# Intensity of Micro-Irrigation Technology Adoption: Evidence from India

**Abstract**

Farmers in South Asia face significant climate-related risks, especially due to erratic monsoon and increased drought incidents. Micro-irrigation technologies (such as drip and sprinkler systems) offer a promising risk-mitigation strategy by conserving water and improving crop resilience to water stress. Despite these benefits, the adoption and intensity of micro-irrigation use among farmers have remained abysmally low in many regions. This paper examines the adoption of micro-irrigation (MI) technology and seeks new insights into the factors affecting the intensity of water-conserving irrigation technology adoption in India, with an emphasis on implications for drought risk management. Using a nationally representative dataset and employing the Heckman sample selection, we analyze the key drivers of the intensity of adoption of MI technology. We consistently find that the education of the household head, availability of electric pumps, and the agro-ecological regions have a significant impact on the intensity of adoption, which can enhance adaptation benefits against drought risks. Using a simple theoretical framework, we show that the intensity choices are consistent with the expected utility of profit maximization conditions.

**Keywords:** Water-saving technology, drip, sprinkler, climate change adaptation, sample selection correction, spatial patterns of adoption

**JEL Code:** Q15, Q16, Q18

# 1 Introduction

The rapid decline in groundwater resources in agriculture is a growing concern for policymakers throughout the world. This is especially concerning for India, the largest user of groundwater resources in the world, to effectively respond to weather variation and resource scarcity to avoid further degradation of groundwater resources (Fishman et al., 2015; United Nations, 2022). As a result, there is increasing policy interest in enhancing water conservation efforts and arresting the over-exploitation of groundwater resources through the promotion of water-saving agricultural technologies (Larson et al., 2016; Fishman et al., 2023). In this paper, we study the adoption of micro-irrigation (MI) technologies, a popular irrigation technology that can substantially improve water use efficiency, leading to increased profitability for adopting farmers as well as ensuring environmental sustainability of groundwater irrigation.

The rate of diffusion of these technologies have remained very slow in India, which can partially explain the reason why groundwater tables are fast declining across the major crop producing states of India. Due to the dominance of conventional irrigation techniques, such as flood irrigation, irrigated agriculture in India suffers from a low water use efficiency (around 38%) compared to the developed countries (around 50-60%) (Gandhi et al., 2021). Modern irrigation technologies, such as MI, are proposed as a demand management strategy, which can (at least theoretically) tackle the issues of water use efficiency embedded in traditional irrigation methods (Narayanamoorthy, 2004; Fishman et al., 2015; Perry and Steduto, 2017). In particular, drip systems are an efficient method of irrigating crops as they directly deliver water to the root zones of crops. Farm-level studies suggest that well-designed drip systems can have up to 90 percent on-farm application efficiency, minimizing the risk of losses during evaporation, runoff, or deep percolation (von Westarp et al., 2004). In particular, drip irrigation system has been found to have higher on-farm irrigation efficiency (90%) and conveyance efficiency (100%) compared to traditional methods (40-70% and ¡50%, respectively). Therefore, the shift towards the adoption of MI technologies, is expected to reduce groundwater use, improve crop yield, and minimize the loss of water through evaporation (**?**). In a similar vein, studies also claim that MI systems would be highly effective if they are adopted in arid and

semi-arid agro-ecological regions, with deep water table conditions, for row crops, and under well or lift irrigation (**?**).

The adoption of MI technology is also a significant climate change adaptation strategy for Indian farmers. By improving the effectiveness (increased efficiency) and the productivity (more crop per drop) of (finite) groundwater resources, farmers can effectively adapt to the growing incidences of extreme weather events (Rosa, 2022; Frisvold and Bai, 2016; Fabri et al., 2024). In addition to water conservation at the plot level [1], the impacts of MI technology on increased farm income have also been well documented in the Indian context (Gandhi et al., 2021; Fishman et al., 2023). The reason why the operating costs of production under drip and sprinkler systems are relatively lower than traditional (flood and furrow irrigation) systems is due to decreased requirements of many critical inputs of production, such as energy, fertilizers, and labor hours (Bhamoriya and Mathew, 2014). The upfront costs of purchase and installation of MI systems, pumps, and other water lifting equipment (e.g. diesel or electric pumps), and borewells, tubewells, and other field distribution systems are still very high for most farm households in India (Mohan et al., 2024).To reduce the burden of high upfront costs of adoption, these systems are often heavily subsidized by the government. In India, under the *Pradhan Mantri Krishi Sinchayee Yojana*, farms can avail up to 70-80% subsidy on the purchase of the MI systems (Malik et al., 2018). Despite the apparent gains from adopting MI technologies, substantial amounts of subsidies offered by the government, and the fact that sprinkler and drip technologies were introduced almost half a century back, the diffusion of these technologies has remained slow (Nair and Thomas, 2023).

Several studies have attempted to uncover the patterns, determinants, and impact of micro-irrigation adoption in India. Most of the current research work has focused on household-level adoption studies to examine the binary decision problem [2]. For instance, a recent study by Mohan et al. (2024) uses the IHDS wave-II survey dataset to uncover the adoption patterns in

[1] The rebound effect of MI technology on water conservation, occurring through informal water selling and increased area under cultivation, is also observed in recent studies in the Indian context (Bahinipati and Viswanathan, 2019; Fishman et al., 2023; Singh et al., 2024).

[2] An exception worth mentioning is Bahinipati and Viswanathan (2019), which extends the household-level MI adoption analysis to understand how they affect water savings at the 'systems' level, and reports a significant impact of metering of electricity connections as a contributor to water savings

semi-arid regions of India using probit models.

Our study utilizes a novel dataset, which combines the All India Debt and Investment Survey (AIDIS), collected as part of National Sample Survey (77th round) (NSSO, 2021), and district-level agro-ecological region information, obtained from the National Bureau of Soil Survey and Land Use Planning (ICAR-National Bureau of Soil Survey & Land Use Planning, 2015) to analyze the determinants of intensity of MI technology adoption at the household level. The estimation of the "intensity" aspect of adoption is important not only due to the differences in the adaptation benefits enjoyed by adopter farmers and non-adopter farmers against drought incidences but also for the sustainable use of groundwater irrigation, by shifting away from water-guzzling crop production towards horticultural-orchards-plantation crops. Therefore, we look beyond the binary decisions of adoption by separating the initial adoption decision from the intensity decision. We estimate a Heckman Sample Selection Model, allowing for the correction sample selection bias, in a two-tier process (Heckman, 1979).

The outline of the study is as follows. Section 2 presents the theoretical framework of the study and the specific hypotheses to be tested. Section 3 describes the data and methodology of the paper. The penultimate section (Section 4) presents and discusses the main findings, and the final section (Section 5) discusses the main implications and offers some direction for future research.

# 2 Theoretical Framework

Under the profit-maximization framework, a farm household contemplates adoption decisions based on the discounted stream of profits from switching to a new technology relative to the existing technology. In a given period $t$, a farm household $i$ may either choose to adopt a technology (T = 1) or maintain the status quo (T = 0). New technologies are only adopted when the expected net returns are higher. We describe the binary adoption decisions (yes/no) and the intensity decisions (how much to adopt) by considering the costs and benefits of adoption in the production function (Subsection 2.1) and decision-making under production uncertainty (Subsection 2.2).

## 2.1 Benefits and costs of MI technology are known

Consider a representative farm household that faces the decision to adopt a new technology before the start of every cropping season. For simplicity, assume that the farmer $i$ operates their field using flood irrigation or furrow irrigation (FI) method (existing technology) and faces the opportunity to adopt micro irrigation technology (MI), such as drip or sprinkler systems (new technology).[3] When the benefits and costs of two technologies are known, a risk-neutral farm household $i$ compares the maximized cost functions to arrive at the adoption decision:

$$C^{MI}(c_a, c_b, c_w, c_z)$$

$$C^{FI}(c_b, c_w, c_z)$$

where $c_a$ is the fixed cost of installation of MI technology, $c_b$ is the operating costs of irrigation, $c_w$ is the irrigation water price, and $c_z$ is the vector of input prices for conventional inputs, such as fertilizers.[4]

The fixed costs of investment $c_a$ of MI technology is the most significant cost to consider, especially for smallholder farmers, who face poor collateral options constraining their access to credit (Feder et al., 1988). The fixed cost is an irreversible form of investment, at least in some ways, which can significantly alter the timing of adoption (Dixit and Pindyck, 1994).[5] In particular, drip and sprinkler systems can have an "irreversible" cost aspect due to two reasons. Firstly, the initial investment cost is not fully recoverable even if adopters change their minds after incurring the initial cost. Secondly, there are uncertainty regarding the future benefits after adopting the technology.[6] When the upfront costs of technology adoption are high, farm households can weigh the opportunity cost of waiting versus the potential benefits of adopting

[3] Carey and Zilberman (2002) have also modelled technology adoption with the same assumption of initial point for the farmers being the traditional technology, who faces the option to switch to modern technology.

[4] Suri (2011) analyzes the yield functions of hybrid versus traditional seed varieties and finds the heterogeneity in the costs and benefits of the two technologies driving their adoption rates, respectively.

[5] For instance, prospective adopters can wait for more information, though always incomplete, before deciding to adopt the technology.

[6] For instance, MI systems are more suitable for certain kinds of crops, such as vegetables and fruits (Fishman et al., 2023). Therefore, it may yield good results for other crops.

the technology.[7]

Following Caswell and Zilberman (1986) and Schoengold and Zilberman (2007), we can summarize the annualized repayment costs of investment ($c_a$ in the case of MI technology) and annual operating costs ($c_b$ for the two technologies) as $k^i$, which is the per acre of cost of farming under the $i^{th}$ technology. Since MI technology is more capital intensive, $k^{MI} > k^{FI}$. On the other hand, since MI technology has a higher water use efficiency, it has more irrigation effectiveness compared to traditional irrigation; therefore, the relationship $1 > h^{MI} > h^{FI} > 0$ holds, where $h^i(\alpha)$ is the term for irrigation effectiveness for the $i^th$ technology and $\alpha$ captures the parameters that determine the effectiveness. Caswell and Zilberman (1986) defines irrigation effectiveness as the ratio of effective water used per acre $e^i(\alpha)$ to the total amount (measured in acre-feet) of applied water $x_w^i(\alpha)$, which depends on the quality of the land.

In our formulation, we follow Koundouri et al. (2006) and define $\alpha$ as the parameter that captures the heterogeneity in the water application effectiveness. The management skills of the farm households in operating irrigation systems determine it. Thus, $\alpha$ ranges from 0 to 1, where one implies that fully efficient utilization of water is applied to the crops under production.

Assuming a constant return to scale production function, the per acre output is determined by the irrigation effectiveness and the amount of conventional inputs:

$$y_i = f(h^i(\alpha)x_w^i, x_z^i) \tag{1}$$

where y is the output per acre (yield), $x_w$ is the amount of irrigation water applied, and $x$ is the amount of the conventional inputs used in the production for the $i^{th}$ unit.

Assuming that the production function is well-defined, the output will follow an increasing trend at a decreasing rate $f'(.) > 0$ and $f''(.) < 0$. The profit-maximizing problem for the farm household is the decision of how much water to apply on their farm and the appropriate

[7]To increase the uptake of profitable technologies, such technologies are frequently subsidized, which needs to be incorporated in the opportunity cost, which is simply the difference in the profit functions with immediate adoption $\pi(1,S)$ and adoption with delay $\pi(0)$.

irrigation technology for optimal results (Schoengold and Zilberman, 2007):

$$\pi_i = \max_i \{pf(h^i(\alpha)x_w^i, x_z^i) - x_w^i c_w^i - k^i - x_z^i c_z^i\} \tag{2}$$

where p is the price of each unit of the output, $x_w^i c_w$ is the cost of irrigation water for $i^{th}$ unit of $x_w$ amount of water, and $x_z^i c_z^i$ represents the costs of conventional inputs for the $i^{th}$ unit of $x_z$ amount of conventional inputs.

Optimal production occurs when the price of effective water equals the marginal product of the applied water. The first-order condition solves the following optimal condition:

$$\frac{\partial \pi_i}{\partial x_w^i} = \frac{\partial}{\partial x_w^i}\left[Pf\left(h^i(\alpha)\cdot x_w^i\right) - x_w^i c_w^i - x_z^i c_z^i\right]$$

$$Pf'\left(h^i(\alpha)\right) - c_w^i = 0$$

$$pf' = \frac{c_w^i}{h^i(\alpha)} \tag{3}$$

From the optimal condition eq.3, it follows that since MI technology is associated with higher irrigation effectiveness, effective water prices will be lower than traditional technology. At this juncture, it is important to note that while farmers face zero marginal cost of groundwater extraction, they still have to pay for the electricity or diesel (depending on pumps) required to pump groundwater from borewells or tubewells. In fact, the requirements for energy increase linearly in the depth of wells ($D_i$), implying that the amount of water extracted from the ground ($W_i$) is inversely proportional to depth (Ryan and Sudarshan, 2022). The deeper the water source, the more energy is required to pump water to the surface — this increased energy requirement results in higher operational costs. As the depth increases, the energy costs rise, making it less economically viable to extract large amounts of water. Hence, as depth increases, the quantity of water extracted $W_i$ tends to decrease, illustrating an inverse relationship. Further, the efficiency of the pump equipment ($C_i$) also affects the amount of water extracted through its impact on the number of pumping hours ($H_i$) and the capacity of the pump equipment (measured in horsepower, denoted by $HP_i$). Therefore, the amount of groundwater extraction (measured in cubic meters) under MI technology is a linear function of pump capac-

ity, pumping equipment efficiency, and pumping operation hours. In contrast, it is an inverse function of the depth of wells:

$$W_i = \frac{(Ci * Hi * HP_i)}{D_i} \tag{4}$$

From our first-order condition formulation in eq.3, we find that the price of effective water will be lower under MI technology compared to traditional technology. This is true even when the depth of wells increases due to higher irrigation effectiveness under MI systems. Therefore, it can be postulated that MI technology will be the optimal technology choice for a profit-maximizing farm household. In other words, farming under MI systems can increase profits per acre of output or lower the costs of extracting water due to the lower pumping requirement, as irrigation effectiveness is higher, compensating for high initial investment costs. [8]

## 2.2 Production under risk and uncertainty

In the previous formulation, we assumed the profit-maximizing agent to be a risk-neutral farm household. However, agricultural technologies are inherently risky and profit approximations are difficult to make in an ex-ante manner. In particular, gains from MI technology adoption can be assumed to be risky with uncertain payoffs (unknown outcomes with unknown probability distribution). Here, we consider a case when the costs and benefits of production are known with uncertainty.

Agricultural production is subject to several forms of uncertainty. For simplicity, let us assume that there is only one source of uncertainty in the production decision, which arises from climatic shocks. It can be conveniently represented as a random shock in the production function, captured by the term $\varepsilon$. The distribution of this stochastic term $G(.)$ is exogenous to the actions of the farm households .[9] Depending on the random variations in the climatic conditions, $\varepsilon$ acts as an important source of production risk for the farm household $i$. This is especially true for arid and semi-arid regions, where weather fluctuations affect the agricultural

[8] Schoengold and Zilberman (2007) concludes the same from the Caswell & Zilberman theory.

[9] This is a reasonable assumption given the fact that agricultural production has become increasingly risky in recent years due to climate change and extreme weather events. Farm households are expected to make decisions about production technologies to maximize their expected utility of profit, considering this exogenously determined production risk.

production sector. We further assume that farmers are price takers in both input and output markets and exclude the possibility of non-random prices.

To model technology adoption decision-making under production risk, we follow the Koundouri et al. (2006). Accordingly, we incorporate risk aversion in the adoption decision by adopting a von Neumann Morgenstern utility function. The profit-maximization problem, described in eq.2, can be modified as the maximization of the expected utility of profit $[E(U(\pi)]$, where $U(.)$ is a real-valued utility function. Assuming that the production function F(.) is well-behaved[10] (increasing and concave in its arguments), we obtain the following equation:

$$E[U(\tilde{\pi})] = \max_i \int \{U[pf(h^i(\alpha)x_w^i, x_z^i, \varepsilon) - x_w c_w^i - k^i - x_z^i c_z^i]\} dG(\varepsilon) \tag{5}$$

where $U(\tilde{\pi^i})$ is the expected utility function of profit $(\pi)$ and $dG(\varepsilon)$ is the distribution of the stochastic term $\varepsilon$. Solving for marginal conditions w.r.t irrigation water price variable $(x_w)$ results in the following:

$$\frac{\partial}{\partial x_w}\left[E\left[U\left(pf(h(\alpha)x_w^i, x_z^i, \varepsilon) - x_w c_w^i - k^i - x_z^i c_z^i\right)\right]\right] = 0$$

$$E\left[c_w^i \cdot U'\right] = E\left[p\frac{\partial f(\varepsilon, h(\alpha)x_w, x)}{\partial x_w}U'\right] \tag{6}$$

Eq.6 captures the fact that the expected marginal utility of profit should equal the expected marginal product of irrigation water. Under uncertainty, a farmer will adopt MI technology if the marginal expected utility of profits with adoption $\tilde{\pi}^{MI}$ exceeds the expected utility without adoption $\tilde{\pi}^{FI}$.

The above equation does not capture the optimal timing of adoption. The timing depends not only on the relative difference between adoption and non-adoption but also on the availability of information. In the adoption literature, studies are increasingly documenting the role of social networks in overcoming informational barriers, which accelerates the rate of adoption. Farmers share information with whom they share homophilic relationships (Rogers, 2003; Granovetter, 1973). One main form of such relationships can be observed among those sharing the

[10] A utility function is $U(\pi)$ is considered well-defined if $U'(\pi) > 0$ and $U"(\pi) \leq 0$ for all value of $\pi$.

same religions (Bandiera and Rasul, 2006) or those who attend religious congregations (Burlig and Stevens, 2024). In India, due to social stratification and caste hierarchy, another form of homophily exists, which can be observed among those sharing similar castes. Research indicates that technology adoption results differ among different caste groups due to differential access to resources and perceptions on modern technologies (Negi et al., 2020; Varshney et al., 2022). These studies model the technology adoption decisions based on the utility functions (profit) from adopting new technology as a function of the number of adopters in their social network.

## 2.3 Theoretical predictions & hypotheses

Adverse climate shocks, such as drought incidences, reduce groundwater availability in the following years of onset due to an increase in the lag time and recovery time for the aquifer in the region to get replenished again (Schreiner-McGraw and Ajami, 2021). During years of groundwater scarcity, we expect that MI technology will enable the adopting farm households to produce the same level of output level even with a decreased level of water availability. In particular, we expect that risk-averse farmers are more likely to adopt MI technologies than risk-neutral farmers in order to hedge against adverse climatic shocks. In normal years (without adverse climatic shocks), the high irrigation effectiveness of the MI technology increases farm productivity at a lower cost of production as less energy is required to pump groundwater for cropping activities. Therefore, risk-neutral farm households are also expected to choose MI technologies over traditional technologies as an optimal irrigation water technology decision based on the relative costs and benefits from adoption, which also depend on their knowledge of the current season and their forward-looking expectations about the conditions in next growing seasons (Suri, 2011).

While risk-averse farm households are expected to have a higher likelihood of adopting MI technology, due to the "informational friction" in the market, adoption may be delayed until more information is available (Dixit and Pindyck, 1994). The literature on social network theory suggests that Bayesian farmers update their beliefs either through their own trials (learning-by-doing) or through others' experiences (learning-from-others, e.g., informal social

networks and homophilic relations). It is expected that with each trial, on-farm application efficiency improves as the actual efficiency approaches optimal. Since we do not have information on social networks in our dataset, we postulate that the human capital of farm households should predict the number of MI technologies adopted. Since human capital is correlated with farm management skills (captured by $\alpha$ in our theoretical framework), households with more human capital should adopt a higher number of MI technologies. This leads us to our first testable hypothesis of the study:

**Null Hypothesis 1**: Human capital of the farm households do not effect the intensity decision of MI technology adoption.

In our theoretical framework, we do not explicitly account for the fact that the adoption of MI technologies should be related to spatial features of the spatial units. Instead, we simply provide the conditions under which adoption and non-adoption occur. Based on the same assumption that risk-averse farm households are more likely to adopt and that the source of risk can be traced back to climatic shocks, we can postulate that the intensity of adoption should be correlated with the spatial features. Therefore, the second hypothesis of the study is the following:

**Null Hypothesis 2**: The frequency of climatic shocks frequently occurring in certain regions does not have any relationship with the intensity of MI technology adoption.

Here, the null hypothesis is spatial randomness in the distribution of the MI technology adoption. Our alternative hypothesis is that specific clusters should characterize the adoption patterns of MI technology in India. This is based on our understanding that since some regions are more likely to experience water scarcity than others (due to the higher frequency of drought occurrences), we expect that the adoption of MI technologies would be spatially autocorrelated. For example, high-high clusters could be forming in certain regions, such as Northern and Western India, which are frequently observed to face situations of drought and water scarcity. Similarly, rain-fed regions, such as those in the North-Eastern regions and per-humid regions, are expected to have low-low clusters.

# 3 Data and methodology

## 3.1 Data Sources

The main data source for the study is the 77th round of the National Sample Survey, All India Debt and Investment Survey, Schedule 18.2 (NSSO, 2021). The survey collected data from cross sections of households from both rural and urban areas, which are representative of India's population. The sampling design adopted follows a two-stage stratified sampling with the first stratum as districts, first stage units as villages/urban blocks/sub-units, and households as the ultimate stage units.

The AIDIS is conducted every ten years, starting in the year 1961. The first survey was conducted by the Reserve Bank of India (RBI), followed by a collaboration between RBI and NSSO in the years till 1991, after which NSSO conducted all the rounds. There have been seven such surveys, with the last round being conducted in 2019, which is the focus of the present study. Given the lack of nationally representative official statistics on income and wealth, several studies have relied on AIDIS datasets to examine the patterns of wealth inequality, especially the concentration of wealth in the hands of the few (see, e.g., Bharti et al., 2024).

The present study makes an exception in this tradition and utilizes the AIDIS to evaluate the adoption of agricultural technology in India. Another micro-level data set containing information on MI technologies is the Indian Human Development Survey (wave II), which was conducted in 2011-12. Given that AIDIS is relatively recent and covers a larger number of households, we choose AIDIS dataset and restrict our analysis to the period 2018-19. The survey was completed in two phases: visit 1 (January to August 2019) and (September to December 2019). While the survey covered both rural and urban households, we restrict our analysis to a cross-section of 46,233 households from rural areas since our focus is on technology adoption by farm households. It contains information on 666 districts, spread across 28 states and 6 union territories of India.

The survey collects detailed data on household wealth and indebtedness, especially focusing on different forms of investments, assets, and loans undertaken by households. In particular,

information on seven different types of assets and investments was collected: (1) landholdings, (2) buildings and other constructions, (3) livestock and poultry, (4) transport equipment, agricultural machinery and implements, and non-farm business equipment, (5) investments on shares and related instruments, (6) financial assets, and (7) investments on repair and maintenance of buildings and machinery. Further, the information on the total debt of the sampled households was collected by focusing on outstanding cash and kind loans and dues on various forms of transactions and borrowings.

Apart from the survey data, we utilize the information on agro-ecological regions (AER hereafter) of Indian districts to complement the survey data. Districts classified under a specific AER are homogeneous in the sense that they share similar physiography, soil characteristics, climate, topographic features, and length of the growing period (ICAR-National Bureau of Soil Survey & Land Use Planning, 2015; Dwivedi and Patil, 2023). Consequently, farmers belonging to a certain AER are expected to grow similar crops and cultivars. In the absence of household-level information on the types of crops cultivated by the sampled households (a relevant factor in the decision of MI adoption), AERs becomes a suitable proxy for cropping patterns and other characteristics related to soil, topography, and climate patterns.

In the past, there have been several attempts in classifying AER for the Indian sub-continent (see, eg., Planning Commission of India, 1985; Ghosh, 1991; Mandal et al., 2016. In the present study, we follow the most recent classification, undertaken by the National Bureau of Soil Survey and Land Use Planning in 2016 (Mandal et al., 2016). By utilizing a rich source of soil information (owing to the completion of soil resource mapping on a 1:1 million scale), a modified length of growing period, and new climatic data, the revised AER map provides a finer resolution dataset that substantially sharpens the extent and area of different ecosystems prevailing in the country (Dwivedi and Patil, 2023). Given that the data is not readily available for extraction and amenable for easy use in a GIS environment, we manually match 666 districts of India with the districts present in our survey data.

The shape files for the state and district boundaries are obtained from the Survey of India website (Survey of India, 2019). Lastly, we extract the area under drip and sprinklers under the The Pradhan Mantri Krishi Sinchayee Yojana (PMKSY) scheme, from the website of is an

initiative of the Ministry of Jal Shakti and the Ministry of Agriculture & Farmers Welfare.

## 3.2 Variable selection and descriptive analysis

The set of explanatory variables includes a comprehensive array of household-level characteristics, such as years of education of the household head, number of adults, caste groups, farm size, land tenurial security, irrigation infrastructure access (number of electric pumps), access to formal and informal credit, and uptake of insurance (proxies risk attitude).

Studies have ascertained the impact of farm debt and subsidies to be important for modern irrigation technologies (see, e.g., Koundouri et al., 2006). In line with the literature, we also expect that households with higher farm investment-related loans are more likely to have adopted and intensified MI technology. The financial assets of the households are also included in our models. We expect that the value of financial assets would be positively linked with MI technology adoption, as having more assets is likely to influence the decision to adopt new farm technologies.

Lastly, we include four agro-ecological regions in our regression model. We hypothesize that households in arid and semi-arid regions are more likely to adopt MI technologies as they are frequently affected by drought incidents and face uncertain water availability issues. Therefore, we expect positive coefficients on these two variables. Households in the per-humid regions are less likely to adopt these technologies as many of these regions are rain-fed or non-irrigated.

Table 1 breaks out the summary statistics for all independent variables by adopters and non-adopter categorization. The table shows that only 3.7 per cent of the sampled cultivator households had adopted MI technologies (as of the reference date: 30 June 2018). MI technologies refer to both drip and sprinkler systems (NSSO, 2021).

We do not find much difference in the adopter and non-adopter groups in terms of the demographic features of the household. Adopter households were mostly headed by male members. On average, the head had a primary level of schooling and was aged 53 years. The adopter households were mostly from the Hindu religion and backward castes compared to non-adopter households, and the difference is statistically significant.

In terms of land operation, adopter households operated more land and had more number of irrigated plots compared to non-adopter households. We also find that adopter households owned more electric pumps and other forms of irrigation equipment. The magnitude of the differences is large for these technologies, which are also statistically significant. We do not find statistically significant differences in the ownership of diesel pumps.

**Table 1**: Comparison of predictors by adoption status

| **Variables** | **Adopters** **(N = 1421)** | **Non Adopters** **(N = 44,812)** | **Difference** | **P value** |
|---|---|---|---|---|
| **Land characteristics** | | | | |
| Area Operated (in hectares) | 2.16 | 0.94 | 1.23 | 0.000 |
| Number of irrigated plots owned | 0.72 | 0.37 | 0.35 | 0.000 |
| **Household characteristics** | | | | |
| Education of household head (years of schooling) | 6.24 | 5.46 | 0.78 | 0.000 |
| Age of the household head (in years) | 52.70 | 49.47 | 3.22 | 0.000 |
| Religion (Hinduism=1, Others=0) | 0.89 | 0.80 | 0.08 | 0.000 |
| Social Category (Forward Caste=1, Others=0) | 0.31 | 0.24 | 0.07 | 0.000 |
| Male-headed Household (Yes=1, No=0) | 0.95 | 0.89 | 0.06 | 0.000 |
| Household Size | 5.12 | 4.56 | 0.551 | 0.000 |
| **Complementary and related technologies** | | | | |
| Number of diesel pumps owned | 0.20 | 4.56 | 4.36 | 0.862 |
| Number of electric pumps owned | 0.58 | 0.12 | 0.46 | 0.000 |
| Number of other irrigation equipment owned | 2.02 | 0.16 | 1.86 | 0.000 |
| Number of laser land levellers owned | 0.06 | 0.01 | 0.05 | 0.000 |
| Number of manual implements owned | 7.63 | 6.15 | 1.48 | 0.000 |
| **Debt and assets** | | | | |
| Outstanding loans on farm capital (in INR) | 165969 | 44269 | 121700 | 0.000 |
| Value of financial assets (in INR) | 303371 | 136895 | 166476 | 0.000 |

| | | | | |
|---|---|---|---|---|
| Total number of livestock | 12.23 | 4.82 | 7.408 | 0.000 |
| **Agro-ecological Region & Rainfall** | | | | |
| Arid Region (yes=1, no=0) | 0.18 | 0.07 | 0.11 | 0.000 |
| Semi-arid Region (yes=1, no=0) | 0.73 | 0.52 | 0.21 | 0.000 |
| Sub-humid Region (yes=1, no=0) | 0.29 | 0.39 | 0.10 | 0.000 |
| Per-humid Region (yes=1, no=0) | 0.06 | 0.14 | 0.09 | 0.000 |
| Coastal & Island Region (yes=1, no=0) | 0.12 | 0.15 | 0.03 | 0.000 |
| Cov of Rainfall (in mm.) | 0.33 | 0.31 | 0.03 | 0.000 |
| **Instrument** (Selection Equation) | | | | |
| Number of Adopters in district | 2.79 | 12.10 | 9.32 | 0.000 |

Furthermore, a very small number of households have adopted laser land leveller (LLL) technology, an important water-saving technology. In the sample, 400 out of 46,233 (0.009%) reported to have adopted LLL technology. These households are also likely to have adopted MI technology (t-statistic above critical value at 0% significance level).

We find that households with higher amounts of loans are more likely to have adopted MI technology. The difference in outstanding loans (on farm capital) between MI adopters (1,65,969 INR) and non-adopters (44,269 INR) is statistically different. Similarly, farm households with more financial assets and livestock were likely to have adopted MI technologies. These are also found to be statistically significant at 0% level of significance. Lastly, as anticipated, farmers located in regions with more occurrence of droughts (e.g., arid and semi-arid) are found to be likely adopters of MI technology.

An important caveat from the literature suggests that farm size and returns from farming (measured in terms of net returns per hectare) have an inverse relationship. On the other hand, as detailed in Feder et al. (1988), the relationship between farm size and modern technologies is mediated by the "riskiness" of the technology. If the technology is risk-reducing, larger farm households tend to adopt more of these technologies compared to smaller farms. We find this evidence from our descriptive statistics. Further, using the 59th round of NSSO's Situation Assessment Survey data, Birthal et al. (2015) shows that smaller farmers are further disadvantaged due to lower access to information. In order to shed light on how MI technology adoption varies with the size of the operated area, we present a kernel density of the size of

land operation for adopters and non-adopters of MI technology.

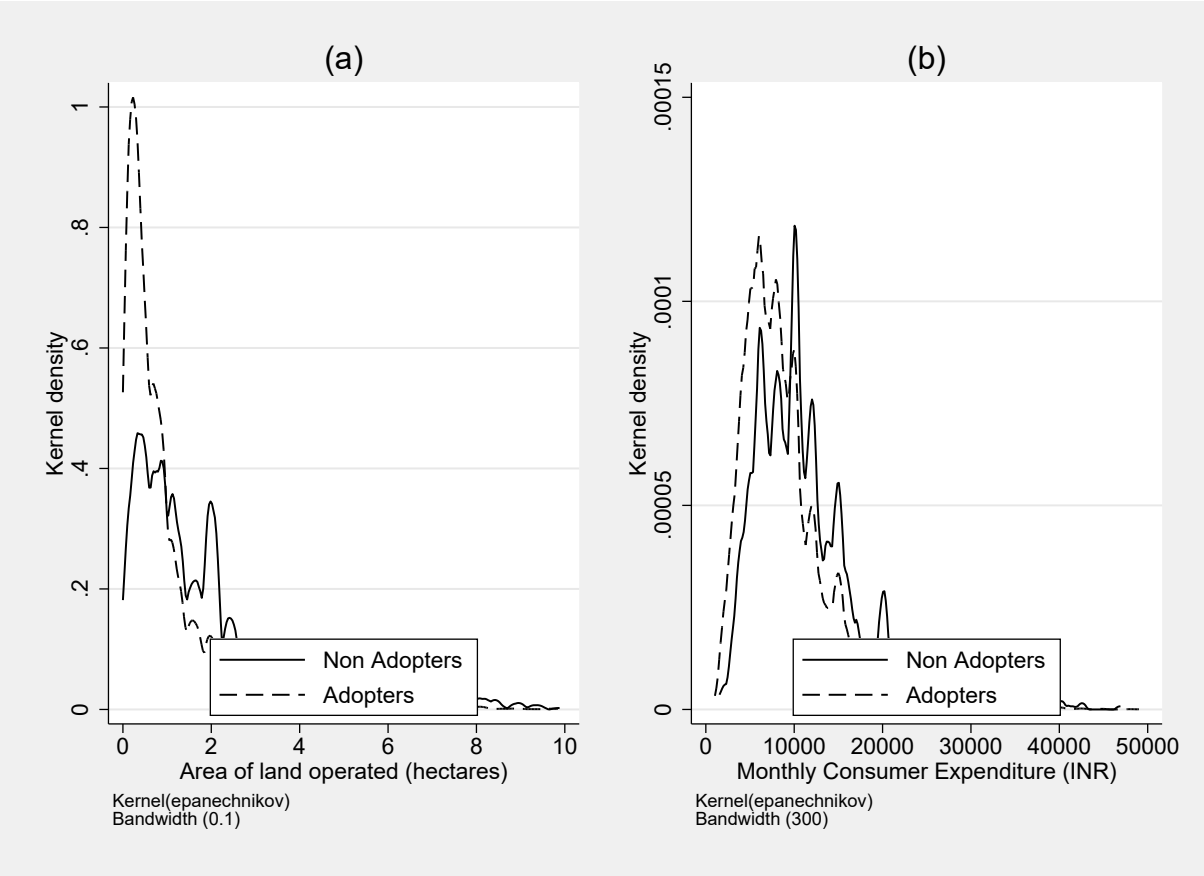



Figure 1. Kernel densities of operated land & monthly consumption expenditure for the adopters and non-adopters of MI technology

Figure 1 (a) shows that the density of non-adopters of MI peaks at a smaller area of land operation compared to the adopters. It is also observed that toward the tail of the distribution of the operated area, the density of adopters lies above that of non-adopters. Further, we also look at the variation of MI adoption with respect to monthly consumer expenditure (a proxy for income) in Figure 1 (b). It shows a similar pattern of the peak of non-adopters at lower levels of monthly consumer expenditure compared to adopters. However, the difference between adopters and non-adopters on the monthly consumer expenditure front is not as stark as operated land size. Birthal et al. (2015) expresses that such patterns could be explained by the inverse land size and net returns relationship.

## 3.3 Empirical strategy and econometric specification

### 3.3.1 Outcome variable

The outcome variable in our study measures the intensity of MI adoption at the household level. It is constructed using the household survey responses on the number of MI technologies owned by the farm households and the area under irrigated agriculture (in hectares). Adjusting for the survey weights, it is obtained as a ratio:

$$\text{MI Intensity}_h = \frac{\sum_{i \in h} w_i \cdot MI_i}{\sum_{i \in h} w_i \cdot Area_i} \tag{7}$$

where $w_i$ is the sampling weight provided in the NSS data for the $i$th household.

Following (Burbidge et al., 1988), we apply the inverse hyperbolic sine (IHS) transformation on the weighted value of MI adoption for each household. This is undertaken in order to account for the presence of zero values. This approach is increasingly used in the agricultural and development economics literature, (see, e.g., Afridi et al. (2023), for a recent application on gendered labour use). The transformation is obtained by applying the following formula:

$$y_h = \sinh^{-1}\left(100 \cdot \text{MI Intensity}_h\right) \tag{8}$$

For interpretational convenience, we pre-multiply the weighted value of MI adoption by 100. It helps stabilize the values ensuring that they do not fall outside a range, further enabling the interpretation of IHS coefficients as semi-elasticities (Bellemare and Wichman, 2020). Further, it allows for a broad range of regression models once the IHS transformation results in continuous and non-negative $y_d$ variable.

### 3.3.2 Econometric modeling

One possible approach to analyze the correlates of the intensity of adoption would be the construction of a full dynamic optimization model, where farming households choose current technologies, taking into account Bayesian learning, the current and future benefits, and the costs of the alternative technologies. This approach has been proposed several times in the literature

(see, e.g., Besley and Case, 1993; Doss, 2006). However, in the absence of panel data, we consider three modelling approaches, which are frequently employed in the adoption literature: the tobit model (Tobin, 1958), the double hurdle model (Cragg, 1971), and the Heckman sample selection model (Heckman, 1979).

One of the main drawbacks of the Tobit model is that the same underlying process determines both the decision to participate in the adoption decision and the decision regarding the number of technologies to adopt (Burke, 2009).

Based on our theoretical framework and the extant literature on technology adoption, it is conceivable that certain variables related to the characteristics of the household are correlated with both the binary and intensity decisions of technology adoption. Further, despite the outcome for all the observations of non-adopters being zero in terms of the number of technologies adopted, their values do not truly reflect potential outcomes.[11] This introduces "selection bias" if one is comparing the outcomes of adopters and non-adopters. The possibility of sample selection bias due to incidental truncation, which occurs when the outcome of interest is observed for a sub-population that is not randomly selected, cannot be discounted (Greene, 2018).

In our context, it is possible that farm households may have self-selected themselves when making the decision to adopt MI technology. Farmers may also likely have adopted MI technologies because of targeting by extension workers. In any of these cases, naive Tobit or double hurdle models would be inconsistent and biased (Heckman, 1979). To address such sample selection concerns, we apply Heckman's two-step estimator, which is also considered as an extension of the Tobit model (also known as the Type III Tobit model) (Heckman, 1979; Amemiya, 1985).

**Stage 1: Selection Equation (Adoption Decision)**

It involves sequentially estimating two equations. The first equation is known as the selection equation, which is estimated using the probit model. It deals with the selection mechanisms influencing the outcome variable.

[11] The counterfactual here is the number of technologies adopted by the non-adopter had they participated in adopting the technology.

$$\text{Selection eq.:} \quad d_i^* = \boldsymbol{x}_i^\top \boldsymbol{\pi}_1 + \boldsymbol{w}_i^\top \boldsymbol{\pi}_2 + v_i, \tag{9}$$

$$d_i = \mathbb{I}(d_i^* > 0), \tag{10}$$

where $\boldsymbol{x}_i$ denotes the variables included in both the selection and outcome equations, $\boldsymbol{w}_i$ represents the variables excluded from the outcome equation (serving as the "instruments" for identification), and $\widehat{\lambda}_i$ is computed using both $\boldsymbol{x}_i$ and $\boldsymbol{w}_i$, such that $\boldsymbol{z}_i = (\boldsymbol{x}_i, \boldsymbol{w}_i)$.

Since it is a probit model (normality of errors is required), a dummy coded variable is used as a selection-dependent variable, which determines the probability of observations from the population being selected into the sample. An instrument that meets two criteria is needed to be included in the selection equation. First, it should affect the dependent variable in the probit equation but not the outcome equation's dependent variable. This is done to ensure that the correlation between the omitted factor and the error terms is captured and accounted for in the outcome equation. However, in the absence of exclusion criteria, the estimates may not be robust or even valid (Bendig and Hoke, 2022).

In line with this reasoning, we construct two dependent variables: binary adoption variable, to be applied in the probit equation, and MI technologies, which is a continuous variable, to be used in the second equation as a dependent variable. We use the number of adopters of MI technology in districts as instruments for the selection equation. While instruments are expected to affect the selection process in the probit stage, they do not directly influence the number of technologies adopted. Once the probit equation is estimated with the instrument, the inverse mills ratio (IMR) is retrieved and used as a correction term in the second equation. The coefficient of the IMR (denoted by lambda) captures the unobservable and unmeasurable information of the sample and corrects for the potential sample selection bias (Certo et al., 2016). The level of significance and sign of this coefficient indicates the magnitude of the correlation between the error terms of the selection equation and the outcome equation, which represents the level of endogeneity (induced by omitted variable bias) present in the model (Bendig and Hoke, 2022).

Crucially, to achieve identification of the Heckman model, we include an exclusion restriction: a variable that predicts adoption but is not expected to directly influence the intensity of

use. We construct this instrument as the *district-level exposure to PMKSY policy*, measured by a dummy taking the value 1 if the proportion of MI area in the district (excluding the respondent's own village) in the period prior to the survey is above median. This variable is theoretically exogenous at the household level and empirically predictive of exposure to MI promotion efforts.

**Stage 2: Outcome Equation (Conditional Intensity of Use)**

The second stage estimates the determinants of the intensity of MI use, measured as the ihs transformed value of the area (in hectares) under MI technology. The estimation is conducted only on the subsample of adopters and includes the IMR derived from the first stage to correct for selection bias.

$$\text{Outcome eq.:} \quad y_i = \boldsymbol{x}_i^{\top}\boldsymbol{\beta} + \delta\,\widehat{\lambda}_i + \eta_i, \quad d_i = 1. \tag{11}$$

The covariates mirror those used in the selection equation, with the exclusion restriction omitted to preserve identification. We also omit farm size and land tenurial security, which drives mechanical correlation with the outcome variable. We include an additional variable: state level groundwater pumping policy for electricity use. It takes the value 1 if electricity is freely provided to pump groundwater, which is expected to enhance the intensification decision. We cluster standard errors at the district level to account for intra-district policy correlation and spatial clustering.

As shown in Carlson and Zhao (2025), the Full Information Maximum Likelihood estimator for the Heckman sample selection model becomes inconsistent under heteroskedasticity, whereas the two-step estimator remains consistent provided the minimal consistency condition is satisfied. We therefore rely on the two-step estimates and verify estimator validity via a Hausman test. We conducted a Hausman test which rejected the null of systematic equivalence between FIML and two-step estimators (p ¡ 0.001), suggesting the presence of heteroskedasticity. Thus, we rely on the more robust LIML estimates.

We tested the minimal consistency condition (MCC) using the link test for model specification (Wooldridge, 2010; Carlson and Zhao, 2025). In our preferred specification, the squared

predicted value (phat²) was statistically insignificant (p ¿ 0.16), indicating correct functional form. Thus, the LIML (Heckman two-step) estimator remains consistent under heteroskedasticity.

## 3.4 Relevance and Falsification test

We assess the robustness of our instrumental variable (Policy Exposure) using multiple diagnostics. Using an linear probability model and checking the F-statistics on the instrument, we reject the null hypothesis of a weak instrument. The first-stage F-statistic far exceeds 10 (F-stats = 15.67, p-value = 0.000), confirming strong instrument relevance.

Following Di Falco et al. (2011), we apply a falsification test similar to the paper but in a different settting, where we run the second stage regression on adopters and find non-significant impact of the included instrument, after conditioning on all the control variables (see Table A1, in Appendix). Therefore, it satisfies the exclusion restriction of being an instrument. Further, the Ramsey RESET test indicates no evidence of model misspecification.

However, Oster (2019) bounds suggest some caution. The estimated $\delta = 0.08$ implies that even modest selection on unobservables could undermine the exclusion restriction. While this does not invalidate the instrument, it highlights the importance of interpreting the IV results with care, particularly regarding causal inference on the intensity of MI adoption (Aïhounton and Henningsen, 2024).

## 3.5 Robustness checks

We conduct a battery of robustness checks using diagnostic checks of the validity of the assumptions, incorporating alternative definitions of outcome and explanatory variables, and implementing different regression models. In terms of the choice of regression models, we estimate four count data models as an additional check of robustness, which includes standard poisson model, negative bionomial model, zero-inflated poisson model, and hurdle count model (Cameron and Trivedi, 2013).

# 4 Results & discussion

## 4.1 Parameter Estimates

The estimates from the Heckman sample selection, along with their corresponding standard errors, are presented in Table 1. The significant Chi-square test confirm the suitability of the model specification for the sampled data. The exclusion restriction is highly significant in determining the binary decision of adoption ($p<0.000$). The IMR is also statistically significant ($p<0.000$), indicating the presence and capturing the selection bias concern.

Probit Regression Results and Marginal Effects for MI Adoption

| **Variable** | **Coefficient (Robust SE)** | **Average marginal effects (Robust SE)** |
|---|---|---|
| IHS_Educ | 0.0408*** (0.0149) | 0.00211*** (0.00079) |
| Adults_HH | 0.0104 (0.0123) | 0.00054 (0.00064) |
| OBC (1=Yes) | 0.0426 (0.0628) | 0.00222 (0.00328) |
| SC (1=Yes) | 0.0910 (0.0820) | 0.00501 (0.00477) |
| ST (1=Yes) | −0.0289 (0.1047) | −0.00147 (0.00524) |
| IHS_Electric Pumps | 0.5360*** (0.0557) | 0.02777*** (0.00351) |
| IHS_Farm Size | 0.2280*** (0.0426) | 0.01181*** (0.00227) |
| IHS_Land Tenure | 0.2164** (0.1062) | 0.01121** (0.00560) |
| Access to Credit (1=Yes) | 0.1023** (0.0404) | 0.00506*** (0.00192) |
| IHS_Insurance | 0.0145*** (0.00552) | 0.00075** (0.00029) |
| Agro Zone: Arid | 0.4652** (0.2131) | 0.01891** (0.00906) |
| Agro Zone: Semi-Arid | 0.3993** (0.1697) | 0.01517*** (0.00481) |
| Agro Zone: Sub-Humid | 0.3931** (0.1770) | 0.01484*** (0.00571) |
| Agro Zone: Coastal | −0.1692 (0.2695) | −0.00360 (0.00562) |
| IHS_Asset Based Wealth | 0.0911** (0.0381) | 0.00472** (0.00201) |
| Off-Farm Business (1=Yes) | −0.1287* (0.0746) | −0.00607* (0.00328) |

**Table 2 (continued)**

| Variable | Coefficient (Robust SE) | AME (Robust SE) |
|---|---|---|
| SHG Membership (1=Yes) | 0.0167<br>(0.0671) | 0.00087<br>(0.00354) |
| PMKSY Median Exposure (1=Yes) | 0.3468***<br>(0.0768) | 0.01666***<br>(0.00373) |
| Constant | −4.6355***<br>(0.5633) | — |
| Observations | 33,937 | |
| Wald $\chi^2(18)$ | 372.38 | |
| Prob $> \chi^2$ | 0.0000 | |
| Pseudo $R^2$ | 0.1416 | |

Notes: Robust SEs clustered at district level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

LIML (Outcome Equation) Regression Results for MI Intensity

| Variable | Coefficient (Robust SE) |
|---|---|
| IHS_Educ | 0.0803**<br>(0.0400) |
| Adults_HH | −0.0712***<br>(0.0195) |
| OBC (1=Yes) | 0.4625***<br>(0.1261) |
| SC (1=Yes) | 0.5284***<br>(0.1683) |
| ST (1=Yes) | 0.3510*<br>(0.2114) |
| IHS_Electric Pumps | 1.1227***<br>(0.2100) |
| Access to Credit (1=Yes) | 0.3504***<br>(0.0900) |
| IHS_Insurance | 0.0331***<br>(0.0122) |
| Agro Zone: Arid | 1.0818*<br>(0.5583) |
| Agro Zone: Semi-Arid | 0.8522**<br>(0.3981) |
| Agro Zone: Sub-Humid | 0.7453**<br>(0.3551) |
| Agro Zone: Coastal | −1.6743***<br>(0.3838) |
| IHS_Asset Based Wealth | 0.0520<br>(0.0601) |
| Off-Farm Business (1=Yes) | −0.1793<br>(0.1798) |
| SHG Membership (1=Yes) | 0.0597<br>(0.1146) |
| State Electricity Pumping Policy (Cat 2) | 0.5674***<br>(0.2182) |

**Table 3 (continued)**

| Variable | Coefficient (Robust SE) |
|---|---|
| Inverse Mills Ratio (IMR) | 2.6304*** |
| | (0.3835) |
| Constant | −3.8477* |
| | (1.9657) |
| Observations | 864 |
| $R^2$ | 0.2852 |
| F(17, 212) | 16.50 |
| Prob > F | 0.0000 |
| Root MSE | 1.1249 |

Notes: Robust SEs clustered at district level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

### Human and social capital

We find several factors strongly affecting the binary and intensity decision to adopt MI technology. Consistent with literature and our first hypothesis (Huffman, 2001), we find education of the household head to have a positive and statistically significant coefficient (0.08, p<0.05), implying that an additional year of schooling increases the probability of intensity adoption by approximately 8 percentage points, holding other factors constant. It leads us to reject our null hypothesis on the role of farm management skills (embedded in human capital or education) on the intensity decision of MI technology.

Household size has a small, statistically insignificant effect, suggesting that the number of adult members does not materially influence adoption decisions. However, we find its significance and sign to play a reverse role in influencing the intensification decision. This is substantiated in the literature, provided the fact that MI technology is highly labor-saving (Gallardo and Sauer, 2018).

### Caste groups

Farmers share information with whom they share homophilic relationships (Rogers, 2003; Granovetter, 1973). One main form of such relationships can be observed among those sharing the same religions (Bandiera and Rasul, 2006) or those who attend religious congregations (Burlig and Stevens, 2024). In India, due to social stratification and caste hierarchy, another form of

homophily exists, which can be observed among those sharing similar castes. Research indicates that technology adoption results differ among different caste groups due to differential access to resources and perceptions on modern technologies (Negi et al., 2020; Varshney et al., 2022). These studies model the technology adoption decisions based on the utility functions (profit) from adopting new technology as a function of the number of adopters in their social network.

Social learning mediates the adoption of technologies. In India, social learning operates in homophilic networks through caste networks. Therefore, caste group effects are interesting to note. While belonging to either of the caste group, such as OBC, SC, or ST (compared to Other groups, notably forward castes), do not statistically affect the binary decision-making, caste group variable exhibit statistically significant role in influencing the decision to intensify the area under MI technology. These indicate that caste remains a structural barrier to accessing profitable agricultural technologies as many households in marginalized caste face poor collateral options constraining their access to credit (Feder et al., 1988). However, once the barrier is crossed, households belonging to these groups are more likely to intensify in comparison to forward castes.

**Irrigation Infrastructure**

Access and availability of irrigation infrastructure shows a particularly strong effect. We find that having more number of electric pumps is associated with a 2.8 percentage point higher probability of adoption ($p<0.01$). It also increases the probability of intensifying adoption by bringing additional hectares of land under MI irrigation. It suggests that having access to pumping equipment and electricity-run pumps incentivises households to invest in more MI technologies to reap the benefits of irrigation effectiveness.

The level of water savings from the adoption differs based on the state-level policies. Bahinipati and Viswanathan (2019) suggests that water savings are feasible for a region if there is metering of electricity connections for the adopter households. In our robustness check model, we replace the electric with the "access to groundwater" variable, which leads us to conclude the same positive and statistically significant effect with respect to the outcome vari-

able.

**Land resources**

Farm size and land tenurial security are also positively associated with adoption. A 1% increase in farm size and land tenurial security (inverse hyperbolic sine) raises adoption probability by 1.1 percentage points, respectively. The positive and significant coefficient for the area operated by the farm household negates the idea that farm size and the technology adoption are inversely related. Households who operate on larger lands tend to adopt MI technologies to increase their net returns from farming (or to reduce the cost of water extraction).

**Access to credit and Wealth**

Access to formal and informal forms of credit increases adoption probability by 0.5 percentage points, while agricultural insurance has a smaller but significant effect of 0.07 percentage points. Membership in self-help groups, however, is not found to be significant in influencing either of the binary adoption or intensity decision.

Wealth plays a significant role in meeting the up-front costs of drip and sprinkler irrigation systems (0.04%, $p<0.05$). However, its effect dissipates in the second stage, once we control for selection bias and relevant covariates. A possible explanation is that government subsidy, as per of PMKSY, is sufficient to meet the needs of most of the farm households, as they can expand area under MI technologies, up to 5 hectares of land. Secondly, the increased yield and profitability under MI technology reduces the reliance on assets. This is further noticed in the off-farm business activity, which plays no role in influencing the intensity decision.

**Agro-ecological regions**

The magnitude and the level of significance of the agro-ecological region variables further shed light on the role of spatial and ecological factors in determining the intensity of adoption decisions. We find that household-level intensity of MI technology is positive and significant in arid districts where water scarcity is high.

We find the agro-ecological regions, such as arid, semi-arid, and sub-humid regions exert

strong influence on binary adoption as well as intensity decision. Relative to the per-humid zone, arid (1.9%), semi-arid (1.5%), and sub-humid (1.5%) regions show substantially higher adoption probabilities. We further expect arid ( 1.1 hectares), semi-arid ( 0.85 hectares), and sub-humid ( 0.75 hectares) to have higher intensity probabilities. Coastal households, however, are significantly less likely ( -1.7 hectares) to intensify adoption, potentially reflecting limited water scarcity pressures or issues with water quality, such as salinization.

## 4.2 Robustness checks: count data models

We start our count data regression modeling using the standard Poisson model. After rejecting the null hypothesis that over-dispersion is not an issue in the Poisson model (statistic = 16.38, p = 0.000), we estimate the negative binomial regression model, which can adequately handle over-dispersion. We further check for the presence of excess zeroes using the ratio of observed zeroes and predicted zeroes in the negative binomial model. While we do not find sufficient evidence of excess zeroes, we found Poisson model be severely suffering from zero-inflation. Therefore, we also estimate a zero-inflation Poisson model and a hurdle count model for completeness. While the first stage of the zero-inflation model estimates the probability of the outcome always being zero (i.e., the probability that households will never adopt MI technology), the hurdle count model's first stage estimates the probability of having a positive count (i.e., the probability of households adopting versus not adopting MI technology).

Table 6: Estimated parameters for the intensity decisions (Count Data Regression Models)

| | *Dependent variable: the number of MI technologies adopted* | | | |
|---|---|---|---|---|
| | *Poisson* | *Negative Binomial* | *Zero-inflated* | *Hurdle* |
| | (1) | (2) | (3) | (4) |
| Male headed | 0.916*** | 0.640*** | 0.418*** | 0.465*** |
| | (0.071) | (0.154) | (0.079) | (0.082) |
| Age of Head | −0.0001 | 0.001 | −0.001 | −0.001 |
| | (0.001) | (0.003) | (0.001) | (0.001) |
| Education of Head (years) | 0.024*** | 0.024*** | 0.044*** | 0.044*** |
| | (0.002) | (0.009) | (0.002) | (0.002) |

| | | | | |
|---|---|---|---|---|
| Log of MPCE | $0.134^{***}$ | 0.073 | $-0.213^{***}$ | $-0.232^{***}$ |
| | (0.026) | (0.097) | (0.028) | (0.028) |
| Log of Wealth | $0.030^{***}$ | $0.116^{***}$ | $-0.196^{***}$ | $-0.196^{***}$ |
| | (0.011) | (0.043) | (0.012) | (0.012) |
| Off Farm Business | $-0.042$ | 0.008 | $-0.056$ | $-0.050$ |
| | (0.033) | (0.105) | (0.035) | (0.035) |
| Islam | $-1.162^{***}$ | $-0.618^{***}$ | $-0.294^{***}$ | $-0.294^{***}$ |
| | (0.074) | (0.166) | (0.078) | (0.081) |
| Christianity | $-0.708^{***}$ | 0.218 | $-0.203$ | $-0.686^{**}$ |
| | (0.139) | (0.210) | (0.213) | (0.272) |
| Other Religion | $-2.933^{***}$ | $-0.822^{***}$ | $-1.616^{***}$ | $-1.840^{***}$ |
| | (0.088) | (0.212) | (0.096) | (0.110) |
| Other Backward Classes | $0.283^{***}$ | $0.310^{***}$ | $-0.044^{**}$ | $-0.041^{*}$ |
| | (0.022) | (0.098) | (0.022) | (0.022) |
| Scheduled Castes | $-0.353^{***}$ | 0.144 | $-0.805^{***}$ | $-0.832^{***}$ |
| | (0.043) | (0.137) | (0.045) | (0.046) |
| Scheduled Tribes | $-0.334^{***}$ | 0.210 | $-0.395^{***}$ | $-0.429^{***}$ |
| | (0.049) | (0.135) | (0.054) | (0.056) |
| Number of Adults | $-0.003$ | 0.027 | $0.015^{**}$ | $0.016^{**}$ |
| | (0.007) | (0.031) | (0.007) | (0.007) |
| Area operated | $0.078^{***}$ | $0.292^{***}$ | $0.091^{***}$ | $0.092^{***}$ |
| | (0.002) | (0.023) | (0.003) | (0.003) |
| Irrigated plots (n) | $0.231^{***}$ | $0.337^{***}$ | $0.210^{***}$ | $0.213^{***}$ |
| | (0.005) | (0.035) | (0.006) | (0.006) |
| Land Tenurial Security | $0.070^{**}$ | $0.406^{***}$ | $0.256^{***}$ | $0.267^{***}$ |
| | (0.034) | (0.114) | (0.037) | (0.037) |
| Share of Orchards & Plantations | $-0.652^{***}$ | $-0.424^{**}$ | $-1.111^{***}$ | $-1.221^{***}$ |
| | (0.109) | (0.178) | (0.135) | (0.182) |
| Rainfall (cov) | $1.339^{***}$ | $-0.253$ | $1.436^{***}$ | $1.462^{***}$ |
| | (0.067) | (0.293) | (0.087) | (0.088) |
| Access to Groundwater | $0.960^{***}$ | $1.017^{***}$ | $0.399^{***}$ | $0.397^{***}$ |
| | (0.008) | (0.052) | (0.009) | (0.009) |
| Membership in SHG | $0.077^{***}$ | 0.032 | $-0.135^{***}$ | $-0.140^{***}$ |
| | (0.025) | (0.104) | (0.026) | (0.026) |
| Access to Credit | $0.265^{***}$ | $0.462^{***}$ | $0.112^{***}$ | $0.108^{***}$ |
| | (0.024) | (0.089) | (0.025) | (0.026) |

| | | | | |
|---|---|---|---|---|
| Farm Capital Loan | 0.129*** | −0.243 | 0.280*** | 0.279*** |
| | (0.041) | (0.242) | (0.042) | (0.042) |
| Arid Districts | 2.549*** | 1.951*** | 2.023*** | 2.020*** |
| | (0.031) | (0.154) | (0.038) | (0.038) |
| Semi-Arid Districts | 0.098*** | 0.281** | −0.372*** | −0.372*** |
| | (0.029) | (0.124) | (0.030) | (0.030) |
| Sub-Humid Districts | 0.624*** | 0.591*** | 0.078** | 0.086** |
| | (0.035) | (0.123) | (0.040) | (0.040) |
| Coastal & Island Districts | 0.459*** | 0.519*** | 0.491*** | 0.501*** |
| | (0.048) | (0.133) | (0.054) | (0.056) |
| Northern States | 0.236** | −0.069 | −0.031 | −0.004 |
| | (0.117) | (0.237) | (0.188) | (0.192) |
| Central States | 0.417*** | −0.163 | 0.746*** | 0.756*** |
| | (0.117) | (0.223) | (0.187) | (0.191) |
| Western States | 0.924*** | 1.158*** | 0.445** | 0.453** |
| | (0.117) | (0.231) | (0.188) | (0.191) |
| Eastern States | −1.713*** | −1.097*** | −4.526*** | −4.456*** |
| | (0.140) | (0.237) | (0.243) | (0.470) |
| Southern States | 0.278** | 0.284 | 0.627*** | 0.647*** |
| | (0.122) | (0.240) | (0.190) | (0.194) |
| Constant | −7.207*** | −8.326*** | 3.685*** | 3.798*** |
| | (0.276) | (0.924) | (0.336) | (0.339) |
| Observations | 46,061 | 46,061 | 46,061 | 46,061 |
| Log Likelihood | −32,626.230 | −8,555.122 | −15,718.400 | −15,686.620 |
| $\theta$ | | 0.029*** (0.001) | | |
| Akaike Inf. Crit. | 65316.45 | 17173.16 | 31564.8 | 31501.25 |

*Note: The base category for Islam, Christianity, and other religions is Hinduism.*

*For Other Backward Classes, Scheduled Castes, and Scheduled Tribes, the base category is Forward Castes.*

*For arid, semi-arid, sub-humid and coastal and island agro-ecological region dummies, Per-Humid is the base category*

*For Northern, Central, Western, Eastern and Southern States dummies, North-Eastern States is the base category.*

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

Based on the Vuong test, we choose the zero-inflation Poisson model over the standard Poisson model (AIC corrected Z-statistic = - 12.76, p = 0.000). However, the lowest AIC among the four count models is for the negative binomial model (17173.16). Therefore, we

choose the negative binomial model as the preferred model for interpretation.

In line with our main regression models, we could find evidence of the role of farm management skills, religion, access to groundwater, number of irrigated plots owned, and the agro-ecological regions in determining the intensity of MI technology adoption. Since we have chosen to estimate our count models using additional variables and alternative definitions of variables, a brief discussion of the results is done in this section.

While MI technologies are expected to provide adaptation benefits in the face of rainfall variability and drought incidents, we do not find a significant positive relationship between rainfall variability (measured by the coefficient of variation of annual rainfall for 51 year period) and the intensity of MI technology adoption, in our main regression models (Tobit, double hurdle, and Heckman model) as well as in the negative binomial model.

We find that physical and financial assets (a proxy of wealth) significantly and positively affect the intensity of MI technology. For the monthly per capita expenditure (MPCE), a proxy for monthly income, we could not find a significant relationship in the negative binomial model. In line with past literature, we find that access to credit and land tenurial security have a positive and significant relationship with the intensity of MI technology adoption. In our theoretical framework, we alluded to the fact that social learning mediates the adoption of technologies. Based on the findings, it is also likely that they also influence the intensity of adoption, where social learning operates in homophilic networks through religious networks. Based on our count data model, we found that compared to Hinduism, Islam and Christianity were less likely to intensify the adoption of MI technologies. In terms of castes, Other Backward Classes were more likely to adopt intensely than forward castes. Lastly, we also found strong evidence that households in the arid, semi-arid, sub-humid, and coastal-island districts are more likely to intensify adoption compared to per-humid regions.

On the other hand, we consistently find that households with more irrigated plots exhibit a greater adoption intensity than those with a lesser number of irrigated plots, which draws a similar picture as the ownership of a large farm size. Therefore, we argue that the number of irrigated plots has a better explanatory power in the intensity decision of water-saving technologies, such as drip and sprinkler systems.

# 5 Conclusion and future work

The study assessed the factors affecting the intensity of MI technology adoption using several econometric models and regression specifications. As hypothesized, the study finds the role of farm management skills in the intensification decision of MI technologies. We also find that farm households operating more irrigated plots are highly likely to intensify the adoption of MI technologies. Based on our theoretical framework, this can be conjectured as a profit-maximizing behaviour, related to economies of scale. Thirdly, social groups (caste) turned out to be a crucial factor in affecting the intensity of adoption decisions. It follows from the literature that households sharing the same caste facilitate the transmission of relevant agricultural information (Bandiera and Rasul, 2006; Burlig and Stevens, 2024) through homophilic networks.

Further, we find that spatial features, such as soil quality, length of growing period, topography, and climate, embedded in the agro-ecological regions to be a significant predictor of intense adoption of MI technologies. Lastly, we find that ownership of high number of electric pumps and the access to groundwater are important drivers for the intense adoption of MI technologies. In order to improve the diffusion of MI technology, we suggest considering these factors in policy decisions as they are consistently found to have significant relationships with the intensity of adoption decision.

These findings underscore the importance of a dual policy strategy that simultaneously expands MI adoption and scales up intensity among adopters. First, investments in rural infrastructure, particularly in electric pump availability, appear to yield the highest marginal gains in both adoption probability and intensity. This is further driven by the state level pumping policies that makes the marginal cost of extraction of groundwater zero or negligible. However, drip and sprinkler irrigated agriculture is less likely to create groundwater overdraft issues, provided that the rebound effect of these efficient technologies are not very high. Second, easing access to formal credit and insurance can help overcome liquidity and risk constraints, particularly for socially disadvantaged groups who already exhibit higher adoption responsiveness.

It is likely that there are other sources of heterogeneity affecting our estimates, which re-

main unobservable to us. For instance, information on the access to subsidies or the amount of subsidies received by households for the purchase of MI technologies is unavailable in our dataset. Further, we do not have information on the kind of crops grown by the farm households and the net returns from the disposal of crops in the market. We partially offset these limitations by including several control variables, such as the "agro-ecological region" variable to proxy the cropping patterns in our models.

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# A Appendix

Table A1. Falsification test: validating the exclusion restriction of the instrument used

| Variables | IHS_MI_intensity |
|---|---|
| Education (IHS) | −0.026 (0.036) |
| Household size (Adults_HH) | −0.114 (0.019)*** |
| OBC (1=yes) | 0.332 (0.135)** |
| SC (1=yes) | 0.373 (0.165)** |
| ST (1=yes) | 0.401 (0.222)* |
| Electric pumps (IHS) | −0.383 (0.108)*** |
| Access to credit (1=yes) | 0.008 (0.100) |
| Insurance (IHS) | 0.001 (0.014) |
| Agro-zone: Arid | −0.866 (0.623) |
| Agro-zone: Semi-Arid | −0.706 (0.490) |
| Agro-zone: Sub-Humid | −0.454 (0.492) |
| Agro-zone: Coastal | −1.031 (0.611)* |
| Asset-based wealth (IHS) | −0.182 (0.050)*** |
| Off-farm business (1=yes) | 0.234 (0.185) |
| SHG membership (1=yes) | −0.105 (0.118) |
| State electricity policy: Subsidy | 0.266 (0.206) |
| PMKSY median exposure (1=yes) | 0.094 (0.163) |
| Constant | 8.309 (0.874)*** |
| N | 864 |

Notes: Robust SEs clustered at district level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

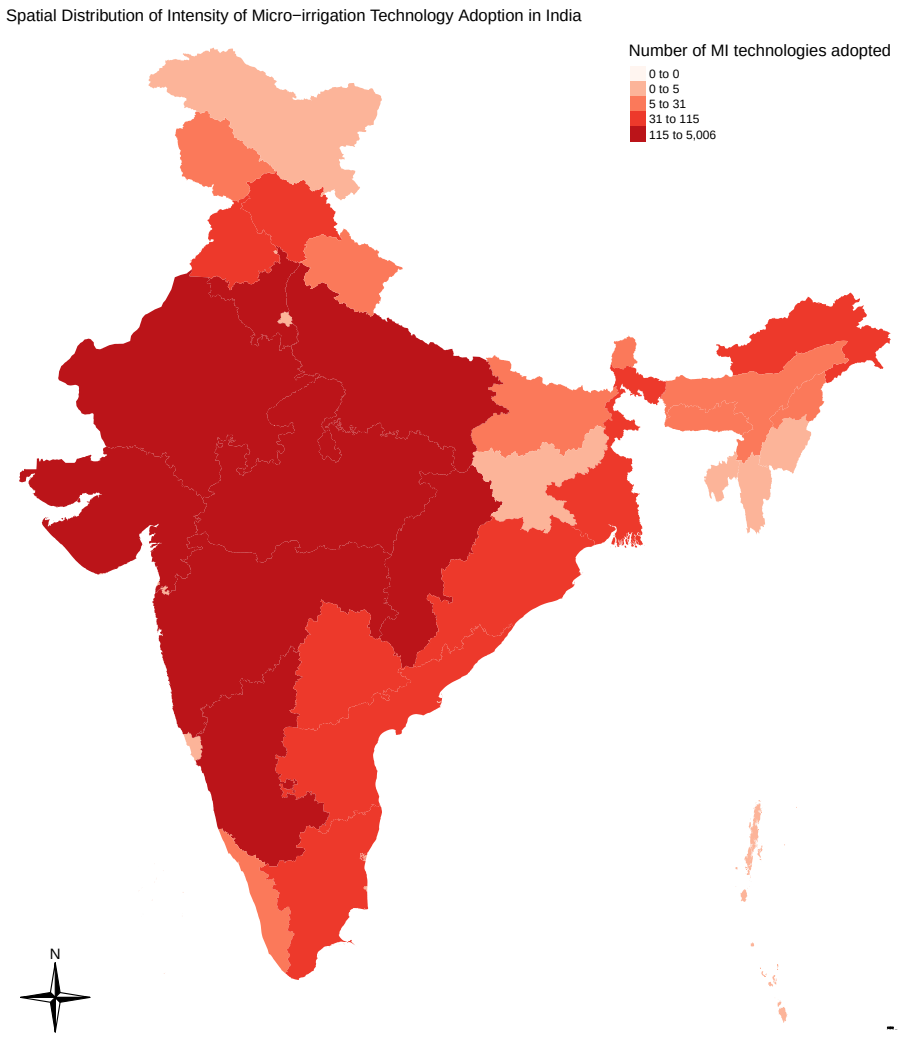



Figure A1. Choropleth map of MI technology adoption in India[12]

[12]Figure 2 shows the spatial distribution of the intensity of MI technology adoption in India. Rajasthan is found to have adopted the highest number of MI technologies, followed by Gujarat, Madhya Pradesh, Karnataka, and Maharashtra.