.165**	-1.578
	(0.074)	(0.082)	(1.199)
Share of farmers producing pulses	-0.117	-0.060	-4.627*
	(0.127)	(0.139)	(2.446)
Share of farmers producing sugar/spice	0.197*	0.190	0.598
	(0.110)	(0.133)	(1.862)
Share of farmers producing fruits/vegetables	0.402***	0.146	6.475***
	(0.110)	(0.118)	(2.167)
Share of farmers producing other crops	0.237**	0.202**	-3.643**
	(0.098)	(0.095)	(1.509)
Share of farmers producing oil seeds	0.195**	0.254**	-2.228
	(0.097)	(0.104)	(1.414)
Constant	0.065	0.268**	
	(0.088)	(0.128)	
Observations	664	664	664
R-squared	0.206		

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