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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

We evaluate a large-scale model of agricultural advisory services, known as *Krishi Vigyan Kendra* (KVK) or Farm Science Centers, introduced by the Government of India to facilitate smallholder adoption of new agricultural technologies. The study first evaluates the impact of frontline demonstrations and capacity-building programs conducted by KVKs and aimed at promoting a new wheat variety (HD-2967); it then examines gains in the speed of diffusion at the district level. The study's second objective is to estimate the spillover effects of KVKs through social networks. The study identifies network beneficiaries based on a "networks within sample" approach. The study uses a matched difference-in-differences approach and sample of 1496 wheat farmers in Uttar Pradesh, India. The finding shows that frontline demonstrations and capacity-building programs positively impact the adoption of HD-2967. The magnitude of the impacts is larger for KVK beneficiaries, but substantial gains also arise for network beneficiaries. The study underscores the importance of frequently conducting interventions to influence adoption on aggregate at the district level. 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, emphasizing frontline demonstrations, capacity-building programs, and spillovers in extending the scope of KVKs.

1. Introduction

Frontier technologies and their adoption are vital to increasing agricultural productivity and farmers' income. Despite this, the adoption of frontier technologies remains low in many developing countries (Bergoeing, Loayza, & Piguillem, 2010; Takahashi, Muraoka, & Otsuka, 2020). Existing agricultural extension models in developing countries have been scrutinized for quite some time in the literature (Anderson & Feder, 2007; Davis, Babu, & Ragasa, 2020; Leeuwis, 2013; Norton & Alwang, 2020; Swanson, 2008). Constraints such as lack of awareness, insufficient access to credit, inherent risk, and lack of proficiency (Barrett, Carter, & Timmer, 2010; Besley & Case, 1993; Feder, Just, & Zilberman, 1985; Simtowe, Amondo, Marenya, Sonder, & Erenstein, 2019; Wossen et al., 2017) limit the level and speed of adoption.

Several attempts have been made to identify best practices for diffusing information, including network-driven targeting approaches to identify seed farmers and individuals in the community, experimental methods with different variants of training and visitation models, and the use of digital means (Banerjee, Chandrasekhar, Duflo, & Jackson, 2019; Beaman, BenYishay, Magruder, & Mobarak, 2021; Magruder, 2018; Oyinbo, Chamberlin, & Maertens, 2020; among others). Magruder (2018) reviews existing extension models extensively and highlights experimental approaches in which different variants of extension practices are evaluated. However, experimental techniques have a scaling problem. It is not clear if methods that appear superior in terms of reach and adoption in experimental settings also do so at scale. To reduce the transaction costs of smallholders seeking new technologies, the Indian government introduced a nationwide model of agricultural advisory services, known as *Krishi Vigyan*

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Kendra (KVK) or Farm Science Centers. KVKs are available at the district level (an administrative subdivision of states) and provide a complete package of demand-driven advisory services to farmers—including assisting with the identification of suitable new technologies, conducting frontline demonstrations, and organizing capacity-building programs. See Section 3 for details on frontline demonstrations and capacity-building programs. Frontline demonstrations of frontier technologies are carefully conducted under the direct supervision of scientists, who get regular feedback from smallholders that allows them to refine technologies for specific local environments. Thus, the system is implemented in a learning-by-doing framework. We focus on agricultural advisory services that improve awareness and proficiency in studying the adoption process.

The objectives of this study are threefold. The first is to assess the impact of frontline demonstrations and capacity-building programs, conducted by KVKs, on adopting a new wheat variety. Since KVKs are highly scalable, we want to understand the process of diffusion at the aggregate level. Thus, the second objective is to examine gains in the speed of diffusion on aggregate at the district level. The third is to estimate KVKs' spillover effects through social networks. In particular, the paper first identifies network beneficiaries and then evaluates the impact on network beneficiaries of adopting a new wheat variety. Quantifying the contribution of spillover effects through social networks thus adds new insights to the literature. The study uses survey data on 1,496 wheat farmers in Uttar Pradesh, India, and information on farmers' relationships (friend, neighbor, relative) with other randomly surveyed farmers in the same village. The survey uses a phased-out strategy of selecting villages for KVK interventions and a recall-based panel dataset for 2014–15, 2015–16, 2016–17, and 2017–18 on farmers' adoption of a new wheat variety, HD-2967.[1] Finally, the study uses a matched difference-in-differences approach to evaluate the impacts.

This paper contributes to the literature in several ways. First, it is one of the recent studies to evaluate the impact of a large-scale agricultural advisory service.[2] Evaluation of frontline demonstrations, in particular, connects this paper with the "seeing is believing" literature on the adoption of agricultural technologies (see Kondylis, Mueller, & Zhu, 2017). Second, the study extends the social network literature by estimating how social networks can generate information spillovers associated with public-sector agricultural advisory services.[3] Finally, the study focuses on implications for the design of large-scale agricultural advisory services and thus contributes to the growing literature on technology adoption to understand the diffusion process.

The study finds that frontline demonstrations increased the adoption rate of HD-2967 (a new wheat variety) by 22 percent and that capacity-building programs increased the adoption rate by 26 percent. Although the impact is larger for primary and secondary beneficiaries, substantial gains also arise for network beneficiaries (10.4 percent for frontline demonstrations and 10.6 percent for capacity-building programs). To influence adoption on aggregate at the district level, the findings from this study emphasize the importance of conducting frequent interventions.

The rest of the paper is organized as follows. Section 2 discusses KVKs' role 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 and offers policy implications.

[1] Wheat is cultivated in the rabi season (November to April).

[2] Exceptions include a study by Kumar, Singh, Saroj, Madhavan, and Joshi (2019) that conducts a macro analysis of KVKs, but they do not study the adoption of new technologies as a consequence of KVKs.

[3] Literature on social networks (Munshi, 2004; Bandiera & Rasul, 2006; Conley & Udry, 2010; Maertens & Barrett, 2013; Beamen et al. 2021) has focused largely on the impact of information diffusion through social networks, but does not study the extent to which social network can generate information spillovers of public-sector agricultural advisory services.

2. Farm Science Centers in India

The Farm Science Centers (known as KVK) model was launched by the Indian Council of Agriculture Research (ICAR) in 1974 in the Pondicherry district of India to provide institutional support to agricultural 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. KVKs are wholly financed by the council and serve state agricultural universities, council institutes, government departments, and non-governmental organizations working in the agriculture sector. KVKs are unique in that they rely on scientists to deliver agricultural advisory services. KVKs operate in all 725 districts of India.[4] Today Uttar Pradesh has 83 KVKs in operation across its 75 districts. Appendix Fig. A1 presents the distribution of KVKs by state in India.

The Government of India mandates that KVKs provide several specific services, including (a) conducting "on-farm testing" for the assessment of agricultural technologies across different farming systems; (b) carrying out frontline demonstrations to demonstrate the implementation of frontier technologies; (c) working to increase the capacity of farmers and extension workers by creating awareness of frontier technologies; (d) serving as a knowledge and resource center for the agricultural economy in each district; and (e) advising farmers on various subjects related to production agriculture. Amid changing technology and agricultural scenarios, KVKs' activities have been extended to include diffusing technology, empowering women, and increasing awareness of government agricultural schemes. Moreover, KVKs produce technological products such as seeds, planting material, bio-agents, and irrigation systems. KVKs' total budget in India was about 6.9 billion Indian rupees (INR) in 2016–17. This is equivalent to INR 34 per hectare, a relatively minuscule investment in the frontline extension system.[5] A recent study by Gulati, Sharma, Samantra, and Terway (2018) showed that India spends about 0.70 % of its agricultural gross domestic product on agricultural research, education, extension, and training. About 0.54 % of the budget was spent on agricultural research and education, and 0.16 % was spent on extension and training programs.

3. Data

3.1. Survey and study area

The survey was conducted in Uttar Pradesh, a northern state of India. Uttar Pradesh is the most populous state, home to more than 200 million people and accounting for 17 % of the country's population. The geographical area of Uttar Pradesh is about 24.1 million hectares, or 7 % of India's total area. About 16.5 million hectares (68 %) are under crop cultivation. The gross cropped area in Uttar Pradesh is about 25.9 million hectares. More than 70 % of the state's population depends on agriculture and allied sectors for livelihood. Marginal holdings account for about 79 % of total land holdings, followed by 13 % for small holdings, 6 % for semi-medium holdings, 2 % for medium holdings, and 0.1 % for large holdings. Uttar Pradesh's climate is humid, with temperatures varying from 0 to 50 degrees Celsius.

[4] Bigger districts have multiple KVKs. For example, Uttar Pradesh's Gorakhpur district has two KVKs.

[5] In India, the average revenue farmers earn from cereal cultivation on one hectare of land is INR 50,000–60,000.

Average rainfall varies from 650 mm (mm) in the southwest corner to 1,000 mm in the eastern and southeastern parts of the state. The primary sources of irrigation are tubewells (71 %) and canals (18 %). In Uttar Pradesh, soil textures vary widely, from loam soil, sandy loam, and sand soil to alluvial soil, rocky soil, and clay loam. Uttar Pradesh 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 Vindhyan. Appendix Table A1 presents the major crops grown in Uttar Pradesh's various agro-ecological zones and in all zones: wheat (41 %), paddy (24 %), sugarcane (9 %), pearl millet (4 %), and maize (3 %). This study focuses on wheat.

The primary survey was collected from farmers in three agro-ecological zones of Uttar Pradesh: the southwestern semi-arid, central plains, and eastern plains. The survey was conducted in 12 districts of Uttar Pradesh.[6] Four districts were selected from each agro-ecological zone. To select villages, we classified them into KVK and non-KVK villages. We define KVK villages as those in which KVK staff has conducted any type of intervention, such as frontline demonstrations or capacity-building programs. Non-KVK villages are those in which staff has not conducted any type of intervention. We prepare the list of KVK villages by the intersection of KVK activity types, such as frontline demonstrations or capacity-building programs, and the region's key crop (wheat). We also ensure that the list includes only villages that received KVK interventions in 2016–17 but received none in 2014–15, 2015–16, or 2017–18. KVK villages were selected randomly from this list, and non-KVK villages were selected randomly from their respective list. A complete household listing was compiled for each selected village in selecting farming households. After that, we formed four quartiles based on total cultivable land. Five farming households then were selected randomly from each quartile. Appendix Table A2 summarizes a sample size by KVK (923 farmers) and non-KVK villages (573 farmers). Among KVK villages, 227 farmers belong to villages where only frontline demonstrations have been implemented, 399 farmers belong to villages where only capacity-building programs have been implemented, and 297 farmers belong to villages where both frontline demonstrations and capacity-building programs have been implemented.

The household questionnaire (or module) collected information on farmers' awareness of KVKs and the benefits they received regarding frontier agriculture technologies (frontline demonstrations, capacity-building programs, and others). Farmers were queried on production, sales, and cultivation costs and asked to provide detailed household information and demographic characteristics for 2017–18. The module also included information on wheat varieties and recall-based information on adoption and dis-adoption patterns of seed varieties from 2014–15, thus enabling us to construct a panel dataset from 2014–15 to 2017–18 on the adoption of wheat varieties.

The survey followed a "network within sample" approach to identify network beneficiaries, asking each farmer about his or her link to every other person in the sample (Chandrasekhar and Lewis 2011). Ideally, a village census is needed to identify network beneficiaries, with all farmers asked to list their network members, a time- and budget-intensive approach in large villages (Van den Broeck and Dercon, 2011). Therefore, we follow a second-best strategy and use a "network within sample" approach. Although this technique truncates the network and may provide estimates with a downward bias, it nevertheless offers valuable insights into quantifying the extent of network beneficiaries and spillover effects of an extensive public program such as KVKs in India. We query farmers about their links to every other person in the sample (Chandrasekhar and Lewis, 2011; Santos and Barrett, 2008). We collected information on farmers' relationships (friend, neighbor, relative) with each of the other 19 randomly surveyed farmers in the same village, whether farmers discussed agricultural matters, and whether they accepted the advice of others, including advice concerning the adoption of new wheat varieties. This information allowed us to construct a social map of each randomly surveyed farmer within the sample to capture knowledge spillovers and information flows among farmers through social networks and identify network beneficiaries of KVKs (details of this are presented in Section 4 of this paper). In this study, beneficiaries of frontline demonstrations can be classified into three categories:

- Primary beneficiaries—smallholders who receive benefits directly from KVKs. Farmers who lend their fields to KVKs for frontline demonstrations directly benefit from activities undertaken in the demonstrations and from direct interaction with KVK scientists.
- Secondary beneficiaries—curious smallholders who visit the frontline demonstration site to learn from the primary beneficiary.
- Network beneficiaries—smallholders who receive benefits from having primary and secondary beneficiaries in their social networks.

In sum, primary beneficiaries benefit directly from KVKs; secondary beneficiaries benefit from being present at the intervention location at the local level[7]; and network beneficiaries receive spillover benefits.

Likewise, beneficiaries of capacity-building programs can be classified into two categories:

- Primary beneficiaries—smallholders who receive training on the varietal evaluation of wheat under capacity-building programs directly from KVKs.
- Network beneficiaries—smallholders who receive benefits from having primary beneficiaries in their social networks.

3.2. Descriptive statistics

Table 1 shows that the average household head (HH) is about 46 years old. Younger farmers are more likely to adopt new technologies earlier than older farmers because they have longer planning horizons (Liu, 2013; Vecchio, Agnusdei, Miglietta, & Capitanio, 2020). Mueller and Jansen (1988) used age as a proxy for farmers' experience, finding that a farmer's age is positively associated with the adoption of new technologies. Findings suggest that men head 95 % of the surveyed households. Accounting for this variable captures the systematic difference, if any, in technology adoption by gender. The average household head has five years of schooling. Ojo and Baiyegunhi (2020) showed that education is essential for adopting improved technologies. The average household size is about five members. The survey reveals that 98 % of farmers are Hindus.

Almost half (48 %) of surveyed farmers belong to the Scheduled Caste/Scheduled Tribes (SC/ST) category. SC/ST households face disadvantages in access to public-sector interventions in India. About 23 % of farmers possess a below-poverty-line (BPL) card.[8]

[6] Agra, Allahabad, Ambedkar Nagar, Auraiya, Bhadohi, Etah, Etawah, Hathras, Jaunpur, Mathura, Raebareli, and Varanasi.

[7] We do not have information on whether secondary beneficiaries visit frontline demonstration sites in the presence of scientists.

[8] 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.

Table 1
Profile of wheat farmers, Uttar Pradesh, 2017–18.

Farmer characteristics	All farmers: Mean (Standard deviation)	All farmers: Minimum	All farmers: Maximum	KVK Village, Mean (Standard deviation)	Non-KVK Village, Mean (Standard deviation)	Difference (KVK-non KVK), Mean (Standard deviation)
Age (Year)	45.8 (11.4)	21	85	44.8 (10.9)	47.5 (11.9)	−2.7***
Male (Yes = 1)	0.95 (0.21)	0	1	0.96 (0.20)	0.95 (0.23)	0.01
Education (Year)	5.31 (4.09)	0	16	5.51 (3.9)	4.99 (4.3)	0.52*
Household size (#)	4.97 (2.06)	1	45	4.89 (1.9)	5.09 (2.2)	−0.20
Hindu (Yes = 1)	0.98 (0.15)	0	1	0.99 (0.10)	0.96 (0.21)	0.03***
Scheduled Caste/Tribes (Yes = 1)	0.48 (0.50)	0	1	0.49 (0.50)	0.46 (0.50)	0.03
Below poverty line (Yes = 1)	0.23 (0.42)	0	1	0.22 (0.41)	0.25 (0.43)	−0.03
Land own (ha)	0.74 (0.63)	0	4.01	0.72 (0.60)	0.76 (0.68)	−0.05
Source of income (Agriculture = 1)	0.78 (0.42)	0	1	0.80 (0.40)	0.75 (0.43)	0.05*
Asset index (Value)	0.01 (1.70)	−2.3	6.1	0.02 (1.74)	0.02 (1.63)	0.00
Household head experience (Year)	18.3 (9.9)	3	45	17.3 (9.5)	19.9 (10.5)	−3***
Kisan Credit Card (Yes = 1)	0.44 (0.50)	0	1	0.45 (0.49)	0.42 (0.49)	0.03
Soil health card (Yes = 1)	0.15 (0.36)	0	1	0.18 (0.38)	0.11 (0.31)	0.07***
Pradhan Mantri Fasal Bima Yojana (Yes = 1)	0.14 (0.35)	0	1	0.15 (0.36)	0.13 (0.33)	0.02
Soil color (Black = 1)	0.84 (0.37)	0	1	0.89 (0.31)	0.75 (0.43)	0.14***
Irrigation (Groundwater = 1)	0.78 (0.41)	0	1	0.82 (0.38)	0.72 (0.45)	0.10***
Soil fertility (High = 1)	0.20 (0.40)	0	1	0.17 (0.37)	0.24 (0.45)	−0.07***
	1,496			923	573	

Source: ICAR-IFPRI KVK Survey, 2019.
Note: Standard deviations are in parentheses. Below-poverty-line (BPL) cards are issued to poorer households. The 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 through 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. Land, asset index, and HH experience have been winsorized at the bottom and top percentile.

The average landholding is approximately 0.74 ha.[9] The survey revealed that 78 % of household heads report farming as their primary occupation. The average value of the asset index is about 0.01 on a scale of −2.30 to 6.10.[10] The positive value of the index suggests that ownership of an asset is highly indicative of ownership of other assets. The average value of the asset index for the poorest quintile is about −1.68 and for the richest quintile is about and 2.8. Feder et al. (1985) and Awotide, Diagne, Wiredu, and Ojehomon (2012) argued that wealthier farmers are more likely than poor farmers to take risks associated with adopting new technology.

The survey reveals that the average household head has 18 years of farming experience. Only 44 % of households have a Kisan Credit Card (KCC) that would allow them access to institutional credit.[11] For example, Varshney, Joshi, and Roy (2019) showed that a Kisan Credit Card is vital for adopting improved technologies. Table 1 shows that 15 % of households have a soil health card, which analyzes farmers' land and offers recommendations for nutrient management.[12] Accounting for this variable helps us understand farmers' scientific approaches to agriculture. About one in seven (14 %) farmers have access to *Pradhan Mantri Fasal Bima Yojana*, a crop insurance program. Crop insurance can serve as a risk-sharing mechanism for farmers adopting new technology. Presumably, farmers with crop insurance are more likely than their counterparts to adopt new and improved technology. We also present plot characteristics such as soil color, irrigation, and soil fertility, which play an essential role in technology adoption. For instance, improved irrigation conditions are expected to influence the adoption of new technology that requires greater irrigation.

Table 1 also compares the profile of wheat farmers across KVK and non-KVK villages. Compared to farmers in non-KVK villages, farmers in KVK villages are generally younger (by 2.7 years), have higher educational attainment (0.52 years), are 5 % more likely to engage in farming for a livelihood, have less farm experience (3.0 years), and are 7 % more likely to have a soil health card. Further, farmers across KVK and non-KVK villages have varying soil color, fertility, and irrigation conditions. Figure 1 shows the adoption patterns of wheat cultivars for 2015–16 and 2017–18. In 2015–16, 34 % of farmers adopted PBW-343, a wheat variety released in 1996. PBW-502, released in 2004, was adopted by 24 % of farmers, and HD-2967, released in 2011, was adopted by 26 % of farmers. Almost one in five (17 %) farmers adopted other cultivars.[13] In 2017–18, 32 % of farmers adopted PBW-343, 8 % adopted PBW-502, 47 % adopted HD-2967, and 14 % adopted other cultivars. The above findings suggest varietal substitution away from PBW-502 and toward HD-2967.

To gain further insights, Table 2 compares the yield, revenue, operational costs, and profits associated with HD-2967, PBW-502, and PBW-343.[14] The evidence shows that farmers using the HD-2967 wheat variety, compared to PBW-343, experienced higher yields (14 %, column 5/column 3), higher revenues (13 %), higher operational costs (5 %), and greater profits (about INR 6,320 per hectare). Adopters of HD-2967 had about 3.7 quintals per hectare more yield (10 % higher) than farmers using the PBW-502 wheat variety.

[9] Nyariki (2011) showed a significant variation across farm size of modern farming technologies. Akinola (1987) suggested a positive correlation between landholding size and the likelihood of adopting improved technology.

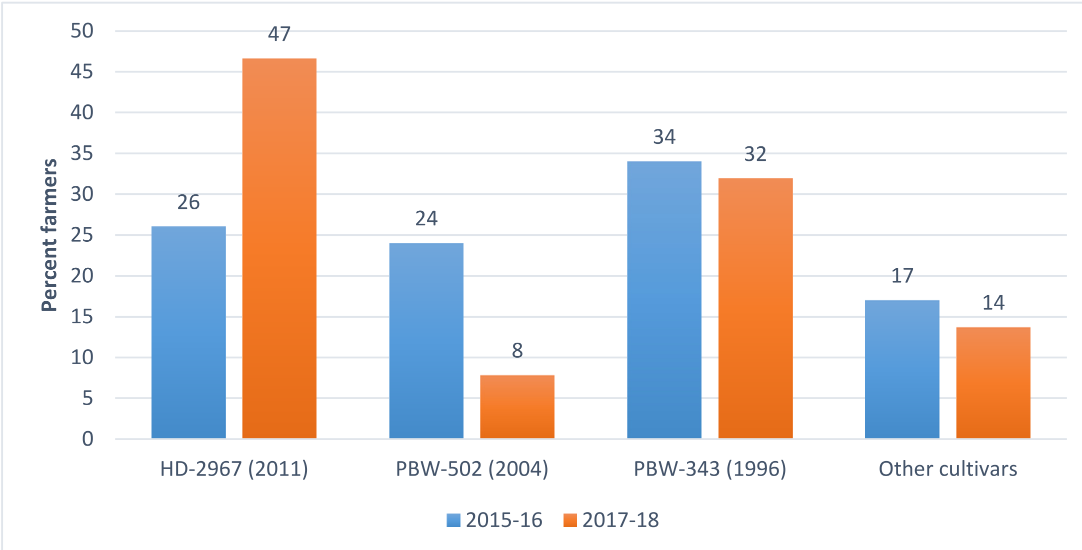
[10] Asset index is constructed by applying principal component analysis using the ownership of 22 assets (e.g., tractor, two-wheeler, four-wheeler, etc.).

[11] The Kisan Credit Card was introduced by the Government of India to provide short-term credit to farmers during the planting and harvesting seasons.

[12] 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.

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

[14] Yield is measured as the ratio of production (quintals) and crop acreage(hectare). We measure profit as the difference of revenue and operational cost.



Source: ICAR-IFPRI KVK Survey, 2019

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

Fig. 1. Adoption pattern of wheat cultivars for Uttar Pradesh, India, 2015-16 and 2017-18.

Table 2
Yield and profit of major wheat cultivars, Uttar Pradesh, 2017–18.

	HD-2967 (1)	PBW-502 (2)	PBW-343 (3)	Difference (4 = 1–2)	Difference (5 = 1–3)
Yield (quintals/ha)	38.8 (0.30)	35.1 (0.43)	34.4 (0.24)	3.7*** (0.70)	4.4*** (0.4)
Revenue (INR/ha)	62,592 (497)	56,485 (722)	55,183 (412)	6107*** (1163)	7409*** (664)
Operational cost (INR/ha)	24,689 (265)	26,126 (604)	23,611 (237)	−1437 (653)	1078*** (363)
Profit (INR/ha)	37,822 (492)	30,358 (827)	31,502 (458)	7464*** (1164)	6320*** (683)
Number of observations	520	103	427	623	947

Source: ICAR-IFPRI KVK Survey, 2019.
Note: Standard errors are in parentheses. Data on the cost of cultivation variables are available for 1,235 farmers. (HD-2967 adopter = 520, PBW-502 adopter = 103, PBW-343 adopter = 427, Other cultivar adopter = 185).

Similarly, adopters of HD-2967 earned 10 % (column 4/column 2) higher revenue than farmers using PBW-502. Farmers using HD-2967 had lower operational costs (5 %) than those using PBW-502, but the difference was statistically insignificant. Overall, the adoption of HD-2967 resulted in higher profits (about INR 7,464 per hectare) than the adoption of PBW-502.

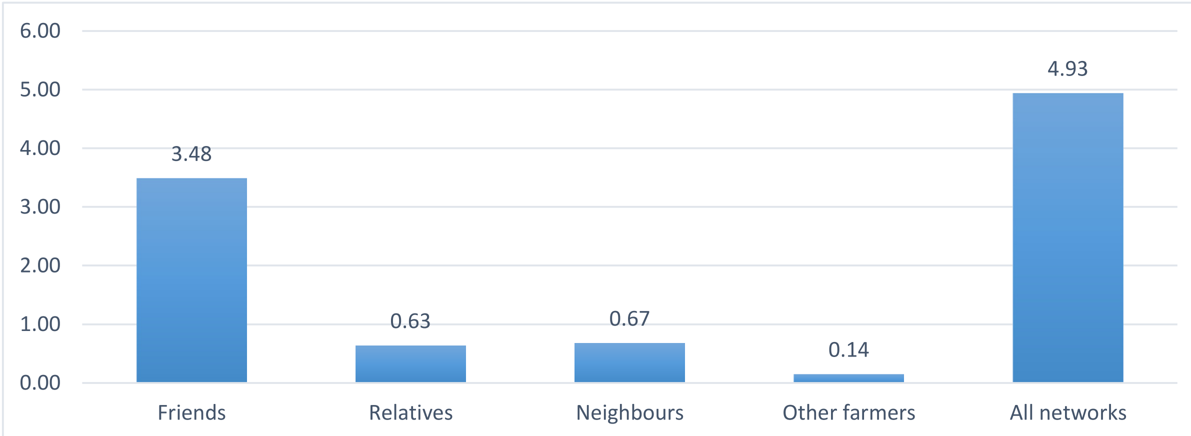
Appendix Table A4 presents the distribution of farmers by the number of social interactions within the sample. Note that we randomly surveyed 20 households per village, so each farmer could have social interactions with anywhere from zero to 19 other farmers. Zero social interactions would indicate social isolation, implying that a farmer did not discuss agriculture-related matters with anyone else in the sample. Nineteen social interactions would suggest that a farmer interacted with every other farmer in the sample. One in 14 (7.2 %) farmers did not interact with anyone else in the sample, and about 4 % interacted with only one other farmer in the sample. About 3 % of farmers in the sample had two social connections, 7 % had three, 17 % had four, 19 % had five, and 18 % had six social connections. Fig. 2 presents the average social network of farmers within the sample by relationship. On average, a farmer networked with about 3.5 friends, 0.63 relatives, 0.67 neighbors, and 0.14 other farmers. Overall, a farmer networked with about five other farmers in the sample.

4. Empirical strategy

4.1. Identification

To select villages for interventions, KVKs adopt a cluster villages approach that covers four to five villages annually. The model considers those villages where farm households are dominated by small and marginal farmers from different agro-ecosystems. A KVK worked in the selected cluster(s) for three years. After that, the program moved to a new cluster of villages elsewhere in the district in a phased-out manner for another three-year cycle to implement similar activities. Fig. 3 plots the predicted probability of selection of KVK villages,[15] suggesting that villages with higher average land size have a lower likelihood of being a KVK village. To select farmers for frontline demonstrations, KVKs look for easily approachable plots for the demonstration trials (such as farms near roads or in a prime location where farmers have high mobility) and for farmers who are receptive, willing, cooperative, and eager to attend pre-demonstration training at the site. To select farmers for

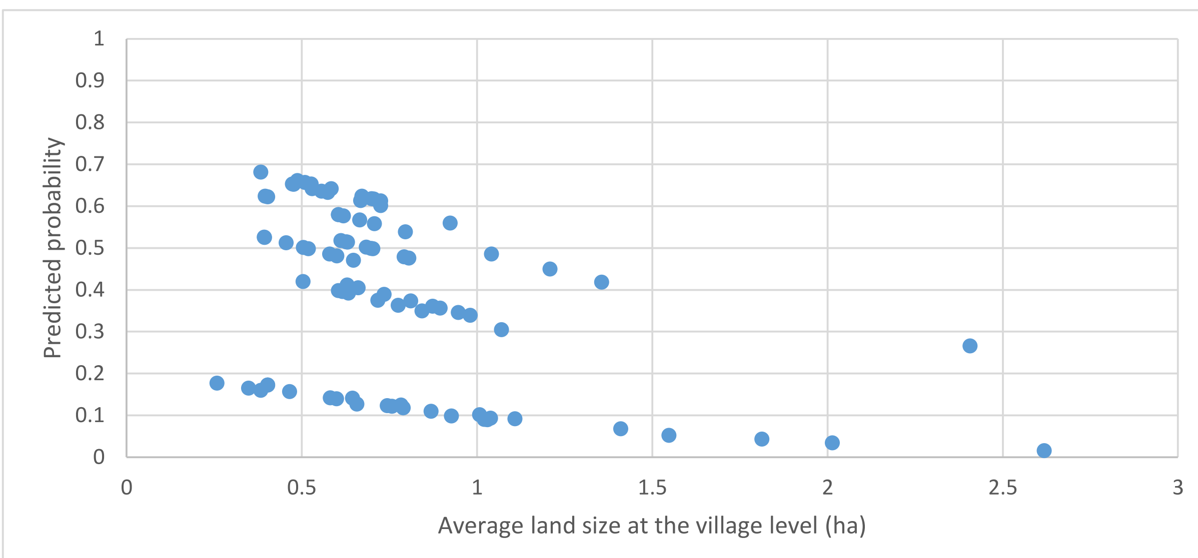
[15] We run a simple probit model where the left-hand side takes a value of 1 if the village is a KVK village and 0 otherwise. The right-hand side is the average land size at the village level along with district dummies.



Source: ICAR-IFPRI KVK Survey, 2019.

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

Fig. 2. Number of social networks for a farmer (within-sample) and by relationship.



Source: ICAR-IFPRI KVK Survey, 2019

Notes: A simple probit model is estimated to select KVK villages conditional on the average village land size and district dummies.

Fig. 3. Predicted probability of selection of KVK village.

capacity-building programs, KVKs aim to provide an opportunity to equip farmers with the necessary technical know-how and technical “do-how” about new technologies (especially for small and marginal farmers, young farmers, and farm women).

Our empirical strategy exploits two crucial aspects of KVK interventions. The first is its phased-out strategy for interventions, enabling us to identify the control group. The second is the availability of recall-based panel data from 2014–15 to 2017–18 on adopting improved wheat varieties. 2014–15 and 2015–16 serve as pre-intervention years, 2016–17 is the intervention year, and 2017–18 is the post-intervention year. We compare changes in outcomes between the treatment group (KVK beneficiary) and the control group (non-KVK beneficiary) over the period 2015–16 and 2017–18 in a difference-in-differences framework. In this case, the impact estimate can be interpreted as the causal impact of KVKs under the identification assumption that in their absence, changes in outcomes would not be systematically different across treatment and control groups. The identification relies on the assumption that no omitted time-varying and district- (or village-) specific effects are correlated with the program. This assumption could be invalid because the two groups of farmers may differ and grow differently if their villages have different time trends.[16] It is possible that the estimate could confound the program's effect with the mean reversion in the program's absence (Duflo, 2001). Therefore, identifying the assumption of similar time trends in the absence of KVK may not hold. Further, the identifying assumption may be violated if another new program was implemented or if existing programs were expanded in the study districts or villages during KVK program placement.

The above concerns are addressed using the following approaches. First, we match each treated farmer with a weighted combination of control farmers such that the predicted probability of treating is the same. This allows us to make "like with like" comparisons and increases the likelihood that our assumption will hold. Second, we include a time-varying, district-level variable to account for other agricultural extension programs of the Government of India. If any systematic change occurred in these programs across these years, we could not attribute the change in outcomes over the period solely to KVKs.[17]

Third, we test the implications of identifying assumptions by looking at data from the pre-intervention years (2014-15 and 2015-16), when neither the treatment group nor the control group was exposed to KVK interventions. The change in adoption rates should not differ systematically across groups, although the pre-intervention trends are neither necessary nor sufficient to guarantee parallel trends in the counterfactuals (Kahn-Lang & Lang, 2020). Nonetheless, we continued to test for parallel trends as our results suggest that the matched difference-in-differences estimates are not driven by an inappropriate identification assumption (Duflo, 2001).

4.2. Empirical specification

We adopted a matched difference-in-differences approach to identify KVKs' impact (Heckman, LaLonde, & Smith, 1999; Santanna & Zhao, 2020). The basic idea behind this approach is that it implements a matching procedure across treatment and control groups before applying a standard difference-in-differences approach. Implementing the matching approach essentially involves three steps. First, we derive farmer-level weights using a kernel matching procedure.[18] In this procedure, the counterfactual for each treatment unit is constructed by taking weighted averages of all farmers in the control group to construct the counterfactual unit. Where weights are determined based on distance (in terms of predicted probability of receiving treatment) between each treatment and control group. Thus, the higher weights are assigned to those control units close to the treatment unit, and lower weights are set when the control unit is farther from the treatment unit. Unlike the other matching procedure, the main advantage of the kernel procedure is that it provides lower variance because more information is used. In the second step, we define a common support region by dropping the treated farmers whose propensity score is more than the maximum or less than the minimum of control farmers and vice versa.[19] In the final step, we apply farmer-level weights to the difference-in-differences specification in the common support region to arrive at the matched difference-in-differences impact estimates.

4.2.1. Effect of frontline demonstrations and capacity-building programs: KVK beneficiaries

To identify the effect of frontline demonstrations on the adoption of improved technology for primary or secondary beneficiaries,[20] we define the treatment group as primary or secondary beneficiaries of frontline demonstrations. We exclude farmers who also receive the benefit of capacity-building programs to remove the effect of those programs. Additionally, we have excluded non-beneficiary farmers from frontline demonstration villages who are likely to receive demonstration benefits from being in local village networks or from any spillover of knowledge and information flows. The treatment group comprises 53 farmers. Our control group includes non-beneficiary farmers in non-KVK villages or in capacity-building program villages. The control group consists of 813 farmers — 573 from the non-KVK villages and 240 from the capacity-building villages (Appendix Table A2).[21] To match farmers across groups, we consider factors like age, age squared, gender, education, household size, caste, source of income, asset index, household head experience, soil color, source of irrigation, average land size at the village level, and plot location (near a road).[22] Average land size at the village level is included to account for selecting villages in the program, and plot location is included to account for selecting farmers in the program. Table 3, Panel A, presents the covariates after matching across treatment and control groups.[23] The differences across treatment and control groups are all insignificant. The following specification uses matching weights to obtain the matched difference-in-differences estimates:

$$Y_{ivdt} = \alpha_0 + \alpha_1 Time_t + \alpha_2 [FLD(PorS)]_{ivd} + \alpha_3([FLD(PorS)]_{ivd} * Time_t) + X_{dt} + \varepsilon_{ivdt} \quad (1)$$

where i represents an individual farmer, v stands for a village, d stands for the district, and t stands for the year (2015–16 or 2017–18). Y takes a value of 1 if a farmer adopts wheat variety HD-2967 and 0 otherwise. $Time_t$ is a dummy variable for 2017–18. $FLD(PorS)$ is a dummy variable with a value of 1 if the farmer is either a primary or a secondary beneficiary of frontline demonstrations (but not of capacity-building programs), and 0 if the farmer resides in a non-frontline demonstration village. X is the percentage of farmers who received extension services from other government programs at the district level. ε is the error term. The coefficient of interest, α_3, can be interpreted as the impact on primary or secondary beneficiaries of frontline demonstrations, and it captures the effect of frontline demonstrations only.

Likewise, to identify the impact of capacity-building programs on primary beneficiaries, we define the treatment group as primary beneficiaries of capacity-building programs but exclude farmers who also receive the benefit of frontline demonstrations to remove the effect of such demonstrations. We also exclude non-beneficiary

[16] Table 1 shows that farmers across KVK and non-KVK villages are different in terms of age, education, income, experience, access to government schemes, and plot characteristics.

[17] From the situation assessment survey of agricultural households for 2013 and 2019, we estimate the percentage of farmers who received extension services from other governmental agricultural extension programs. We use 2013 estimates for 2015–16 and 2019 estimates for 2017–18.

[18] The kernel matching procedure uses the weighted averages of all farmers in the control group to construct the counterfactual of treated farmers.

[19] We use an epanechnikov kernel function and the bandwidth parameter equals 0.06.

[20] In estimating the impact of frontline demonstrations, we combine primary and secondary beneficiaries because the former benefit directly from KVKs and the latter benefit by taking advantage of locally available frontline demonstrations. Also, the sample of primary beneficiaries is small and lacks power, so we combine primary and secondary beneficiaries.

[21] Out of 399 farmers from capacity-building program village, we exclude 159 farmers who are benefited either directly or indirectly through KVKs and thus included only 240 farmers from the capacity-building program village in the control group.

[22] Appendix Table A5 presents the unmatched difference across groups. and reveals significant differences across groups in terms of caste, income, asset, soil color, and source of irrigation.

[23] After matching, none of the farmers in the treatment or control groups appears to be in the "out of common" support region. Therefore, with and without matching, the number of treatment and control farmers is the same (53 treatment and 813 control).

Table 3
Summary statistics for FLDs' *primary or secondary* and *network* beneficiaries: Treatment vs control group (matched differences).

	Primary or secondary beneficiary (treatment) vs control				Network beneficiary (treatment) vs control			
	Treatment (1)	Control (2)	Difference (3 = 1–2)	p value (4)	Treatment (5)	Control (6)	Difference (7 = 5–6)	p value (8)
Age (Year)	46.47	46.28	0.19	0.93	43.91	44.19	−0.28	0.82
Male (Yes = 1)								
Education (Year)	5.60	5.53	0.07	0.93	5.74	5.80	−0.06	0.90
Household size (#)	5.17	5.13	0.04	0.90	4.64	4.67	−0.03	0.85
Scheduled caste/tribe (Yes = 1)	0.38	0.39	−0.01	0.93	0.37	0.38	−0.01	0.80
Source of income (Agriculture = 1)	0.94	0.92	0.03	0.62	0.82	0.82	0.00	0.94
Asset index (Value)	0.60	0.49	0.11	0.79	−0.11	−0.07	−0.05	0.81
Household head experience (Year)	18.64	18.47	0.17	0.93	15.74	16.02	−0.28	0.79
Soil color (Black = 1)	0.92	0.92	0.01	0.92	0.90	0.89	0.00	0.91
Irrigation (Groundwater = 1)	0.91	0.89	0.01	0.80	0.88	0.88	0.00	0.95
Plot location (Road side = 1)	0.04	0.04	0.00	0.90	0.07	0.07	0.00	0.98
Village average land size (ha)	0.71	0.71	0.00	0.98	0.77	0.76	0.01	0.90
Number of observations	53	813	866		146	813	959	
Number of observations used in the regression	106	1626	1,732		292	1,626	1,918	

Notes: A kernel matching procedure is used to match farmers across treatment and control groups. We use an epanechnikov kernel function and the bandwidth parameter equals 0.06. 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. FLDs = Frontline demonstrations to promote the new wheat variety (HD-2967).

farmers from capacity-building program villages who are likely to receive these programs' benefits from being in local village networks or from any spillover of knowledge and information flows. The treatment group comprises 19 such farmers. Control group comprises of farmers who reside in non-KVK villages, as non-beneficiary farmers belonging to capacity-building program villages or frontline demonstration villages are likely to receive spillover of knowledge and information flows. The control group comprises 573 such farmers (Appendix Table A2). Appendix Table A6, Panel A, presents the unmatched difference across groups and reveals significant differences across groups in terms of caste, land size, asset, source of irrigation, and average village land size. Table 4, Panel A, presents the covariates after matching across treatment and control groups.[24] The differences across treatment and control groups are insignificant: age, age squared, gender, education, household size, caste, source of income, asset index, household head experience, soil color, and source of irrigation. The following specification uses matching weights to obtain the matched difference-in-differences estimates:

$$Y_{ivdt} = \alpha_0 + \alpha_1 Time_t + \alpha_2 [CBP(P)]_{ivd} + \alpha_3([CBP(P)]_{ivd} * Time_t) + X_{dt} + \varepsilon_{ivdt} \quad (2)$$

Other notations remain the same as in Eq. (1). *CBP* (*P*) takes a value of 1 if the farmer is a primary beneficiary (but did not receive frontline demonstration benefits) and 0 if the farmer resides in a non-KVK village. The coefficient α_3 is interpreted as the impact on primary beneficiaries of capacity-building programs, and captures the effect of such programs only.

4.2.2. Identifying network beneficiaries

The study follows a "network within sample" approach to capture social networks, asking each farmer about his or her link to every other person in the sample (Chandrasekhar & Lewis, 2011). The basic intention is to identify network beneficiaries as those farmers who benefited from having primary or secondary beneficiaries of frontline demonstrations in their social network. Identifying network beneficiaries involves two steps. The first step is to calculate the number of network members for each farmer who benefited from such demonstrations, as measured by the following equation:

$$SN\_A\_FLD_i = \sum_{v=1}^{19} (SN_{iv} * A_{iv} * FLD_{iv}), \quad (3)$$

where i denotes an individual farmer and v denotes the remaining surveyed farmers of the same village.[25] *SN* takes a value of 1 if farmer i is socially connected with farmer v, and 0 otherwise.[26] *A* takes a value of 1 if farmer *i* discusses and accepts agricultural advice from a socially connected farmer *v*, and 0 otherwise. *FLD* takes a value of 1 if farmer v is either a primary or secondary beneficiary of frontline demonstrations and 0 otherwise. The second step is to define network beneficiaries (***N***) as farmers who benefited from a frontline demonstration intervention due to inclusion in a social network. Specifically,

$$\boldsymbol{N}_i = 1 if SN\_A\_FLD_i > 0 \quad (4)$$

To quantify spillovers, we estimate the percentage of network beneficiaries of frontline demonstrations in demonstration villages as the ratio of the total number of network beneficiaries in such villages to the total number of farmers in such villages. Similarly, we estimate the percentage of network beneficiaries of capacity-building programs in capacity-building program villages as the ratio of the total number of network beneficiaries in such villages to the total number of farmers in such villages.[27]

4.2.3. Effect of frontline demonstrations and capacity-building programs: Network beneficiaries

To identify the effect of frontline demonstrations on the adoption of improved technology for network beneficiaries, we define the treatment group as network beneficiaries of frontline demonstrations, but exclude farmers who also received capacity-building program benefits to remove the effect of such programs. Again, the control group comprises non-beneficiary farmers who reside either in non-KVK villages or in non-capacity-building program villages, and it contains 813 farmers for the reasons discussed above. We use the same set of covariates as in Eq. (1). Table 3,

[24] After matching, one farmer in the treatment group appears to be in the "out of common" support region. With matching, the number of treatment and control farmers is 19 and 573, respectively. Without matching, the number of treatment and control farmers is 20 and 573, respectively.

[25] We surveyed 20 farmers in each village.

[26] A socially connected farmer is a friend, neighbor, relative, or other known farmer with whom farmer *i* interacts.

[27] Note that, to identify network beneficiaries as those farmers who benefited from having primary beneficiaries of CBPs in their social network.

Table 4
Summary statistics for CBPs' *primary* and *network* beneficiaries: Treatment vs control group (matched differences).

	Primary beneficiary (treatment) vs control				Network beneficiary (treatment) vs control			
	Treatment (1)	Control (2)	Difference (3 = 1–2)	p value (4)	Treatment (5)	Control (6)	Difference (7 = 5–6)	p value (8)
Age (Year)	48.74	48.28	0.45	0.89	44.53	44.49	0.04	0.97
Male (Yes = 1)					0.95	0.95	−0.01	0.75
Education (Year)	5.79	5.62	0.17	0.91	5.69	5.58	0.11	0.80
Household size (#)	5.37	5.30	0.07	0.91	5.02	5.06	−0.04	0.84
Scheduled caste/tribe (Yes = 1)	0.16	0.28	−0.12	0.38	0.44	0.44	0.00	0.93
Source of income (Agriculture = 1)	0.79	0.81	−0.02	0.90	0.84	0.84	0.00	0.92
Land own (ha)	1.09	1.01	0.08	0.80	0.72	0.76	−0.04	0.55
Asset index (Value)	1.22	1.32	−0.11	0.89	0.05	0.07	−0.01	0.94
Household head experience (Year)	22.32	21.49	0.83	0.80	16.80	16.78	0.02	0.99
Soil color (Black = 1)	0.79	0.79	0.00	0.99	0.87	0.86	0.01	0.88
Irrigation (Groundwater = 1)	0.89	0.83	0.06	0.58	0.87	0.86	0.00	0.90
Plot location (Road side = 1)	0.11	0.12	−0.01	0.91	0.05	0.06	0.00	0.92
Village average land size (ha)	0.94	0.90	0.04	0.83	0.73	0.75	−0.02	0.58
Number of observations	19	573	592		182	573	755	
Number of observations used in the regression	38	1,146	1,184		364	1,146	1,510	

Source: ICAR-IFPRI KVK Survey, 2019.
Notes: A kernel matching procedure matches farmers across treatment and control groups. We use an epanechnikov kernel function and the bandwidth parameter equals 0.06. 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. CBPs = Capacity-building programs on the varietal evaluation of wheat.

Panel B, presents the covariates after matching across treatment and control groups.[28] The differences across treatment and control groups are all insignificant: age, age squared, gender, education, household size, caste, source of income, asset index, household head experience, soil color, source of irrigation, average land size at the village level, and plot location (near a road). The following specification uses matching weights to obtain the matched difference-in-differences estimates:

$$Y_{ivdt} = \alpha_0 + \alpha_1 Time_t + \alpha_2 [FLD(N)]_{ivd} + \alpha_3 ([FLD(N)]_{ivd} * Time_t) + X_d + \varepsilon_{ivdt} \quad (5)$$

Other notations remain the same as in Eq. (1). *FLD (N)* takes a value of 1 if the farmer is a network beneficiary (but not of capacity-building programs) and 0 if the farmer resides in a non-frontline demonstration village. The coefficient of interest, α_3, is interpreted as the impact on network beneficiaries of frontline demonstrations and captures the effect of such demonstrations only.

Finally, to identify the impact of capacity-building programs on network beneficiaries, we define the treatment group as primary beneficiaries of such programs but exclude farmers who also receive the benefit of frontline demonstrations to remove the effect of such demonstrations. Again, the control group comprises farmers who reside in non-KVK villages and comprises 573 farmers for the reasons mentioned above. Table 4, Panel B, presents the covariates after matching across treatment and control groups.[29] The differences across treatment and control groups are all insignificant: age, age squared, gender, education, household size, caste, source of income, asset index, household head experience, soil color, and source of irrigation. The following specification uses matching weights to obtain the matched difference-in-differences estimates:

$$Y_{ivdt} = \alpha_0 + \alpha_1 Time_t + \alpha_2 [CBP(N)]_{ivd} + \alpha_3 ([CBP(N)]_{ivd} * Time_t) + X_{dt} + \varepsilon_{ivdt} \quad (6)$$

Other notations remain the same as in Eq. (1). *CBP(N)* takes a value of 1 if the farmer is a network beneficiary (but not of frontline demonstrations), and 0 if the farmer resides in a non-KVK village. The coefficient α_3 is interpreted as the impact on network beneficiaries of capacity-building programs, and captures the effect of such programs only.

5. Results and discussion

5.1. KVKs' impact on the adoption of HD-2967: Effects on KVK beneficiaries

Table 5 presents the impact estimates of frontline demonstrations on primary or secondary beneficiaries from adopting a modern wheat variety, namely HD-2967. Columns 1 and 2 present the matched difference-in-differences estimates with and without a time-varying district control.[30] In Column 1, the coefficient α_1 shows a 16 % increase in adoption of HD-2967 between 2015–16 and 2017–18. The coefficient α_2 captures the difference in adoption of HD-2967 between beneficiaries and non-beneficiaries in 2015–16. Consistent with the covariates balance, the difference in the adoption rate of HD-2967 between primary or secondary beneficiaries and non-beneficiaries was insignificant in 2015–16 (before the frontline demonstration intervention program). Our coefficient of interest, α_3, measures the impact of frontline demonstrations on the adoption of HD-2967. Primary or secondary beneficiaries have about 22 % higher adoption rates than non-beneficiaries. In other words, this study indicates that exposure to frontline demonstrations increases the adoption rate of new technology by about 22 %.

This interpretation relies on the conditional independence assumption. In other words, it is conditional on similar covariates and no omitted time-varying and district- or village-specific effects being correlated with frontline demonstration interventions. Note that selection of a village in the program is based on the number of small and marginal farmers residing in it. Therefore, the estimate may potentially be confounded with the mean reversion in the absence of frontline demonstrations. We partly address this by including the average land size at the village level as a covariate while conducting a matching procedure. Table 3 shows an insignif-

[28] After matching, none of the farmers in the treatment or control group appears to be in the "out of common" support region. Therefore, with and without matching, the number of treatment and control farmers are same (146 treatment and 813 control).
[29] After matching, six farmers in the treatment group appear to be in the "out of common" support region. With matching, the number of treatment and control farmers is 182 and 573, respectively. Without matching, the number of treatment and control farmers is 188 and 573, respectively.

[30] MDID estimates are based on Equation (1).

Table 5
Estimates of FLDs' impact on *primary or secondary* beneficiaries' adoption of HD-2967, new wheat variety, Uttar Pradesh.

	Impact estimates		Falsification test
	Model 1	Model 2	Model 3
FLD (P or S)*Time,α_3	0.218^{**} (0.093)	0.215^{**} (0.093)	−0.107 (0.084)
FLD (P or S),α_2	−0.025 (0.061)	−0.020 (0.060)	0.082 (0.058)
Time,α_1	0.159^{***} (0.029)	0.177^{***} (0.033)	0.125^{***} (0.025)
Time varying district control	No	Yes	No
Matching before DID	Yes	Yes	Yes
Constant	0.251^{***} (0.020)	0.232^{***} (0.025)	0.126^{***} (0.015)
Number of observations	1,732	1,732	1,732
Number of farmers	866	866	866

Notes: Each column represents a separate regression. The dependent variable takes a value of 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 2017–18 and 0 for 2015–16. In Model 3, it takes a value of 1 for 2015–16 and 0 for 2014–15. In all models, *FLD (P or S)* takes a value of 1 if farmers benefited from FLDs in 2016–17 (i.e., *primary or secondary* beneficiaries), but not from CBPs, and takes a value of 0 if farmer resides in a non-FLD village. Models 1 and 2 present the impact estimates. Models 3 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 squared, gender, education, household size, caste, source of income, asset index, HH experience, soil color, source of irrigation, plot location (near a road), and average village land size. A kernel procedure is used for performing matching. All regressions are in the common support region. We use an epanechnikov kernel function and the bandwidth parameter equals 0.06. Time-varying district control is the percentage of farmers who received other government extension programs. FLDs = Frontline demonstrations to promote the new wheat variety (HD-2967). CBPs = Capacity-building programs on the varietal evaluation of wheat. Robust standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table 6
Estimates of CBPs impact on *primary* beneficiaries' adoption of HD-2967, new wheat variety, Uttar Pradesh.

	Impact estimates		Falsification test
	Model 1	Model 2	Model 3
CBP (P)*Time,α_3	0.261^{*} (0.153)	0.286^{*} (0.148)	0.041 (0.129)
CBP (P),α_2	0.057 (0.106)	0.033 (0.099)	0.017 (0.074)
Time,α_1	0.212^{***} (0.055)	0.236^{***} (0.058)	0.117^{**} (0.039)
Time-varying district control	No	Yes	No
Matching before DID	Yes	Yes	Yes
Constant	0.206^{***} (0.032)	0.180^{***} (0.037)	0.088^{***} (0.022)
Number of observations	1,184	1,184	1,184
Number of farmers	592	592	592

Notes: Each column represents a separate regression. The dependent variable takes a value of 1 when wheat farmers adopt *HD-2967* and 0 otherwise. *Time* is a dummy variable. Models 1 and 2 take a value of 1 for 2017–18 and 0 for 2015–16. Model 3 takes a value of 1 for 2015–16 and 0 for 2014–15. In all models, *CBP (P)* takes a value of 1 if a farmer benefited from CBPs in 2016–17 (i.e., *primary* beneficiaries), but not from FLDs, and takes a value of 0 if the farmer resides in a non-KVK village. Models 1 and 2 present the impact estimates. Model 3 tests 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 squared, gender, education, household size, caste, land holding, source of income, asset index, HH experience, soil color, source of irrigation, plot location (near a road), and average village land size. A kernel procedure is used for performing matching. All regressions are in the common support region. We use an epanechnikov kernel function, and the bandwidth parameter equals 0.06. Time-varying district control is the percentage of farmers who received extension services from other programs. FLDs = Frontline demonstrations to promote the new wheat variety (HD-2967). CBPs = Capacity-building programs on the varietal evaluation of wheat. Robust standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$.

icant difference in average land size across treatment and control groups at the village level. The identification assumption also will not hold if the program placement is correlated with the initiation of another new agricultural extension program or the expansion of an existing one. For robustness, we include a time-varying control at the district level: the percentage of farmers who received extension services from other government programs.[31] Column 2 presents the results, which show a pattern similar to that of Column 1.

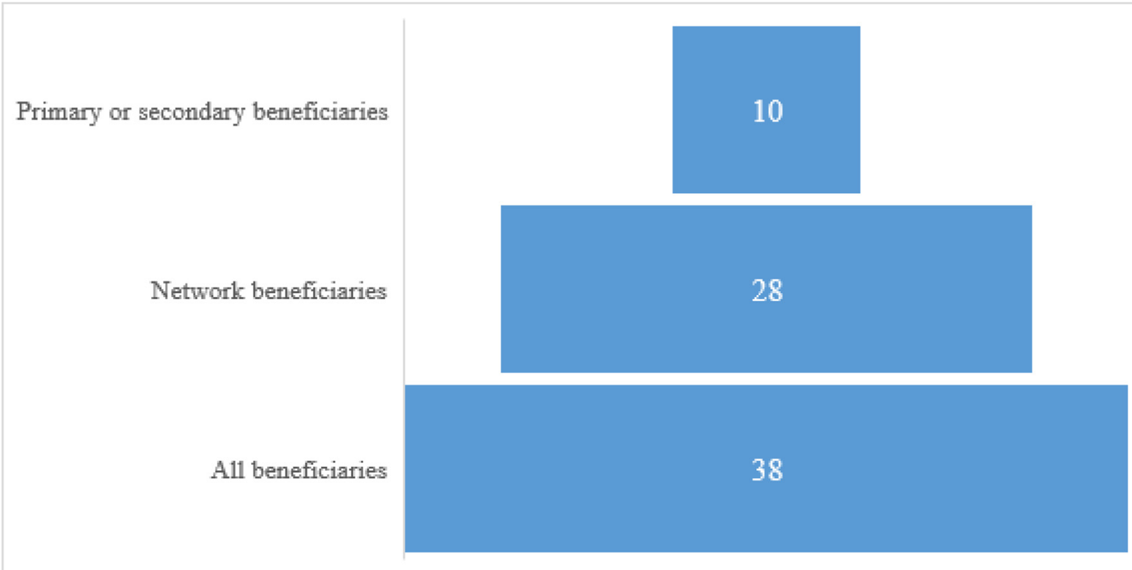
Column 3 shows the results of falsification tests (whether pre-intervention trends exist across primary or secondary beneficiaries and non-beneficiaries).[32] To do this, we estimate equation (1) using 2014–15 and 2015–16 data. The coefficient α_3 is insignificant, suggesting a similar trend across primary or secondary beneficiaries and non-beneficiaries in the absence of frontline demonstration interventions. The results indicate that inappropriate identification assumptions do not drive the matched difference-in-differences estimate.

Table 6 presents the impact estimates for the adoption of HD-2967 by farmers who received capacity-building program benefits from KVK staff (Columns 1 and 2).[33] In Column 1, the coefficient α_1 shows a 21 % increase in adoption of HD-2967 between 2015–16 and 2017–18. The estimated coefficient α_2 reveals that the difference in adoption of HD-2967 was insignificant between primary beneficiaries and non-beneficiaries in 2015–16. In other words, the adoption pattern of primary beneficiaries of capacity-building programs was similar to that of non-beneficiaries (before such program interventions). The coefficient of interest, α_3, shows that primary beneficiaries had a 26 % higher adoption rate than non-beneficiaries, suggesting that KVKs' capacity-building program interventions increased adoption of HD-2967. When we include a time-varying district control in Column 2, the coefficient α_3 is marginally higher (29 % versus 26 %) than in Column 1, which suggests the estimates are not upward-biased. We perform the falsification test in Column 3 by testing whether pre-intervention trends exist across primary beneficiaries and non-beneficiaries.[34] The coefficient α_3 is insignificant, suggesting a similar trend across primary beneficiaries and non-beneficiaries in the absence of any capacity-building program interventions. Overall, the above findings show that both KVK interventions—frontline demonstrations and capacity-building programs—positively impact technology adoption.

5.2. Estimating network beneficiaries

About 10 % of farmers in these villages are primary or secondary beneficiaries of frontline demonstrations, of whom 3 % are farmers with such demonstrations on their fields (primary beneficiaries), and 7 % are farmers who report accessing such demonstrations by visiting another farmer's field (secondary beneficiaries). Eqs. (3) and (4) estimate the percentage of network beneficiaries in frontline demonstration villages (plotted in Fig. 4), and results show that 28 % of farmers are network beneficiaries of such demonstrations. Fig. 5 presents the percentage of network beneficiaries of capacity-building programs conducted on varietal evaluations in capacity-building program villages: 27 % of farmers are network beneficiaries. Our estimates of network beneficiaries for both frontline demonstrations and capacity-building programs may have a downward bias because the study captures the

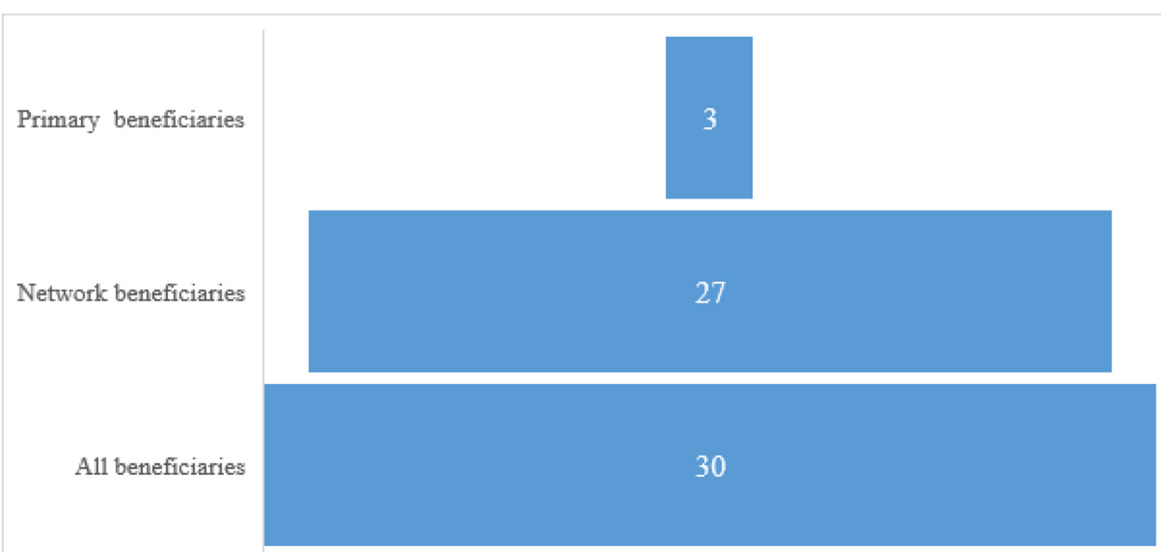
[31] Data are not available at the village level.
[32] MDID estimates are based on Equation (4), employing 2014–15 and 2015–16 data.
[33] MDID estimates are based on Equation (3).
[34] MDID estimates are based on Equation (4), employing 2014–15 and 2015–16 data.



Source: ICAR-IFPRI KVK Survey, 2019

Note: *Primary* beneficiary farmers receive benefits directly from KVKs (i.e., an FLD is conducted on their 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 having *primary* and *secondary* beneficiaries in their social network. All beneficiaries include *primary*, *secondary*, and *network* beneficiaries.

Fig. 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 through CBPs conducted by KVKs. Network beneficiary farmers benefit from having primary beneficiaries in their social network. All beneficiaries include primary and network beneficiaries.

Fig. 5. Capacity-building program (CBP) beneficiaries of wheat varietal evaluation, % farmers in CBP villages.

"network within the sample." Despite this, the magnitudes are large and reflect the importance of social network channels in disseminating public agricultural advisory service information. Next we explore whether this information flow results in adopting a new wheat variety.

5.3. KVKs' impact on the adoption of HD-2967: Effects on network beneficiaries

Table 7 presents the effect of frontline demonstrations on the adoption of wheat variety HD-2967 by network beneficiaries. Columns 1 and 2 present network beneficiaries' impact estimates with and without a time-varying district control, respectively. In Column 1, the coefficient α_1 shows a 19 % increase in adoption of HD-2967 between 2015–16 and 2017–18. Consistent with the covariates balance, the estimated coefficient α_2 is insignificant and reveals that the adoption pattern for network beneficiaries of frontline demonstrations is similar to that of non-beneficiaries (before the demonstration interventions). The coefficient of interest, α_3, reveals that network beneficiaries' adoption rate is about 10.4 % higher than that of non-beneficiaries. Again, when we include a time-varying district control in Column 2, the coefficient α_3 is marginally higher (10.5 % versus 10.4 %) than in Column 1, which suggests that the estimates are not upward-biased. Note that the magnitude of increased adoption is smaller than that of primary or secondary beneficiaries of frontline demonstrations.[35] This result is consistent with Kondylis et al. (2017), who showed that directly trained contact farmers saw a larger impact on adoption behavior than other farmers. Moreover, the coefficient α_3 Column 3 is insignificant, suggesting a similar trend across network beneficiaries and non-beneficiaries in the absence of frontline demonstration interventions.

Table 8 presents the impact of capacity-building programs on the adoption of HD-2967 by network beneficiaries. Columns 1 and 2 present the impact estimates for network beneficiaries with and without a time-varying district control. In Column 1, the coefficient α_1 represents a 24 % increase in adoption of HD-2967 between 2015 and 16 and 2017–18. The estimated coefficient α_2 is insignificant and reveals that the adoption pattern of network beneficiaries of capacity-building programs is similar to those of non-beneficiaries (before such program interventions). The coefficient of interest, α_3, reveals that network beneficiaries' adoption rate is about 10.6 % higher than that of non-beneficiaries. When we include a time-varying district control in Column 2, the coefficient α_3 is marginally higher (10.8 % versus 10.6 %) than in Column 1, which suggests that the estimates are not upward-biased. Again, the magnitude of increased adoption is smaller than that of primary beneficiaries of capacity-building programs. The above results are robust to pre-intervention trends in Column 3. This study establishes evidence of a positive impact of frontline demonstrations and capacity-building programs on network beneficiaries' adoption of wheat variety HD-2967.

5.4. District-level trends in adoption of HD-2967

This section examines the association of frontline demonstrations with district-level adoption of HD-2967.[35] Fig. 6 summarizes information on the implementation of such demonstrations for HD-2967 at the district level from 2012 to 2017. Based on this information, we classify districts into five categories: i) districts where no frontline demonstrations were conducted in the years between 2012 and 2017 (Agra, Etawah, Jaunpur, and Raebareli), referred to

[35] Information on district-level capacity-building program interventions is not available.

Table 7
Estimates of FLDs on *network* beneficiaries' adoption of HD-2967, new wheat variety, Uttar Pradesh.

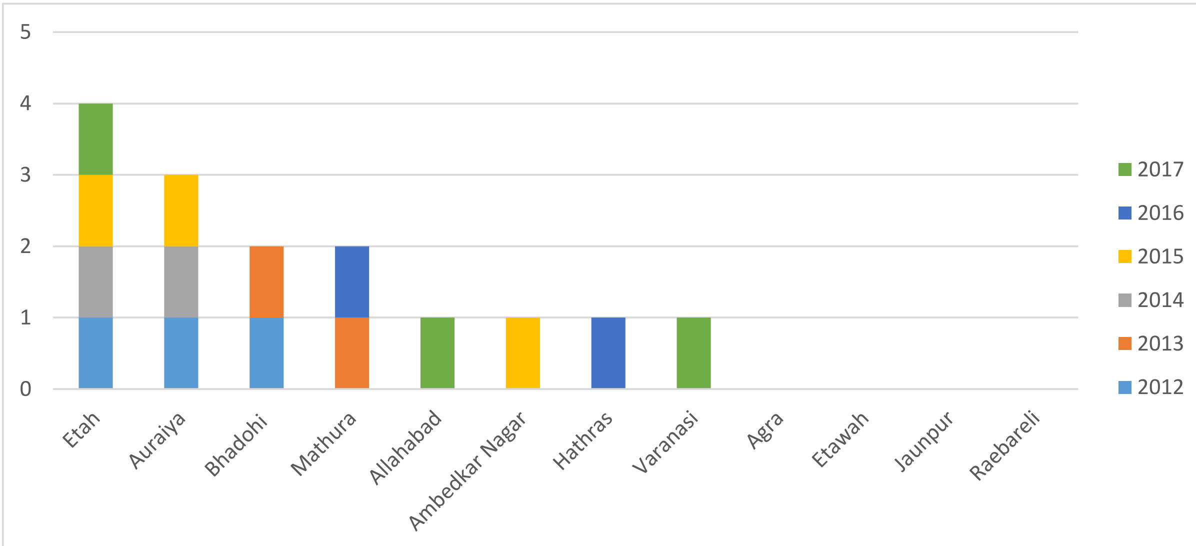
	Impact estimates		Falsification test
	Model 1	Model 2	Model 3
FLD (N)*Time,α_3	0.104* (0.061)	0.105* (0.061)	0.005 (0.052)
FLD (N),α_2	0.060 (0.041)	0.059 (0.041)	0.055* (0.033)
Time,α_1	0.191*** (0.026)	0.187*** (0.028)	0.118*** (0.021)
Time-varying district control	No	Yes	No
Matching before DID	Yes	Yes	Yes
Constant	0.221*** (0.017)	0.225*** (0.019)	0.102*** (0.012)
Number of observations	1,918	1,918	1,918
Number of farmers	959	959	959

Notes: Each column represents a separate regression. The dependent variable takes a value of 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 2017–18 and 0 for 2015–16. Model 3 takes a value of 1 for 2015–16 and 0 for 2014–15. In all models, the treatment group is defined as *network* beneficiaries. It takes a value of 1 if the farmer is a *network* beneficiary but has not received the benefit of CBPs, and 0 when the farmer is a resident of a non-FLD village. Models 1 and 2 present the impact estimates. Model 3 tests 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 squared, gender, education, household size, caste, source of income, asset index, HH experience, soil color, source of irrigation, plot location (near a road), and average village land size. A kernel procedure is used for performing matching. All regressions are in the common support region. We use an epanechnikov kernel function, and the bandwidth parameter equals 0.06. Time-varying district control is the percentage of farmers receiving extension services from other government programs. FLDs = Frontline demonstrations to promote the new wheat variety (HD-2967). CBPs = Capacity-building programs on the varietal evaluation of wheat. Robust standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.001$.

Table 8
Estimates of CBPs on *network* beneficiaries' adoption of HD-2967, new wheat variety, Uttar Pradesh.

	Impact estimates		Falsification test
	Model 1	Model 2	Model 3
CBP (N)*Time,α_3	0.106* (0.059)	0.108* (0.059)	−0.002 (0.048)
CBP (N),α_2	0.036 (0.039)	0.034 (0.039)	0.038 (0.029)
Time,α_1	0.240*** (0.032)	0.235*** (0.034)	0.134*** (0.025)
Time varying district control	No	Yes	No
Matching before DID	Yes	Yes	Yes
Constant	0.222*** (0.021)	0.227*** (0.023)	0.089*** (0.014)
Number of observations	1,510	1,510	1,510
Number of farmers	755	755	755

Notes: Each column represents a separate regression. The dependent variable takes a value of 1 when wheat farmers adopt *HD-2967* and 0 otherwise. *Time* is a dummy variable. Models 1 and 2 take value 1 for 2017–18 and 0 for 2015–16. Model 3 takes a value of 1 for 2015–16 and 0 for 2014–15. In all models, the treatment group is defined as *network* beneficiaries and takes a value of 1 if a farmer is a *network* beneficiary but has not received the benefit of FLDs, and 0 when the farmer is a resident of a non-KVK village. Models 1 and 2 present the impact estimates. Model 3 tests 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 squared, gender, education, household size, caste, land holding, source of income, asset index, HH experience, soil color, source of irrigation, plot location (near a road), and average village land size. A kernel procedure is used for performing matching. All regressions are in the common support region. We use an epanechnikov kernel function, and the bandwidth parameter equals 0.06. Time-varying district control is the percentage of farmers who received extension services of other government programs. FLDs = Frontline demonstrations to promote the new wheat variety (HD-2967). CBPs = Capacity-building programs on the varietal evaluation of wheat. Robust standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.001$.



Source: Indian Council of Agriculture Research, Government of India.

Fig. 6. Number of times FLDs of HD-2967 have been conducted between 2012 and 2017 by the district.

as control districts; ii) districts where such demonstrations were conducted in only one year between 2012 and 2017 (Allahabad, Ambedkar Nagar, Hathras, and Varanasi); iii) districts where such demonstrations were conducted in any two years between 2012 and 2017 (Bhadohi and Mathura); iv) districts where such demonstrations were conducted in any three years between 2012 and 2017 (Auraiya); and (v) districts where such demonstrations were conducted in any four years between 2012 and 2017 (Etah). We estimate the following specification to examine the association between frontline demonstrations and the adoption of HD-2967 at the district level. Note that we cannot interpret the estimates of this specification as causal; the specification presents the trends across demonstration and non-demonstration districts.

$$Y_{idt} = \alpha_0 + \alpha_1 Time_t + \alpha_2[FLD - D]_d + \alpha_3([FLD - D)]_d * Time_t) + \varepsilon_{ivdt} \quad (7)$$

where i represents an individual farmer, d stands for the district, and t takes value 1 for 2014–15, 2 for 2015–16, 3 for 2016–17, and 4 for 2017–18. Y takes a value of 1 if a farmer adopts wheat variety HD-2967, and 0 otherwise. $FLD - D$ takes a value of 1 if frontline demonstrations were conducted in any of the years in district d between 2012 and 2017 and 0 if not (control districts). The coefficient of interest, α_3, estimates the difference in adoption rates of HD-2967 across frontline demonstration and non-frontline demonstration districts. We cluster the standard errors at the district-time level. The difference between demonstration and non-demonstration districts between 2014–15 and 2017–18 is insignificant (see Table 9, Column 1).

To gain further insights, we exploit the variation in the implementation of frontline demonstrations at the district level and run the following variants of Eq. (7) to compare control districts with i) districts where frontline demonstrations were conducted four times between 2012 and 2017; ii) districts where such demonstrations were conducted three times between 2012 and 2017; iii) districts where such demonstrations were conducted twice between 2012 and 2017; and iv) districts where such demonstrations were conducted once between 2012 and 2017. The results are presented in Table 9 in Columns 2, 3, 4, and 5, respectively. Districts where frontline demonstrations were conducted four and three times between 2012 and 2017 saw significantly higher adoption of HD-2967 (8 % and 5 %, respectively) than control districts. Interestingly, the results are insignificant in districts where frontline demonstrations were conducted once or twice between 2012 and 2017. Nonetheless, these magnitudes are smaller than the impact on primary or secondary beneficiaries and network beneficiaries of frontline demonstrations. The evidence suggests that districts where frontline demonstrations are implemented frequently are more likely to influence diffusion speed at the aggregate level than districts where such demonstrations are conducted infrequently.

6. Conclusions and implications

In developing and emerging economies like India, large-scale agricultural advisory services can serve as the most important knowledge- and information-dissemination institutions for accelerating the adoption of modern technologies and improving farmers' learning ability. The KVK model has emerged as an influential blueprint for enhancing outcomes among smallholders. KVKs now serves as the primary source of knowledge and information for millions of Indian farmers.

This study evaluated the outreach efforts of public-sector KVKs. In particular, the study estimated the impact of knowledge and information transfer on primary or secondary beneficiaries of frontline demonstrations and on network beneficiaries (farmers who benefited from having primary and secondary beneficiaries in their social networks). The study also evaluated the impact of capacity-building programs on the adoption of HD-2967, a newly released wheat variety, by primary and network beneficiaries. The study established the strong positive impact of frontline demonstrations and capacity-building programs on beneficiaries' adoption of HD-2967. Although the effect on primary beneficiaries is significant, substantial gains also arise for network beneficiaries compared to non-KVK farmers.

The above findings underscore the vital role that social networks play in diffusing technology. The results reinforce the argument put forth by Banerjee et al. (2019) and Beaman, BenYishay, Magruder, and Mobarak (2021). In other words,

Table 9
Estimates of FLDs at the district level on the adoption of HD-2967, new wheat variety, Uttar Pradesh.

	Model 1	Model 2	Model 3	Model 4	Model 5
FLD-D (I ≥ 1)*Time	−0.004 (0.032)				
FLD-D (I = 4)*Time		0.083** (0.025)			
FLD-D (I = 3)*Time			0.055** (0.026)		
FLD-D (I = 2)*Time				−0.101 (0.063)	
FLD-D (I = 1)*Time					0.007 (0.032)
FLD-D (I ≥ 1)	−0.023 (0.069)				
FLD-D (I = 4)		−0.212** (0.074)			
FLD-D (I = 3)			−0.169** (0.060)		
FLD-D (I = 2)				0.165 (0.114)	
FLD-D (I = 1)					−0.027 (0.071)
Time	0.133*** (0.020)	0.133*** (0.020)	0.133*** (0.020)	0.133*** (0.020)	0.133*** (0.020)
Constant	−0.011 (0.050)	−0.011 (0.050)	−0.011 (0.050)	−0.011 (0.050)	−0.011 (0.050)
Standard error clustered at the district-time level	Yes	Yes	Yes	Yes	Yes
Number of observations	5,984	2,376	2,428	2,892	3,772

Notes: Each column represents a separate regression. The dependent variable takes a value of 1 when wheat farmers adopt *HD-2967* and 0 otherwise. *FLD-D (I ≥ 1)* takes a value of 1 if the district saw the implementation of FLDs of HD-2967 at least once between 2012 and 2017 and 0 otherwise. *FLD-D (I = 4)* takes a value of 1 if the district saw the implementation of FLDs of HD-2967 four times between 2012 and 2017 and 0 otherwise. *FLD-D (I = 3)* takes a value of 1 if the district saw the implementation of FLDs of HD-2967 three times between 2012 and 2017 and 0 otherwise. *FLD-D (I = 2)* takes a value of 1 if the district saw the implementation of FLDs of HD-2967 two times between 2012 and 2017 and 0 otherwise. *FLD-D (I = 1)* takes a value of 1 if the district saw the implementation of FLDs of HD-2967 once between 2012 and 2017 and 0 otherwise. *Time* takes value 1 for 2014–15, 2 for 2015–16, 3 for 2016–17, and 4 for 2017–18. FLDs = Frontline demonstrations to promote the new wheat variety (HD-2967). Standard errors in all models are clustered at the district-time level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$.

technology transfer by central individuals,[36] or network theory-based targeting approaches in villages, could lead to higher diffusion rates than technology transfer initiated by random individuals or opinion leaders. This study provides a new avenue of exploration for researchers examining the transfer of knowledge and information on farming when the primary beneficiary is a central individual or is best placed to disseminate information. The study also highlighted the critical role 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 frontline demonstrations and capacity-building programs.

Finally, the study attempted to evaluate how widespread the adoption and diffusion of technologies are at the district level. Findings showed that districts that saw frequent frontline demonstration interventions over the years were likely to see gains in diffusion speed at the district level. The evidence on spillover effects provides new insights into the approaches that maximize returns on investments in publicly funded knowledge- and information-transfer programs. From a policy perspective, the strong impact of KVKs suggests that these services should be scaled up to reach more Indian farmers.

CRediT authorship contribution statement

Deepak Varshney: Conceptualization, Data curation, Formal Analysis, Methodology, Writing-original draft. **Pramod K. Joshi:** Supervision, Conceptualization, Writing- review, and editing. **Anjani Kumar:** Conceptualization, Writing- review, and editing. **Ashok K.Mishra:** Conceptualization, Writing- reviewing, and editing. **Shantanu Kumar Dubey:** Data curation, Writing- reviewing, and editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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

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Appendix A. Supplementary data

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