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Direct and Spillover Effects of Agricultural Advisory Services

Evidence from the Farm Science Centre in Uttar Pradesh, India

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Contents

Abstract

Agricultural advisory services are the most important knowledge-delivery institutions for accelerating the adoption of advanced technologies, and for improving farmers' learning abilities for their implementation. These technologies have implications for the larger goal of agricultural development and farmers' welfare. This study explores the spillover effects of an innovative public-sector program in India that provides agricultural advisory services. At the Farm Science Centre (known locally as *Krishi Vigyan Kendra* [KVK]), scientists demonstrate modern technologies and develop capacity-building programs. This paper examines the extent of direct and spillover benefits of KVKs. It also evaluates the impact of KVKs on the adoption of improved technologies for *primary* beneficiaries (those who receive the benefits directly from KVKs), and for those farmers who receive information flow from them.

The study is based on a primary survey of 1,496 wheat farmers in Uttar Pradesh, India. Spillover information flows are captured by: a) farmers who visit frontline demonstration (FLD) sites by their own curiosity and are categorized as secondary beneficiary farmers, and b) farmers who obtain information flows from primary and secondary beneficiaries being in their social network and are categorized as network beneficiary. Identification is achieved by exploiting non-universal coverage of KVKs, and through the availability of recall-based panels for pre- and post-intervention years on the adoption of improved technologies. The study applied matched difference-in-difference (MDID) approach to examine the effect of frontline demonstrations (FLDs) and training programs. It also examine pre-intervention trends to provide a check on the validity of our estimates.

Findings revealed that 3% of primary beneficiaries of FLDs can generate information spillover to 31% of farmers. For capacity building, the results showed that 3% of primary beneficiaries can generate information spillover to 27% of farmers. The key channel for spillover information flow was the network beneficiary. On a further note, the study establishes evidence of a positive impact on the adoption of a modern wheat variety—namely HD-2967—by primary beneficiaries, as well as secondary and network beneficiaries. Consistent with the information transmission channels, the magnitude of impact estimates are highest for primary followed by secondary and network beneficiaries. From a policy perspective, the study suggests a scaling-up of KVK's interventions. Establishing evidence on the role of social network channel to diffuse information flows for public-sector programs provides new insights for strengthening the outreach of such programs. Moreover, the evidence of intra-regional spillover effects have an implications for accounting these effects in conducting a cost-benefit analysis of these programs.

Keywords: Adoption, Krishi Vigyan Kendra, Social Network, Spillover

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Acronyms

AEZ	Agro Ecological Zone
BPL	Below Poverty Line
DID	Difference in Difference
FLD	Front Line Demonstration
FSC	Farm Science Centre
ICAR	Indian Council of Agricultural Research
KCC	Kisan Credit Card
KVK	Krishi Vigyan Kendra
MDID	Matched Difference in Difference
NGO	Non Government Organization
OFT	On Farm Trial
SC	Scheduled Caste
ST	Scheduled Tribe

1. Introduction

Frontier technologies and their adoption are key 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, Just, and Zilberman 1985; Duflo, Kremer, and Robinson 2011; Asfaw et al. 2012). However, providing agricultural advisory services to the larger farmer community is challenging due to a lack of economic resources.[2] An emerging literature examines alternative channels for diffusing information to highlight the role of social networks in technology dissemination (Bandiera and Rasul 2006; Conley and Udry 2010; Munshi 2004; Varshney, Joshi, and Roy 2019a). This literature focuses largely on identifying the social network effects of information diffusion. Less documented is the extent to which social networks can generate information spillovers. Although there is a large body of research that measures the spillover effects on research and development, the extent of spillover benefits of agricultural advisory services is still unknown.[3] This paper contributes to this strand of the literature by quantifying the extent of spillovers through social network channels for agricultural advisory services.

The study considers an innovative model of agricultural advisory services designed and implemented by the Indian Council of Agricultural Research (ICAR), known as *Krishi Vigyan Kendra* (KVK) or the Farm Science Centre, to estimate the extent of information spillovers. The key objective of KVKs is to provide a complete package of advisory services to farmers, ranging from identifying a suitable technology, to conducting frontline demonstrations (FLDs), to organizing capacity building programs, to ensuring demand-driven advisory services to farmers.[4] We consider the utility of FLDs and capacity-building programs for estimating direct and spillover benefits.[5]

FLDs of the frontier technologies are closely conducted under the direct supervision of scientists, and there is a provision for getting regular feedback from farmers to refine the technology for the local environment. This practice is analogous to on-site training in the context of the labor market. It advances farmers by highlighting its advantage over traditional technologies in a learning-by-doing framework and, in turn, has implication for reducing the risks involved (Foster and Rosenzweig, 1995). Neoclassical growth theory

[1] Griliches (1957); Feder, Just, and Zilberman (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%.
[3] See for example, Evenson (1989) and Griliches (1991).
[4] For more details, see Section 2.

highlights the role of the learning-by-doing framework to explain the formation of human capital and to predict its implications for the longer term income gains.[5] KVKs also conduct training programs for farmers on various agricultural activities, such as varietal evaluation, integrated crop management, and integrated nutrient management. Therefore, it is hypothesize that farmers who received training are more likely to switch away from traditional practices and move towards modern approaches of cultivation.

Studies on spillover benefits is largely focused on explaining the inter-regional diffusion of particular technology.[6] The studies on the intra-regional diffusion of particular technology are more limited. These studies largely focused on explaining the reasons regarding time taken by farmers to adopt agricultural technologies.[7] Less attempt has been made to understand the channels of diffusion in a smaller geography (for example, village). Within the village, the extent of spillover of information flows of public programs is still not known. Exploring the channels of diffusion for a smaller geography expand this stream of literature, and provide new insights to the policy makers for strengthening the effectiveness of public programs.

The primary objective of this paper is to examine the extent of spillovers for KVKs. We categorize farmers into the following categories: (1) *primary* beneficiary farmers who receive benefits directly from KVKs i.e. FLD is conducted on their own farm field and have a direct interaction with KVK scientists, (2) *secondary* beneficiary farmers who are curious about and visit the FLD sites to gain knowledge and learnt from primary beneficiaries, and (3) *network* beneficiary farmers who benefit from primary and secondary beneficiaries being in their social network. Categorizing *secondary* and *network* beneficiaries to capture the spillover of information flows provides an innovative feature to identify the channels within the village. In particular, the identification of *network* beneficiaries of public-sector programs provides novelty to this paper.

The secondary objective of the paper is to evaluate the impact of KVK's interventions on the adoption of improved technologies (disseminated through FLDs) for the following categories of farmers: (1) *primary* beneficiary, (2) *secondary* beneficiary, and (3) *network* beneficiary.[8] This analysis is warranted for several reasons. The first is to expand the regional literature that documents the impact of KVKs employing approaches which are associative in nature, rather than the identification based approaches. Second, to test whether the spillover of information flows can lead to in change in outcome indicators (for example,

[5] Arrow (1971).
[6] Griliches (1957)
[7] See, for example, Alcon et al. (2011)
[8] For training, we only define *primary* and *network* beneficiaries. See the section on empirical strategy for more detail.

adoption of new technology). Further, to examine whether the impact estimates vary by different sets of beneficiaries.

The study is based on a primary survey of 1,496 wheat farmers in Uttar Pradesh. Using 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*, we applied the matched difference-in-difference (MDID) approach to examine the effect of FLDs and training programs on these sets of farmers.

Our findings reveal that 3% of *primary* beneficiaries of FLD can generate an information spillover to 31% of farmers. In the case of training, findings show that 3% of *primary* beneficiaries can generate information spillover to 27 % of farmers. Our paper establishes evidence of a positive impact on the adoption of *HD-2967* for *primary, secondary* and *network* beneficiaries.

This paper contributes to the literature in several ways. It is among the few studies to document the extent of spillover benefits of any public-sector agricultural advisory service that operates through social network channel. Second, it provides an innovative design of collecting data to capture the spillover benefits that generate through a social network of farmers. Finally, the study contributes to the regional literature on the impact assessment of KVKs on the adoption of improved technologies employing robust econometric approaches.

Section 2 discusses KVKs in India and their objectives. Section 3 explores the study area and sampling design and provides summary statistics. In the review of summary statistics, we discuss farmers' profiles, adoption patterns of wheat cultivars, economics of major cultivars, and statistics on the social connections of farmers. Section 4 formulates the empirical strategy, and Section 5 discusses the results. The paper presents a conclusion and offers policy implications.

2. Farm Science Centre in India

The FSC (known locally as KVK), was launched by ICAR in 1974 in the Pondicherry district of India. The goal was to provide institutional support to the agriculture and allied sectors in order to assess location-specific technologies through assessment, refinement, and demonstrations. ICAR completed the rollout of KVKs in 2010s, and support services are now available in every district of the country. The total number of KVKs in India is 703. Figure 1 presents the state-wise number of KVKs in India. The top five states in terms of KVKs are Uttar Pradesh (83 KVKs), Madhya Pradesh (52), Maharashtra (47), Rajasthan (44), and Bihar (39). Other states have KVKs roughly equivalent to the number of districts in the state.

With the changing agricultural scenario, the activities of KVKs have been extended to technology diffusion, and women's empowerment, as well as to spreading awareness of government agricultural schemes. KVKs serve as a knowledge and resource center for agricultural technology and link the national agriculture research system with an extension system and farmers. The KVKs are financed 100% by ICAR, India, and have been sanctioned to serve agricultural universities, ICAR institutes, related government departments, and nongovernment organizations (NGOs) working in the agriculture sector. The mandate of KVKs is to (1) conduct "On-Farm Testing" (OFT) for the assessment of agricultural technologies across different farming systems, (2) carry out FLDs to demonstrate the implementation of frontier technologies, (3) increase the capacity development of farmers and extension workers to create awareness about frontier technologies, (4) work as a knowledge and resource center for the agricultural economy of the district, and (5) advise farmers on various subjects related to agriculture. Moreover, KVKs are involved in producing technological products such as seed, planting material, bio-agents, and so forth. KVK conducts FLDs in collaboration with other stakeholders to selected farmers and arranges field activities such as visits, training, and field days on site. This paper, however, is limited to studying FLDs and training programs conducted by KVKs.

In terms of budget allocation, the total budget of KVKs in India is about Rs 6860 million in 2016-17. In other metric, this is equivalent to Rs 34 per hectare which is a very small amount to be spent on the frontline extension system.[9] Gulati et al. (2018) shows that India spends about 0.70 percent of agriculture GDP on agricultural research, education, extension and training. Out of this 0.54 percent goes for agriculture research and education, and while a meagre 0.16 percent goes to extension and trainings. Direct involvement of scientists in agricultural advisory services is an innovative feature of KVKs. The report published by ICAR-ATARI (2017) finds that the average number of staff is about 13 per KVK for Uttar Pradesh; 60% are scientific staff and 40 % are nonscientific staff.[8]

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

3. Study Area, Sampling Design, and Summary Statistics

3.1.Study Area

The study region is Uttar Pradesh, a northern state of India. Uttar Pradesh is the most populous state and home to more than 200 million people, accounting for 17% of the country's population. Its geographical area is about 24.1 million hectares, which accounts for 7% of the area of India. About 16.5 million hectares of the land (68%) is under cultivation. An area sown more than once is 9.2 million hectares, and the gross cropped area is about 25.9 million hectares. More than 70% of the state's population depends on the agriculture and allied sectors. However, the land holding is less than a hectare per farmer. Marginal holding accounts for 79.4% of total land holdings, followed by 13.0, 5.7, 1.7, and 0.1 % land holdings for small, semi-medium, medium, and large holdings, respectively. Uttar Pradesh has a humid climate, with temperatures varying from 0 degrees Celsius to 50 degrees Celsius. Average rainfall varies from 650 mm from the southwest corner to 1,000 mm in the eastern and southeastern parts of the state. Tube wells (71%) and canals (18%) are the main sources of irrigation. In Uttar Pradesh, soil textures vary widely from region to region; types of soil include loam soil, sandy loam, sand soil, alluvial soil, rocky soil, and clay loam.

Uttar Pradesh is divided into nine agro-ecological zones (AEZs): the *bhabhar* and *tarai* region, western plain, midwestern plain, southwestern semi-arid, central plain, Bundelkhand, northeastern plain, eastern plain, and the *Vindhyan* region. Table 1 presents the major crops grown in the state's AEZs. These are wheat (41%), paddy (24%), sugarcane (9%), pearl millet (4%), and maize (3%). The present study is focused on wheat.

3.2.Sampling Design

The study is based on a primary survey of three AEZs of Uttar Pradesh, namely, southwestern semi-arid, central plain, and eastern plain.[10] The survey was conducted by IFPRI, the South Asia Regional Office, New Delhi, and supported by ICAR, New Delhi.

The survey was conducted in 12 districts of Uttar Pradesh. Four districts were selected from each AEZ. To select villages, we classified them into two categories: KVK villages and non-KVK villages. We define KVK villages as those where any type of intervention, such as FLDs or training programs, have been conducted by KVK staff; non-KVK villages are those where staff have not conducted any type of

[10] See Table 1.

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 done on a random basis. To select households, the complete household listing was compiled for each selected village. The four quintiles based on the total cultivable land were formed. From each quintile, five households were randomly selected.

Our household module collects information on awareness, participation, benefits (FLD, OFT, and others), and training regarding frontier agriculture technologies introduced by KVK. In addition, it captures information pertaining to varietal evaluation and recall-based information on the year of first adoption, and the adoption and dis-adoption pattern of the seed varieties. This module enabled us to construct a panel from 2014–2015 to 2017–2018 on the adoption of technologies. It also collects information on production, sale, and cost of cultivation, as well as details on household and demographic characteristics for the reference year 2017–2018.

The survey also gathers information on the relationships (friend, neighbor, and so on) for each farmer with the remaining 19 surveyed farmers of the same village. It also asked whether farmers discussed agricultural matters with each other and whether they accepted the advice of others including whether they adopted the new wheat variety.[11] This information is particularly important to capture the spillovers of information flows among farmers. This represents the novel aspect of this survey, which enables us to identify the *network* beneficiaries and to estimate the extent of information spillovers through social network channels.

3.3.Sample Profile of Wheat Farmers

This subsection discusses the sample profile of wheat farmers presented in Table 2 and how it relates to the adoption of improved technology. The average age of the household head is 45.8 years. Bultena and Hoiberg (1983) suggest 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 surveyed households were headed by men. This variable captures the systematic difference (if any) in the adoption of technology by different genders. In terms of years of schooling, the head of the household has an average 5.31 years of education. Feder, Just, and Zilberman (1985) highlight the role of education and argue for its positive role in the adoption of improved technology. Average household size is five. With regard to religion, the survey reveals that 98% of farmers are Hindu; remaining farmers belong to other religions. By social group, the survey shows that 46% of farmers belong to the schedule caste/tribe

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

(SC/ST) category. In the context of India, the SC/ST category of households is disadvantaged in terms of access to public-sector interventions and is an important correlate of poverty. About 23% of farmers possess a below-poverty-line (BPL) card.[12] Average land holding is about 0.77 hectares. Akinola (1987) suggests that as land size increases, farmers are more likely to adopt improved technology. Of all farmers surveyed, 78% reported cultivation activity as their primary occupation. The value of asset index is 0.02 on a scale from -2.7 to 9.3.[13] Feder, Just, and Zilberman (1985) argue that wealthier farmers have a greater ability to take the risks involved in the adoption of new technology. The survey also considered the average number of years of experience in farming, which was 18.3 years. In terms of institutional credit access, only 44% of household possess the Kisan Credit Card.[14] Varshney, Joshi, and Roy (2019b) show that this card is an important driver for the adoption of improved technologies. Our survey reveals that 15% of households possess a soil health card.[15] This card provides an analysis of soil and offers recommendations for nutrient management. This variable is important to capture a farmer's scientific approach to agriculture. In terms of access to crop insurance, 14% of farmers had access to Pradhan Mantri Fasal Bima Yojna (PMFBY: Prime Minister's Crop Insurance Scheme). Crop insurance can serve as a risk mechanism for farmers in the adoption of new technology. It is likely that farmers who have access to crop insurance have a higher likelihood of adopting 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 condition is expected to play an important role in 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 who belonged to KVK villages as compared to non-KVK villages were younger by 2.7 years, had a higher education level by 0.52 years, had a 3% greater Hindu population, were 5% more likely to belong to households whose primary source of income was agriculture, had less farm experience (three years), and had a 7% greater rate of having a soil health card. Further, farmers across KVK and non-KVK villages had different characteristics in terms of their soil color, soil fertility, and irrigation conditions.

[12] 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.

[13] Asset index is constructed by applying principal component analysis using the ownership of 22 assets such as tractor, two-wheeler, four-wheeler, etc.

[14] Kisan credit card was introduced by the government of India to provide short-term credit for farmers during the planting and harvesting seasons.

[15] The soil health card scheme, launched in 2015, issues a card that provides farmers with crop-wise recommendations for nutrients and fertilizers on the basis of a soil testing analysis.

3.4. Adoption Patterns

Figure 2 shows the adoption patterns of wheat cultivars for 2015–2016 and 2017–2018. In 2015–2016, the results show that 34% farmers adopted *PBW-343* (the variety released in 1996). *PBW-502* (in 2004) was adopted by 24% of farmers; *HD-2967* (in 2011), by 26% of farmers, while 17% of farmers adopted other cultivars.[16] In 2017–2018, *PBW-343*, *PBW-502*, and *HD-2967* were used by 32%, 8%, and 47% of farmers, respectively, while 14% adopted other cultivars. These results suggest varietal substitution away from *PBW-502* and toward *HD-2967.*

Table 3 compares the yield, revenue, operational cost, and profit of *HD-2967* with those of *PBW-502* and *PBW343*, respectively. Panel A shows that *HD-2967* adopters earned 2.1 quintal per hectare more yield (6% higher) as compared to farmers using *PBW-502*. It also reveals that *HD-2967* adopters earned 7.7% higher revenue. Panel A also shows that farmers using *HD-2967* had a 4% lower operational cost as compared to those using *PBW502*, but the results were insignificant. Overall, the adoption of *HD-2967* resulted in Rs of 4449 more profit (per hectare) as compared to the use of *PBW-502*. The evidence shows that farmers using *HD-2967* had an 8% higher yield, 8% higher revenue, and 6% higher operational costs, and had Rs 3355 more profit (per hectare) as compared to farmers using *PBW-343*. These results may explain the pattern of increasing use of *HD-2967* and decreasing use of *PBW502* in the study region.

3.5. Social Connections

Table 4 presents the percentage of farmers with social connections in the village. According to the survey design, these connections ranged from zero, indicating that a farmer was social isolated and didn't discuss agriculture-related matters with anyone, to 19 social connections, indicating interaction with everyone. We first estimate the number of farmers with zero social connections, finding that 7.2% didn't interact with anyone in the village. With regard to one social connection, the result shows that there were 4% who interacted with only one person in the village. For two, three, four, five, and six connections, the result reveals percentages of 2.7, 6.6, 16.9, 18.9, and 18.5 , respectively. This information enables to estimate the social connections of farmers within the village.

Figure 3 summarizes Table 4 and presents the average social connection for each farmer within the village by relationship. The results reveal that, on average, each farmer is connected with 3.5 friends, 0.63 relatives, 0.67 neighbors, and 0.14 other farmers. Overall, each farmer in the village is connected with 4.94 farmers.

[16] Other cultivars include *WH-511*, *WH-711*, *HD-3086*, and *HD-2329*.

Estimates of social connections provides new insights to policy makers to better strategize the information diffusion programs through social network channel. This finding clearly reveals that the key relationship for social network formation is friendship.

4. Empirical Strategy

4.1. Quantifying Spillovers

To capture the extent of spillovers of KVKs, we categorized the farmers into the following categories: (1) *primary* beneficiary farmers, who received benefits directly from KVK interventions;[17] (2) *secondary* beneficiary farmers, who due to their own curiosity had visited FLD sites and gained knowledge;[18] and (3) *network* beneficiary farmers, who benefited from having *primary* and *secondary* beneficiary farmers in their social network. *Secondary* beneficiaries received information flows from *primary* beneficiaries, while *network* beneficiaries received information through both *primary* and *secondary* beneficiaries and capture spillovers.

In the case of FLDs, the idea of proximity to the source of information may serve as a key channel for attracting other farmers to visit and learn about the technology (Munshi, 2004). Therefore, it is likely the case that the FLDs may attract farmers to visit and learn from the demonstration. Our household module includes direct questions to capture *secondary* beneficiaries and is denoted by '*S*'—in other words S_i=1, if farmer 'i' visits FLDs conducted by KVK on any other farmer's plot in the same village. Therefore, the percentage of *secondary* beneficiaries in FLD villages can be estimated as follows:

Secondary beneficiaries (%) = (total number of *secondary* beneficiaries in the FLD villages/total number of farmers in the FLD villages)*100

The second spillover channel operates through social networks. A growing literature (Bandiera and Rasul 2006; Conley and Udry 2010) has shown a positive and significant impact of social networks on information diffusion. Identifying *network* beneficiaries that operate through social network channels involves two steps. The first step is to calculate the number of network members benefited by KVK's intervention for each farmer. This is done through the following equation:

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

[17] Primary beneficiaries are defined on the basis of farmers receiving KVK intervention for 2016–2017.
[18] Secondary beneficiaries are defined only in the case of FLD, but not for training programs.

Where 'i' denotes an individual farmer and 'v' denotes the remaining surveyed farmers of the same village.[19] *SN* takes value 1 if farmer 'i' is socially connected with farmer 'v', and 0 otherwise.[20] A takes value 1 if farmer 'i' discusses and accepts agricultural advice from the socially connected farmer 'v', and 0 otherwise. *KVKB* takes value 1 if farmer 'v' is either a *primary* or *secondary* beneficiary, and 0 otherwise. Therefore, *SN_A_KVKB* (the total number of social network-member farmers) corresponds to farmer 'i', who benefited from KVK intervention.

Then, we define *network* beneficiary (N) as those farmers which comprises at least one member from their social network members as the beneficiaries of KVK's intervention i.e.

$$\boldsymbol{N}_i = 1 \;\; if \; SN\_A\_KVKB_i > 0. \qquad \text{(Eq.2)}$$

Now, the percentage of *network* beneficiaries in FLD villages can be estimated as follows:

Network beneficiaries (%) = (total number of *network* beneficiaries in the FLD villages/total number of farmers in the FLD villages)*100

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

Our empirical strategy exploits the two important aspects of KVK's interventions to measure the impact of FLDs and training programs on the adoption of improved technology. The first aspect is the non-universal coverage of KVK's interventions. The second aspect is the availability of the recall-based panel's data for 2014–2015, 2015–2016, 2016–2017, and 2017–2018 on the adoption of improved technologies. Where 2014-2015 and 2015-2016 are the pre-intervention years. And 2016-2017 and 2017-2018 are the intervention and post-intervention years, respectively.

This enables us to compare changes in outcomes between the treatment group (KVK beneficiary) and the control (non-beneficiary) group from 2015–2016 to 2017–18. In this case, the MDID impact estimates can be interpreted as the impact of KVK under the assumption that in the absence of KVK, a change in outcomes

[19] In each village, we surveyed 20 farmers.

[20] A socially connected farmer is either a friend, neighbor, relative, or other known farmer with whom the farmer interacts.

would not be systematically different in either the treatment or control groups. To identify the impact, we estimate the following DID specification:

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

(Eq.3)

where *i* stands for individual, *v* for village, *d* for district, and *t* for year (either 2015–2016 or 2017–2018). Y takes value 1 when wheat farmers adopt *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 being treated by KVK in 2016–2017. ε is the error term and it captures residual factors that affect adoption rates. The impact parameter of interest is given by α_3. The key identifying assumption is that the treatment and control group grow with similar time trends in the absence of KVK intervention.

We adopted a matched MDID approach introduced by Heckman et al. (1999) to identify the impact of KVKs. It 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 FLD, the evolution of adoption of *HD-2967* (a new wheat variety) would be the same across the two groups—namely, treatment, and control—then any observed difference in the presence of FLD may be attributed to the intervention itself.

What makes one hesitate in making this assumption is that the two groups of farmers may be different from each other, and they may grow differently if their villages have differential time trends: On average, KVK villages: are younger (in terms of age); have a higher education level by 0.52 years; have less farm experience; have 5% more households with agriculture as a primary source of income; have 7% more farmers with a soil health card; and have different characteristics in terms of soil texture, soil fertility, and irrigation conditions (see Table 2). Moreover, tables 5 and 6 present the unmatched differences in farmers' characteristics for FLDs and training programs, respectively. These tables suggest that farmers' characteristics are different and that it is more likely that identifying the assumption of similar time trends may not hold.

We attempt two approaches to address this concern. First, we match each treated farmer with a weighted combination of control farmers such that the predicted probability of treating is similar in both. We then compare the outcomes in treated farmers with the weighted average of adoption rate across matched control farmers. This ensures comparing like with like in terms of the likelihood of being treated and makes it more likely that the assumption holds. Appendix Tables 2 and 3 show that matching improves the likelihood of similarity among treatment and control groups. Second, we test the assumption by looking at data from pre-intervention years (2014–2015 and 2015–2016) and verifying that it holds during this period. Finding similar trends in the outcomes (adoption of new wheat variety) across treatment and control group before the intervention ensures that identifying assumption holds good.

Implementing the matching procedure essentially involves three steps. First, we derive farmer-level weights using the kernel matching procedure,[21] Next, 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. Finally, using farmer-level weights to the double-difference specification in the common support region provides MDID impact estimates.

We estimate the following regression on farmers belonging to the region of common support to identify the effect of FLD on the adoption of improved technology for primary beneficiaries:

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

where *i* stands for individual, *v* for village, *d* for district, and *t* for year (either 2015–2016 or 2017–2018). Y takes value 1 when wheat farmers adopt 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 control group of farmers from non-KVK villages is that farmers belongs to KVK village are more likely to receive benefits of KVKs from spillover of information flows.[22] In that case, the control group is not considered as a true counterfactual group of farmers. ε is the error term and captures residual factors that affect adoption rates. Estimating the above equation with matching weights makes α_3 a MDID estimator. It captures the differential effect of the FLDs on primary beneficiaries.

We run the similar specification (4) for *secondary* (S) and *network* (N) beneficiaries separately to identify the impact of FLD. The treatment variable for each is defined as follows: *FLD (S)* takes value 1 if the farmer

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

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

is the *secondary* beneficiary and 0 if the farmer resides in non-KVK village, *FLD (N)* takes value 1 if the farmer is a *network* beneficiary and 0 if the farmer resided in non-KVK villages.

To identify the impact of training programs, we run the similar specification (4) for *primary* (P) and *network* (N) beneficiaries separately to identify the impact of training programs. *Training (P)* takes value 1 if the farmer is the *primary* beneficiary and has not received the benefits of FLD, and 0 if the farmer resided in non-KVK villages. Here, we consider only those farmers who received only training but not FLDs as our treatment group. Our sample comprises few cases where farmers received the benefits of both FLDs and trainings. We drop those farmers in order to see the effect of training programs only. Training (N) takes value 1 if the farmer is a *network* beneficiary and has not received the benefits of FLD, and 0 if the farmer resided in a non-KVK village.

5. Results and Discussion

5.1. Estimating Spillovers

This subsection presents the percentage of *secondary* and *network* beneficiaries who received the information flows generated through KVK's interventions. Figure 4 plots the percentage of *primary*, *secondary*, and *network* beneficiaries of FLDs in FLD villages. Out of all surveyed farmers in the FLD villages, 3% farmers reported FLD access on their own field, that is, *primary* beneficiaries, while 6% reported access through visiting the FLDs, which were conducted on another farmer's field, that is, *secondary* beneficiaries. Using equation 1 and 2, we estimate the percentage of *network* beneficiaries. The result shows that 25% of farmers benefited from FLDs through the social network channel. This clearly suggests that 3% of *primary* beneficiaries can generate spillover flows to 31% of farmers. Thus, a total of 34% beneficiaries were helped through FLDs.

Figure 5 presents the percentage of *network* beneficiaries of training conducted on varietal evaluation in KVK villages. Results indicate that 3% of farmers are primary beneficiaries such that they have received training on varietal evaluation conducted by KVKs. In addition, 27% of farmers were helped through beneficiaries through the social network channel. Overall, 30% of beneficiaries were aided through trainings. It is important to note that the *network* beneficiaries are almost the same in both cases.

Above findings reflect the importance of the social network channel for the information flows. The extent of spillovers is very prominent. There is currently no research that estimates the extent of spillovers through the social network channel. Therefore, these finding provides new insights to the literature on the intra-regional technology diffusion. At the same time, it corroborates with the literature that shows the importance of social network channel in the information diffusion (see for example, Bandiera and Rasul 2006; Conley and 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 coefficients of impact estimates, respectively.[23] We interpret the MDID coefficients, as these estimates are more robust and more likely to validate the identifying assumption.

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

The coefficient α_1 captures the effect of time on the adoption of *HD-2967* for wheat farmers. The estimated coefficient shows a 16.9% increase in the adoption of *HD-2967* over the period 2015–2016 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 of *HD-2967* is 7.4% lower for *primary* beneficiaries compared to non-beneficiaries in 2015–2016, that is, before KVK's intervention.

Our coefficient of interest is α_3 that measures the impact of FLD on the adoption of *HD-2967.* It shows that *primary* beneficiaries have 51.8% higher adoption rates compared to non-beneficiaries. This shows a strong positive impact of FLDs on *primary* beneficiaries for the adoption of improved technologies. It is important to recall from the previous paragraph that *primary* beneficiaries had lower adoption rates before KVK's intervention. Despite this fact, the results for *primary* beneficiaries are large and significant. Kondylis, Mueller, and Zhu (2017) conducted an extension network experiment in Mozambique showing that those farmers who directly benefit from extension agents have a large (ranging from 28.3% to 65%) impact on the adoption of technologies.[24] Our findings are robust to the pre-intervention trend that shows a similar trend across *primary* beneficiaries and nonbeneficiaries over the period 2014–2015 and 2015–2016, in the absence of any FLD interventions.[25]

Table 8 presents the impact estimates for the adoption of *HD-2967* for those who received training from KVK staff. The coefficient α_1 shows a 20.8% increase in the adoption of *HD-2967* over the periods 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 in *primary* beneficiaries of training was similar to those of non-beneficiaries i.e. before KVK's intervention. The coefficient α_3 that measures the impact of training revealed a 21.3% higher adoption rate in *primary* beneficiaries as compared to non-beneficiaries. It is important to observe that the magnitude of impact estimate is smaller for training as compared to the FLD beneficiaries. Munshi (2004) highlights that the demonstration has reduced the perceived risks and increased the likelihood of adoption. This may explain the stronger impacts for FLDs. The results are robust to pre-intervention trends.[26]

Overall, the result shows a strong positive impact of KVK's interventions; however, the effect is more pronounced for FLDs than for the training program.

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[24] They estimate the impact estimates for the adoption of strip-tillage, pit planting, and contour farming.
[25] See coefficient of Model 4 in Table 7.
[26] See coefficient α_3 of Model 4 in Table 8.

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

This subsection presents the impact of FLD and training programs on *secondary* and *network* beneficiaries. Table 9 presents the FLD's impact on the adoption of *HD-2967* on these beneficiaries. Panel *A* and *B* present the regression coefficients from the DID and MDID models, respectively. Model 1 and 2 present the impact estimates for *secondary* and *network* beneficiaries, respectively, while Models 3 and 4 of the same table present the pre-intervention trends corresponding to Model 1 and 2, respectively. Below, 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's interventions on *secondary* and *network* beneficiaries.[27]

In the case of FLDs, the impact estimates reveal that *secondary* beneficiaries have a 12.6 % higher adoption rate of *HD-2967* as compared to non-beneficiaries. Although the effect on secondary beneficiaries is positive, the magnitude is smaller than for *primary* beneficiaries. This result is consistent with Kondylis, Mueller, and Zhu (2017), who show a limited impact on other indirect beneficiaries. Our findings on *secondary* beneficiaries suggest that FLDs also benefit those farmers who were curious and visited FLDs. This was the intended objective of FLDs. With regard to the *network* beneficiaries, the result shows an 11.5% higher adoption rate of *HD-2967* for these beneficiaries as compared to non-beneficiaries. This result is in line with the literature, which indicates that farmers' adoption choice is influenced by the adoption decision of their network members.[28] Models 3 and 4 of the same table shows that the results are robust to pre-intervention trends for *secondary* and *network* beneficiaries, respectively.

Table 10 presents the training's impact on the adoption of *HD-2967* on *network* beneficiaries. The impact estimates demonstrate that *network* beneficiaries have shown a 16.1% higher adoption rate of *HD-2967* as compared to non-beneficiaries.[29] As expected, the magnitude of increased adoption is smaller as compared to those who benefited directly (*primary* beneficiary) from training programs. The above results are robust to pre-intervention trends.

In sum, we establish evidence of a positive impact on the adoption of wheat variety *HD-2967,* for *secondary* as well as *network* beneficiaries. Further, the results reveal that the impact estimates are marginally higher for *secondary* beneficiaries as compared to *network* beneficiaries.

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[27] Interested readers may refer to Table 9 for the estimated coefficients of α_1 and α_2.
[28] See for example, Bandiera and Rasul (2006).
[29] See Table 10 for α_1 and α_2.

6. Conclusions and Implications

This paper had two broad objectives. The first was to examine the extent of spillovers for public-sector KVKs by categorizing farmers as (1) *primary* beneficiaries, who received the benefits directly from KVKs; (2) *secondary* beneficiaries, who, due to curiosity, visited the FLD sites and gain knowledge, and (3) *network* beneficiaries, who benefited from *primary* and *secondary* beneficiaries being in their social network. The second objective was to evaluate the impact of FLDs and training programs on these sets of farmers for the adoption of *HD-2967* (a demonstrated modern wheat variety that provides higher yield and profit than local varieties).

Our findings revealed that 3% of FLDs can benefit 6% of farmers who visit and learn from FLD locally, that is, *secondary* beneficiaries, and can benefit 25% of farmers who may take advantage of beneficiary farmers being in their social network, that is, *network* beneficiary. In the case of trainings, 3% of training beneficiaries can benefit 27% of farmers who may take advantage from beneficiaries being present in their network channel, that is, *network* beneficiary. These results reflect the significance of the social networking channel in technology diffusion. Banerjee et al. (2014) showed that central individuals in the village can result in higher diffusion rates as compared to random individuals or opinion leaders.[30] Their study also provide evidence that it is possible to identify central individuals cost effectively without gathering any network information. This provides a new avenue researchers can take to explore the change in the extent of spillovers when the *primary* beneficiary is the central individual. Establishing the evidence on the role of social network channel to diffuse information flows of public programs provides new insights to the policy makers in strengthening the outreach of such programs.

We also provide evidence on the impact of FLDs and training programs on the adoption of *HD-2967*. Our results reveal that KVK's interventions have a strong positive impact on *primary* beneficiaries for the adoption of *HD-2967*. The effects are more pronounced for FLDs as compared to *training* beneficiaries. With regard to the spillover effects, the results show that *secondary* and *network* beneficiaries of FLDs also have a positive impact on the adoption of *HD-2967*. Consistent with the information transmission channels, the magnitude of impact estimates are highest for *primary* followed by *secondary* and *network* beneficiaries.

For training, the results reveal that *network* beneficiaries also have a positive impact on the adoption of *HD-2967*.

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

From a policy perspective, the strong impact of KVKs, particularly for FLDs, suggests a scaling-up of these interventions, and the evidence on spillover effects provides new insights into how to account for these effects in cost-benefit analyses of such programs.

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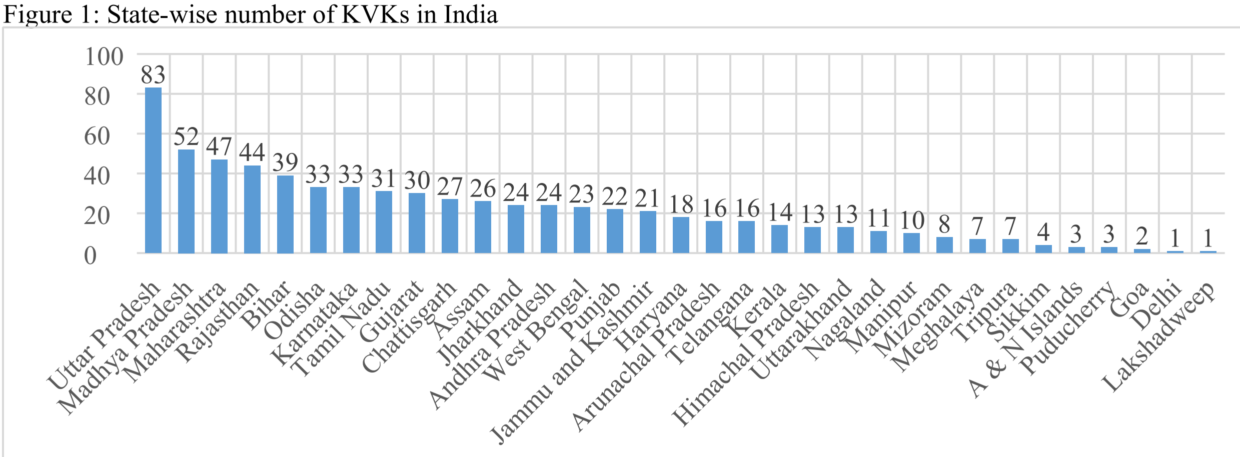
Tables and Figures

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

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

Figure 1: State-wise number of KVKs in India



Source: Indian Council of Agriculture Research (ICAR), New Delhi, information accessed in February 2019.

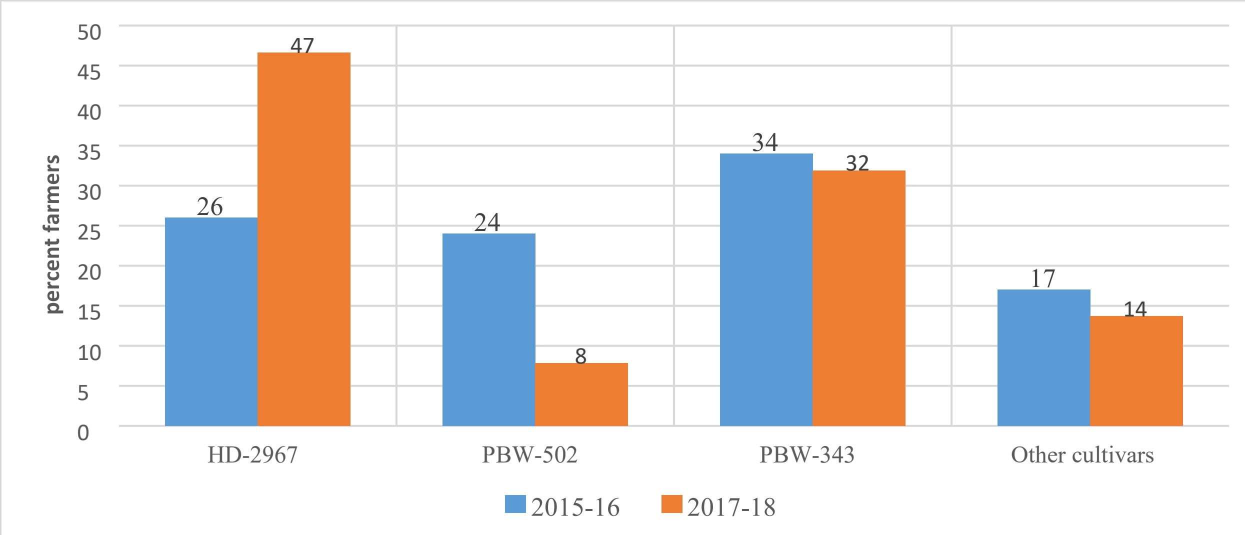
Table 2: Profile of wheat farmers, for Uttar Pradesh

Farmer's characteristics	All farmer				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 yojna (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 such as tractor, two-wheeler, four-wheeler, etc. Kisan credit cards provide an institutional credit to farmers for providing 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 yojna provides insurance for crops. KVK villages are those where KVKs have conducted interventions such as FLDs. Non-KVK villages are those where KVK has not conducted any type of intervention.

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 the public sector. HD-2967 was released in 2011. PBW-502 was released in 2004. PBW-343 was released in 1996.

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

Panel A			
	(1)	(2)	(3)
	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			
	(1)	(2)	(3)
	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.

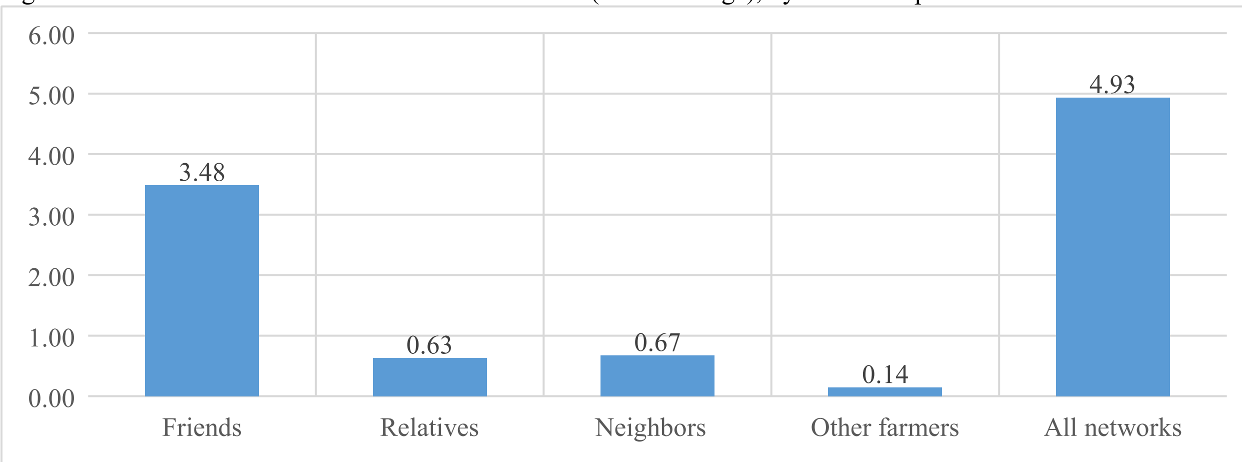
Table 4: Estimating social connections (within village), % farmers

Number of social connections 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.

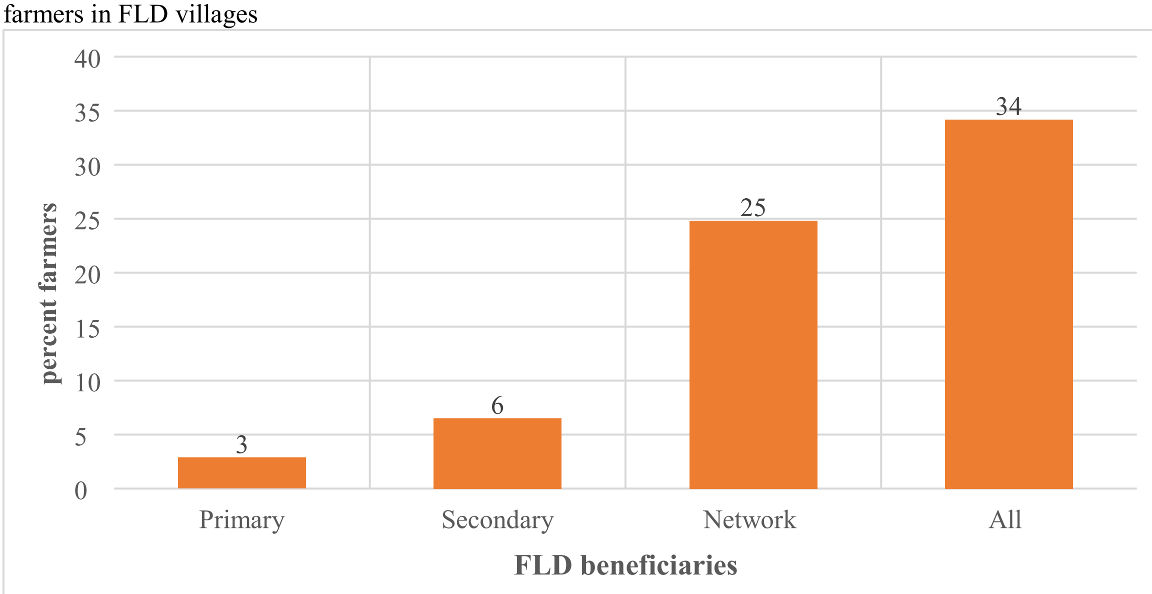
Note: Farmers with zero social connections in the village are interpreted as those who didn't interact with anyone regarding agriculture-related matters. Farmers with 19 social connections suggests that they interact with everyone regarding agricultural matters.

Figure 3: Estimated social connections for each farmer (within village), by relationship



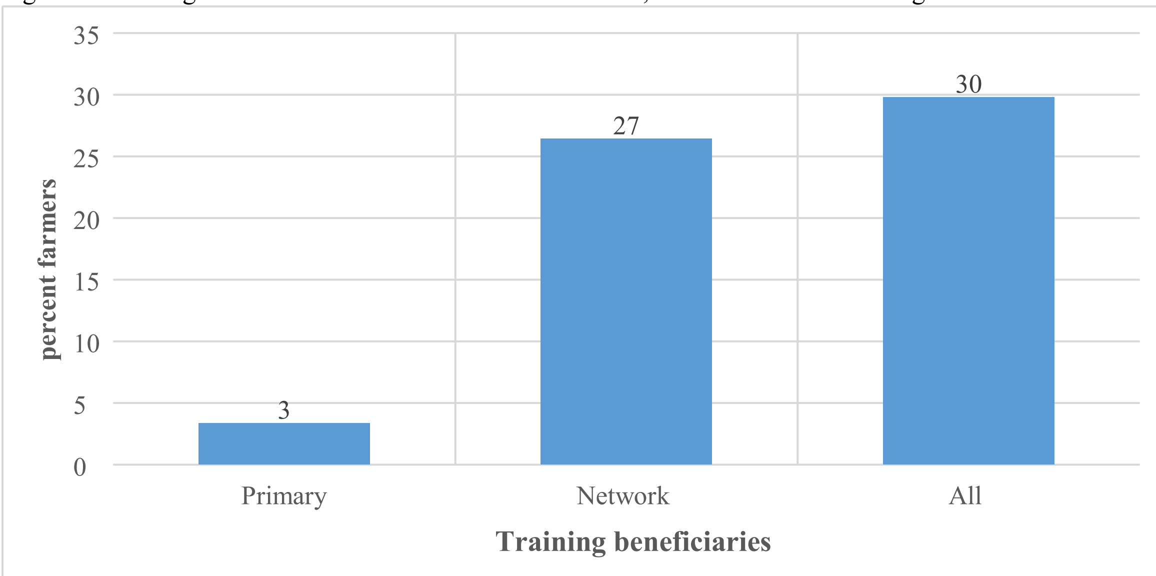
Source: ICAR-IFPRI KVK Survey, 2019.
Note: All networks include friends, relatives, neighbors, and other farmers.

Figure 4: Frontline demonstrations (FLD) beneficiaries of varietal evaluation wheat cultivar HD-2967, % farmers in FLD villages



Source: ICAR-IFPRI KVK Survey, 2019.
Note: Primary beneficiary farmers who receive benefits directly from KVKs i.e. FLD is conducted on their own farm field and have a direct interaction with KVK scientists. Secondary beneficiary farmers who are curious about and visit the FLD sites to gain knowledge and learnt from primary beneficiaries. Network beneficiary farmers who benefit from primary and secondary beneficiaries being in their social network. All beneficiaries include primary, secondary, and network beneficiaries.

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



Source: ICAR-IFPRI KVK Survey, 2019.

Note: Primary beneficiary farmers who receive benefits directly from KVKs i.e. FLD is conducted on their own farm field and have a direct interaction with KVK scientists. Network beneficiary farmers who benefit from primary beneficiaries being in their social network. All beneficiaries include both primary and network beneficiaries.

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 yojna (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 yojna (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: Impact estimates of FLDs on primary beneficiaries for the adoption of HD-2967 (new wheat variety)

	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: Impact estimates of trainings on the adoption of HD-2967 (new wheat variety)

	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 training programs in 2016–2017, i.e., primary beneficiaries, and is denoted by a dummy variable *Training (P).* In Models 1 and 2, *Training (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 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, and soil fertility. Kernel procedure is used to perform matching. Models 2 and 4 regressions are in the common support region. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.00$

Table 9: Impact estimates of FLDs secondary and network beneficiaries on the adoption of HD-2967 (new wheat variety)

	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, 2, 5, and 6, it takes value 1 for 2017–2018 and 0 for 2015–2016. In Models 3, 4, 7, and 8, it takes value 1 for 2015–2016 and 0 for 2014–2015. *FLD (S)* is a dummy variable and takes value 1 if farmers are secondary beneficiaries, and 0 for farmers residing in non-KVK villages. *FLD (N)* is a dummy variable and takes value 1 if the farmer is in a social network of FLDs beneficiaries, and 0 for farmers residing 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, agriculture dependency, 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. In Panel B, all regressions are in the common support region. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table 10: Impact estimates of trainings on network beneficiaries on the adoption of HD-2967 (new wheat variety)

	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

Appendix Table A1: Adoption of wheat cultivars by its 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 yojna (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, 2019.

Appendix Table A3: Summary statistics for trainings 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 yojna (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.

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