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IFPRI Discussion Paper 02324

January 2025

Stakeholder Disconnect

Differences between Farmers, Extension Workers, and Researchers on Preferred Strategies for Timely Wheat Sowing in Bihar, India

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Notices

Abstract

Late sowing of wheat is a persistent problem in South Asia despite widespread awareness that it lowers crop yields. We asked 2034 farmers, 33 researchers, and 114 frontline extension workers (EW) in Bihar, India to rank 6 commonly recommended solutions for their effectiveness. Respondents faced repeated rounds of best-worst choices to obtain a full ranking of the options. Responses were analyzed using random utility models. Farmers ranked timely and affordable irrigation as the most effective solution and zero-tillage (ZT) the least effective one; researchers ranked ZT the highest. The EW were somewhere in the middle. A better understanding of the reasons behind the differences in the assessments of researchers, extension personnel, and farmers about what will work the best will generate better solutions.

Keywords: Late-sowing, Bihar, best-worst scaling, wheat

Acknowledgments

We gratefully acknowledge the Bill & Melinda Gates Foundation (BMGF) for funding this research through the Cereal Systems Initiative for South Asia (CSISA). The authors would like to thank all the farmers who willingly participated in the primary survey and shared valuable information and insights with us.

1. Introduction

Late sowing of wheat is a widespread problem in the rice-wheat cropping systems (RWCS) in the eastern Indo-Gangetic Plains (covering eastern Uttar Pradesh, Bihar, and Nepal Terai) of South Asia (McDonald et al., 2022). It exposes wheat to heat stress, thereby shortening the grain filling period, and thus reducing the yield (Monasterio et al, 1994). Farmers in western Indo-Gangetic plains (covering North-West India and Pakistan Punjab) frequently resort to extreme steps like burning rice residues to save time to ensure that wheat is sown on time (Korav et al., 2022; Pathak et al., 2003; Kalra et al., 2008). In the eastern IGP, however, the problem persists even when every day's delay in sowing after 15th November is associated with a reduction in yield of 25 kg/hectare (McDonald et al., 2022).

It is possible to increase wheat production by nearly 70% with achievable adjustments to wheat sowing dates (McDonald et al, 2022). There are a few studies that identify the enabling factors to make these adjustments (Newport et al, 2020; Montes et al, 2022; Ishtiaque et al., 2022). However, the practicability or feasibility of these approaches at the local level is not as widely discussed. The standard transfer of technology (TOT) model is based on the research-extension-farmer linkage (Röling, 1982, 1988; Nagel, 1997). The knowledge asymmetries among various stakeholders involved in this linkage such as farmers, researchers, policymakers, etc. could hinder innovation and adoption of best farming practices (Long et al., 2016). On one hand, the inability of research to consider the issues prevailing at the local level might limit researchers' understanding of the choices available to the farmers (Meijer et al., 2015; Šūmane et al., 2018). On the other hand, farmers' decision-making process regarding technology adoption too might be governed by mental models significantly different from researchers (Scholl & Binder, 2010).

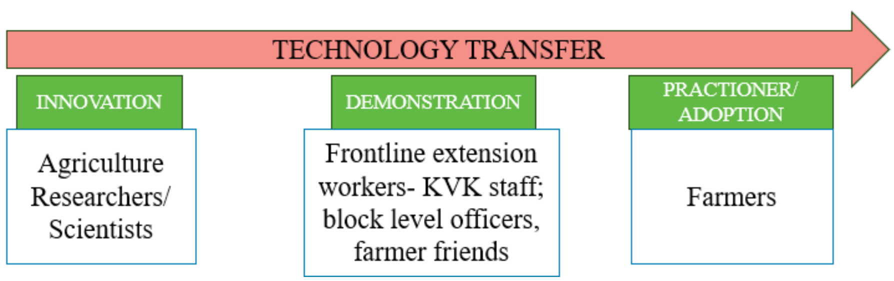
We reviewed literature on farming systems and consulted with researchers, policymakers, EW, and farmers to identify six strategies that can help farmers in Bihar sow wheat on time. The six strategies are: availability of cheaper irrigation, timely availability of labor, timely availability of tractor, timely weather forecast, availability of short duration paddy seeds, and sowing wheat by zero-tillage. We surveyed 2034 farmers, 33 agricultural researchers, and 114 and extension workers (EW) and asked them to rank the 6 strategies in order of their importance and effectiveness.

We conducted a best-worst scaling experiment (a variant of discrete choice experiments) to obtain relative rankings of the six strategies by different respondents. We find that farmers rank availability of cheap irrigation the highest and as adoption of ZT the lowest. Researchers rank ZT and short duration paddy the highest and irrigation the lowest. EW's rankings are different from both. They consider timely availability of labor and adoption of short duration paddy seeds the highest and timely weather forecasts the lowest.

Section 2 gives a background on the transfer technology model and BWS experiments. Section 3 describes the data used in the study. Section 4 gives a description of the methodology used for analysis. Section 5 gives the results and findings from the study. Section 6 provides a discussion of the findings. Section 7 finally concludes.

We follow the standard Transfer of Technology (TOT) model which highlights the link between research, extension, and farmers for diffusion of innovation (DOI). Ban and Hawkins (1988) have highlighted the importance of opinion leaders or progressive farmers in reaching the last mile farmers, given that extension agents are not able to work closely with all farmers in their region. Thus, the TOT model follows a trickle-down process with the following key parties involved (Koutsouris, 2018) (Figure 1):

Figure 1: Transfer of technology in agriculture



Source: (Koutsouris, 2018)

The first step involves innovation and development of technology by researchers, but before it gets adopted by the actual practitioners/farmers, a key role is played by extension workers and progressive farmers in demonstrating the new technology to the community, for them to make an informed decision. In India, there are two kinds of extension personnel: those with professional degrees in agriculture sciences such as researchers from Agricultural science centers (*Krishi Vigyan Kendras*) and, local extension workers who are often high school graduates with experience in farming but no formal training in it, such as farmer friends (*Krishi Salahakar*), block level officers, etc., who are in proximity of the farmers. For simplicity, we combine them into the category of frontline extension workers, or demonstrators of technology. However, a growing portfolio of evidence criticizes such a top-down approach for disregarding local contexts and constraints for technology (Sumberg, 2005; Whitfield et al., 2015). Farmer decision-making is dynamic and contextual, making technology transfer a non-linear process (Hermans et al., 2021) It can be based on perceptions and mental models which are different from experts (Scholl & Binder, 2010; Halbrendt et al., 2014; Rios-Gonzalez et al. 2013).

We explore these differences using data from the state of Bihar in India. Rice and wheat occupy about 61% and 42% of the net cropped area in the state and 90 percent of farmers in the state grow wheat after harvesting rice (NCAER xx). The state contributes roughly 6% of national level rice and wheat production (DA&FW, 2021-22).

We use best-worst scaling experiments (BWSE) to measure the perceptions towards a set of strategies for timely wheat sowing by obtaining relative rankings. Unlike traditional ranking exercise, it decomposes the problem of ranking all items together into a few repeated problems of ranking a subset of items at a time. This approach has been found to be cognitively easier for the respondent to rank (Wittenberg et al., 2016; Ratcliffe et al., 2020; Chrzan & Golovashkina, 2006) and improves the reliability of the findings (Chapman & Staelin, 1982; Lee et al., 2007). One obtains a full ranking of items by displaying each item with others on a rotating basis. Moreover, it is found to take less time than traditional ranking exercise (Lee, Soutar, and Louviere, 2008). The method was originally invented by (Finn & Louviere, 1992) to supersede the existing Likert scale methods. Likert scales require one to rate each object on a scale and then compare across objects ignoring the fact that people may use different interpretation of end points and 'cluster' responses at end points (Flynn & Marley, 2014).

BWS avoids this response bias since in each choice, there is only one best and only one worst outcome, distinct from each other. The respondent cannot choose the middle point, end point or one end of a scale. These repeated choice tasks help the respondents clearly discriminate between the items being assessed thereby providing more reliable data (Cohen, 2003; Cohen and Markowitz 2002). Moreover, BWS is found to be correlated with Likert rating at group level but outperforms it at the individual level analysis (Burton et al., 2019; Heo et al., 2022). The high precision and quality of results also improve their policy relevance (Beres et al., 2024).

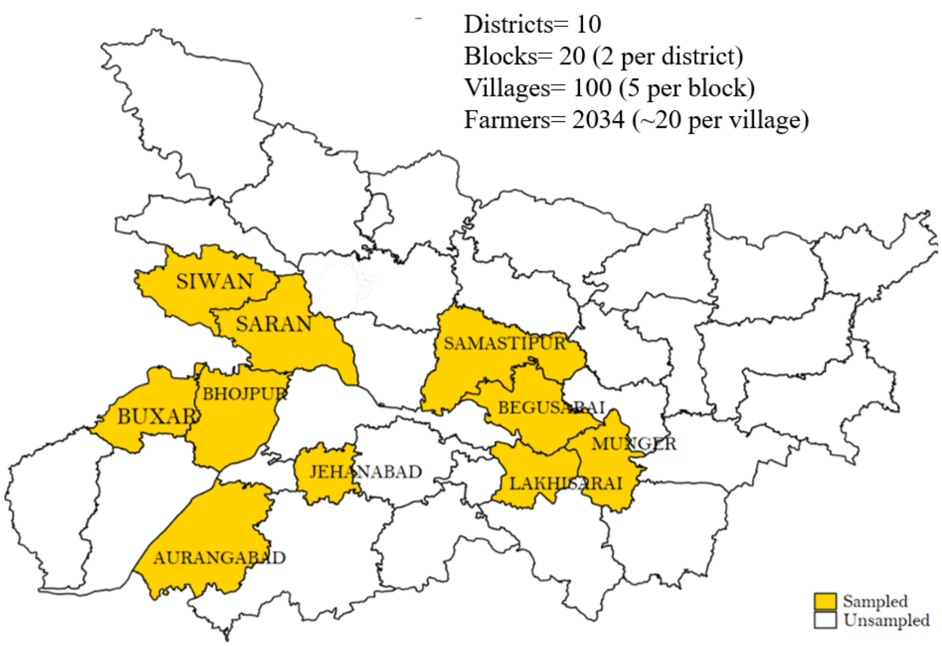
They are being increasingly used in agriculture to measure farmer's perceptions about sources of risk (Atta & Micheels, 2020), relative importance of agriculture innovations (Zakou, 2023), adoption preferences for sustainable agriculture practices (Nong et al., 2020) and even in farm policy assessments (Cooper et al, 2023; Villanueva & Glenk, 2021). However, there are limited applications of the method comparing researchers' and farmers' underlying preferences in agriculture except a few related to livestock: dairy farming (Valeeva et al., 2005) and sheep production systems (Jones et al., 2013).

2. Data

We selected 10 districts in Bihar (Figure 2) where delays in wheat sowing is common. Two blocks (a district sub-division containing clusters of villages) per district, and 5 villages per block were randomly selected using the 2011 Census. Within each village, 20 farmers were surveyed using a systematic random sampling approach: for each village, the total number of households was divided by 20 to arrive at an interval value of 'n', and thus, every 'n'th household in the village was surveyed.

Only farmers who had at least one plot of land on which they had cultivated both rice in Kharif 2021 (monsoon season) and wheat in rabi 2021-22 (winter season), who were the primary agricultural decision maker of the household and were at minimum 18 years of age were surveyed. We conducted computer assisted personal interviews (CAPI) and reached a sample of 2034 farmers (Figure 3).

Figure 2: Sampled districts for the study



Source: Authors

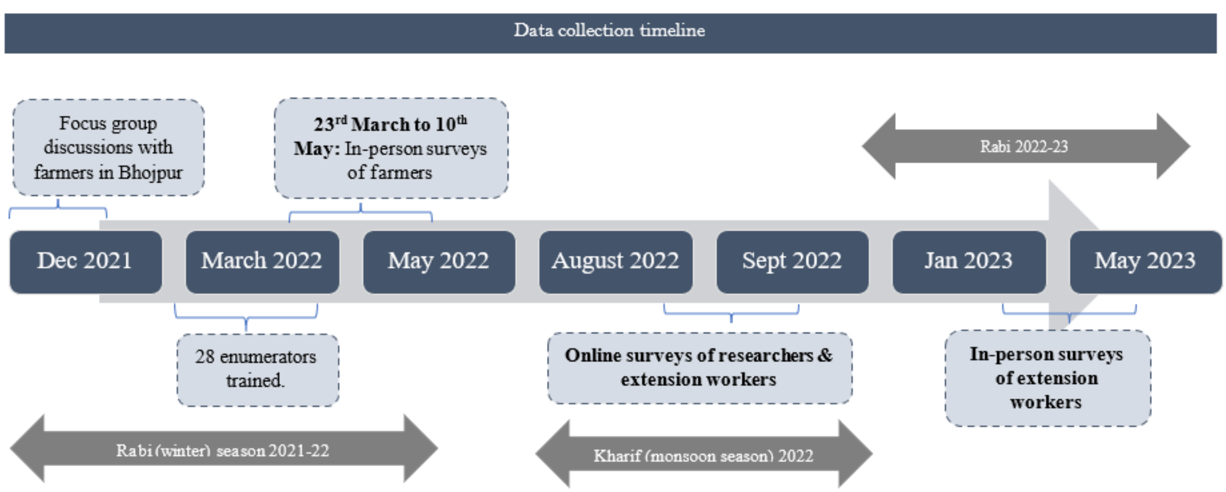
The farmer survey included questions related to their demographic characteristics, cropping pattern, inputs used, the timing of different agricultural operations for rice and wheat (making nursery, transplanting/sowing, harvesting), irrigation, and constraints faced in paddy and wheat transplanting/sowing and harvesting decisions. This was followed by a best-worst scaling experiment where they were asked to rank 6 key factors in their relative importance for sowing wheat on time (see the next section for details).

We utilized snowball sampling to survey researchers. This method involves current respondents identifying additional potential participants. Through this approach, we reached a total of 76 individuals from local and international research institutions. The respondents were invited to complete an online questionnaire from which we received 40 responses. Out of these, 33 were from researchers and the remaining 7 were from frontline extension workers.

We also surveyed 107 additional frontline extension workers in-person, such as district & block agriculture extension officer, farmer friends (*Krishi Salahakar*), ATMA technical officers and KVK (Krishi Vigyan Kendra) researchers in Bihar from the same 20 blocks where farmers were surveyed. These in-person respondents were reached with support from existing CSISA staff in Bihar.

The surveys of researchers and frontline extension workers covered questions on demographic profile, their experience in agriculture, own recommendations about optimal timings for key rice and wheat operations, and the best-worst scaling experiment (like the farmer survey). All surveys- farmers, researchers, extension workers- were conducted between March 2022 and May 2023.

Figure 3: Data collection timeline of the surveys



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3. Methodology

Identification of six strategies for timely wheat sowing

We reviewed scientific papers and interviewed leading rice-wheat cropping systems experts who work in eastern IGP to identify scalable strategies or options that can help farmers in Bihar sow wheat on time. We also conducted a series of focus group discussions (FGD) and key informant interviews with nearly 50 rice-wheat growing farmers in Bihar during Rabi 2021-22 and pre-tested a preliminary version of the BWS experiment during these interactions. The objective was to understand how farmers plan their cultivation of rice and wheat, challenges they face in performing agricultural operations on time, and understand different strategies that can help timely sowing of wheat in rice-wheat cropping systems. Poor access to affordable irrigation makes farmers heavily dependent upon rainfall and uneven supply of canal water, labor scarcity during paddy harvests, lack of timely availability of combined rice harvester and high wages of labor at peak demand. Some reported lack of new seed varieties in the village cooperative societies or block offices which forced them to purchase seeds from the retailers or the black market at higher prices while others reported no issues in accessing tractors or labor on time.

We used the information gleaned from the literature and personal interaction with researchers and farmers to identify six key strategies that can help farmers in Bihar sow wheat on time. Each strategy can be seen as a solution to a potential problem that limits farmer's ability to conduct timely wheat sowing: (See Appendix A1):

1) **Irrigation** becomes cheaper for rice and wheat,
2) Timely availability of **tractors** for preparing land for rice and wheat,
3) Timely availability of **laborers** for critical farm operations for rice and wheat,
4) Sowing wheat by **zero-tillage**,
5) Improved access to shorter duration paddy **seeds** and,
6) More reliable and timelier **weather** forecasts of coming season for rice and wheat.

All farmers in our sample irrigated their crops, used own or rented tractors and hired laborers for different farm operations. However, not everyone had used ZT or subscribed to weather forecast services. To mitigate any potential bias arising out of lack of information about a strategy, enumerators were required to give background information about it with visual materials.

Best worst scaling experiment

BWSE is a method to measure individuals' preferences. It is a variant of discrete choice experiment with 3 types: - Case 1 (object case), Case 2 (profile case), and Case 3 (multi-profile). In Case 1, several different subsets of items from a list of items are constructed using an experimental design. Each subset is shown to the respondent who then must select the most important (best) and least important (worst) *items* in the choice set. This question is repeated until all the subsets are evaluated. Case 2 constructs profiles containing combinations of attribute levels and asks one to select the best and worst *levels* in each profile. Case 3 constructs combinations of profiles themselves with varying attributes and asks one to select the best and worst *profiles* on each choice set. In simple terms, they are a variant of discrete choice experiments, except that along with the 'best' option, the respondent is also asked to select a 'worst' option. We employ the object case (Case 1) in this study.

We used a Balanced Incomplete Block Design (BIBD) to construct choice sets, which specifies the number of choice-sets (blocks or questions), number of items per choice set (size of the block), the number of times (frequency) each pair of items will appear within a question and the position of each item in the block. We constructed 10 choice sets, named A to J, each showing 3 items. The BWS module was a part of a longer interview schedule administered to farmers. To avoid survey fatigue, the set of 10 sets were blocked into 2 sets of 5, and each farmer answered only one set. Researchers and extension workers completed all 10 sets.

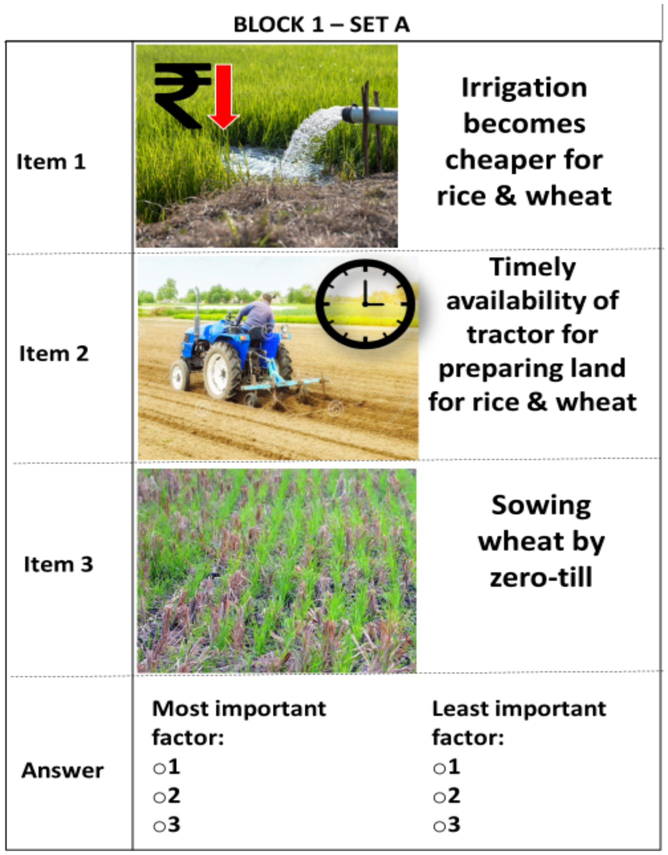
In each choice set, the respondent was asked the following question:

"As shown on this card, out of these three options, which one do you think is most important to sow wheat on time for YOU, namely, item 1., item 2., item 3.?

And which one of them do you think is the least important for YOU to sow wheat on time?"

It was highlighted that the two choices selected on each card must be distinct from each other (Figure 4).

Figure 4: A choice set used in the experiment



Source: Authors

The BWSE approach can only identify relative rankings of items: it does not identify the absolute value of an item. Thus, farmers may be asked which approach is better, and can rank 2 items in a relative sense, but they may still believe that neither is a useful approach in practice. It is possible to extend the BWSE approach by including 'anchor' questions that ask if an item meets some threshold criteria, independently, without any comparison with other items in the list (Lattery, 2011). By including the responses to the anchor questions in the analysis it is possible to place the relative ratings of items on an absolute scale, as defined by the criteria used for the anchor threshold.

There are two approaches to the anchor questions: asking questions after every choice set (called Indirect Dual Response Method) or asking a set of questions at the end of the experiment, one for each item (called the Direct method). We used the latter.

Best-worst score analysis

The basic approach for obtaining rankings of individual attributes in Case 1 BWS involves using a count method to construct a descriptive best-worst score for each strategy (Adamsen et al., 2013; Goodman et al., 2005; Ochieng & Hobbs, 2016). The BW score for a strategy and individual is defined as the best score for the strategy for that individual, B_{ji}, minus the worst score for the strategy for that individual, W_{ji}.

B_{ji} = number of times strategy j is voted as best by individual i

W_{ji}= number of times strategy j is voted as worst by individual i

BW_{ji}= B_{ji}- W_{ji}= Best-Worst score for strategy j and individual i.

A standardized best worst score is calculated by dividing BW_{ji} by *r,* the number of times each strategy appears across all 10 questions (See Appendix A2 for r values):

$$\text{Standardized }(BW_{ji})=\frac{\text{Bwji}}{r}$$

The mean value of these scores gives the sample mean and standard deviation of the score for each strategy. The strategies are thus ranked in descending order of the mean standardized BW score.

Parametric approaches

While non-parametric methods such as BW score can be helpful to examine the distributions, parametric approaches allow one to also control for the presence of heterogeneity. Therefore, we use a parametric approach for estimating rankings.

We employ the max-diff model of choice. We assume that each item has a value associated with it on a latent scale that identifies its importance. Given the 3 items presented in any choice set, it is assumed that the pair of items selected as 'best' and 'worst' are the pair that has the maximum difference in their values on the latent scale i.e. the selected pair is the most extreme of the 6 pairings possible from 3 items (given that ordering matters). The max-diff model can be estimated using a conditional logit model if it is assumed that all respondents have the same values for the items, and the unobserved individual specific error process follows a Gumbel distribution. For identification, the value of one item must be set to zero.

The probability that items i and i` are selected as best and worst from a set M is given by:

$$P_{ii'}=\frac{\exp(v(i)-v(i'))}{\sum_{\substack{j,j'\in M\\ j\neq j'}}\exp(v(j)-v(j'))}$$

Where v(i) represents the value of item i.

We estimate this model using a sequence of logit models. First, we estimate a conditional logit (CL) model, which assumes homogenous preferences for everyone in the sample. We then relax this assumption and estimate mixed logit/random parameter logit models (RPM), which assume that preferences are individual specific, and thus allow one to control for unobserved heterogeneity. This gives a distribution of parameters for each strategy. Moreover, for greater flexibility, precision, and to control for any presence of correlated unobserved effects among alternatives in a choice situation (Hensher, Rose, & Greene, 2005), we allow the parameters to be freely correlated with one another. We also estimate these models using the information from the anchor questions (imposing that the value of the anchor is zero) to identify not only the ranking of items but also whether they clear the threshold of being useful.

The coefficients of the model (conditional or RPM) should be interpreted as the ranking of a strategy relative to the omitted strategy. In the case of the model without the anchor, this will be one of the six strategies. In the case where the anchor is used, the value of the anchor is set to zero, and all six strategies are scored relative to it. We can also calculate the share of strategies in total preferences for everyone.

4. Results

Descriptive statistics

The average age of farmers in our sample was 45 years and 95% of the respondents were men (Table 1). Nearly one-fifth of the respondents had no formal education and 4 in 5 farmers could read and write. Most farmers were either small (18%) or marginal (66%).

Table 1: Summary statistics from farmer survey

Characteristics	Mean (SD) / proportion
Age (years)	44.5 (11.4)
Male (%)	94.8%
Education & literacy	
No formal education (%)	18.3%
Can read and write (%)	77.3%
Household caste	
General caste (%)	24.8%
Scheduled tribe (%)	3.8%
Scheduled caste (%)	12.2%
Other backward class (%)	59.1%
Land details	
Owns land in Rabi 2021-22 (%)	92%
Total land owned in Rabi (acres)	2 (2.1)
Rented land in Rabi 2021-22 (%)	49%
Total land rented in Rabi (acres)	1.7 (1.7)
Total land cultivated in Rabi (acres)	2.4 (2.4)
Total land under wheat in Rabi (acres)	1.6 (1.7)
Land class of farmers:	
Landless farmers (rental only) %	8.11%
Marginal farmers [<1 ha] (%)	65.88%
Small farmers [1-2 ha] (%)	17.75%
Semi-medium farmers [2-4 ha] (%)	6.05%
Medium farmers [4-10 ha] (%)	2.06%
Large farmers (%)	0.15%
Common paddy-wheat plot:	
Number Of common paddy-wheat plots	7 (6)
Average size of the common plot (hectares)	0.2 (0.16)
Number of observations	2,034

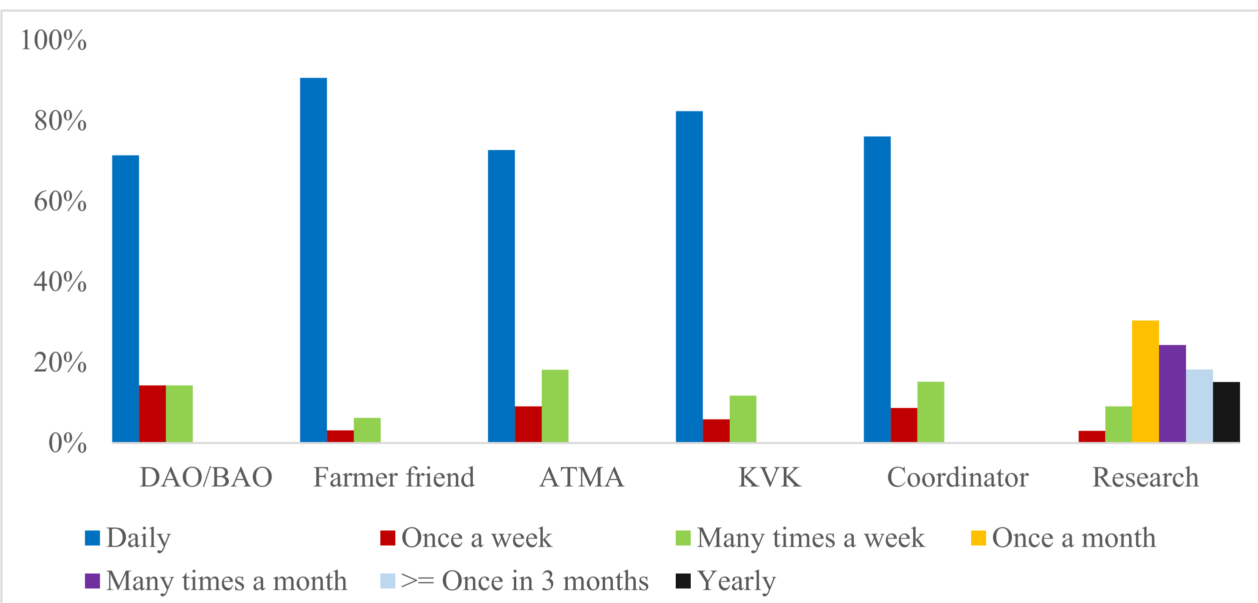
We surveyed 33 researchers and 114 extension workers. out of which 10 were females (Table 2). All but 11 (7.5%) had completed 15 or more years of education and expertise in areas such as agronomy (24%), agriculture extension (32%) or rural development (7%). More than 80 percent of them identified themselves as belonging to a farming family. This means that at least one member in their families owned and managed farmlands.

Table 2: Education and experience of researchers and extension workers

Characteristics	Mean (SD) / proportion	N
Designation:		
Agriculture coordinators	31.3%	46
Researchers	22.5%	33
Farmer friends (FF)	21.8%	32
KVK researchers	11.6%	17
ATMA technical officers	7.5%	11
District/block agriculture officers	4.8%	7
Other	0.7%	1
Working experience (years)	15.2 (7.7)	
Male	92.5%	136
Highest qualification:		
Class 12th	7.5%	11
Graduation (BSc or equivalent)	44.9%	66
Post-graduation	21.1%	31
PhD	26.5%	39
Belongs to a farming family	81.6%	120
Number of observations		147

We asked researchers and EW about the frequency of their interaction with farmers. Most of the EW interact with farmers daily or weekly; researchers interact with farmers less frequently (Figure 5).

Figure 5: Frequency of interaction of experts with the farmers



Source: Authors

Best worst score analysis

Table 3 shows the BW scores and rankings derived using the count method. Add a sentence of what this method does. We calculated Chronbach's alpha to check the internal consistency of BW scores. Cronbach's alpha is a coefficient that ranges from 0 to 1. A higher alpha value indicates greater internal consistency among the items in the scale, suggesting that the items are measuring the same underlying construct or concept reliably. For farmers, the alpha value ranges from 0.5 to 0.6 for each strategy, and for experts, it ranges from 0.5 to 0.9 for each strategy--an acceptable range (See Appendix A3).

Farmers ranked affordable irrigation as the most important and zero-tillage as the least important strategy for timely wheat sowing. Both researchers and extension workers (EW) rank short duration paddy seeds high—unlike farmers who do not rank it in top three of the six strategies. EWs rank irrigation, labor, and weather higher than researchers, but do not rank adoption of zero till, the strategy ranked highest by researchers, in top three. Timely availability of labor was ranked as the third most effective by all three groups. Thus, EW have assessments somewhat like the researchers for certain strategies, and those like farmers for others.

Table 3: Mean standardized Best-worst scores of the six strategies

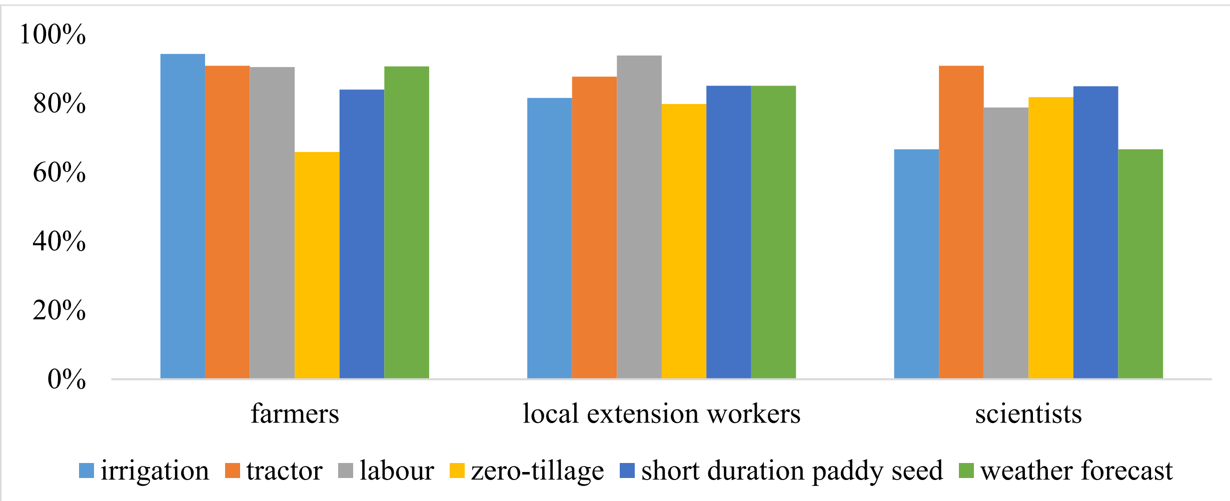
	Farmers		Extension workers		Researchers	
Strategy	Standardized BWS	Ranking	Standardized BWS	Ranking	Standardized BWS	Ranking
Irrigation	0.234 (0.557)	1	0.154 (0.622)	2	-0.055 (0.718)	5
Tractor	0.167 (0.520)	2	-0.277 (0.495)	6	0.000 (0.512)	4
Labor	-0.006 (0.596)	3	0.132 (0.551)	3	0.030 (0.548)	3
Weather	-0.054 (0.585)	4	-0.149 (0.575)	5	-0.388 (0.626)	6
Seed	-0.106 (0.547)	5	0.154 (0.512)	1	0.133 (0.547)	2
Zero-tillage	-0.223 (0.554)	6	-0.014 (0.518)	4	0.279 (0.661)	1

Standard deviation in parentheses

The distributions of the standardized BW scores for each strategy shows stark difference between rankings by farmers, researchers, and EW. The charts also show significant heterogeneity in rankings among farmers (See Appendix A5).

Responses to anchor question revealed that a large majority of respondents considered all 6 strategies to be relevant for timely wheat sowing (Figure 6). A lower share of farmers reported ZT as relevant (66%) as compared to other strategies (more than 80%) which could be the reason for its lowest rank. 80% or more of extension workers thought that all 6 strategies were relevant for the decision, while researchers had a mixed response. Tractor, zero-tillage, and short duration paddy seeds were considered relevant by more than 80% of the researchers.

Figure 6: Share of respondents who said a strategy is relevant for timely sowing of wheat



Source: Authors; Note: N=2034 for farmers, 114 for local extension workers and 33 for researchers.

Controlling for unobserved heterogeneity

We estimated a sequence of logistic regressions. The stability of estimates in each model was tested by varying the number of Halton draws from 100 to 500. The random parameters logit model with correlated coefficients, anchor adjustments and the largest number of Halton draws is the most preferred model for farmers and local extension workers, given in column 10. However, for researchers, the conditional logit model with anchor adjustment is the most preferred model, given in column 2, since the coefficients don't remain stable as we relax the constraints on coefficients and increase the number of Halton draws. This could probably be due to a small sample size of only 33 researchers. Henceforth, we will use results from the preferred models only to make comparisons between respondents (Table 4). Full logistic regression tables can be found in Appendix A5.

Table 4: Results from logistic regression models

Item	Farmers	Extension workers	Researchers
Irrigation	2.991***	2.735***	1.208***
	(0.0644)	(0.196)	(0.191)
Tractor	2.871***	1.805***	1.336***
	(0.0610)	(0.162)	(0.191)
Labor	2.609***	2.848***	1.344***
	(0.0608)	(0.195)	(0.191)
Seed	2.376***	2.825***	1.488***
	(0.0592)	(0.231)	(0.192)
Weather	2.470***	2.103***	0.777***
	(0.0574)	(0.235)	(0.191)
Zero-tillage	2.060***	2.392***	1.668***
	(0.0656)	(0.204)	(0.194)
Model type	RPL	RPL	CL
N	85428	8208	2376
Chi squared	1969.9		124.3
Log likelihood	-21581.0	-1962.2	-666.3
No. of iterations	11	17	3
No. of Halton draws	500	500	-

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; RPL= Random parameters logit model; CL= Conditional logit model

The omitted category in the regressions is the anchor, which is set equal to 0. So, the coefficient for each strategy in the regression reflects whether that strategy is preferred over 0 (the anchor?). In other words, a positive coefficient implies that the strategy is relevant overall in making the decision on when to sow wheat, whereas a negative coefficient means it is not. A comparison of coefficients for different strategies then informs about their relative preferences.

First, we see that the coefficients for all strategies for farmers, local extension workers, and researchers are statistically significant and lie above the anchor indicating that all 6 items are relevant for the respondents. The regression output for farmers and researchers confirms the original rankings obtained through BW scores and all coefficients. There are some changes in the rankings obtained for extension workers compared with BW scores, with labor, seed and irrigation as the 1st, 2nd and 3rd rank respectively.

5. Discussion

Delays in critical farm operations in the predominant RWCS in the eastern IGP are a major reason for lower system yields and higher vulnerability to weather shocks like droughts, dry-spells, and heat waves. Researchers from CGIAR and the national research systems (NRS) have been trying to identify the reasons for this problem, generate awareness, and find scalable solutions to this problem for nearly 30 years—since the launch of the Rice-Wheat Consortium (RWC) for the Indo-Gangetic Plains in 1994 (Seth, Fisher, Anderson, and Jha, 2003).

Three decades of research and extension have led to widespread awareness among farmers and policymakers that timely sowing of wheat is essential to increase wheat productivity in eastern IGP. Our data shows that while 80% of farmers were late in sowing wheat (Table 1); nearly half (51.3%) of them said that it was ideal to sow wheat by 15th November. Likewise, while half of the sample transplanted paddy late and about 83% were late in harvesting it, 84% perceived that it was ideal to transplant paddy by the 3rd week of July and harvest it by the 2nd week of November. Moreover, 77% of researchers and extension workers said that farmers indeed knew about ideal time windows for different farming operations. This suggests that farmers do realize the importance of timely operations but face constraints that prevent them from doing so.

Researchers have proposed various strategies or solutions that can help farmers adjust the crop calendar. We tested the perceived importance of 6 such strategies using the best-worst scaling experiment. The anchor responses to the 6 strategies show that about two-thirds of farmers and researchers and 80% of extension workers think the proposed strategies are relevant measures to achieve timely wheat sowing. However, BWS rankings and multinomial logit regressions show that their views on what will work best varies considerably. Researchers rank adoption of zero-tillage of wheat as the most effective solution to the problem, followed by use of short-duration varieties of seeds for the preceding paddy crop. Farmers rank ZT as the least effective of the solutions. The assessment of extension workers, who act as a bridge between the researchers and the farmers, is different from both farmers and researchers. Extension workers rank labor the highest, followed by seeds. Unlike farmers, they do not rank better access to tractors quite highly and unlike researchers, they do not rank adoption of zero tillage in top three of the 6 options.

There may be several reasons behind these key differences in the assessments of the effectiveness of the potential solutions among the three groups. First, it is possible that accumulated scientific knowledge about the benefits and functioning of ZT is not well communicated or effectively implemented in the study area. In our sample, technology use was found to be low. About 94% of farmers had sown wheat by direct sowing with tillage. Only 9% reported that they had either done zero-tillage this season (N=32) or done it before but stopped doing it (N=154). Likewise, 91% of farmers had harvested paddy manually, with only 9% using combine harvesters. Moreover, among others, the uptake of widely discussed solutions such as adoption of DSR was also low (4%).

Second, farmers' assessment is based on what makes sense to them in the particular circumstances of their farm, family, and community (Higgins et al., 2017). Extension workers who interact with them frequently, understand the context better than the researchers, and therefore, it's not a surprise that their views are closer to the farmers'. Influencing farmers' behavior requires researchers and policymakers to understand farmers' rationality and to gain better insight into how they see the situation and the various options it offers to them. For example, ZT users who discontinued its use cited unavailability of machines (50%), prolonged wetness in the fields making machine use unfit (20%), and paddy residue getting stuck in ZT machinery (17%) as key reasons for doing so. These experiences must feed into the scaling strategies with more. Open and frequent dialogues and more participatory research and extension can reduce the social distance between farmers, EW, and the researchers and help with reconciling agricultural research with practice.

This discrepancy is important to address, especially for a state like Bihar where investing in research and extension systems could be a potential solution to enhance the cropping system's sustainability (Pandey et al., 2019). There are nearly a dozen state and national level schemes that earmark funds for technology demonstrations and promotion, yet the state is lacking in strengthening a bottom-up planning process and generating more demand-driven extension and advisory programs (USAID, 2013). The extension system must incorporate local knowledge to create a more holistic researcher-extension-farmer linkage approach towards technology diffusion.

6. Conclusion

There is a lack of concrete case studies where the differences in perceptions between farmers, extension workers, and researchers are analyzed using rigorous quantitative methods. Our research tries to fill this gap. The persistence of the late sowing of wheat despite widespread awareness of its downsides and its potential solutions is a puzzle. Understanding the similarities and the considerable differences in the perceptions or assessments of the effectiveness of the different solutions is an important piece of the puzzle. Aligning farmers' assessments and scientific knowledge can enhance the quality and relevance of research and policy initiatives.

While the paper seeks to find common ground and differences between farmers, extension workers, and researchers, it does not "validate" one over the other. Furthermore, all farmers do not think alike. There are also differences among farmers. This paper does not analyze heterogeneity in farmers' rankings of the effectiveness of different approaches to enable timely sowing of wheat. Analysis to understand factors associated with differences among farmers will be undertaken in a different paper.

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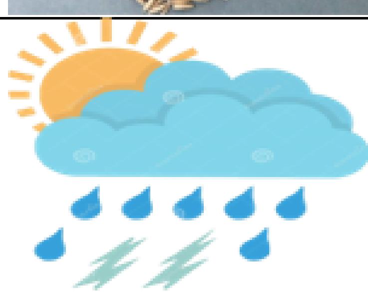
Appendix

A1: Strategies used in the experiment.

	**1. Irrigation becomes cheaper for rice and wheat:** If this happens, then you will pay less than what you are paying right now to irrigate your paddy and/or wheat crop.
	**2. Timely availability of tractors for preparing land for rice and wheat**
	**3. Timely availability of laborers for critical farm operations for rice and wheat**
	4. **Sowing wheat by zero-till:** Zero-tillage is a technique of sowing wheat in which, you sow wheat without any land preparation unlike conventional sowing techniques. Here, a zero-tillage machine sows the seed and fertilizer in proportion simultaneously in the soil.
	**5. Improved access to shorter duration paddy seeds:** (That is, the variety that takes less duration to mature as compared to the variety that you are currently using)
	**6. More reliable and timelier weather forecasts of coming season for rice and wheat**

Source: Authors

A2. R value for standardizing BW scores:

Table A2: r value

Respondent	Block	Strategy number	r value
Farmers	1	1,2,6	3
Farmers	1	3,4,5	2
Farmers	2	1,2,6	2
Farmers	2	3,4,5	3
Experts	1 & 2	1,2,3,4,5,6	5

A3. Chronbach's alpha test for internal reliability of BW scores

Table A3.1: Chronbach's alpha for farmer survey

	Farmer		Local Extension workers	Researchers
Strategy	Block 1	Block 2		
Irrigation	0.619	0.512	0.764	0.858
Tractor	0.551	0.478	0.706	0.615
Labor	0.629	0.565	0.619	0.518
Zero-tillage	0.554	0.637	0.621	0.812
Short duration paddy seed	0.555	0.541	0.641	0.657
Weather forecast	0.630	0.559	0.708	0.820

A4. Regression results

Table A4.1: Logit models farmer

	(1) LogitNo Anc	(2) LogitAnc	(3) RPMNo AncUnco r100	(4) RPMNo AncUnco r500	(5) RPMAnc Uncor10 0	(6) RPMAnc Uncor50 0	(7) RPMNo AncCor1 00	(8) RPMNo AncCor5 00	(9) RPMAnc Cor100	(10) RPMAnc Cor500
main										
irrigation	0.546***	2.127***	0.652***	0.654***	2.384***	2.416***	0.730***	0.728***	2.933***	2.991***
	(0.0231)	(0.0302)	(0.0307)	(0.0309)	(0.0376)	(0.0388)	(0.0333)	(0.0334)	(0.0619)	(0.0644)
tractor	0.502***	2.068***	0.571***	0.572***	2.264***	2.295***	0.633***	0.632***	2.808***	2.871***
	(0.0229)	(0.0301)	(0.0277)	(0.0279)	(0.0341)	(0.0353)	(0.0316)	(0.0317)	(0.0583)	(0.0610)
labor	0.271***	1.846***	0.308***	0.308***	2.021***	2.038***	0.364***	0.367***	2.559***	2.609***
	(0.0227)	(0.0297)	(0.0307)	(0.0307)	(0.0357)	(0.0364)	(0.0367)	(0.0371)	(0.0586)	(0.0608)
seed	0.134***	1.684***	0.0737**	0.0732**	1.808***	1.823***	0.184***	0.185***	2.331***	2.376***
	(0.0227)	(0.0296)	(0.0315)	(0.0315)	(0.0339)	(0.0346)	(0.0285)	(0.0288)	(0.0570)	(0.0592)
weather	0.200***	1.776***	0.271***	0.272***	1.909***	1.927***	0.238***	0.240***	2.422***	2.470***
	(0.0226)	(0.0297)	(0.0325)	(0.0326)	(0.0349)	(0.0357)	(0.0325)	(0.0327)	(0.0553)	(0.0574)
zerotill		1.469***			1.477***	1.487***			2.021***	2.060***
		(0.0295)			(0.0374)	(0.0382)			(0.0637)	(0.0656)
SD										
irrigation			0.582***	0.585***	0.661***	0.699***	0.771***	0.76***	1.722***	1.764***
			(0.0411)	(0.0412)	(0.0386)	(0.0390)	(0.05)	(0.052)	(0.064)	(0.066)
tractor			0.330***	0.339***	0.329***	0.410***	0.741***	0.735***	1.511***	1.566***
			(0.0505)	(0.0499)	(0.0528)	(0.0454)	(0.045)	(0.049)	(0.06)	(0.062)
labor			0.674***	0.677***	0.649***	0.678***	1.121***	1.131***	1.557***	1.602***
			(0.0399)	(0.0402)	(0.0382)	(0.0380)	(0.047)	(0.049)	(0.061)	(0.062)

	(1) LogitNoAnc	(2) LogitAnc	(3) RPMNoAncUncor100	(4) RPMNoAncUncor500	(5) RPMAncUncor100	(6) RPMAncUncor500	(7) RPMNoAncCor100	(8) RPMNoAncCor500	(9) RPMAncCor100	(10) RPMAncCor500
seed			-0.557***	0.557***	0.535***	0.572***	0.536***	0.56***	1.472***	1.526***
			(0.0503)	(0.0509)	(0.0391)	(0.0379)	(0.049)	(0.052)	(0.06)	(0.061)
weather			0.598***	0.596***	0.610***	0.655***	0.861***	0.864***	1.3***	1.339***
			(0.0444)	(0.0453)	(0.0365)	(0.0367)	(0.047)	(0.05)	(0.062)	(0.062)
zerotill					0.918***	0.962***			1.968***	2.004***
					(0.0384)	(0.0394)			(0.064)	(0.066)
l11										
_cons							0.771***	0.760***	1.722***	1.764***
							(0.0498)	(0.0517)	(0.0636)	(0.0656)
l21										
_cons							0.471***	0.475***	1.411***	1.444***
							(0.0536)	(0.0578)	(0.0642)	(0.0654)
l31										
_cons							0.660***	0.696***	1.336***	1.355***
							(0.0629)	(0.0664)	(0.0668)	(0.0682)
l41										
_cons							0.0377	0.0549	1.231***	1.265***
							(0.0568)	(0.0611)	(0.0660)	(0.0676)
l51										
_cons							0.126**	0.132*	0.994***	1.011***
							(0.0645)	(0.0705)	(0.0687)	(0.0695)
l22										
_cons							0.572***	0.560***	0.542***	0.607***
							(0.0408)	(0.0426)	(0.0496)	(0.0453)
l32										
_cons							0.734***	0.758***	0.646***	0.596***

	(1) LogitNoAnc	(2) LogitAnc	(3) RPMNoAncUncor100	(4) RPMNoAncUncor500	(5) RPMAncUncor100	(6) RPMAncUncor500	(7) RPMNoAncCor100	(8) RPMNoAncCor500	(9) RPMAncCor100	(10) RPMAncCor500
							(0.0569)	(0.0610)	(0.0618)	(0.0573)
l42										
_cons							0.332***	0.356***	0.447***	0.431***
							(0.0603)	(0.0607)	(0.0621)	(0.0648)
l52										
_cons							0.441***	0.452***	0.469***	0.399***
							(0.0623)	(0.0643)	(0.0690)	(0.0611)
l33										
_cons							0.532***	0.470***	-0.472***	-0.613***
							(0.0684)	(0.0839)	(0.0696)	(0.0512)
l43										
_cons							0.230***	0.241***	0.0520	-0.0465
							(0.0722)	(0.0838)	(0.0864)	(0.0651)
l53										
_cons							0.321***	0.354***	0.0252	-0.122*
							(0.0793)	(0.0937)	(0.109)	(0.0635)
l44										
_cons							-0.350***	0.355***	0.669***	0.735***
							(0.0648)	(0.0745)	(0.0472)	(0.0395)
l54										
_cons							0.0157	-0.0842	0.148**	0.213***
							(0.103)	(0.146)	(0.0648)	(0.0495)
l55										
_cons							0.655***	0.626***	0.677***	0.743***
							(0.0515)	(0.0755)	(0.0422)	(0.0373)
l61										
_cons									1.732***	1.747***
									(0.0722)	(0.0730)
l62										

	(1) LogitNoAnc	(2) LogitAnc	(3) RPMNoAncUncor100	(4) RPMNoAncUncor500	(5) RPMAncUncor100	(6) RPMAncUncor500	(7) RPMNoAncCor100	(8) RPMNoAncCor500	(9) RPMAncCor100	(10) RPMAncCor500
_cons									0.362^{***}	0.288^{***}
									(0.0806)	(0.0752)
l63										
_cons									0.516^{***}	0.296^{***}
									(0.0980)	(0.0731)
l64										
_cons									0.576^{***}	0.647^{***}
									(0.0811)	(0.0586)
l65										
_cons									0.324^{***}	0.339^{***}
									(0.0703)	(0.0538)
l66										
_cons									0.203	0.508^{***}
									(0.186)	(0.0697)
N	61020	85428	54942	54942	85428	85428	61020	61020	85428	85428
Chi squared	882.4	8230.8	351.0	345.3	843.3	900.2	709.7	700.4	1918.4	1969.9
Log likelihood	-17781.0	-22566.0	-15786.8	-15789.6	-22144.3	-22115.9	-17426.2	-17430.8	-21606.8	-21581.0
No. of iterations	3	4	6	5	6	7	9	9	20	11
No. of Halton draws			100	500	100	500	100	500	100	500

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4.2: Logit model local extention worker

	(1) LogitNoAnc	(2) LogitAnc	(3) RPMNoAncUncor100	(4) RPMNoAncUncor500	(5) RPMAncUncor100	(6) RPMAncUncor500	(7) RPMNoAncCor100	(8) RPMNoAncCor500	(9) RPMAncCor100	(10) RPMAncCor500
main										
irrigation	0.217***	1.975***	0.429*	0.558**	2.377***	2.663***	0.623***	0.348	2.724***	2.735***
	(0.0674)	(0.118)	(0.238)	(0.225)	(0.185)	(0.211)	(0.183)	(0.229)	(0.183)	(0.196)
tractor	-0.344***	1.450***	-0.567***	-0.590***	1.613***	1.661***	-0.759***	-0.676***	1.606***	1.805***
	(0.0684)	(0.117)	(0.127)	(0.147)	(0.143)	(0.153)	(0.161)	(0.184)	(0.138)	(0.162)
labor	0.187***	1.977***	0.172	0.387**	2.434***	2.608***	0.388**	0.365**	2.684***	2.848***
	(0.0673)	(0.118)	(0.157)	(0.184)	(0.165)	(0.184)	(0.162)	(0.175)	(0.173)	(0.195)
seed	0.216***	1.984***	0.280**	0.335**	2.289***	2.591***	0.356***	0.338**	2.550***	2.825***
	(0.0674)	(0.118)	(0.116)	(0.130)	(0.156)	(0.181)	(0.135)	(0.155)	(0.174)	(0.231)
weather	-0.174***	1.606***	-0.326**	-0.363**	1.824***	1.937***	-0.632***	-0.388**	1.969***	2.103***
	(0.0674)	(0.117)	(0.143)	(0.165)	(0.161)	(0.181)	(0.204)	(0.187)	(0.178)	(0.235)
zerotill		1.761***			2.217***	2.178***			2.083***	2.392***
		(0.117)			(0.162)	(0.169)			(0.164)	(0.204)
SD										
irrigation			1.616***	1.960***	1.357***	1.536***	2.313***	2.321***	1.456***	1.496***
			(0.174)	(0.219)	(0.126)	(0.182)	(0.208)	(0.241)	(0.205)	(0.212)
tractor			1.081***	1.152***	0.806***	0.855***	1.278***	1.565***	0.526***	0.793***
			(0.137)	(0.142)	(0.120)	(0.129)	(0.141)	(0.185)	(0.162)	(0.149)
labor			1.224***	1.502***	1.134***	1.173***	1.797***	1.934***	1.155***	1.159***
			(0.131)	(0.175)	(0.133)	(0.146)	(0.17)	(0.194)	(0.148)	(0.14)

	(1) LogitNoAnc	(2) LogitAnc	(3) RPMNoAncUncor100	(4) RPMNoAncUncor500	(5) RPMAncUncor100	(6) RPMAncUncor500	(7) RPMNoAncCor100	(8) RPMNoAncCor500	(9) RPMAncCor100	(10) RPMAncCor500
seed			0.831***	0.941***	0.946***	1.105***	1.206***	1.383***	1.485***	1.774***
			(0.123)	(0.131)	(0.123)	(0.133)	(0.136)	(0.188)	(0.139)	(0.172)
weather			1.221***	1.557***	1.286***	1.462***	1.997***	1.836***	1.608***	1.822***
			(0.153)	(0.185)	(0.147)	(0.175)	(0.245)	(0.22)	(0.15)	(0.161)
zerotill					0.931***	1.106***			1.365***	1.502***
					(0.130)	(0.152)			(0.125)	(0.148)
l11										
_cons							2.313***	2.321***	-1.456***	-1.496***
							(0.208)	(0.241)	(0.205)	(0.212)
l21										
_cons							0.633***	0.762***	0.500***	0.285
							(0.183)	(0.224)	(0.167)	(0.196)
l31										
_cons							1.333***	1.329***	-0.376**	-0.362
							(0.183)	(0.197)	(0.185)	(0.223)
l41										
_cons							0.363**	0.506***	-0.0595	-0.509*
							(0.158)	(0.178)	(0.203)	(0.274)
l51										
_cons							0.406*	0.547**	-0.0155	-0.206
							(0.208)	(0.225)	(0.206)	(0.240)
l22										
_cons							1.111***	1.368***	0.163	0.739***
							(0.116)	(0.154)	(0.134)	(0.167)
l32										
_cons							0.266**	0.306*	-1.078***	-0.103
							(0.115)	(0.168)	(0.143)	(0.195)

	(1) LogitNoAnc	(2) LogitAnc	(3) RPMNoAncUncor100	(4) RPMNoAncUncor500	(5) RPMAncUncor100	(6) RPMAncUncor500	(7) RPMNoAncCor100	(8) RPMNoAncCor500	(9) RPMAncCor100	(10) RPMAncCor500
l42										
_cons							0.389***	0.475***	-0.290*	1.182***
							(0.137)	(0.171)	(0.162)	(0.193)
l52										
_cons							0.819***	0.649***	0.0266	0.905***
							(0.147)	(0.206)	(0.180)	(0.218)
l33										
_cons							-1.177***	1.371***	-0.173	-1.096***
							(0.123)	(0.153)	(0.157)	(0.121)
l43										
_cons							-0.256*	0.0866	0.790***	-0.617***
							(0.139)	(0.235)	(0.159)	(0.156)
l53										
_cons							-0.0951	-0.179	0.491***	-0.416**
							(0.138)	(0.211)	(0.187)	(0.163)
l44										
_cons							1.051***	1.193***	1.222***	1.053***
							(0.117)	(0.152)	(0.132)	(0.150)
l54										
_cons							0.834***	0.140	0.460***	0.343**
							(0.152)	(0.156)	(0.129)	(0.174)
l55										
_cons							1.565***	1.612***	1.459***	1.473***
							(0.218)	(0.205)	(0.166)	(0.154)
l61										
_cons									0.205	-0.0280
									(0.186)	(0.234)
l62										
_cons									-0.0669	0.226

	(1) LogitNoAnc	(2) LogitAnc	(3) RPMNoAncUncor100	(4) RPMNoAncUncor500	(5) RPMAncUncor100	(6) RPMAncUncor500	(7) RPMNoAncCor100	(8) RPMNoAncCor500	(9) RPMAncCor100	(10) RPMAncCor500
									(0.207)	(0.199)
l63										
_cons									-0.368**	-0.411***
									(0.156)	(0.130)
l64										
_cons									1.268***	1.333***
									(0.134)	(0.160)
l65										
_cons									0.267*	0.471***
									(0.149)	(0.141)
l66										
_cons									0.00497	0.187
									(0.139)	(0.221)
N	6840	8208	6840	6840	8208	8208	6840	6840	8208	8208
Log likelihood	-1983.1	-2267.7	-1758.1	-1733.0	-2026.4	-2002.0	-1706.7	-1698.8	-1972.2	-1962.2
No. of iterations	3	4	5	6	5	5	12	11	12	17
No. of Halton draws			100	500	100	500	100	500	100	500

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4.3: Logit model researchers

	(1) LogitNoAnc	(2) LogitAnc	(3) RPMNoAncUncor100	(4) RPMNoAncUncor500	(5) RPMAncUncor100	(6) RPMAncUncor500	(7) RPMNoAncCor100	(8) RPMNoAncCor500	(9) RPMAncCor100	(10) RPMAncCor500
main										
irrigation	-0.439***	1.208***	-0.798**	-0.967***	1.046***	2.301***	-0.807**	-0.227	2.674***	2.083***
	(0.128)	(0.191)	(0.324)	(0.372)	(0.354)	(0.455)	(0.353)	(0.411)	(0.364)	(0.481)
tractor	-0.368***	1.336***	-0.397*	-1.387***	2.078***	2.168***	-1.793***	-2.033***	2.681***	3.015***
	(0.128)	(0.191)	(0.238)	(0.368)	(0.281)	(0.353)	(0.355)	(0.555)	(0.355)	(0.421)
labor	-0.329**	1.344***	-0.743***	-1.680***	2.324***	2.926***	-1.551***	-1.252**	2.405***	3.004***
	(0.128)	(0.191)	(0.272)	(0.407)	(0.335)	(0.454)	(0.378)	(0.567)	(0.342)	(0.432)
seed	-0.195	1.488***	-0.212	0.171	2.512***	3.167***	-1.439***	-0.966	2.678***	3.162***
	(0.128)	(0.192)	(0.256)	(0.345)	(0.308)	(0.452)	(0.314)	(0.627)	(0.422)	(0.441)
weather	-0.892***	0.777***	-2.983***	-3.038***	1.245***	0.920**	-3.886***	-3.954***	1.966***	0.881**
	(0.135)	(0.191)	(0.428)	(0.588)	(0.328)	(0.468)	(0.510)	(0.736)	(0.346)	(0.395)
zerotill		1.668***			3.578***	3.978***			4.835***	3.731***
		(0.194)			(0.404)	(0.542)			(0.482)	(0.514)
SD										
irrigation			2.867***	4.689***	3.182***	3.813***	5.955***	5.342***	3.811***	4.377***
			(0.342)	(0.675)	(0.438)	(0.633)	(0.796)	(0.667)	(0.488)	(0.589)
tractor			-1.195***	2.442***	1.131***	1.586***	3.945***	3.776***	2.479***	2.33***
			(0.205)	(0.365)	(0.237)	(0.279)	(0.546)	(0.543)	(0.317)	(0.35)
labor			2.421***	3.298***	2.215***	2.341***	4.981***	5.389***	2.458***	2.769***
			(0.333)	(0.568)	(0.422)	(0.426)	(0.688)	(0.634)	(0.359)	(0.41)

	(1) LogitNoAnc	(2) LogitAnc	(3) RPMNoAncUncor100	(4) RPMNoAncUncor500	(5) RPMAncUncor100	(6) RPMAncUncor500	(7) RPMNoAncCor100	(8) RPMNoAncCor500	(9) RPMAncCor100	(10) RPMAncCor500
seed			2.003***	2.150***	1.466***	1.724***	4.446***	4.309***	2.314***	4.352***
			(0.285)	(0.358)	(0.262)	(0.312)	(0.564)	(0.53)	(0.316)	(0.89)
weather			3.436***	3.551***	2.858***	2.516***	4.863***	5.387***	2.775***	3.813***
			(0.576)	(0.626)	(0.442)	(0.382)	(0.666)	(0.888)	(0.361)	(0.603)
zerotill					-3.150***	3.331***			4.96***	5.014***
					(0.356)	(0.520)			(0.509)	(0.695)
l11										
_cons							5.955***	5.342***	3.811***	4.377***
							(0.796)	(0.667)	(0.488)	(0.589)
l21										
_cons							2.023***	2.459***	1.110***	0.658*
							(0.404)	(0.461)	(0.363)	(0.399)
l31										
_cons							3.632***	3.363***	1.565***	1.753***
							(0.557)	(0.489)	(0.372)	(0.403)
l41										
_cons							2.269***	1.104**	0.594	-0.142
							(0.425)	(0.443)	(0.466)	(0.435)
l51										
_cons							0.128	0.538	-0.0683	0.432
							(0.393)	(0.410)	(0.375)	(0.362)
l22										
_cons							3.387***	2.866***	2.217***	2.235***
							(0.495)	(0.509)	(0.276)	(0.355)
l32										
_cons							2.895***	3.301***	1.390***	0.949***
							(0.535)	(0.517)	(0.250)	(0.297)

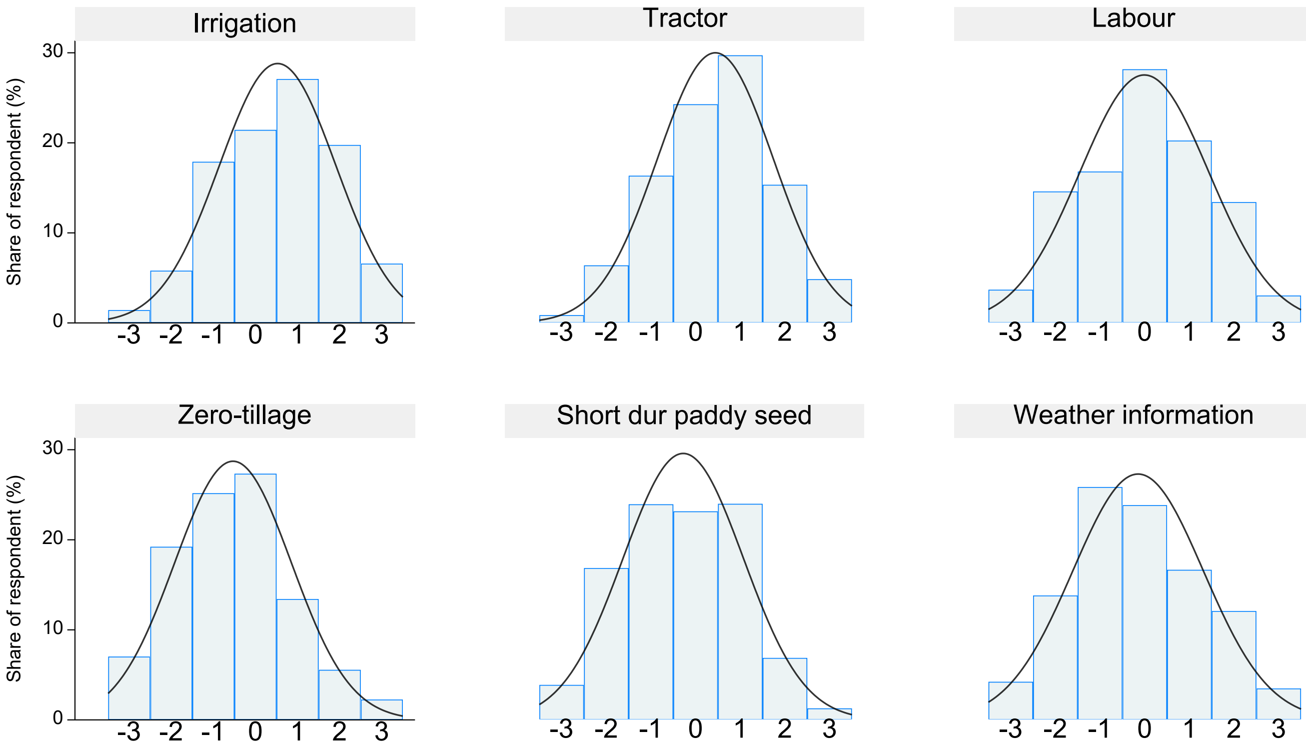
	(1) LogitNoAnc	(2) LogitAnc	(3) RPMNoAncUncor100	(4) RPMNoAncUncor500	(5) RPMAncUncor100	(6) RPMAncUncor500	(7) RPMNoAncCor100	(8) RPMNoAncCor500	(9) RPMAncCor100	(10) RPMAncCor500
l42										
_cons							1.287***	2.579***	0.366	1.780***
							(0.303)	(0.465)	(0.230)	(0.372)
l52										
_cons							2.802***	-0.394	-0.349	-0.183
							(0.426)	(0.570)	(0.240)	(0.349)
l33										
_cons							1.798***	-2.615***	-1.288***	-1.921***
							(0.375)	(0.473)	(0.298)	(0.325)
l43										
_cons							1.895***	-0.0385	1.086***	-0.825**
							(0.293)	(0.501)	(0.336)	(0.350)
l53										
_cons							-2.286***	1.841***	2.276***	2.112***
							(0.554)	(0.607)	(0.323)	(0.393)
l44										
_cons							3.062***	3.270***	1.921***	3.882***
							(0.449)	(0.476)	(0.243)	(0.825)
l54										
_cons							2.006***	2.499***	0.238	1.503**
							(0.380)	(0.485)	(0.218)	(0.587)
l55										
_cons							2.556***	4.352***	1.529***	2.757***
							(0.360)	(0.705)	(0.251)	(0.489)
l61										
_cons									2.172***	1.644***
									(0.431)	(0.465)
l62										
_cons									1.735***	1.032***

	(1) LogitNoAnc	(2) LogitAnc	(3) RPMNoAncUncor100	(4) RPMNoAncUncor500	(5) RPMAncUncor100	(6) RPMAncUncor500	(7) RPMNoAncCor100	(8) RPMNoAncCor500	(9) RPMAncCor100	(10) RPMAncCor500
									(0.312)	(0.314)
l63										
_cons									2.816^{***}	0.552^{*}
									(0.348)	(0.332)
l64										
_cons									1.126^{***}	2.168^{***}
									(0.247)	(0.734)
l65										
_cons									0.955^{***}	2.398^{***}
									(0.290)	(0.448)
l66										
_cons									2.600^{***}	3.257^{***}
									(0.358)	(0.418)
N	1980	2376	1980	1980	2376	2376	1980	1980	2376	2376
Chi squared	53.25	124.3	242.9	272.0	348.8	365.4	364.2	344.4	397.3	411.4
Log likelihood	-564.7	-666.3	-443.2	-428.6	-491.9	-483.6	-382.6	-392.5	-467.7	-460.6
No. of iterations	3	3	12	9	12	8	15	22	14	19
No. of Halton draws			100	500	100	500	100	500	100	500

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

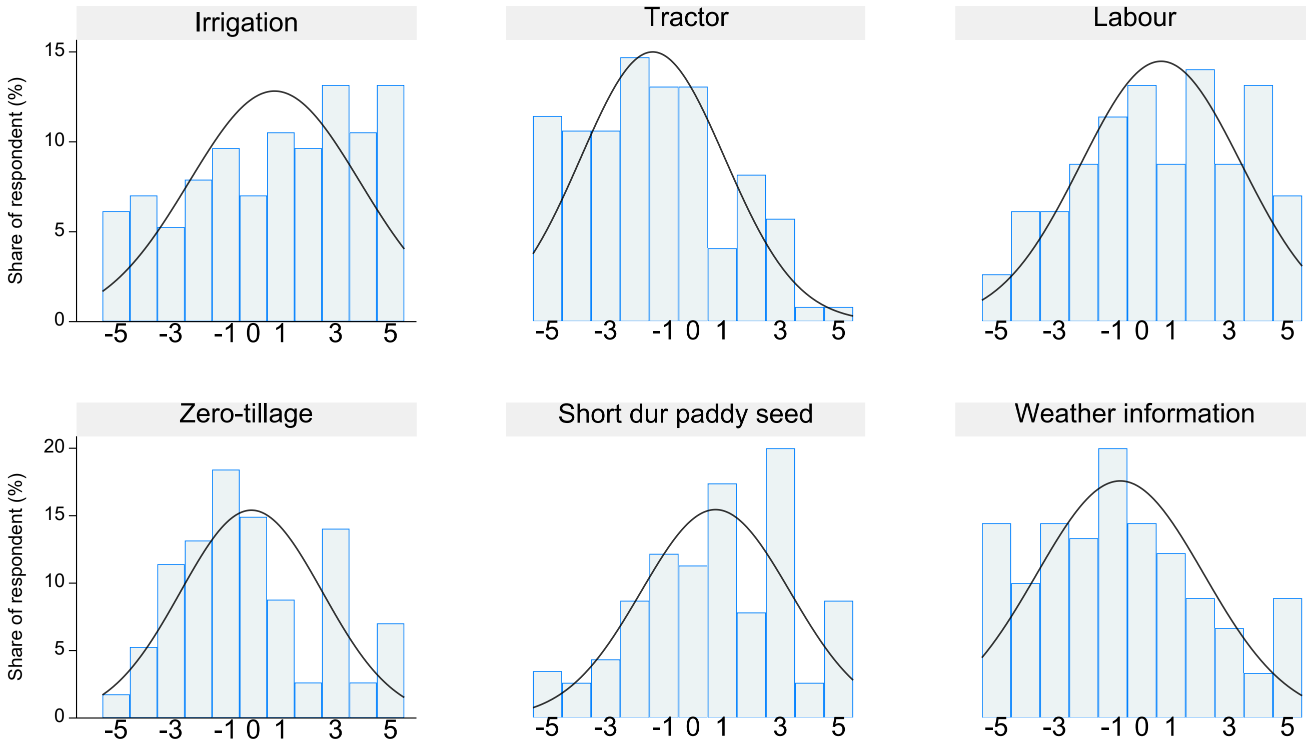
A5. Distribution of BW scores

Figure A5.1: Bar plots of BW scores for farmers



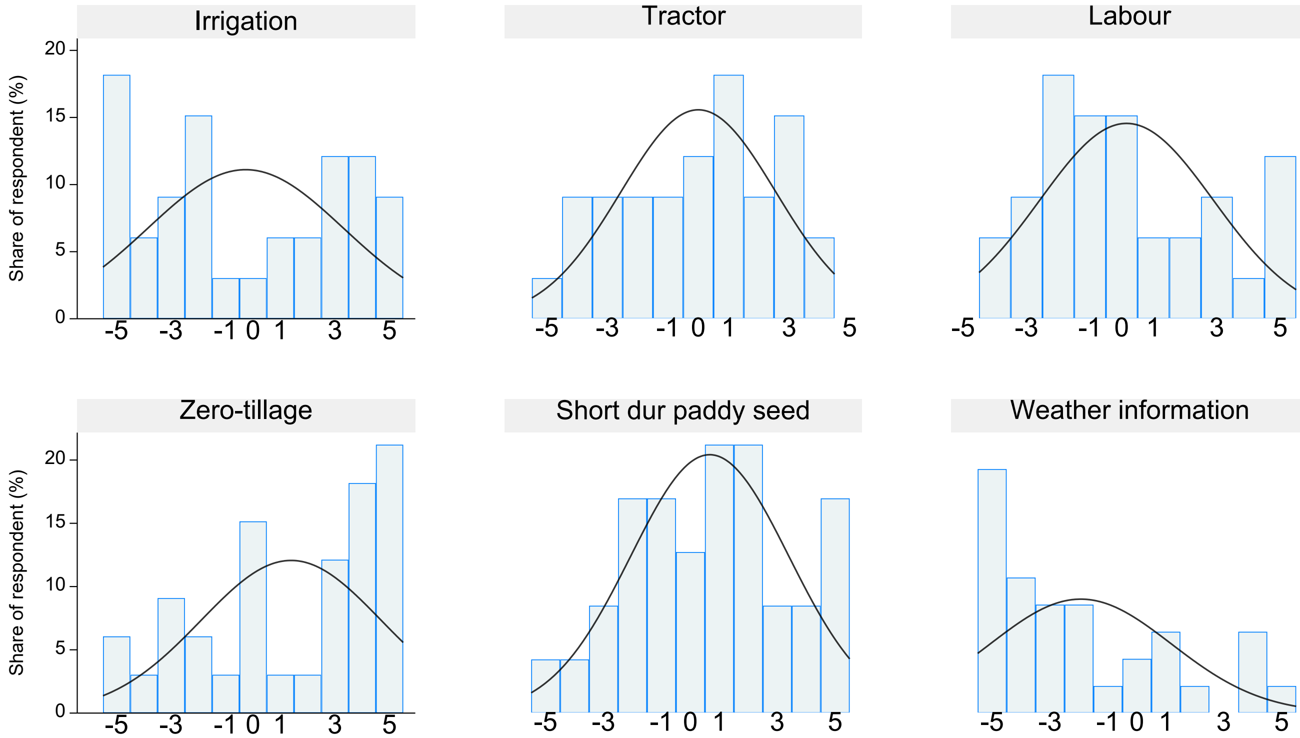
Source: Authors

Figure A5.2: Bar plots of BW scores for local extension workers



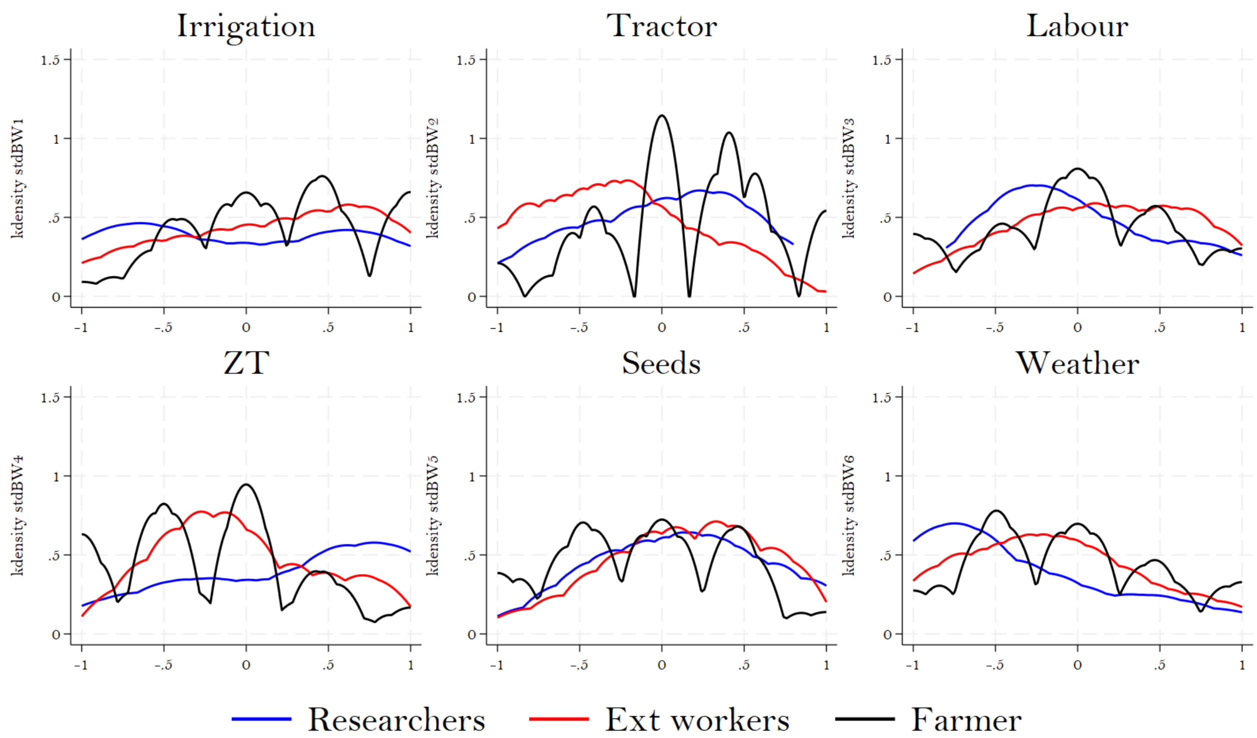
Source: Authors

Figure A5.3: Bar plots of BW scores for researchers



Source: Authors

Figure A5.4: Kernel density curves of standardized BW scores of respondents



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