Examining the Transfer of Knowledge and Training to Smallholders in India: Direct and Spillover Effects of Agricultural Advisory Services in an Emerging Economy

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Abstract

To accelerate the adoption of improved crop technologies among smallholders in India, the government of India created Farm Science Centers (known as *Krishi Vigyan Kendra* [KVK]). KVKs are responsible for conducting frontline demonstrations (FLDs) and capacity-building training programs for local farmers. The objective of this study is to examine the direct benefits captured by *primary* beneficiaries (defined as farmers whose fields are used to implement the FLD program) and spillover benefits—captured by *secondary* and *network* beneficiaries—of KVK initiatives as they relate to the adoption of new technology. We define *secondary* beneficiaries as farmers who visit FLD sites out of curiosity and a desire to learn, and *network* beneficiaries as farmers who obtain knowledge and information through social networks. The study uses a matched difference-in-difference (MDID) approach, along with a survey of 1,496 wheat farmers in Uttar Pradesh, India. Findings show that 3% of *primary* beneficiaries generate the knowledge and information spillover captured by about 31% and 27% of *secondary* and *network* recipients, respectively. Our analysis of spillover benefits suggests that the *network* beneficiary is a crucial channel for knowledge and information transmission. Further, the study establishes a positive impact of KVKs for *primary*, *secondary*, and *network* beneficiaries. Consistent with the knowledge and information transmission channels, the magnitude of adoption impact is highest for the *primary* beneficiaries, followed by *secondary* and *network* beneficiaries. From a policy perspective, the study offers new insights for strengthening outreach and extension services designed to facilitate the transfer of agricultural knowledge and information, with an emphasis on FLDs, training programs, and social networks in extending the scope of KVKs.

Keywords: Diffusion, Frontline demonstrations, Knowledge, Social Network, Technology

1. Introduction

Frontier technologies and their adoption are vital to increasing agricultural productivity and the income of farmers.[1] Agricultural advisory services are the most important knowledge- and information-dissemination institutions for accelerating the adoption of modern technologies and improving farmers' learning abilities. These technologies have direct implications for the larger goal of enriching agricultural development and farmers' welfare (Garforth, 1982; Feder et al.,, 1985; Duflo et al., 2011; Asfaw et al., 2012). At the same time, due to a lack of economic resources, providing agricultural advisory services to the broader farmer community is challenging.[2] Strengthening outreach activities and information-transmission channels as they relate to technological knowledge through spillover flows is vital for farmers in developing and emerging economies (DEEs). To this end, several channels can exhibit information transmission through spillovers. These include the idea of proximity, social networks, and local agricultural markets. The idea of proximity to the source of information about technology may serve as a critical channel for attracting other farmers prone to curiosity (Munshi, 2004). Social networks consisting of friends, relatives, and neighbors play a significant role in the dissemination of new technology (Bandiera & Rasul, 2006; Conley & Udry, 2010; Munshi, 2004). Finally, local agricultural markets may also produce local spillovers on new technology. Farmers' access to new technology—that is not yet available in the local market—through scientific intervention might drive input dealers to

[1] Griliches (1957); Feder et al. (1985); Mendola (2007); Shiferaw et al. (2014); among others.

[2] Lipton (1977) finds that 60% to 80% of the population in developing countries depends on agriculture for their livelihood; however, the allocation of funds for developing the agriculture sector is less than 20%.

add the technology to their basket. In DEEs, where input dealers serve as a source of information, any expansion of their basket of technological offerings might encourage the adoption of new technology (Varshney, 2019). Since input dealers are interested in large scale buyers, gaining access to information on new technology could be costly for smallholders.

To reduce the expense burden of smallholders seeking new technologies, the Indian government created an innovative model of agricultural advisory services, known as *Krishi Vigyan Kendra* (KVK) or the Farm Science Centers, designed and implemented by the Indian Council of Agricultural Research (ICAR). KVKs provide a complete package of demand-driven advisory services to farmers—including assistance in identifying suitable new technologies, conducting frontline demonstrations (FLDs), and organizing capacity building programs.[3] FLDs of frontier technologies are carefully conducted under the direct supervision of scientists, who get regular feedback from smallholders allowing them to refine technologies for specific local environments. This practice is analogous to on-site training in the context of the labor market. The program advises smallholders and large farmers by highlighting the advantages of new technology over traditional technologies in a learning-by-doing framework. In turn, FLDs could help mitigate production and financial risks (Foster & Rosenzweig, 1995). Neoclassical growth theory highlights the role of the learning-by-doing framework in explaining the formation of human capital and longer-term income gains (Arrow, 1971). Additionally, to spread awareness of technologies, KVKs conduct capacity-building training programs (CBPs). These programs are conducted as on-farm trials in villages without FLDs. Presumably, farmers who receive FLDs or participate in CB training programs are more likely to switch to modern approaches of cultivation.

[3] For more details, see Section 2.

A novel feature of KVKs is that FLDs and CBPs can have direct and spillover effects on smallholders. Beneficiaries of FLDs and CBPs could be classified into three categories. First, the *primary* beneficiary—the smallholder receiving benefits directly from KVKs. Farmers who lend their fields to KVKs for FLDs receive a direct benefit from the activities undertaken in the FLD, and benefit from direct interaction with KVK scientists. Second, the *secondary* beneficiary—the curious smallholder who visits the FLD site to gain knowledge and learns from the *primary* beneficiary. Third, the *network* beneficiary—the smallholder receiving benefits from *primary* and *secondary* beneficiaries as a result of being in their social networks. One can conclude that the latter two groups receive spillover benefits.

Studies on spillover benefits are focused mainly on explaining the inter-regional diffusion of a particular technology (Abdulai & Huffman, 2005). These studies are primarily concerned with factors that impact the speed of adoption of agricultural technologies (Alcon et al., 2011). However, studies investigating the channels of spillover benefits of agricultural advisory services, such as FLDs and CBPs, in a smaller geographic area (say, a village) are nonexistent.[4] An emerging literature on social networks largely focuses on the impact of social networks on the adoption of agricultural technologies, but does not address the extent to which social networks can diffuse these technologies. Exploring the channels of diffusion within a smaller geographic area expands this stream of literature and provides new insights that policymakers can use to develop more effective public programs.

[4] Bandiera and Rasul (2006); Conley and Udry (2010); Munshi (2004).

While there is a large body of research that measures the spillover effects of research and development, studies that examine spillover of knowledge and information flows are scarce.[5]

Herein lies the twofold objective of this study. First, we aim to examine the extent of direct (to *primary* beneficiaries) and spillover (to *secondary* and *network* beneficiaries) benefits of KVKs. Identifying *network* beneficiaries provides an innovative mechanism for capturing the extent of spillover of information flows and brings novelty to this study. Second, we aim to evaluate the impact of KVK interventions on the adoption of improved wheat technology for the *primary*, *secondary*, and *network* beneficiaries.[6] This analysis is warranted for several reasons: first, to expand the regional literature that documents the impact of KVKs by employing approaches that are associative in nature, rather than identification-based approaches; second, to test whether the spillover of knowledge and information flows leads to changes in the outcome indicators (for example, adoption of new technology); and finally, to assess whether the direct and spillover effects vary across different sets of beneficiaries. The study uses survey data from 1,496 wheat farmers in Uttar Pradesh. The survey uses a non-universal coverage of KVK and recall-based panel data for 2014–2015, 2015–2016, 2016–2017, and 2017–2018 on the adoption of a modern wheat variety, namely *HD-2967*. Additionally, the study uses a matched difference-in-difference (MDID) approach to examine the effect of FLDs and CBPs on wheat farmers. Due to data limitations, we only assess spillover effects that are generated through the idea of proximity

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5 See, for example, Evenson (1989) and Griliches (1991), and McCunn and Huffman (2000).

6 For training, we only define *primary* and *network* beneficiaries. See the section on empirical strategy for more detail.

and social networks. The study considers the utility of FLDs and capacity-building programs for estimating direct and spillover benefits.

This paper contributes to the literature in several ways. First, it is one of few studies to study spillover benefits associated with any public-sector agricultural advisory services. Second, the study identifies the knowledge information transmission channels (such as social networks) and quantifies the spillover effects associated with these channels, thus contributing to the emerging literature on social networks. Third, the study provides an innovative approach to capturing spillover effects of knowledge and information flows generated by social networks in the farming community. Finally, the study contributes to the regional literature assessing the impact of KVKs on the adoption of improved technologies by employing robust econometric approaches.

The rest of the paper is organized as follows: Section 2 discusses the role of KVKs in India. Section 3 explores the study area and sampling design and provides summary statistics. Section 4 formulates the empirical strategy and Section 5 discusses the results. The last section concludes the study and offers policy implications.

2. Farm Science Centers in India

The Farm Science Center (known as KVK) was launched by the ICAR in 1974 in Pondicherry district of India, to provide institutional support to the agriculture and allied sectors in assessing location-specific technologies through assessment, refinement, and demonstration trials. The KVK model links the national agriculture research system with an extension system and smallholders. The KVKs are wholly financed by ICAR and serve state agricultural universities, ICAR institutes, government departments, and nongovernment organizations (NGOs) working in the agriculture sector. KVKs are unique in that they rely on scientists to deliver agricultural advisory services. In terms of reach, KVKs operate in every district of the country.[7] Figure 1 presents the state-wise distribution of the 703 KVKs in India.[8] The five states with the most KVKs are Uttar Pradesh (83), Madhya Pradesh (52), Maharashtra (47), Rajasthan (44), and Bihar (39).[9]

The government of India mandates that KVKs provide a number of distinct services, including: conducting "On-Farm Testing" (OFT) for the assessment of agricultural technologies across different farming systems; carrying out FLDs to demonstrate the implementation of frontier technologies; working to increase the capacities of farmers and extension workers by creating awareness of frontier technologies; serving as a knowledge and resource center for the agricultural economy within the district; and finally, advising farmers on various subjects related to production agriculture. Amidst changing technology and agricultural scenarios, the activities of KVKs have been extended to include technology diffusion and women's empowerment and increasing awareness of government agricultural schemes. Moreover, KVKs are involved in producing technological products such as seed, planting material, bio-agents, and irrigation systems.

The total budget of KVKs in India is about Rs 6.9 billion for the year 2016-17. For context, this is equivalent to Rs 34 per hectare, a relatively miniscule investment in the frontline extension system.[10] In a recent study, Gulati et al. (2018) showed that India spends about 0.70% of agriculture GDP on agricultural research, education, extension, and training. Of that 0.70%, about 0.54% is spent on agricultural research and education, while a meagre 0.16% is allocated to extension and training programs.

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[7] In bigger districts, there are multiple KVKs. For example, Gorakhpur district of Uttar Pradesh has two KVKs.

[8] Total number of districts in India is 725.

[9] Other states have KVKs roughly equivalent to the number of districts in the state.

[10] In India, the average revenue farmers earn from one hectare of land is between Rs 50,000 to 60,000 on the cereal cultivation.

3. Data

The survey was conducted in the state of Uttar Pradesh (UP), a northern state of India. UP is the most populous state and home to more than 200 million people, accounting for 17% of the country's population. The geographical area of UP is about 24.1 million hectares, accounting for 7% of the area of India. About 16.5 million hectares (68%) is under crop cultivation. The gross cropped area in UP is about 25.9 million hectares. More than 70% of the state's population depends on the agriculture and allied sectors for livelihood. Marginal holdings account for about 79% of total land holdings, followed by 13%, 6%, 2%, and 0.1% for small, semi-medium, medium, and large holdings, respectively. UP has a humid climate, with temperatures varying from 0 degrees Celsius to 50 degrees Celsius. Average rainfall varies from 650 millimeters (mm) in the southwest corner to 1,000 mm in the eastern and southeastern parts of the state. Tubewells (71%) and canals (18%) are the main sources of irrigation. In UP, soil textures vary widely from loam soil, sandy loam, sand soil, alluvial soil, rocky soil, and clay loam. UP is divided into nine agro-ecological zones (AEZs). These include the *bhabhar* and *tarai* regions, western plains, midwestern plains, southwestern semi-arid, central plains, Bundelkhand, northeastern plains, eastern plains, and the *Vindhyan* region. Table 1 presents the major crops grown in the state's AEZs; specifically, wheat (41%), paddy (24%), sugarcane (9%), pearl millet (4%), and maize (3%). The present study focuses on wheat crop.

The primary survey was collected from farmers in three AEZs of UP, namely, southwestern semi-arid, central plains, and eastern plains. The survey was conducted in 12 districts of Uttar Pradesh. Four districts were selected from each AEZ. To select villages, we classified them into KVK villages and non-KVK villages. We define KVK villages as those where any type of intervention, such as FLDs or CBPs, have been conducted by KVK staff. Non-KVK villages are those where staff have not conducted any type of intervention. The list of villages was prepared by the intersection of KVK activity type, such as FLD, and the selected crops of the region. From this list, the selection of villages was made on a random basis. In selecting farming households, a complete household listing was compiled for each selected village. Thereafter, four quintiles, based on the total cultivable land, were formed. From each quintile, five farming households were selected randomly.

The household questionnaire (or module) collected information on farmers' awareness of KVKs and the benefits (in terms of FLDs, OFT, training, and others) they received regarding frontier agriculture technologies. The module also included information on wheat varieties and recall-based information on adoption and dis-adoption patterns of seed varieties since 2014–2015, thus enabling us to construct a panel of data from 2014–2015 to 2017–2018 on the adoption of wheat varieties. The farmers were queried on production, sales, and cultivation costs, and asked to provide detailed information on household and demographic characteristics for the reference year 2017–2018. Other household-level information was also collected through the household module. A novel feature of the household survey is that it collected information on farmer's relationships (friend, neighbor, relative) with the other 19 surveyed farmers in the same village. This approach provided a complete social map of each surveyed farmer. To gain insights on agricultural information exchange, the survey asked whether farmers discussed agricultural matters with each other and whether they accepted advice from others, including advice concerning the adoption of new wheat varieties.[11] The information collected forms our basis for capturing the spillovers of knowledge and information flows among farmers through social networks, and for the identification of *network* beneficiaries of KVKs.[12]

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[11] Whether farmer discussed new seed varieties or any new agricultural technology.

[12] See more detail in Section 4.

Table 2 shows that the average household head (HH) is about 46 years old. Bultena and Hoiberg (1983) suggested that younger farmers are more likely to adopt new technologies earlier because they have longer planning horizons. Mueller and Jansen (1988) used age as a proxy for farmers' experience, finding that farmer age is positively associated with the adoption of new technologies. Our sample suggests that 95% of the surveyed households were headed by men. Accounting for this variable captures the systematic difference (if any) in the adoption of technology by gender. In terms of education, the average HH has 5 years of schooling. Feder et al. (1985) highlighted the role of education and argued that the adoption of improved technology increases with educational attainment. Average household size was about five members. Regarding religion, the survey reveals that 98% of farmers were Hindu. By social grouping, the survey shows that 46% of farmers belonged to the Schedule Caste (SC)/Scheduled Tribes category.

In terms of access to public-sector interventions in India, the SC/ST households are considered to be disadvantaged. About 23% of farmers possess a below-poverty-line (BPL) card.[13] Average landholding is about 0.77 hectares. Akinola (1987) suggested a positive correlation between landholding size and the likelihood of adopting improved technology. The survey revealed that 78% of the HHs reported farming as their primary occupation. The average value of asset index was about 0.02 on a scale of -2.7 to 9.3.[14] Feder et al. (1985) argued that wealthier farmers are more equipped to take the risks associated with adopting new technology. The survey

[13] In India, the BPL card is issued to those households identified as poor by the government. A set of indicators forms the basis for the government to classify poorer households and provide BPL cards.

[14] Asset index is constructed by applying principal component analysis using the ownership of 22 assets (e.g., tractor, two-wheeler, four-wheeler, etc.).

revealed that the average HH has 18 years of farming experience. In terms of access to institutional credit, only 44% of households had a Kisan Credit Card (KCC).[15] Varshney et al. (2019b) showed that KCC is an important driver for the adoption of improved technologies. The survey revealed that 15% of households had a soil health card.[16] A soil health card provides an analysis of a farmer's land and offers recommendations for nutrient management. Accounting for this variable helps us understand farmers' scientific approaches to agriculture. In terms of access to crop insurance, 14% of farmers had access to *Pradhan Mantri Fasal Bima Yojana* (PMFBY). Crop insurance can serve as a risk-sharing mechanism for farmers adopting new technology. Presumably, farmers with crop insurance are more likely to adopt new and improved technology. We also present plot characteristics such as soil color, irrigation, and soil fertility, all of which play an important role in the adoption of technology. For instance, improved irrigation conditions are expected to influence the adoption of new technology that requires greater irrigation.

Table 2 also compares the profile of wheat farmers across KVK and non-KVK villages. Results show that farmers in the KVK villages are generally younger (by 2.7 years), have a higher educational attainment (0.52 years), are 5% more likely to engage in farming for livelihood, have less farm experience (three years), and are 7% more likely to have a soil health card. Further, farmers across KVK and non-KVK villages had varying soil color, soil fertility, and irrigation conditions. Figure 2 shows the adoption patterns of wheat cultivars for 2015–2016 and 2017–2018. In 2015–2016, 34% of farmers adopted *PBW-343* (a wheat variety released in 1996). *PBW-502*

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15 The Kisan Credit Card was introduced by the government of India to provide short-term credit to farmers during the planting and harvesting seasons.

16 The soil health card scheme, launched in 2015, issues a card that provides farmers with crop-wise recommendations for nutrients and fertilizers based on a soil analysis.

(released in 2004) was adopted by 24% of farmers and *HD-2967* (released in 2011) was adopted by 26% of farmers. In contrast, 17% of farmers adopted other cultivars.[17] In 2017–2018, *PBW-343*, *PBW-502*, and *HD-2967* were adopted by 32%, 8%, and 47% of farmers, respectively, while 14% adopted other cultivars. The above findings suggest varietal substitution away from *PBW-502* and toward *HD-2967.*

To gain further insights, Table 3 compares the yield, revenue, operational costs, and profits associated with *HD-2967*, *PBW-502,* and *PBW-343*. Panel A shows that adopters of *HD-2967* had about 2.1 quintals per hectare more yield (6% higher) than farmers using the *PBW-502* wheat variety. Additionally, adopters of *HD-2967* earned 7.7% higher revenue than farmers using the *PBW-502* wheat variety. Panel A also shows that farmers using *HD-2967* had lower operational costs (4%) than those using the *PBW-502* wheat variety, but the difference was statistically insignificant. Overall, adoption of *HD-2967* resulted in higher profits (about Rs of 4,449 per hectare) compared with adoption of the *PBW-502* wheat variety. The evidence shows that farmers using the *HD-2967* wheat variety experienced higher yields (8%), higher revenues (8%), higher operational costs (6%), and greater profits (about Rs 3,355 per hectare), compared to farmers using the *PBW-343* wheat variety.

Table 4 presents the percentage of farmers with social networks in the village. According to the survey design, social networks ranged from zero, indicating social isolation and implying that farmers did not discuss agriculture-related matters with anyone, to 19, indicating social interaction with every farmer in the village. Table 4 reveals that 7.2% of farmers did not interact with anyone in the village. About 4% of farmers interacted with only one other farmer in the village. Table 4 reveals that about 3%, 7%, 17%, 19%, and 18% of farmers in the village had two,

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17 Other cultivars include *WH-511*, *WH-711*, *HD-3086*, and *HD-2329*.

three, four, five, and six social connections, respectively. Figure 3 presents the average social network of farmers within the village by relationship. Figure 3 show that, on average, a farmer is networking with about 4 friends, 0.63 relatives, 0.67 neighbors, and 0.14 other farmers. Overall, a farmer in the village is networking with about 5 other farmers in the village. This estimate of the size of farmer social networks within a village provides new insights to policymakers designing outreach activities and policies aimed at improving the deployment of public programs. Moreover, the finding reveals that friends within social networks significantly influence the adoption of new technology.

4. Empirical Strategy

4.1. Quantifying Spillovers

To capture the extent of the spillover effects of KVKs, recall that the study categorizes smallholders into *primary* beneficiaries[18], *secondary* beneficiaries[19], and *networ*k beneficiaries. *Secondary* beneficiaries receive knowledge and information flows from *primary* beneficiaries, while *network* beneficiaries receive knowledge and information flows from both *primary* and *secondary* beneficiaries. In the case of FLDs, the idea of proximity to the source of information may serve as a key channel in attracting farmers to visit and learn about a new technology (Munshi, 2004). We define *secondary* beneficiaries, '*S*', if S_i=1; that is, if farmer *'i'* visits FLDs conducted by KVK on any other farmer's field in the same village. Therefore, the percentage of *secondary*

[18] *Primary* beneficiaries are defined on the basis of farmers receiving KVK intervention for 2016–2017.

[19] *Secondary* beneficiaries are defined only in the case of FLDs, but not for training programs.

beneficiaries in FLD villages[20] can be calculated as the total number of secondary beneficiaries in the FLD villages out of all farmers in the FLD villages.

The second spillover channel operates through social networks. Identifying *network* beneficiaries involves two steps. The first step is to calculate the number of network members benefited by KVK's intervention for each farmer. This is represented by the following equation:

$$SN\_A\_KVKB_i = \sum_{v=1}^{19} (SN_{iv} * A_{iv} * KVKB_{iv}) \quad (1)$$

where 'i' denotes individual farmer and 'v' denotes the remaining surveyed farmers of the same village.[21] *SN* takes a value of 1 if farmer 'i' is socially connected with farmer 'v', and 0 otherwise.[22] *A* takes a value of 1 if farmer 'i' discusses and accepts agricultural advice from a socially connected farmer 'v', and 0 otherwise. *KVKB* takes a value of 1 if farmer 'v' is either a *primary* or *secondary* beneficiary, and 0 otherwise. Thus, *SN_A_KVKB* (the total number of social network-member farmers), the right-hand side variable in equation 1, corresponds to farmer 'i', who benefited from KVK intervention. Thereafter, we define *network* beneficiaries (***N***) as farmers who benefited from KVK intervention as a result of inclusion in a social network. Specifically,

$$\boldsymbol{N}_i = 1 \ \ if \ SN\_A\_KVKB_i > 0. \quad (2)$$

Thus, the percentage of *network* beneficiaries in FLD villages is the ratio of total number of *network* beneficiaries in the FLD villages to total number of farmers in the FLD villages.

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20 FLD villages are those where at least one FLD is conducted on any farmer's plot in the sample.

21 In each village, we surveyed 20 farmers.

22 A socially connected farmer is a friend, neighbor, relative, or other known farmer with whom the farmer interacts.

4.2. Matched Difference-in-Difference (MDID) Approach

Our empirical strategy exploits two important aspects of KVK intervention; namely, the impact of FLDs and CBPs on the adoption of improved wheat technology. The first aspect is the non-universal coverage of KVK interventions, which enables us to identify the control group. The second aspect is the availability of the panel data from 2014–2015 to 2017–2018 on the adoption of improved wheat varieties. Note that the 2014-2015 and 2015-2016 periods are pre-intervention years and 2016-2017 and 2017-2018 are the intervention and post-intervention years, respectively. The pre- and post-intervention years and the availability of a control group form the basis of our identification strategy.

Data from the above periods allows us to compare changes in outcomes between the treatment group (KVK beneficiary) and the control (non-KVK beneficiary) group. In this case, a standard difference-in-difference (DID) impact estimate can be interpreted as the impact of KVK under the assumption that in the absence of KVK, outcomes would not be systematically different in either the treatment or control groups. We provide the estimates with causal interpretation only when the treatment and control group exhibit similar time trends. An emerging literature on difference in difference focuses on the need to address why the original levels of the treatment and control groups differed and to use this to justify impact coefficients. Therefore, parallel pre-trends are neither necessary nor sufficient for the parallel counterfactual trends condition to hold (Lang & Lang, 2020). In this paper, however, we stay with the conventional DID practice of interpreting impacts as causal only upon finding parallel trends. To identify the impact, we estimate the following DID specification:

$$Y_{ivdt} = \alpha_0 + \alpha_1 Time_t + \alpha_2 Treatment_{ivd} + \alpha_3 (Treatment_{ivd} * Time_{\ t}) + \varepsilon_{ivdt} \qquad (3)$$

where *i* represents individual, *v* stands for village, *d* stands for district, and *t* represents year (either 2015–2016 or 2017–2018). Y takes a value of 1 when a farmer adopts wheat variety *HD-2967* (a new wheat variety) and 0 otherwise. $Time_t$ is a dummy variable for 2017–2018. $Treatment$ is a dummy variable for farmers in the KVK group in 2016–2017. ε is the error term. The impact parameter of interest is α_3. The key identifying assumption is that in the absence of KVK intervention the treatment and control groups grow with similar time trends.

This assumption could be invalid given that the two groups of farmers may be different from each other and may grow differently if their villages have differential time trends. Tables 5 and 6 present the unmatched differences in farmers' characteristics for FLDs and CBPs, respectively. The tables suggest that farmers' characteristics are different and that it is more likely that the identifying assumption of similar time trends may not hold.

The above concern can be addressed using two approaches. First, we can match each treated farmer with a weighted combination of control farmers such that the predicted probability of treating is same. We compared the outcomes of treated farmers with the weighted average of adoption rates across matched control farmers. This allows us to make accurate comparisons and increases the likelihood that our assumption will hold.. Appendix Tables 2 and 3 show that matching improves the likelihood of similarity among farmers in the treatment and control groups. To implement this, we adopted a matched DID (MDID) approach to identify the impact of KVKs (see Heckman et al., 1999). The MDID is one of the few quasi-experimental methods that reproduce impact estimates close to those provided by randomized control trials. The idea behind the MDID approach is as follows: If we assume that in the absence of KVK, the evolution of adoption of *HD-2967* (new wheat variety) would be the same across the two groups, then any observed differences in the presence of KVK may be attributed to the intervention.

Second, we test the identifying assumption by looking at the data from the pre-intervention years (2014–2015 and 2015–2016) and verify that it holds during this period. Finding similar trends in outcomes (adoption of new wheat variety) across the treatment and control groups before the intervention helps us ensure that the identifying assumption holds. Implementing the matching procedure essentially involves three steps. First, we derive farmer-level weights using the kernel matching procedure.[23] In the second step, we define a common support region by dropping those treated farmers whose propensity score is higher than the maximum or less than the minimum of control farmers, and vice versa. In the final step, we apply farmer-level weights to the DID specification (equation 3) in the common support region to arrive at the MDID impact estimates

To identify the effect of FLDs on the adoption of improved technology for *primary* beneficiaries we estimate the following regression on farmers belonging to the region of common support:

$$Y_{ivdt} = \alpha_0 + \alpha_1 Time_{\ t} + \alpha_2 [FLD\ (P)]_{ivd} + \alpha_3 ([FLD\ (P)]_{\ ivd} * Time_{\ t}) + \varepsilon_{ivdt} \qquad (4)$$

where *i* represents individual, *v* stands for village, *d* stands for district, and *t* stands for year (either 2015–2016 or 2017–2018). Y takes a value of 1 if a farmer adopts wheat variety HD-*2967*, and 0 otherwise. $Time_t$ is a dummy variable for 2017–2018. $FLD\ (P)$ is a dummy variable if the farmer is the *primary* beneficiary in 2016–2017, and 0 if farmers reside in non-KVK villages. The main motivation to consider a control group of farmers from non-KVK villages is that farmers belonging to KVK villages are more likely to receive benefits of KVKs from spillover of knowledge and information flows.[24] In that case, the control group is not considered as a true counterfactual group of farmers. Therefore, we consider farmers from non-KVK villages as our control group. ε is the

[23] Kernel matching procedure uses the weighted averages of all farmers in the control group to construct the counterfactual of treated farmers.

[24] We have considered only those farmers in the control group who reside in the non-KVK villages, and dropped those who reside in the KVK villages and are non-beneficiary.

error term. Estimating the above equation with matching weights makes α_3 an MDID estimator. The estimate captures the differential effect of the FLDs on *primary* beneficiaries.

To identify the impact of FLDs we perform similar estimations (equation 4) for *secondary* (S) and *network* (N) beneficiaries separately. The treatment variable *FLD (S)* takes a value of 1 if the farmer is a *secondary* beneficiary and 0 if the farmer resides in a non-KVK village. Similarly, *FLD (N)* takes a value of 1 if the farmer is a *network* beneficiary and 0 if the farmer resides in a non-KVK village. Likewise, to identify the impact of CBPs we perform a similar estimation (equation 4) for *primary* (P) and *network* (N) beneficiaries separately. Specifically, *P* takes a value of 1 if the farmer is the *primary* beneficiary and did not receive the benefits of FLD, and 0 if the farmer resided in a non-KVK village. Here, we consider farmers who only participated in CBPs but not FLDs as our treatment group.[25] Finally, N takes a value of 1 if the farmer is a *network* beneficiary and has not received the benefits of FLD, and 0 if the farmer resides in a non-KVK village.

5. Results and Discussion

5.1. Estimating Spillovers

Figure 4 plots the percentage of *primary*, *secondary*, and *network* beneficiaries of FLDs in the FLD villages. About 3% of farmers in these villages reported FLD trials on their fields. These farmers are referred to as *primary* beneficiaries. In contrast, about 6% of farmers reported accessing FLDs by visiting another farmer's field. These farmers are referred to as *secondary* beneficiaries. Using equations 1 and 2, we estimate the percentage of *network* beneficiaries. The result shows that about 25% of farmers benefited from FLDs through the social network channel. Our findings suggest

[25] Our sample comprises few farmers who received the benefits of both FLDs and CBPs. We drop those farmers in order to identify the effects of CBPs only.

that 3% of *primary* beneficiaries generated spillover of knowledge and information flows to 31% of farmers. Thus, a total of 34% beneficiaries (or farmers) benefited from FLDs conducted by KVKs.

Figure 5 presents the percentage of *network* beneficiaries of CB training conducted on varietal evaluation in KVK villages. Results indicate that 3% of farmers are *primary* beneficiaries of CB training on varietal evaluation conducted by KVKs. Additionally, 27% of farmers benefited through the social network channel. Overall, 30% of farmers benefited from CB training. The above findings reflect the importance of the social network channel in the dissemination of agricultural knowledge and information. Additionally, we find that the extent of spillover's effect on the transfer of knowledge and information is very prominent. The finding adds new insights to the literature on the intra-regional diffusion of agricultural technology. Further, the findings corroborate the literature that underscores the importance of the social network channel to the dissemination and diffusion of information regarding agricultural technology (see, for example, Bandiera & Rasul, 2006; Conley & Udry, 2010; Munshi, 2004).

5.2. KVK's Impact on Adoption of HD-2967: Effects on Primary Beneficiaries

Table 7 presents the impact estimates for the adoption of a modern wheat variety, namely *HD-2967*, on *primary* beneficiaries. Models 1 and 2 present the DID and MDID estimates, respectively.[26] We interpret the MDID coefficients, as these estimates are more robust and more likely to validate the identification assumptions. The coefficient α_1 shows a 17% increase in the adoption of *HD-2967* over the periods of 2015–2016 and and 2017–2018. The coefficient α_2 captures the difference in the adoption of *HD-2967* between beneficiaries and non-beneficiaries in 2015–2016. The result reveals that the adoption rate of *HD-2967* is about 7.4% lower for

[26] DID and MDID estimates are based on Equations 3 and 4, respectively.

primary beneficiaries, compared to non-beneficiaries, in 2015–2016 (before KVK's intervention program). Our coefficient of interest α_3 measures the impact of FLDs on the adoption of *HD-2967*. Results reveal that *primary* beneficiaries have higher adoption rates (about 52%), compared to non-beneficiaries. Findings suggest that FLDs have a strong positive impact on *primary* beneficiaries when it comes to adopting improved wheat technologies. This is an important finding because it shows that—despite the fact that *primary* beneficiaries had lower adoption rates before KVK's intervention—the impacts of intervention on *primary* beneficiaries are large and significant. Kondylis et al. (2017) conducted an extension network experiment in Mozambique and found that farmers who directly benefit from extension agents are more likely to adopt new technologies (ranging from 28.3% to 65%) .[27] Our findings are robust to the pre-intervention trend that shows a similar trend across *primary* beneficiaries and non-beneficiaries over the periods of 2014–2015 and 2015–2016, in the absence of any FLD interventions (see coefficient of Model 4 in Table 7).

Table 8 presents the impact estimates for the adoption of *HD-2967* for farmers who received CB training from KVK staff. The coefficient α_1 shows a 21% increase in the adoption of *HD-2967* over the periods of 2015–2016 and 2017–2018. The estimated coefficient α_2 reveals that the adoption of *HD-2967* was similar among *primary* beneficiaries and non-beneficiaries in 2015–2016. In other words, the adoption pattern for *primary* beneficiaries of CB training was similar to those of non-beneficiaries (before KVK's intervention). The coefficient α_3 shows a 21.3% higher adoption rate for *primary* beneficiaries, compared to non-beneficiaries. It is important to observe that the magnitude of impact is smaller for CB training beneficiaries, compared to the beneficiaries

[27] They estimate the impact estimates for the adoption of strip-tillage, pit planting, and contour farming.

of FLDs. Munshi (2004) argued that demonstration trials reduce the perceived risks and increase the likelihood of adoption. This may explain our findings of stronger impacts for FLDs compared to CB training by KVKs, and our results are robust to pre-intervention trends (see α_3 of Model 4 in Table 8). Overall, the above findings show that both KVK interventions—FLDs and CB training—have a strong positive impact on technology adoption. However, the effect is more pronounced for FLDs than for the CBPs.

5.3. KVK's Impact on Adoption of HD-2967: Effects on Secondary and Network Beneficiaries

Table 9 presents the impact of FLDs on the adoption of *HD-2967* among *secondary* and *network* beneficiaries. Panels *A* and *B* present the regression coefficients from the DID and MDID models, respectively. Models 1 and 2 present the impact estimates for *secondary* and *network* beneficiaries, respectively, while Models 3 and 4 of Table 9 present the pre-intervention trends corresponding to Models 1 and 2, respectively. We only interpret MDID coefficients for the reason explained in the previous section. Further, we only interpret the coefficient (α_3) that measures the impact of KVK interventions on *secondary* and *network* beneficiaries (see Table 9 for the estimated coefficients of α_1 and α_2).

In the case of FLDs, the impact estimates reveal that *secondary* beneficiaries have a roughly 13% higher adoption rate of *HD-2967*, compared to non-beneficiaries. Although the effect on *secondary* beneficiaries is positive, its magnitude is smaller than for *primary* beneficiaries. Our finding is consistent with Kondylis et al. (2017), who found a limited impact on other indirect beneficiaries. Our findings on *secondary* beneficiaries suggest that FLD intervention also benefits farmers who are curious and make visits to the fields of *primary* beneficiaries where FLDs are being conducted. This was the intended objective of FLDs. Table 9 shows that *network* beneficiaries have roughly a 12% higher adoption rate of *HD-2967*, compared to non-beneficiaries. Our results are consistent with the literature, indicating that farmers' adoption choices are influenced by the adoption decisions of their network members (Bandiera & Rasul, 2006). Models 3 and 4 of Table 9 shows that the results are robust to pre-intervention trends for *secondary* and *network* beneficiaries.

Table 10 presents the CB training's impact on the adoption of *HD-2967* on *network* beneficiaries. The impact estimates demonstrate that *network* beneficiaries have roughly a 16% higher adoption rate of *HD-2967*, compared to non-beneficiaries (see Table 10 for α_1 and α_2). As expected, the magnitude of increased adoption is smaller, compared to *primary* beneficiaries of the CB training programs. The above results are robust to pre-intervention trends. In sum, this study established evidence of a positive impact of FLDs and CB training on the adoption of wheat variety *HD-2967,* for *secondary* and *network* beneficiaries. Finally, the results reveal that the impact estimates are marginally higher for *secondary* beneficiaries, compared to *network* beneficiaries.

6. Conclusions and Implications

In developing and emerging economies like India's, agricultural advisory services are the most important knowledge- and information-dissemination institutions for accelerating the adoption of modern technologies and improving farmers' learning abilities. After independence, the Indian government created KVKs, but due to lack of funding and transportation costs, their impact has been historically limited. In recent years, however, thanks to increased funding and a policy emphasis on increasing smallholder productivity, incomes, and livelihoods, KVKs have become more impactful as knowledge-dissemination channels. Farmers like this approach for two reasons. First, policymakers have made food security a national issue. Secondly, the cost of communication, information transfer, and transportation facilities has decreased tremendously. As a result, farmers are more connected to KVKs and their field advisors. In sum, the KVK model has emerged as an effective blueprint for improving outcomes among smallholders, and KVKs now serve as the primary source of knowledge and information for millions of Indian farmers.

This study explored the direct and spillover effects of the outreach efforts of public-sector KVKs. In particular, the study estimated the direct impact of knowledge and information transfer on *primary* beneficiaries of FLDs (farmers whose field was the site of an FLD); the spillover impact on *secondary* beneficiaries (farmers who visited FLD sites and gained knowledge) and *network* beneficiaries (farmers who benefited from *primary* and *secondary* beneficiaries by being in their social networks). The study also evaluated the impact of FLDs and CB training programs on the same set of farmers for the adoption of *HD-2967*, a newly released wheat variety.

The study used farm-level data from about 1,496 farmers in UP and an MDID approach to accomplish the objectives. Results from the analysis showed that 3% of direct beneficiaries of FLDs (or *primary* beneficiaries) benefited 6% and 25% of *secondary* and *network* beneficiaries, respectively. In the case of CB training, results from this study revealed that 3% of direct or *primary* beneficiaries of CB training programs benefited 27% of *network* beneficiaries. The above findings underscore the vital role that social networks play in technology diffusion. The results reinforce the argument put forth by Banerjee et al. (2014). Indeed, technology transfer by central individuals[28] in the village could lead to higher diffusion rates, compared to transfer initiated by random individuals or opinion leaders. Additionally, KVKs could easily identify central individuals in a cost-effective way without gathering any social network information. Findings from this study provide a new avenue of exploration for researchers examining the transfer of knowledge and information on farming when the *primary* beneficiary is the central individual. This model could generate significant spillover effects (through social networks) for other farmers

[28] Central individuals are those who are most central in a social network and best-placed to diffuse information.

in the village. Finally, the study highlighted the key role that social networks play in the diffusion of knowledge and information from public programs, like KVKs. The findings provide new insights for policymakers developing and implementing farmer outreach initiatives such as FLDs and CB training programs.

The study also provided evidence of the impact of FLDs and CB training programs on the adoption of *HD-2967*, a newly released wheat variety. Findings showed that KVK interventions have a strong positive impact on *primary* beneficiaries when it comes to adoption of *HD-2967*. Regarding the spillover effects, the results showed that *secondary* and *network* beneficiaries of KVK's FLD efforts were also more likely to adopt the variety *HD-2967* compared to the non-KVK farmers. Consistent with the information transmission channels, the magnitude of impact is highest for *primary* beneficiaries, followed by *secondary* and *network* beneficiaries. Lastly, the benefits are more pronounced for FLD program beneficiaries, compared to CB training beneficiaries. Regarding the CB training program, the current study showed that *network* beneficiaries received benefits by adopting *HD-2967*. Lastly, the direct and spillover effects were more pronounced for the FLD program, compared to the CB training program. From a policy perspective, the strong impact of KVKs—and the FLD program, in particular—suggests that these services should be scaled up to reach more Indian farmers., The evidence on spillover effects provides new insights into the approaches that maximize returns on investments in publicly-funded knowledge- and information-transfer programs.

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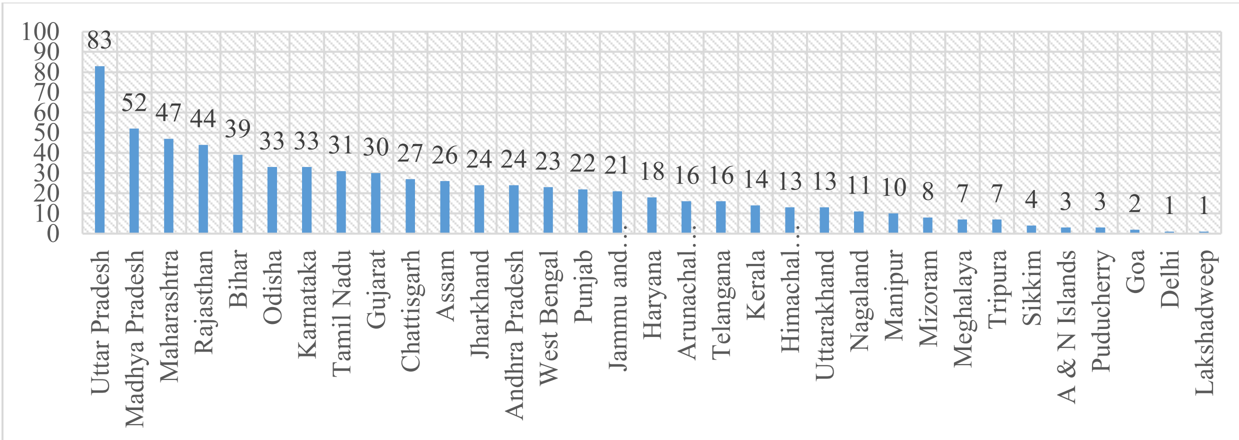
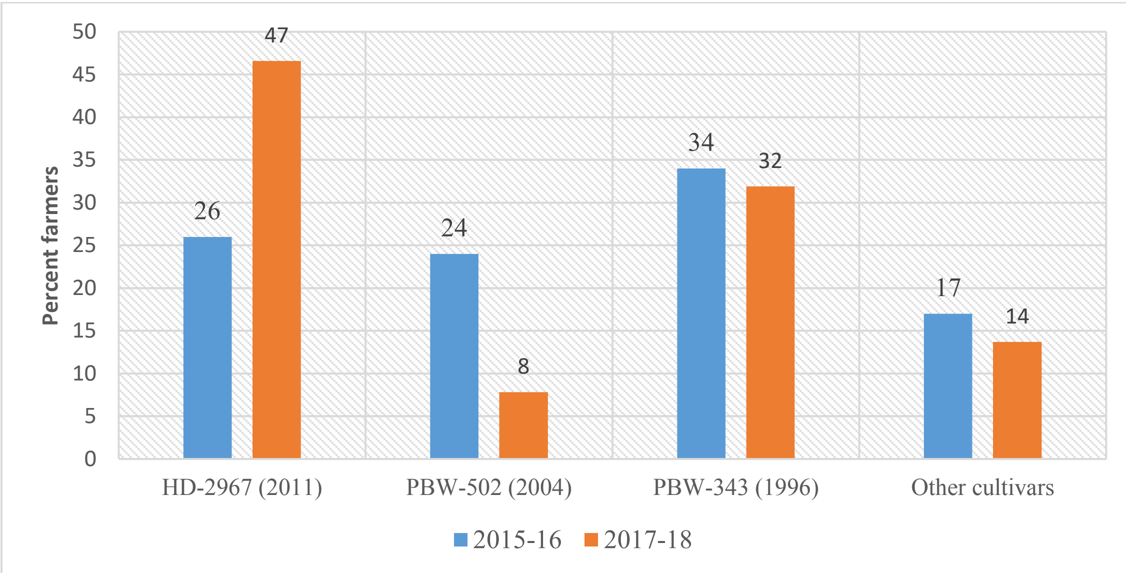
Figure 1: State-wise number of KVKs in India



Source: Indian Council of Agriculture Research (ICAR), New Delhi, Information accessed on February 20

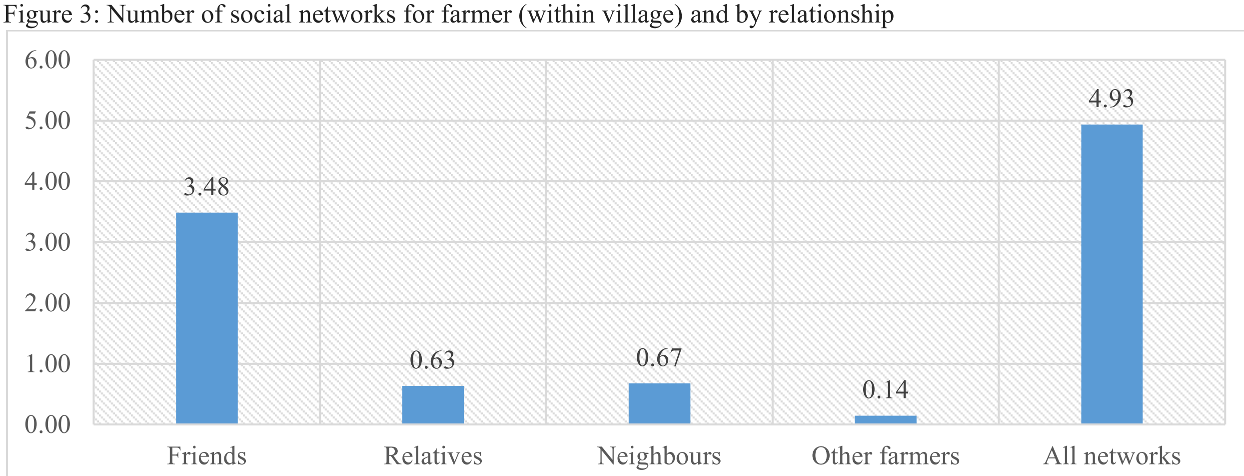
Figure 2: Adoption pattern of wheat cultivars, for Uttar Pradesh



Source: ICAR-IFPRI KVK Survey, 2019

Note: HD-2967, PBW-502, and PBW-343 are all developed by public sector. Variety release year is in parentheses.

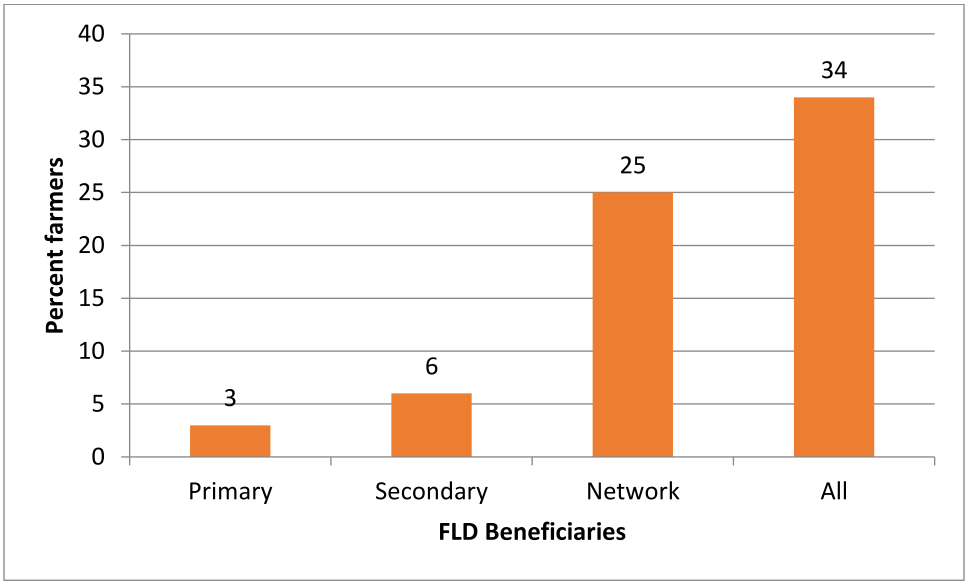
Figure 3: Number of social networks for farmer (within village) and by relationship



Source: ICAR-IFPRI KVK Survey, 2019.

Note: All networks include friends, relatives, neighbors, and other farmers.

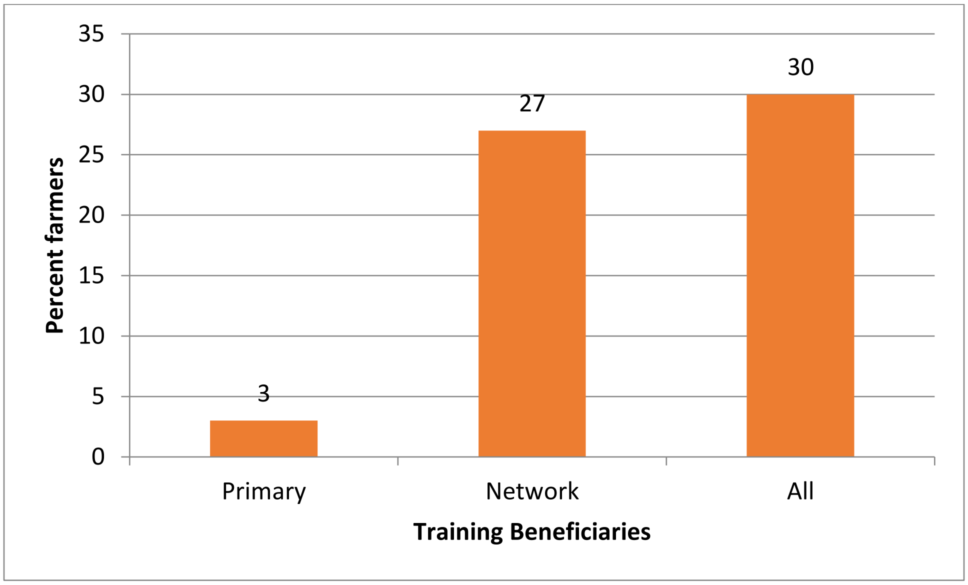
Figure 4: Frontline demonstration (FLD) beneficiaries, wheat cultivar HD-2967, % farmers in FLD villages



Source: ICAR-IFPRI KVK Survey, 2019.

Note: *Primary* beneficiary farmers receive benefits directly from KVKs (i.e., an FLD is conducted on their own farm field leading to direct interaction with KVK scientists). *Secondary* beneficiary farmers who are curious about and visit the FLD sites to gain knowledge learn from *primary* beneficiaries. *Network* beneficiary farmers benefit from *primary* and *secondary* beneficiaries being in their social network. All beneficiaries include *primary*, *secondary*, and *network* beneficiaries.

Figure 5: CB training beneficiaries of wheat varietal evaluation, % farmers in KVK villages



Source: ICAR-IFPRI KVK Survey, 2019.

Note: Primary beneficiary farmers receive benefits directly from KVKs (i.e., an FLD is conducted on their own farm field leading to direct interaction with KVK scientists). Secondary beneficiary farmers who are curious about and visit the FLD sites to gain knowledge learn from primary beneficiaries. Network beneficiary farmers benefit from primary and secondary beneficiaries being in their social network. All beneficiaries include primary, secondary, and network beneficiaries.

Table 1: Agro-climatic zones and the area covered by major crops, for Uttar Pradesh

Agro-climatic zones (AEZs)	Share of major crops (%)	Area covered by major crops (% of the total area of AEZ)
Bhabhar and Tarai	Sugarcane (33), Wheat (33), Paddy (27), and Maize (2)	95
Western plains	Wheat (39), Sugarcane (38), Paddy (13), and Maize (3)	93
Midwestern plains	Wheat (42), Paddy (26), Sugarcane (13), and Bajra (7)	88
Southwestern semi-arid	Wheat (44), Bajra (18), Paddy (11), Potato (8), and Mustard (7)	88
Central plains	Wheat (44), Paddy (23), Sugarcane (8), Maize (4), Mustard (4), and Arhar/Tur (2)	85
Bundelkhand	Wheat (32), Gram (15), Urad (11), Sesamum (9), Masoor (8), and Arhar/Tur (3)	78
Northeastern plains	Wheat (40), Paddy (38), Sugarcane (9), and Maize (5)	92
Eastern plains	Wheat (44), Paddy (38), Sugarcane (3), and Maize (3)	88
Vindhyan	Wheat (35), Paddy (28), Gram (6), and Arhar/Tur (6)	75
All AEZs	Wheat (41), Paddy (24), Sugarcane (9), Pearl millet (4), and Maize (3)	81

Source: Land Use Statistics (2011–2012), Directorate of Economics and Statistics, Ministry of Agriculture, Government of India.

Table 2: Profile of wheat farmers, Uttar Pradesh, 2017-18

Farmer' characteristics	All farmers				KVK village (mean)	Non-KVK village (mean)	Difference (KVK-non KVK)
	Mean	Standard deviation	Minimum	Maximum			
Age (Year)	45.8	11.4	21	85	44.8	47.5	-2.7***
Age square (Year)	2229	1091	441	7225	2128	2393	-265***
Male (Yes=1)	0.95	0.21	0	1	0.96	0.95	0.01
Education (Year)	5.31	4.09	0	16	5.51	4.99	0.52*
Household size (#)	4.97	2.06	1	45	4.89	5.09	-0.20
Hindu (Yes=1)	0.98	0.15	0	1	0.99	0.96	0.03***
Schedule caste/tribe (Yes=1)	0.48	0.50	0	1	0.49	0.46	0.03
Below poverty line (Yes=1)	0.23	0.42	0	1	0.22	0.25	-0.03
Land own (ha)	0.77	0.92	0	20.14	0.75	0.80	-0.05
Source of income (Agriculture=1)	0.78	0.42	0	1	0.80	0.75	0.05*
Asset index (Value)	0.02	1.76	-2.7	9.3	0.02	0.02	0.00
Household head experience (Year)	18.3	10.2	1	60	17.3	20.0	-3***
Kisan credit card (Yes=1)	0.44	0.50	0	1	0.45	0.42	0.03
Soil health card (Yes=1)	0.15	0.36	0	1	0.18	0.11	0.07***
Pradhan mantri fasal bima yojana (Yes=1)	0.14	0.35	0	1	0.15	0.13	0.02
Soil color (Black=1)	0.84	0.37	0	1	0.89	0.75	0.14***
Irrigation (Groundwater=1)	0.78	0.41	0	1	0.82	0.72	0.10***
Soil fertility (High=1)	0.20	0.40	0	1	0.17	0.24	-0.07***
	1496				923	573	

Source: ICAR-IFPRI KVK Survey ,2019

Note: Below-poverty-line (BPL) cards are issued to poorer households. Asset index is constructed by applying principal component analysis using the ownership of 22 assets (e.g., tractor, two-wheeler, four-wheeler, etc.) Kisan Credit Cards provide institutional credit to farmers in the form of short-term credit facilities for cultivation activities. Soil health cards are issued to farmers and provide information on nutrient requirements based on soil analysis. Pradhan mantri fasal bima yojana provides insurance for crops. KVK villages are those where KVKs have conducted interventions such as FLDs. Non-KVK villages are those where KVKs have not conducted any type of intervention.

Table 3: Yield and profit of major wheat cultivars, Uttar Pradesh, 2017–2018

Panel A			
	HD-2967	PBW-502	Difference (1-2)
Yield (q per ha)	37.2	35.2	2.1***
Revenue (Rs per ha)	59903.7	56485.0	3418.7***
Operational cost (Rs per ha)	25046.5	26126.5	-1080.0
Profit (Rs per ha)	34857.2	30358.5	4498.6***
Number of observations			553
Panel B			
	HD-2967	PBW-343	Difference (1-2)
Yield (q per ha)	37.2	34.3	2.9***
Revenue (Rs per ha)	59903.7	55113.1	4790.6***
Operational cost (Rs per ha)	25046.5	23611.7	1434.8***
Profit (Rs per ha)	34857.2	31501.4	3355.7***
Number of observations			877

Source: ICAR-IFPRI KVK Survey, 2019.

Table 4: Social networks, within village, % farmers, Uttar Pradesh

Number of social networks related to agricultural matters (within the village)	Number of farmers (#)	% of farmers (%)
0	107	7.2
1	60	4.0
2	40	2.7
3	99	6.6
4	253	16.9
5	282	18.9
6	276	18.5
7	236	15.8
8	100	6.7
9	28	1.9
10	9	0.6
11	4	0.3
13	1	0.1
16	1	0.1
17	0	0.0
18	0	0.0
19	0	0.0
Total	1,496	100

Source: ICAR-IFPRI KVK Survey, 2019.

Note: Farmers with zero social connections in the village are interpreted as those who do not interact with anyone regarding agriculture-related matters. Farmers with 19 social connections are interpreted as those who interact with everyone regarding agricultural matters.

Table 5: Summary statistics for FLDs *primary, secondary*, and *network* beneficiaries: Control vs. treatment group (unmatched differences)

	Panel A			Panel B			Panel C		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Control	Primary beneficiary	Difference (1-2)	Control	Secondary beneficiary	Difference (1-2)	Control	Network beneficiary	Difference (1-2)
Age (Year)	46.8	45.3	1.4	46.8	46.9	-0.10	46.8	43.9	2.962**
Age square (Year)	2327.1	2263.6	63.4	2329.3	2296.1	33.2	2330.6	2041.3	289.264**
Male (Yes=1)	0.951	0.947	0.004	0.950	1.000	-0.050	0.952	0.948	0.004
Education (Year)	5.182	5.000	0.182	5.177	5.750	-0.573	5.167	5.587	-0.421
Household size (#)	5.014	6.211	-1.19**	5.020	4.909	0.111	5.039	4.605	0.434**
Hindu (Yes=1)	0.971	1.000	-0.029	0.971	1.000	-0.029	0.971	0.988	-0.017
Schedule caste/tribe (Yes=1)	0.498	0.316	0.182	0.498	0.409	0.089	0.496	0.384	0.112**
Below poverty line (Yes=1)	0.229	0.474	-0.244*	0.231	0.091	0.140*	0.229	0.174	0.055
Land own (ha)	0.795	0.730	0.065	0.795	0.807	-0.012	0.801	0.872	-0.072
Source of income (Agriculture=1)	0.768	0.895	-0.127	0.767	0.977	-0.210**	0.773	0.785	-0.012
Asset index (Value)	0.028	0.039	-0.011	0.026	0.773	-0.747**	0.032	-0.087	0.119
Household head experience (Year)	19.2	17.4	1.8	19.2	18.6	0.6	19.3	15.9	3.4***
Kisan credit card (Yes=1)	0.416	0.421	-0.005	0.415	0.659	-0.244**	0.423	0.523	-0.101*
Soil health card (Yes=1)	0.135	0.158	-0.023	0.134	0.250	-0.116*	0.134	0.215	-0.081**
Pradhan mantri fasal bima yojana (Yes=1)	0.135	0.263	-0.128	0.133	0.205	-0.071	0.129	0.174	-0.045
Soil color (Black=1)	0.798	0.842	-0.045	0.797	0.909	-0.112	0.794	0.913	-0.119***
Irrigation (Groundwater=1)	0.741	0.842	-0.101	0.741	0.909	-0.168*	0.748	0.831	-0.083*
Soil fertility (High=1)	0.20	0.63	-0.43***	0.199	0.205	-0.006	0.196	0.256	-0.060
Number of observations			987			1006			1102

Source: ICAR-IFPRI KVK Survey, 2019.

Table 6: Summary statistics for training *primary* and *network* beneficiaries: Control vs. treatment group (unmatched differences)

	Panel A			Panel B		
	(1)	(2)	(3)	(4)	(5)	(6)
	Control	Primary beneficiary	Difference (1-2)	Control	Network beneficiary	Difference (1-2)
Age (Year)	47.4	48.2	-0.8	47.5	44.5	3.0^{**}
Age square (Year)	2393.5	2431.5	-37.9	2393.4	2092.9	300.5^{***}
Male (Yes=1)	0.946	1.000	-0.054	0.947	0.939	0.007
Education (Year)	5.005	5.952	-0.947	4.984	5.654	-0.670^{*}
Household size (#)	5.096	5.095	0.001	5.096	5.037	0.059
Hindu (Yes=1)	0.954	1.000	-0.046	0.954	0.995	-0.042^{**}
Schedule caste/tribe (Yes=1)	0.454	0.238	0.216	0.456	0.421	0.036
Below poverty line (Yes=1)	0.249	0.286	-0.037	0.250	0.201	0.049
Land own (ha)	0.799	1.039	-0.239	0.798	0.898	-0.101
Source of income (Agriculture=1)	0.746	0.810	-0.064	0.742	0.846	-0.104^{**}
Asset index (Value)	0.021	1.359	-1.338^{***}	0.007	0.102	-0.095
Household head experience (Year)	20.040	21.429	-1.388	19.954	17.178	2.776^{**}
Kisan credit card (Yes=1)	0.416	0.619	-0.203	0.410	0.533	-0.123^{**}
Soil health card (Yes=1)	0.107	0.333	-0.226^{**}	0.109	0.173	-0.064^{*}
Pradhan mantri fasal bima yojana (Yes=1)	0.128	0.381	-0.253^{***}	0.128	0.136	-0.007
Soil color (Black=1)	0.747	0.810	-0.062	0.754	0.846	-0.092^{**}
Irrigation (Groundwater=1)	0.723	0.905	-0.182	0.718	0.883	-0.165^{***}
Soil fertility (High=1)	0.246	0.238	0.008	0.246	0.266	-0.020
Number of observations			591			775

Source: ICAR-IFPRI KVK Survey, 2019.

Table 7: Estimates of FLDs on *primary* beneficiaries, adoption of HD-2967, new wheat variety, Uttar Pradesh

	Impact estimates		Falsification test	
	Model 1	Model 2	Model 3	Model 4
Time, α_1	0.222^{***} (0.021)	0.169^{***} (0.034)	0.114^{***} (0.016)	0.119^{***} (0.026)
FLD (P), α_2	-0.096 (0.111)	-0.074^{**} (0.034)	-0.099 (0.088)	-0.094^{***} (0.026)
FLD (P)*Time, α_3	0.397^{**} (0.153)	0.518^{***} (0.049)	0.003 (0.124)	0.006 (0.037)
Constant	0.214^{***} (0.015)	0.199^{***} (0.024)	0.099^{***} (0.012)	0.094^{***} (0.018)
Matching before DID	No	Yes	No	Yes
Number of observations	1958	1108	1926	1080

Notes: Each column represents a separate regression. Dependent variable takes value 1 when wheat farmers adopt *HD-2967*, and 0 otherwise. *Time* is a dummy variable. In Models 1 and 2, it takes value 1 for 2017–2018 and 0 for 2015–2016. In Models 3 and 4, it takes value 1 for 2015–2016 and 0 for 2014–2015. In all models, treatment group is defined as those farmers who directly benefited from FLDs in 2016–2017 (i.e., *primary* beneficiaries), and is denoted by a dummy variable *FLD (P)*. In Models 1 and 2, *FLD (P)* takes value 1 when the farmer is the *primary* beneficiary, and 0 when the farmer is a resident of a non-KVK village. Models 3 and 4 test for the parallel trends across treatment and control groups. Covariates used to perform matching across treatment and control groups before applying DID are as follows: age, age square, gender, education, household size, religion, caste, poor households, land holding, source of income, asset index, household head experience, Kisan Credit Card, soil health card, crop insurance, soil color, source of irrigation, soil fertility, and plot location. Kernel procedure is used for performing matching. Models 2 and 4 regressions are in the common support region. Standard errors in parentheses. $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.001$.

Table 8: Estimates of CBP training, adoption of HD-2967, new wheat variety, Uttar Pradesh

	Impact estimates		Falsification test	
	Model 1	Model 2	Model 1	Model 2
Time, α_1	0.240*** (0.027)	0.208*** (0.045)	0.129*** (0.021)	0.152*** (0.037)
Training (P), α_2	-0.144 (0.128)	0.018 (0.045)	-0.015 (0.100)	0.001 (0.037)
Training (P)*Time, α_3	0.397** (0.178)	0.213*** (0.064)	-0.129 (0.142)	-0.002 (0.052)
Constant	0.221*** (0.019)	0.245*** (0.032)	0.092*** (0.015)	0.099*** (0.026)
Matching before DID	No	Yes	No	Yes
Number of observations	1152	820	1128	814

Notes: Each column represents a separate regression. Dependent variable takes value 1 when wheat farmers adopt *HD-2967*, and 0 otherwise. *Time* is a dummy variable. In Models 1 and 2, it takes value 1 for 2017–2018 and 0 for 2015–2016. In Models 3 and 4, it takes value 1 for 2015–2016 and 0 for 2014–2015. In all models, treatment group is defined as those farmers who directly benefited from FLDs in 2016–2017 (i.e., *primary* beneficiaries), and is denoted by a dummy variable *FLD (P)*. In Models 1 and 2, *FLD (P)* takes value 1 when the farmer is the *primary* beneficiary, and 0 when the farmer is a resident of a non-KVK village. Models 3 and 4 test for the parallel trends across treatment and control groups. Covariates used to perform matching across treatment and control groups before applying DID are as follows: age, age square, gender, education, household size, religion, caste, poor households, land holding, source of income, asset index, household head experience, Kisan Credit Card, soil health card, crop insurance, soil color, source of irrigation, soil fertility, and plot location. Kernel procedure is used for performing matching. Models 2 and 4 regressions are in the common support region. Standard errors in parentheses. $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.001$.

Table 9: Estimates of FLDs on *secondary* and *network* beneficiaries, adoption of HD-2967, new wheat variety, Uttar Pradesh

	Impact estimates		Falsification test	
Panel A	Model 1	Model 2	Model 3	Model 4
Time, α_1	0.222^{***} (0.021)	0.212^{***} (0.021)	0.112^{***} (0.017)	0.109^{***} (0.017)
FLD (S), α_2	0.038 (0.070)		0.150^{**} (0.056)	
FLD (N), α_2		0.082^{**} (0.038)		0.054^{*} (0.031)
FLD (S)*Time, α_3	0.074 (0.099)		-0.112 (0.079)	
FLD (N)*Time, α_3		0.108^{**} (0.054)		0.028 (0.043)
Constant	0.212^{***} (0.015)	0.208^{***} (0.015)	0.100^{***} (0.012)	0.100^{***} (0.012)
Matching before DID	No	No	No	No
Number of observations	1998	2190	1968	2160
	Impact estimates		Falsification test	
Panel B	Model 5	Model 6	Model 7	Model 8
Time, α_1	0.153^{***} (0.033)	0.204^{***} (0.028)	0.093^{**} (0.030)	0.114^{***} (0.024)
FLD (S), α_2	0.026 (0.033)		0.122^{***} (0.030)	
FLD (N), α_2		0.078^{**} (0.028)		0.057^{**} (0.024)
FLD (S)*Time, α_3	0.126^{**} (0.047)		-0.093^{**} (0.043)	
FLD (N)*Time, α_3		0.115^{**} (0.040)		0.019 (0.034)
Constant	0.230^{***} (0.024)	0.212^{***} (0.020)	0.140^{***} (0.021)	0.101^{***} (0.017)
Matching before DID	Yes	Yes	Yes	Yes
Number of observations	1530	2140	1502	2078

Notes: Each column represents a separate regression. Dependent variable takes value 1 when wheat farmers adopt *HD-2967*, and 0 otherwise. *Time* is a dummy variable. In Models 1 and 2, it takes value 1 for 2017–2018 and 0 for 2015–2016. In Models 3 and 4, it takes value 1 for 2015–2016 and 0 for 2014–2015. In all models, treatment group is defined as those farmers who directly benefited from FLDs in 2016–2017 (i.e., *primary* beneficiaries), and is denoted by a dummy variable *FLD (P)*. In Models 1 and 2, *FLD (P)* takes value 1 when the farmer is the *primary* beneficiary, and 0 when the farmer is a resident of a non-KVK village. Models 3 and 4 test for the parallel trends across treatment and control groups. Covariates used to perform matching across treatment and control groups before applying DID are as follows: age, age square, gender, education, household size, religion, caste, poor households, land holding, source of income, asset index, household head experience, Kisan Credit Card, soil health card, crop insurance, soil color, source of irrigation, soil fertility, and plot location. Kernel procedure is used for performing matching. Models 2 and 4 regressions are in the common support region. Standard errors in parentheses. $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.001$

Table 10: Estimates of CBP training on *network* beneficiaries, adoption of HD-2967, new wheat variety, Uttar Pradesh

	Impact estimates	Falsification test
Panel A	Model 1	Model 2
Time, α_1	0.241^{***} (0.028)	0.131^{***} (0.022)
Training (N), α_2	0.019 (0.039)	-0.001 (0.031)
Training (N)*Time, α_3	0.127^{**} (0.055)	0.020 (0.044)
Constant	0.221^{***} (0.020)	0.090^{***} (0.016)
Matching before DID	No	No
Number of observations	1472	1445
	Impact estimates	Falsification test
Panel B	Model 3	Model 4
Time, α_1	0.212^{***} (0.034)	0.136^{***} (0.028)
Training (N), α_2	0.016 (0.034)	-0.013 (0.028)
Training (N)*Time, α_3	0.161^{***} (0.049)	0.031 (0.039)
Constant	0.225^{***} (0.024)	0.099^{***} (0.020)
Matching before DID	Yes	Yes
Number of observations	1432	1408

Notes: Each column represents a separate regression. Dependent variable takes value 1 when wheat farmers adopt HD-2967, and 0 otherwise. *Time* is a dummy variable. In Models 1 and 3, it takes value 1 for 2017–2018, and 0 for 2015–2016. In Models 2 and 4, it takes value 1 for 2015–2016, and 0 for 2014–2015. *Training (N)* is a dummy variable and takes value 1 if farmers are network farmers of training beneficiaries, and 0 for those farmers who reside in non-KVK villages. Covariates used to perform matching across treatment and control groups before applying DID are as follows: age, age square, gender, education, household size, religion, caste, poor households, land holding, source of income, asset index, household head experience, kisan credit card, soil health card, crop insurance, soil color, source of irrigation, and soil fertility. Kernel procedure is used for performing matching. All regressions are in the common support region. Standard errors in parentheses. $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.001$.

Appendix Tables (Online)

Appendix Table A1: Adoption of wheat cultivars by type, for 2017-18

Name of cultivar	Cultivar type	Developers	Year of release	Area (ha)	Share in total area (%)	No. of farmers	Share in total farmers (%)
HD-2967	Variety	Public	2011	366	42	697	47
PBW-343	Variety	Public	1996	62	7	117	8
PBW-502	Variety	Public	2004	293	34	477	32
Other cultivars	Variety	Public/Private	–	150	17	205	14
Total	–	–	–	871	100	1496	100

Source: ICAR-IFPRI KVK Survey, 2019.

Appendix Table A2: Summary statistics for FLDs *primary*, *secondary*, and *network* beneficiaries: control vs. treatment group (matched differences)

	Panel A			Panel B			Panel C		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Control	Primary beneficiary	Diff (2-1)	Control	Secondary beneficiary	Diff (5-4)	Control	Network beneficiary	Diff (8-7)
HD2967 (Yes=1)	0.2	0.13	-0.07**	0.231	0.26	0.03	0.211	0.29	0.0 8
Age (Year)	45	46.5	1.4	46.9	47	0.11	44.15	44	-0.1
Age square (Year)	2199. 3	2355. 8	156.5	2303. 4	2304. 3	0.83	2066. 1	2050. 5	-15. 6
Male (Yes=1)	0.93	0.93	0.001	1	1	0	0.952	0.95	-0.0 1
Education (Year)	5.31	5	-0.31	5.65	6.02	0.38	5.64	5.59	-0.0 5
Household size (#)	6.1	6.4	0.25	4.88	4.91	0.02	4.587	4.6	0.0 1
Hindu (Yes=1)	1	1	0	1	1	0	0.988	0.99	0.0 0
Schedule caste/tribe (Yes=1)	0.41	0.27	-0.15***	0.41	0.41	-0.01	0.406	0.39	-0.0 2
Below poverty line (Yes=1)	0.29	0.53	0.24** *	0.1	0.1	-0.01	0.181	0.18	0.0 0
Land own (ha)	0.69	0.75	0.06	0.79	0.8	0.01	0.762	0.73	-0.0 3
Source of income (Agriculture=1)	0.85	0.87	0.01	0.97	0.98	0.01	0.776	0.79	0.0 1
Asset index (Value)	-0.29	0.14	0.43** *	0.55	0.76	0.21	-0.107	-0.08	0.0 3
Household head experience (Year)	14.9	18.3	3.4***	18.34	18.93	0.59	16.26 8	15.92	-0.3 5
Kisan credit card (Yes=1)	0.38	0.4	0.03	0.61	0.67	0.05	0.504	0.52	0.0 1
Soil health card (Yes=1)	0.15	0.2	0.05	0.22	0.24	0.01	0.22	0.22	0.0 0
Pradhan mantri fasal bima yojana (Yes=1)	0.22	0.27	0.05	0.2	0.19	-0.01	0.167	0.17	0.0 0
Soil color (Black=1)	0.83	0.87	0.04	0.88	0.93	0.05* *	0.907	0.91	0.0 1
Irrigation (Groundwater=1)	0.83	0.93	0.10** *	0.87	0.93	0.06* **	0.822	0.84	0.0 1
Soil fertility (High=1)	0.52	0.6	0.08**	0.21	0.21	0.01	0.24	0.25	0.0 1
Number of observations			972			993			1089

Source: ICAR-IFPRI KVK Survey, 20

Appendix Table A3: Summary statistics for CB trainings of *primary* and *network* beneficiaries: Control vs. treatment group (matched differences)

	Panel A			Panel B		
	(1)	(2)	(3)	(4)	(5)	(6)
	Control	Primary beneficiary	Diff (2-1)	Control	Network beneficiary	Diff (5-4)
HD2967 (Yes=1)	0.25	0.26	0.02	0.23	0.26	0.03
Age (Year)	48.2	47.6	-0.6	44.6	44.7	0.1
Age square (Year)	2420	2375	-45	2108.3	2110.3	2.0
Male (Yes=1)	1.00	1.00	0.00	0.94	0.94	0.00
Education (Year)	5.57	6.05	0.48	5.58	5.62	0.05
Household size (#)	5.06	4.95	-0.11	5.09	5.04	-0.05
Hindu (Yes=1)	1.00	1.00	0.00	0.99	1.00	0.00
Schedule caste/tribe (Yes=1)	0.28	0.26	-0.02	0.45	0.42	-0.02
Below poverty line (Yes=1)	0.35	0.32	-0.04	0.21	0.21	0.00
Land own (ha)	0.93	0.98	0.05	0.81	0.75	-0.06
Source of income (Agriculture=1)	0.79	0.84	0.05	0.85	0.85	0.00
Asset index (Value)	0.82	1.29	0.47**	0.12	0.11	0.00
Household head experience (Year)	21.23	20.42	-0.81	17.30	17.29	-0.01
Kisan credit card (Yes=1)	0.61	0.63	0.02	0.53	0.52	-0.01
Soil health card (Yes=1)	0.32	0.32	0.00	0.18	0.17	-0.01
Pradhan mantri fasal bima yojana (Yes=1)	0.35	0.37	0.02	0.14	0.13	0.00
Soil color (Red=1)	0.79	0.79	0.00	0.84	0.84	0.01
Irrigation (Groundwater=1)	0.91	1.00	0.09***	0.87	0.89	0.01
Soil fertility (High=1)	0.23	0.21	-0.02	0.24	0.26	0.02
			580			764

Source: ICAR-IFPRI KVK Survey, 2019.