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Estimating the Adoption of Modern Cultivars in Rajasthan

A Descriptive Analysis

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ABSTRACT

One of the most promising strategies to boost farmers' income in developing countries is the adoption of improved technologies, such as modern cultivars that may produce higher yields. This study aims to examine the adoption of modern cultivars in Rajasthan, one of India's northern states. Our analysis is based on a primary survey of 1,500 farmers covering four major crops: wheat, mustard, pearl millet, and gram. The study aims to identify the farmer-level constraints in adopting modern cultivars and decomposing into the elasticity of adoption probability and the use intensity. The study also attempts to assess the role of the key characteristics of cultivars in their adoption. The authors implemented McDonald and Moffitt's (1980) approach to decompose the overall elasticity into the elasticity of adoption probability and use intensity. To present cultivar-specific analysis, the authors modeled farmers' decisions to adopt top cultivars accounting for concerns regarding independence of irrelevant alternative assumption in a multinomial logistics framework.

The study finds that the key policy drivers for adoption of modern cultivars are farmers' access to the Kisan Credit Card and the intensity of the extension services they receive. Further, the estimates of elasticity show that both variables are more important for adoption probability than use intensity. The cultivar-specific analysis shows that the main drivers for adoption of modern cultivars are drought (all crops), weather-related risk tolerance of cultivars (all crops), higher yield (wheat and pearl millet), better marketability and storage traits (pearl millet and gram), and pest and disease tolerance (wheat). The main driver for continuing old cultivars is taste attributes (wheat, pearl millet, and gram). Thus, the findings stress the importance of improving credit facilities for poor farmers in particular, and providing extension services to all farmers, beginning with the places where it needed the most. Moreover, breeding efforts should consider the identified traits when developing and up-grading cultivars to ensure the availability of suitable technology.

Keywords: Adoption, Elasticity, Extension, Kisan credit card, Multinomial logit model

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ACRONYMS

APL	Above Poverty Line
BPL	Below Poverty Line
ICAR	Indian Council of Agricultural Research
IIA	Independence of Irrelevant Alternatives
KCC	Kisan Credit Card
OPV	Open Pollinated Varieties
SC	Scheduled Caste
ST	Scheduled Tribe

1 INTRODUCTION

One of the most promising strategies to boost agricultural productivity and increase farmer incomes is the adoption of modern agricultural technology (Duflo et al., 2011; Mason and Smale, 2013). However, this involves several constraints, such as awareness, credit, risk involved, and lack of proficiency (Feder et al., 1985; Besley and Case, 1993; Barrett et al., 2010). These constraints limit the level and the speed of the adoption of modern technology, especially in developing countries (Feder and Umali, 1993; Foster and Rozenzweig, 2010). Although there is considerable literature on the adoption of agricultural inputs such as fertilizers, pesticides, agricultural machinery, and management practices (Morris et al., 2007; Duflo et al., 2011), the literature on the adoption of modern cultivars is limited. One strand of the literature focuses on the role of farmers' characteristics in the adoption of modern cultivars (Feder et al., 1985; Besley and Case, 1993; Abebaw and Haile, 2013. A second strand looks at the role of technology characteristics; however, this line of enquiry has been slim (Adesina and Zinnah, 1993; Batz et al., 1999; Lunduka et al., 2012). Our paper contributes to both strands of the literature by providing a comprehensive analysis of the role of both farmers' and technological constraints on the adoption of modern cultivars.

The empirical literature has taken two different approaches to identify the farmer level constraints for modern cultivars. The most common approach is the binary choice model, where the dependent variable is defined as a dummy variable (adopters vs. nonadopters) to identify the drivers of modern cultivars—see, for example, Lunduka et al. (2012). The main limitation of the binary choice approach is that it does not distinguish adopters in terms of intensity of the implementation. Another approach to identifying the drivers of modern cultivars is the application of censored or continuous variables.[1] However, the main problem in a standard censored framework is that it does not distinguish between the probability of adoption and the use intensity (McDonald and Moffitt, 1980). Therefore, adoption drivers of modern cultivars are better understood by decomposing the overall effects into the adoption probability and use intensity, where the adoption probability helps to track the change in a farmer's status from nonadopter to adopter of modern cultivars, and the use intensity helps in understanding the change in the use intensity of the cultivars adopted. This information is crucial for the policy makers to gain insights for making strategies in a better way to encourage the adoption of modern cultivars.

At the same time, it is important to highlight the role of different traits identified in the adoption of cultivars to understand farmers' decision for future technology selections. In this context, Adesina and Zinnah (1993) examines the role of traits in the adoption of rice cultivars in the African region and shows a significant influence on the adoption of modern cultivars.

[1] See, for example, the Tobit model in Johnston and DiNardo (1972).

This paper has two major objectives. The first is to identify farmer-level constraints in the adoption of modern cultivars,[2] and to explore the role of these constraints by decomposing its overall effect into two parts, specifically by estimating the elasticities of both adoption probability and use intensity. The second is to present a cultivar-specific analysis for the top cultivars to identify how their traits influence their selection for each cultivar.

The cultivar-specific analysis is warranted for following reasons. First, it considers the top cultivars, regardless of whether they are old or modern. The adoption literature, by contrast, largely focuses on modern cultivars and has ignored the analysis of old cultivars. In our view, the analysis of old cultivars is also important to understand the traits that drive their continued adoption. Second, the cultivar-specific analysis modeled in a multinomial logistics framework provides an innovative approach to study farmers' choice decisions, as the adoption literature has largely focused on binary and continuous choice models.

Our analysis is based on a primary survey of 1,500 farmers covering four major crops of the northern Indian state of Rajasthan: wheat, mustard, pearl millet, and gram. For the decomposition exercise, we implement McDonald and Moffitt (1980) to estimate overall elasticity and its two components. To present cultivar-specific analysis, we model farmers' decisions to adopt top cultivars in a multinomial logistics framework. Our framework also accounts for concerns regarding the violation of independence of irrelevant alternatives (IIA) assumption, in cases where each farmer did not have the same choice of available cultivars.[3]

The paper shows that farmers' access to the Kisan Credit Card (KCC)—a credit program developed by government to support the financial needs of the agricultural sector—and the intensity of the extension services they receive are the main channels to increase the adoption of modern cultivars. Further, the findings show that the traits of the cultivars which are significant for its adoption are crop and cultivar type specific.

Through these findings, our paper adds value to the literature in several ways. First, it decomposes the effect of farmers' adoption of modern cultivars into two components (adoption probability and intensity use), a perspective that to date is not well understood for Indian farmers. Second, because the adoption literature has largely ignored old cultivars, this paper makes a significant contribution in identifying traits that drive the cultivation of old cultivars. Finally, the cultivar-specific analysis models farmers'

[2] Our paper defines modern cultivars as those that were released since 2000, and all others as old cultivars.
[3] See Yamamato (2011), for more detail.

decisions in a multinomial logistics framework, and accounts for concerns regarding IIA—both of which are novel approaches for the comprehensive study of technology adoption for the future research.

Following this introduction, the paper is divided into five sections. The second section discusses the agriculture profile of Rajasthan. The third section provides the sampling and approach of primary survey; presenting the farmers' profiles and the adoption profile of cultivars through statistics regarding cultivar age (modern or old), type (hybrid, open pollinated variety, and land race),[4] and development sector (private or public). The fourth section presents the conceptual framework, the McDonald and Moffitt (1980) decomposition approach, and the multinomial logistics framework. The fifth section discusses the findings of the study and leads into the conclusion.

[4] Hybrids are developed by the cross pollination of plants. Open pollinated varieties (OPV) are those which are self-pollinated, or are pollinated by another representative of the same variety. Open pollinated varieties are also often referred to as varieties. Land race is a locally adapted traditional variety that has developed over the time through the adaptation to its natural environment of agriculture.

2. AGRICULTURAL PROFILE OF RAJASTHAN

Rajasthan is the largest state of India, constituting 10.4% and 11.2% of the country's total geographical area and gross cropped area, respectively. It houses 5.5% of India's total population, and two-thirds of the state's population (56.5 million) depend on the agricultural sector (Chandramouli and Registrar, 2011). Therefore, any improvements to the agricultural sector are important for achieving poverty reduction goals. Although agriculture is the main source of livelihood, only 34.5% of the net sown area is irrigated, and agriculture output largely depends on the rainfall. Within the state, 75% of the total area is rainfed, while the remaining 25% is irrigated. In terms of agro-climatic regions, 61% of the state is considered arid, 16% semi-arid, 15% humid, and 8% semi-humid. In terms of rainfall, by agro-climatic region, the average rainfall in arid, semi-arid, humid, and semi-humid regions is 33.2 centimeters (cm), 53.7 cm, 72 cm, and 82.7 cm, respectively.

In arid regions, the main crops cultivated in the kharif (rainy) season are pearl millet, guar, and pulses, and in the rabi (winter) season, the main crops are wheat and mustard (limited to areas with irrigation facilities). In semi-arid regions, the main kharif crops are pearl millet, sorghum, and pulses, and the main rabi crops are wheat, barley, mustard, and gram. In humid regions, the kharif crops are cotton, maize and sugarcane, and the rabi crops are groundnut, mustard, and rapeseed. In semi-humid regions, maize is the chief kharif food crop, and wheat, gram, and mustard are the major rabi crops.

Our analysis considers wheat, mustard, pearl millet and gram. These crops combined cover more than 50% of Rajasthan's total cropped area. The shares of wheat, mustard, pearl millet, and gram account for 12%, 10%, 22%, and 7% of the total cropped area, respectively. Wheat and pearl millet together account for 79% of the total cropped area of cereals and millets in the state.[5] Gram accounts for 37% of the total cropped area of pulses. Mustard accounts for 46% of the total cropped area for oilseeds. On a further interesting note, both mustard and pearl millet each cover more than 40% of India's total cropped area, and both crops are first among all states in terms of area and production.

According to the state's agriculture policy for 2012, Rajasthan's agricultural sector faces the following main constraints: (a) frequent drought, (b) climate change and global warming, (c) low adoption of modern cultivars and technologies in dry land and arid regions, (d) poor soil health improvement measures, and (e) rising cultivation costs. Though all these constraints are important, this paper made an attempt to identify both farmer and technological level constraints in the adoption of modern cultivars in Rajasthan.

[5] Of the total cropped area for cereals and pearl millets, 51% is attributed to pearl millet and 28% to wheat.

3. DATA SET

The survey was conducted in Rajasthan by the International Food Policy Research Institute (IFPRI), New Delhi, as part of a nationwide study supported by the Indian Council of Agricultural Research (ICAR). It compiled representative data on the adoption of major crop cultivars. The selected crops were wheat, mustard, pearl millet, and gram. It collected information pertaining to reference year 2015–2016. The survey was carried out from November 2016 to February 2017. It gathered detailed information on the adoption of cultivars, including information on the traits of each cultivar and farmers' reasons for selecting them.

3.1 Sample Design and Sample Size

The survey was carried out in 13 of Rajasthan's 29 districts.[6] The districts, which were spread across all agro-ecological zones of Rajasthan, were selected randomly from each zone.[7] The number of districts per zone was decided based on the total cropped area of major crops. The selected crops in Rajasthan were wheat, mustard, and gram in the rabi season, and pearl millet in the kharif season. Three blocks from each district and two villages from each block were selected randomly. To select households, a complete household listing was developed for each selected village, with four quintiles based on total cultivable land and five households selected randomly from each quintile.[8] The total sample size in Rajasthan is about 1,500 farmers.

3.2 Farmers' Characteristics

This subsection presents the characteristics of the farmers surveyed and discusses their adoption of modern cultivars. Table 1 presents the characteristics of the sample farmers. The total sample suggests that cultivation in Rajasthan is male dominated; 98% of surveyed households were headed by men. Education measured in terms of years of schooling suggests that the head of the household has an average six years of education, a factor that affects farmers' learning proficiency and ability to understand the information they receive from extension agents (Besley and Case, 1993). Farmers' learning ability—the ability to decipher new information—is also positively related to the adoption of modern technology (Polson and Spencer, 1991; Kebede et al., 1990).

The average age of the household head is about 44 years, which is comparable to results from other developing countries. Two strands of the existing literature have examined the association of farmers' ages and their adoption of modern cultivars. The first strand argues that younger farmers are more likely to adopt new technologies earlier and more likely to take risks because they have longer planning

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[6] The selected districts are Bharatpur, Bikaner, Bundi, Chittorgarh, Churu, Dausa, Hanumangarh, Jhunjhunu, Jodhpur, Karauli, Shri Ganganagar, Sikar, and Sirohi.

[7] The zones are Irrigated North Western Plain, Hyper Arid Partial Irrigated Zone, Internal Drainage Dry Zone, Transitional Plain of Luni Basin, Semi-Arid Eastern Plain, Flood Prone Eastern Plain, Sub-Humid Southern Plains & Aravalli Hills, Humid Southern Plains, and Humid South-Eastern Plains.

[8] The listing module queried the land owned and the total cultivable land. Households with zero cultivable land were not included in the sample frame.

horizons (Bultena and Hoiberg, 1983; Polson and Spencer, 1991). The other strand relates the age of the farmer as the proxy of farm experience in cultivation. Mueller and Jansen (1988) suggest that farmer age is positively associated with the adoption of modern technologies. We also consider the number of family members working on the farm to account for the contributions of family labor. On the surveyed farms, an average of 2.8 members are involved in farming. The survey also considered the average experience in farming and found that it was about 24 years of experience, a figure that is comparable with other studies.

With regard to social groups and income levels, 27% of the surveyed farmers are from Scheduled Castes/Scheduled Tribes (SC/STs), and the remaining 73% are from other social classes. In India, it is vital to account for proportions of SC/STs in farmer surveys, as the literature has thoroughly documented that SC/STs have much more limited access to modern agricultural resources.[9] The farmers' average land size is 1.8 hectare (ha). The empirical literature suggests that as land size increases, farmers are more likely to adopt modern technology (Polson and Spencer, 1991; Akinola, 1987). By contrast, poorer farmers are less likely to adopt modern technologies because these technologies have both an associated fixed cost and a risk involved in their adoption. To put that information into context, about 25% of the sample in our study have Below Poverty Line (BPL) and *antyodaya* (government food subsidy) cards, while 75% have Above Poverty Line (APL) cards.

With regard to farmer access to credit, the government of India has provided Kisan Credit Cards (KCCs) to supply farmers with credit facilities.[10] Only 36% of the total farmers in our survey have KCCs. Further, according to our data, only 20% of the poorest farmers have KCCs. This surprising finding indicates that the government needs to address credit constraints, especially for poor farmers. Without credit facilities, it is less likely that poorer farmers may adopt modern technologies.

Information dissemination is an important channel for the adoption of modern cultivars. Our survey asked whether farmers met with government agricultural extension agents in the past 12 months. Only 13% of farmers surveyed were able to meet with extension workers. Using this information, we constructed a measure of extension intensity for each village, defined as the share of farmers out of the total sample who met extension workers. If we use an indicator of farmers meeting extension agents, then it suggests that farmers may have been able to spread their knowledge (information diffusion) among neighbors, and in that case it is problematic to include as a dummy variable in our specification.[11] To partly address this concern, our paper used extension intensity, defined

[9] See Deshpande (2000).
[10] KCC holders are covered under personal accident insurance up to ₹50,000 for death and permanent disability, and up to ₹25,000 for other types of risk. The premium is borne by both the bank and borrower in a 2:1 ratio. KCC offers two types of credit: cash credit and term credit (for activities such as pump sets, land development, and modern technologies).
[11] Conley and Udry (2003), for example.

as the explanatory variable. The result for extension intensity is 0.13, which suggests that on average, only 13% of village farmers in Rajasthan met with extension workers. It clearly shows a weak outreach of extension workers. In a related variable, smartphone use, 10% of the surveyed farmers carry smartphones. This variable is included to test the hypothesis related to use of smartphones for information diffusion.

Table 1: Rajasthan farmer profiles, 2015–2016

Variables	Mean	Standard deviation	Minimum	Maximum
Female (Yes=1)	0.02	0.16	0	1
Education (in year)	5.51	4.91	0	16
Age (in year)	44.52	14.43	18	86
Scheduled Caste/Scheduled Tribe (SC/ST) (Yes=1)	0.27	0.44	0	1
Below Poverty Line (BPL) (Yes=1)	0.25	0.43	0	1
Family members in farming (#)	2.80	1.80	1	12
Farming experience (year)	23.71	12.00	0	65
Smartphone (Yes=1)	0.10	0.29	0	1
Kisan Credit Card (KCC) (Yes=1)	0.36	0.48	0	1
Met extension worker (Yes=1)	0.13	0.33	0	1
Extension intensity	0.13	0.16	0	0.7
Asset index	0.02	2.22	-2.5	13.7
Land owned (ha)	1.81	2.07	0	21.4
Cropped area attributed to modern cultivars (ha)	0.97	1.49	0	16.32
Number of observations	1,496	–	-	-

Source: ICAR-IFPRI survey, 2017

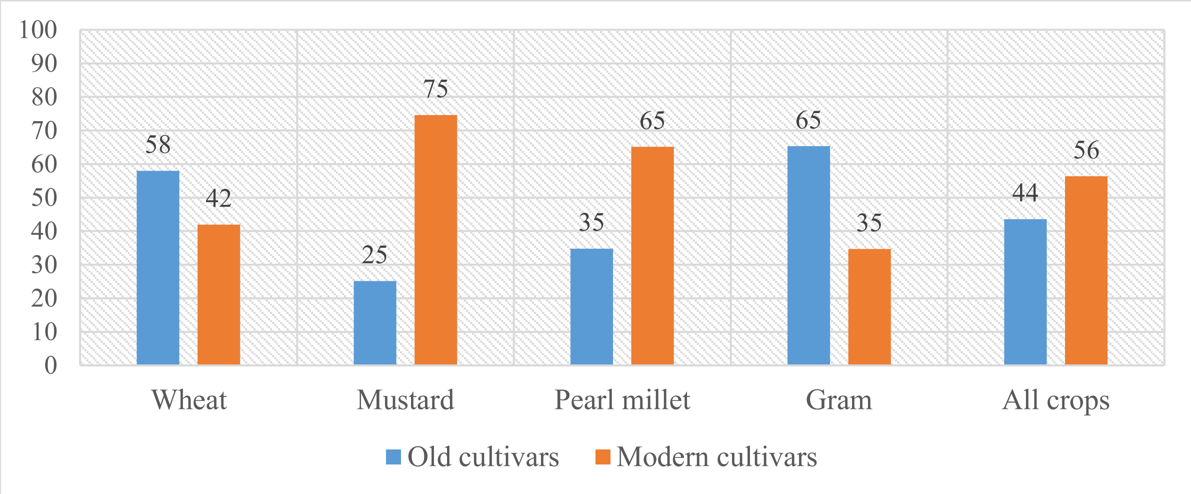
Notes: Asset index is constructed using principal component analysis by considering a wide range of assets owned (e.g., television, refrigerator, tractor) by farmers. Cropped area is calculated considering the cultivation of wheat, mustard, pearl millet, and gram. Modern cultivars are defined as those released since the 2000s; all earlier releases are old cultivars. “Met extension worker” takes the value 1 when farmers have met with a government extension worker in the past 12 months. Extension intensity is defined at the village level, as the share of farmers who met with extension workers in the past 12 months (i.e., if 2 out of 20 farmers met with an extension worker in the past 12 months, then extension intensity is 2/20).

3.3 Adoption Profile

This section presents the adoption profile of modern cultivars of the sample farmers for four major crops: wheat, mustard, pearl millet, and gram. To understand the adoption profile in the state, we summarize the adoption of cultivars in three different categories. First, we provide the share of adoption for modern (post-2000) and old (all earlier) cultivars for each crop and for all crops together. Second, we provide the share of adoption with respect to the type of cultivars—hybrids, OPVs, and land races for each crop and for all crops together. Finally, we provide the share of adoption by developer type (private or public sector) for each crop and for all crops together; this last category illustrates how private and public cultivars have contributed to the seed sector.

Figure 1 presents the adoption of cultivars by their years of release, separated into post-2000 (modern) and all other (old) cultivars. For all crops together, modern cultivars have a share of about 56% of the cultivated area, with 44% still attributed to older cultivars. By crops, the share of modern cultivars for mustard and pearl millet is 76% and 65%, respectively. It is 42% and 35% for wheat and gram, respectively.

Figure 1: Share of modern cultivars (in %), by crop, and for all crops taken together

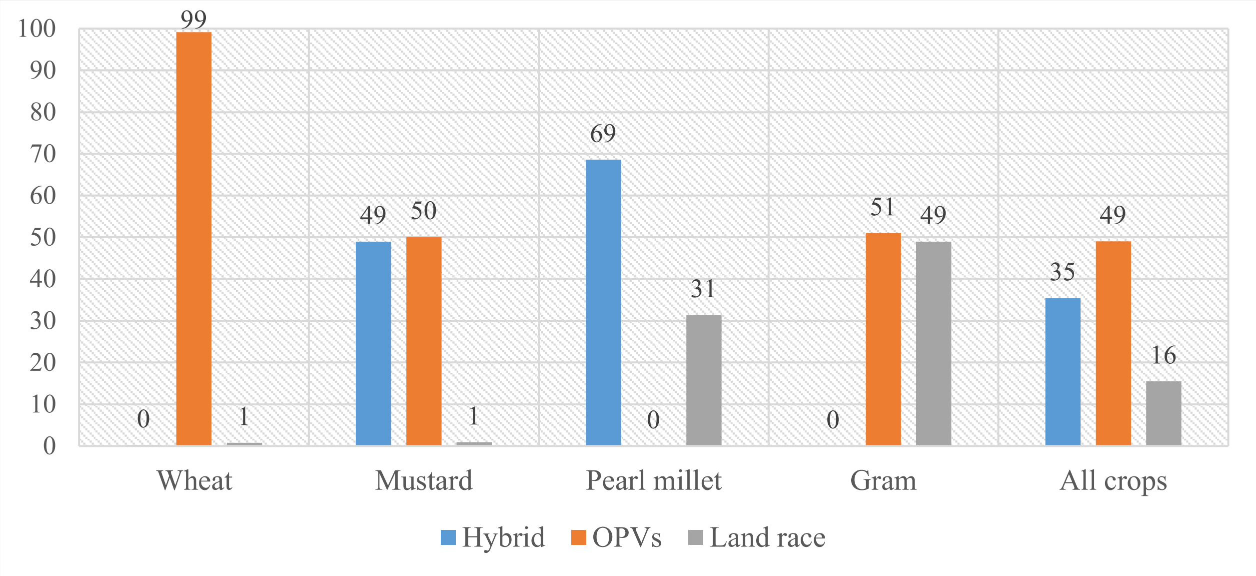


Source: ICAR- IFPRI survey, 2017
Note: Modern cultivars are defined as those released since 2000; all earlier releases are old cultivars.

Figure 2 presents the adoption of cultivars by type: hybrid, OPVs, and land race. For all crops together, the share of hybrids, OPVs, and land race is 35%, 49% and 16%, respectively. In the case of pearl millet, 69% of the cultivated area is attributed to hybrids, with the remaining 31% attributed to land race. In the case of gram, there are no hybrids; 51% of the cultivated area is attributed to OPVs and 49% to land race. In the case of mustard, 49% of the cultivated area is attributed to hybrids, 50% to OPVs, and 1% to land race. In wheat, 99% of the cultivated area is attributed to OPVs, and the remaining 1% to land race. Our results are comparable to cost of cultivation plot-level data for 2012–2013.[12]

[12] According to the cost of cultivation data, for pearl millet, the share of hybrids is 66%, and for wheat, the share of varieties is 52%, and for mustard, the share of hybrids is 38%, and for, the share of varieties is 49%, which is comparable with our survey.

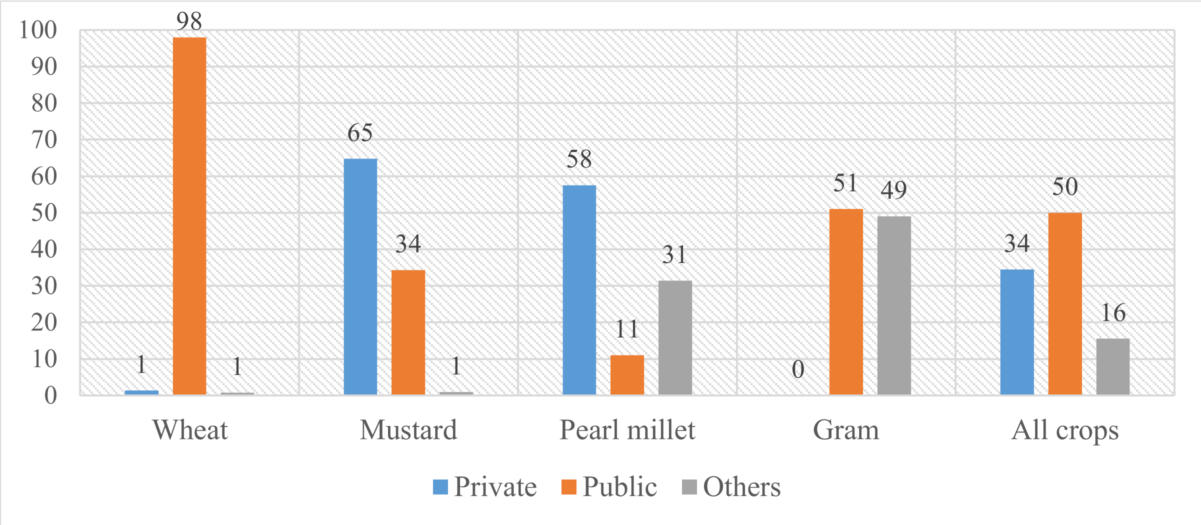
Figure 2: Share of cultivars (in %) developed by type (hybrid, open pollinated varieties [OPVs], land race), by crop, and for all crops taken together



Source: ICAR- IFPRI survey, 2017

Figure 3 presents the adoption of cultivars by developer. For all crops taken together, 50% of the cultivated area is attributed to public sector cultivars, while 34% is attributed to private sector cultivars and 16% to others. This finding shows a strong public sector presence in Rajasthan. By crop, for wheat, about 98% of the cultivated area is attributed to public sector cultivars, and only 1% to the private sector. For mustard, 34% of the cultivated area is attributed to public sector cultivars, and 65% to the public sector. For pearl millet, 58% of the cultivated area is attributed to private sector cultivars, and 11% is attributed to the public sector, with the remaining 31% from others. For gram, there are no private sector cultivars; 51% of the cultivated area is attributed to the public sector, and 49% to other cultivars.

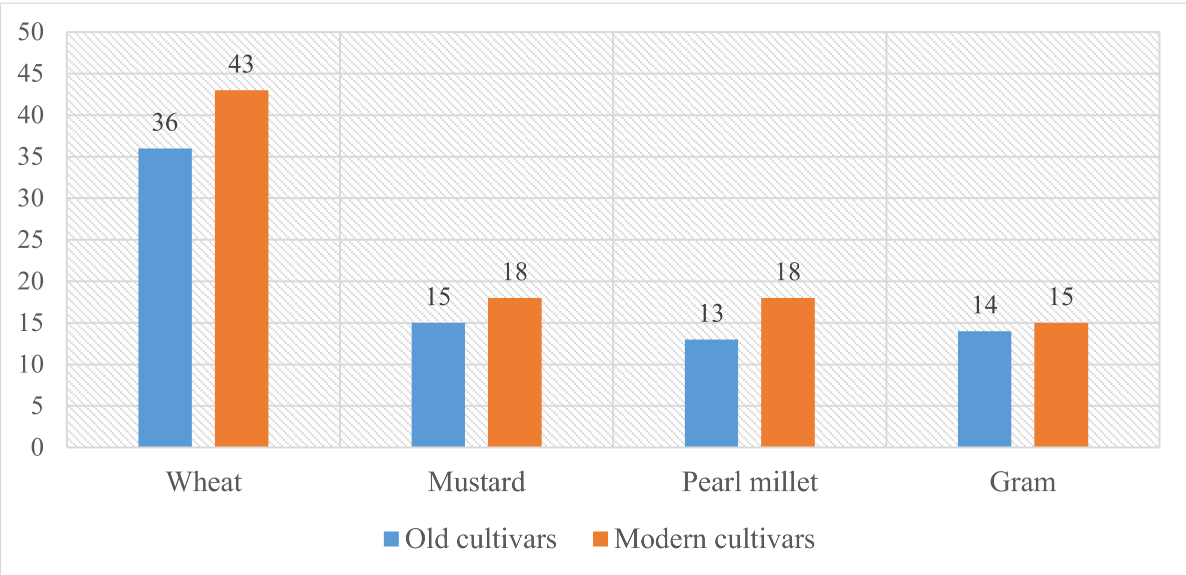
Figure 3: Share of cultivars (in %) developed by private and public sectors, by crop, and for all crops taken together



Source: ICAR-IFPRI survey, 2017
Note: "Others" includes land race.

Figure 4 presents the yield (in quintal/ha), disaggregated by modern and old cultivars, for each surveyed crop. Yield is significantly higher for modern cultivars for wheat, mustard, and pearl millet. For gram, there is an insignificant difference in the yield of modern and old cultivars.

Figure 4: Yield (quintal/ha) by modern and old cultivars, for wheat, mustard, pearl millet, and gram

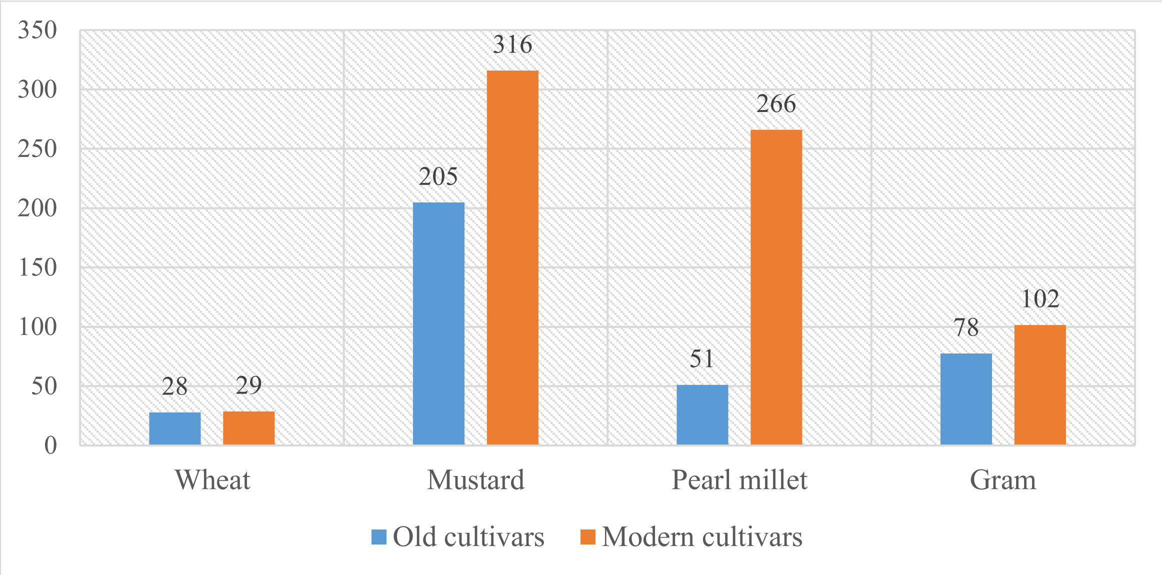


Source: ICAR- IFPRI survey, 2017

Notes: Modern cultivars are defined as those released since 2000; all earlier releases are old cultivars. The statistical difference is significant for wheat, mustard, and pearl millet, but not for gram.

Figure 5 presents the seed cost, in Indian rupees (Rs.) per kilogram (kg), disaggregated by modern and old cultivars, for wheat, mustard, pearl millet, and gram. Seed cost is significantly higher for modern mustard, pearl millet, and gram cultivars. For wheat, there is an insignificant difference in the seed cost of modern and old cultivars.

Figure 5: Seed price (Rs./kg) by modern and old cultivars, for wheat, mustard, pearl millet, and gram



Source: ICAR-IFPRI survey, 2017
Notes: Modern cultivars are defined as those released since 2000; all earlier releases are old cultivars. The statistical difference is significant for mustard, pearl millet, and gram, but not for wheat.

4. METHODOLOGY

4.1 Conceptual Framework

We outline a simple model of farmers' decisions to choose a particular cultivar from an array of available cultivars, following Becerril and Abdulai (2010). The model assumes a farmer decision as the joint decision of the household considered as a single entity, where many family members (e.g., spouse, son, daughter) are farming together.[13] Farmers' decisions to adopt technology can be modeled in a random utility framework. Let U_m be the utility gained from adopting modern cultivars, and let U_o be the utility that a farmer gains from adopting old cultivars. We define Q as the difference between U_m and U_o. Farmers will choose modern cultivar U_m if and only if Q = $U_m - U_o$ > 0. However, the utility that the farmer gains from adopting each type of technology is unobservable, and the utility can be expressed as a function of the observable components in the latent variable model as

$$Q = Z\alpha + \varepsilon \qquad (1)$$

with Q as the binary indicator that values equal to 1 when farmer adopt modern technology, and otherwise 0. α is the vectors of parameter to be estimated. Z is the farmer and farm-level characteristics, and ε is the error term.

There are two different approaches to model the adoption process. The first is a static approach that explains the adoption of modern technology at a point in time and associates a farmer's characteristics with the adoption of modern technology. The second is a dynamic approach that accounts for farmer characteristics that may change over time, such as wealth, accumulation of information, and experience. Besley and Case (1993) argued that farmers will have different characteristics at the time of study data collection than from when they first adopted modern cultivars. To address this concern, they suggest that model needs to be set up in the panel or time series framework. Our data set is cross-section. Therefore, the present paper is limited to model the adoption process in static framework.

4.2 McDonald and Moffitt Decomposition

The majority of the literature models technology adoption in a binary framework (Lunduka et al., 2012). The main limitation of the binary choice approach is that it does not distinguish adopters in terms of the intensity of the implementation. Our paper uses a censored regression model (Tobit model), in complement with the McDonald and Moffitt (1980) decomposition approach, that expresses the overall elasticity into the elasticity of adoption probability and elasticity of use intensity. Here, adoption probability is the probability of adoption of modern technology, and use intensity is prevalence of use in the area attributed to modern technology for those farmers who are ready to adopt it.

[13] See Becker (1981), for example.

We can express McDonald and Moffitt (1980) decomposition framework as follows:

Let y be the outcome variable, and the expected value of y for all observations (both adopters and nonadopters) can be written as E(y),
and let $E(y^{*})$ be the expected value of outcome variable conditional on adopters,
and let F(z) be the probability of being adopter,
Then, E(y) can be written as the multiplication of F(z) and $\mathrm{E}(y^{*})$ $i.e.$

$$\mathrm{E(y)} = \mathrm{F(z)}\ \mathrm{E}(y^{*}) \tag{2}$$

By differentiating both sides of the equation by X (farmers' characteristic), the above equation can be decomposed as follows:

$$\frac{d\,E(y)}{d\,X} = F(z)\ \frac{\mathrm{d\,E}(y^{*})}{d\,X} + \mathrm{E}(y^{*})\ \frac{d\,F(z)}{d\,X} \tag{3}$$

The left-hand side is the marginal change in E(y): the unconditional expected value. The first part of the right-hand-side of equation 3 can be interpreted as the marginal change in E (y^{*}), weighted by the probability of adoption: $F(z)$. The second part of the right-hand side of the equation is the change in the probability of being adopted, weighted by $\mathrm{E}(y^{*})$: the conditional expected value.

To determine the elasticities, multiply both sides of equation 3 by $\frac{X}{E(y)}$.

$$\frac{d\,E(y)}{d\,X}\frac{X}{E(y)} = F(z)\ \frac{\mathrm{d\,E}(y^{*})}{d\,X}\frac{X}{E(y)} + \mathrm{E}(y^{*})\ \frac{d\,F(z)}{d\,X}\frac{X}{E(y)} \tag{4}$$

By simple algebraic rearranging using equation 2, equation 4 can be rewritten as

$$\frac{d\,E(y)}{d\,X}\frac{X}{E(y)} = \frac{\mathrm{d\,E}(y^{*})}{d\,X}\frac{X}{\mathrm{E}(y^{*})} + \frac{d\,F(z)}{d\,X}\frac{X}{F(z)} \tag{5}$$

where the left-hand side of equation 4 is the overall elasticity of outcome variable with respect to a change in X. The first component of the right-hand side is the elasticity of use intensity with respect to a change in X, and the second component is the elasticity of adoption probability with respect to a change in X.

We define dependent variable as the total land attributed to modern cultivars (in hectare terms) for all crops together.[14] Table 1 provides the summary statistics of explanatory variables used in the estimation.

4.3 Multinomial Logistic Regression

To present the cultivar-specific analysis, our paper models a farmer's decision to choose cultivars by estimating the adoption probabilities of each top cultivar (whether modern or old) separately for each crop in a multinomial logistics framework.[15] The cultivar-specific analysis modeled in a multinomial logistics framework provides an innovative approach to study the farmer's choice decision, as the adoption literature on this aspect of research has focused largely on binary and continuous choice models.

The multinomial framework was implemented as follows. First, we ranked the cultivars in terms of area for each crop (see Appendix Tables A1 through A4) to develop a list of the top cultivars for each crop per cultivated area. Next, we picked top three cultivars from each crop in instances where the top cultivar covered more than 5% of the total area. In instances where the area covered was less than 5%, we selected one or two cultivars as our top cultivars. Finally, we considered all remaining cultivars as the base category.

Following the above algorithm, we identified the following top cultivars. For wheat, the top three cultivars are Raj-1482, HD-2967, and Raj-4037. For mustard, we identified only two top cultivars, Pioneer-45s42 and Laxmi-8812, because the third potential cultivar choice covered less than 5% of the cultivated area. For pearl millet, the top three cultivars are Proagro-9444, HHB-67, and Pioneer-86m84. For gram, we picked only one cultivar, GNG-1581, because including the second and third potential cultivar choices leads to the sample size issues.

As pointed out by Yamamato (2011), the underlying assumption of IIA may not be appropriate when farmers do not have the same set of cultivars available for selection. To address this concern as best as possible, we have defined the base category, in which we consider only old cultivars because some modern cultivars may not available at every place. It is likely that old cultivars are more readily available for the selection as compared to modern cultivars. The literature generally does not cover this issue when modeling discrete choice adoption models.

[14] The area attributed to modern cultivars is calculated by aggregating the cropped area attributed to modern cultivars for the four major crops (wheat, mustard, pearl millet, and gram). The total cropped area is calculated by aggregating the crop area for these four major crops.

[15] We define top cultivars in terms of area covered. We considered the top three cultivars for every crop, in which the top cultivar covered at least 5% of the total area.

If m is the set of cultivars available to the farmer, then the probability of choosing an alternative k by the farmer i can be written as

$$\text{Probability } (U_{ik}) = \frac{exp\ (V_{ik})}{\sum_m exp(V_{im})}$$

where V is the observed nonrandom component of the utility derived by farmer i from choosing variety k, which also depends on the characteristics of variety k and of farmer i. The main underlying assumption is that random component of the utility derived by using cultivar k follows a logistic distribution.

The systematic component of the utility from the kth variety to farmer i (Vik) is modeled as:

$$V_{ik} = \gamma_k + \delta_k W_{ik}$$

where γ_k is the alternative specific constant and W_{ik} is the vector of farm and farmer characteristics. Following Adesina and Zinnah (1993), we include cultivar traits along with farm and farmer characteristics. The farm characteristics used in the regressions are plot location (e.g., surrounded by other farmers' plots, command area, near river/pond), soil type (sandy loam, sandy, clay and loam), and soil color (e.g., brown, black, yellow). The regressions also use the farmer characteristics listed in Table 1, and consider cultivar traits such as higher yield, better marketability (higher prices and bold seed), better by product, pest and disease resistance, weather-related risk tolerance, taste, low input requirements, and drought constraints.

5 RESULTS AND DISCUSSION

5.1. Elasticity Estimates: McDonald and Moffitt's (1980) Decomposition

Table 2 presents the elasticity of explanatory variables for the adoption of modern cultivars.[16] Our dependent variable is the area (ha) attributed to modern cultivars of wheat, mustard, pearl millet, and gram. It presents the overall elasticity (for all farmers) and its decomposition into use intensity (for already being adopted) and adoption probability (the probability of adoption of modern cultivars).

[16] See Table 1.

Table 2: Marginal effects and elasticity for use intensity and adoption probability for Rajasthan (using McDonald and Moffitt [1980] decomposition framework)

Independent variables	Tobit coefficients	Marginal Effects			Elasticity		
		All farmers (adopter and nonadopter)	Use intensity for adopters	Adoption probability	All farmers (adopter and nonadopter)	Use intensity for adopter	Adoption probability
Female (Yes=1)	−0.0495 (0.289)	−0.031	−0.022	−0.012	−0.001	0.000	0.000
Education (in year)	−0.000251(0.0109)	0.000	0.000	0.000	−0.001	0.000	−0.001
Age (in year)	0.00951(0.0192)	0.006	0.004	0.002	0.292	0.127	0.165
Age square (in year)	−0.000106(0.0002)	0.000	0.000	0.000	−0.160	−0.069	−0.090
SC/ST (Yes=1)	−0.0228(0.111)	−0.014	−0.010	−0.006	−0.004	−0.002	−0.002
BPL (Yes=1)	0.0613(0.115)	0.038	0.027	0.015	0.011	0.005	0.006
Family members in farming (#)	0.00312(0.248)	0.002	0.001	0.001	0.006	0.003	0.003
Experience in farming (year)	0.00572(0.0061)	0.004	0.002	0.001	0.094	0.041	0.053
Smartphone (Yes=1)	0.153(0.155)	0.095	0.066	0.037	0.010	0.004	0.006
KCC (Yes=1)	0.290*** (0.102)	0.180	0.126	0.070	0.073	0.032	0.041
Extension intensity	0.612*(0.333)	0.379	0.266	0.148	0.056	0.024	0.032
First quintile, base category							
Second quintile	0.179(0.131)	0.113	0.079	0.043	0.027	0.012	0.015
Third quintile	0.860*** (0.138)	0.577	0.407	0.196	0.149	0.070	0.078
Fourth quintile	1.937*** (0.154)	1.393	1.013	0.391	0.330	0.174	0.157
Asset index	0.101*** (0.0232)	0.063	0.044	0.025	0.001	0.001	0.001
Number of observations	1,491	1,491	1,491	1,491	1,491	1,491	1,491

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors in parentheses. The dependent variable is the total area (ha) attributed to modern varieties by farmers cultivating wheat, mustard, pearl millet, and gram. District fixed effects are used in the regressions. Extension intensity is defined at the village level, as the share of farmers who met with extension workers in the past 12 months.

Our results show that KCC is positively associated with the adoption of modern cultivars. The estimate of overall elasticity is about 0.073. Its decomposition result shows that the elasticity of adoption probability is 0.041, while the elasticity of use intensity is about 0.032. Elasticity of adoption probability is therefore higher than the use intensity, suggesting that KCC access is more important for the adoption of modern cultivars than for use intensity. To determine the magnitudes of elasticities, we can interpret our results in marginal effect terms. For example, for adopted cultivars, a farmer's access to KCC increases the area attributed to modern cultivars by 0.13 ha (9%).[17] For adoption probability, a farmer's access to KCC increases adoption probability by 7%. This finding is consistent with theoretical and empirical literature for developing countries (Feder et al., 1985; Besley and Case, 1993).

To corroborate the above findings, it is important to know more about poorer farmers' access to KCC. Our survey shows that only 25% of the poorer farmers have access to KCC, indicating the huge rationing of KCC cards for poorer farmers. In research conducted by Banerjee and Duflo (2007) in the city of Udaipur in Rajasthan, only 7% of the poor households surveyed are able to obtain loans from formal sources such as banks, while 93% borrowing comes from informal sources at nearly triple the formal interest rates. Expensive credit facilities for poor farmers make it difficult for them to use credit in productive activities. A study by Feder et al. (1990) shows that informal credit is not associated with productive activities. In sum, KCC access is a key factor in enabling poor farmers to adopt modern cultivars.

Extension intensity also is positively associated with the adoption of modern cultivars. Overall estimates of elasticity are about 0.056; the decomposition result shows that the elasticity of adoption probability is 0.032 and the elasticity of use intensity is about 0.024. Our elasticity estimates are comparable with Adesina and Baidu-Forson (1995), which estimated the elasticity of adoption probability and use intensity for West Africa.[18] The higher elasticity estimates for the adoption probability suggests that the role of extension intensity is more important for the adoption of modern cultivars rather than the use intensity.

The above finding is consistent with theoretical literature (Feder et al., 1985). The findings from the empirical literature is mixed, Adesina and Baidu-Forson (1995) finds insignificant association of extension services with the adoption of modern cultivars for African region, and Anderson and Feder (2007) finds positive association of extension services with the modern cultivars.

[17] See columns 3 and 4 of Table 5.

[18] The estimates of elasticity of adoption probability and use intensity are 0.006 and 0.0056, respectively. Adesina and Baidu-Forson (1995) estimated it for West Africa, and their results are insignificant.

On the availability of assets (measured by the asset index) and land size, both variables are positively associated with the adoption of modern cultivars. This result confirmed the argument made by Feder et al. (1985) that wealthier and large farmers have a greater capacity to take risks; the adoption of new cultivars involves both associated fixed cost and a greater risk involved in adoption.

The results for other variables are insignificant, but they display expected signs. For example, education, age, and experience show positive correlations with modern cultivar adoption, while SC/ST and BPL farmers show negative correlations.

5.2. Marginal Effects: Multinomial Logistic Regression

Wheat

Table 3 presents the marginal effects of top wheat cultivars adopted by study farmers. The top cultivars are Raj-1482 (old), HD-2967 (modern), and Raj-4037 (modern).[19] The base category comprises a group of older cultivars excluding Raj-1482.

[19] Raj-1482, HD-2967, and Raj-4037 cultivars were released in 1983, 2011, and 2005, respectively. All three cultivars were developed by the public sector. For more details, see Appendix Table A2.

Table 3: Marginal effects for the top cultivars of wheat, multinomial logistics framework

Independent variables	Top cultivars			Old cultivars, base category
	Raj-1482	HD-2967	Raj-4037	
Female (Yes=1)	−0.0742 (45.78)	−0.471 (115.7)	0.0874 (2.468)	0.458 (67.49)
Education (in year)	−0.000373 (0.00269)	0.000994 (0.00183)	−0.00186 (0.00223)	0.00124 (0.00332)
Age (in year)	−0.00930* (0.00490)	0.00585 (0.00382)	0.00104 (0.00426)	0.00241 (0.00598)
Age square (in year)	0.000102** (0.0000509)	−0.0000635 (0.0000420)	−0.0000175 (0.0000460)	−0.0000205 (0.0000640)
SC/ST (Yes=1)	0.0404 (0.0281)	−0.0123 (0.0280)	0.00236 (0.0230)	−0.0305 (0.0374)
BPL (Yes=1)	0.0338 (0.0297)	−0.0130 (0.0216)	−0.00426 (0.0242)	−0.0165 (0.0364)
Family members in farming (#)	−0.00719 (0.00714)	0.0106* (0.00571)	−0.00229 (0.00559)	−0.00109 (0.00908)
Experience in farming (year)	−0.000922 (0.00164)	0.000559 (0.00105)	0.000656 (0.00154)	−0.000293 (0.00201)
Smartphone (Yes=1)	0.00631 (0.0343)	0.0168 (0.0204)	0.0132 (0.0273)	−0.0363 (0.0423)
KCC (Yes=1)	−0.0545** (0.0245)	0.0309* (0.0168)	0.0170 (0.0202)	0.00665 (0.0298)
Extension intensity	−0.0539 (0.0854)	0.110*** (0.0344)	−0.0702 (0.0666)	0.0142 (0.102)
First land quintile, base category	–	–	–	–
Second land quintile	−0.0128 (0.0302)	0.0251 (0.0226)	0.0550** (0.0230)	−0.0673* (0.0356)
Third land quintile	0.00388 (0.0341)	0.00863 (0.0235)	0.0396 (0.0289)	−0.0521 (0.0413)
Asset index	−0.00578 (0.00476)	−0.00390 (0.00256)	0.00314 (0.00535)	0.00655 (0.00631)
Cultivar attributes				
Higher yield	−0.116*** (0.0328)	0.0357* (0.0211)	−0.0295 (0.0309)	0.110*** (0.0422)
Better marketability	−0.0621** (0.0275)	0.0293 (0.0186)	−0.0154 (0.0258)	0.0482 (0.0351)
Better by product	0.0158 (0.0712)	0.0878 (0.0570)	0.0173 (0.0594)	−0.121 (0.0942)
Pest and disease resistance	0.0113 (0.0294)	0.0396* (0.0206)	0.0148 (0.0253)	−0.0656* (0.0366)
Weather-related risk tolerance	−0.0536** (0.0263)	0.0302 (0.0186)	−0.00467 (0.0235)	0.0281 (0.0332)
Better behavioral choice (e.g., taste, smell)	0.0487* (0.0252)	−0.00361 (0.0187)	0.0184 (0.0259)	−0.0635* (0.0344)
Low input requirements	0.0355 (0.0304)	0.0318 (0.0219)	−0.00951 (0.0261)	−0.0578 (0.0386)
Shorter duration	1.151 (1100.8)	−0.210 (1075.7)	0.819 (1574.6)	−1.759 (2444.6)
Better for storage	0.252 (48.96)	−0.522 (123.8)	−0.0376 (2.642)	0.307 (72.18)
Other perceptions	−0.0303 (0.0420)	0.0778*** (0.0251)	0.00902 (0.0352)	−0.0566 (0.0496)
Drought constraints (Yes=1)	−0.0447 (0.0318)	0.0720*** (0.0194)	−0.0317 (0.0220)	0.00432 (0.0371)
Number of observations	759	759	759	759

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors in parentheses. Old cultivars are considered as the base category in the regressions. Other independent variables used in the regressions are plot location (e.g., surrounded by other farmers' plots, command area, near river/pond), soil type (sandy loam, sandy, clay and loam), soil color (e.g., brown, black, yellow), and district dummies.

Column 1 presents the marginal effects for the adoption of Raj-1482.[20] Age is negatively associated and SC/ST is positively associated with its adoption. Because Raj-1482 is the older cultivar, this finding may indicate that older cultivars are associated with farmers from vulnerable sections of society. Farmers with KCC access are less likely to adopt this cultivar. Extension intensity has an insignificant association with the adoption of Raj-1482, which indicates that farmers likely know about it already and extension intensity has little bearing on its adoption. With regard to cultivar traits, farmers looking for greater yield, higher prices, and weather-related risk tolerance are less likely to adopt Raj-1482. It is possible that farmers who are concerned about these traits have chosen to adopt modern cultivars instead. At the same time, farmers who are concerned about behavioral traits, such as taste, are more likely to adopt this cultivar—notably, this trait is the only driver positively (and strongly) associated with taste, which suggests that taste plays a part in the adoption of old cultivars.

Column 2 presents the marginal effects for the adoption of HD-2967. Age and the number of family members involved in farming are both positively associated with its adoption. This finding is consistent with literature that shows that a more intense social network increases the likelihood of adopting modern technology (Maertens and Barrett, 2012). KCC access also appears to increase the likelihood of adopting HD-2967, suggesting that farmers with better access to credit facilities are more likely to adopt modern cultivars. Notably, Raj-1482, an older cultivar, is negatively associated with KCC access, which suggests that access to credit facilities encourages farmers to shift toward modern cultivars. Extension intensity also is positively associated with the adoption of HD-2967, indicating that credit access and additional information channels are important drivers for modern cultivars. With regard to traits, farmers who are looking for greater yield, pest and disease tolerance, and drought constraints are more likely to adopt this variety.

Column 3 presents the marginal effects for the adoption of Raj-4037. The result shows a positive association of second quintile of land with the adoption of Raj-4037. None of the cultivar traits were significant.

In sum, for modern cultivars, traits such as higher yield, pest and disease tolerance, and drought escape are the main drivers of adoption. Interestingly, the only driver for continuing the old cultivar is taste. To encourage farmers to shift to modern cultivars, taste should also be considered while developing modern cultivars. Since financing and extension play important role in adoption of modern cultivars, there is a need for expanding credit and extension facilities.

[20] It estimates the marginal effects with respect to explanatory variables relative to the base category.

Mustard

Table 4 presents the marginal effects of top mustard cultivars adopted by study farmers. The top cultivars are Pioneer-45s42 (modern) and Laxmi-8812 (old).[21] The base category comprises a group of older cultivars excluding Laxmi-8812.

[21] Pioneer-45s42 and Laxmi-8812 were released in 2005 and 1997, respectively. Pioneer-45s42 was developed by the private sector and Laxmi-8812 was developed by the public sector. For more details, see Appendix Table A2.

Table 4: Marginal effects for the top cultivars of mustard, multinomial logistics framework

Independent Variables	**Top cultivars**		**Old cultivars, base category**
	Pioneer-45s42	**Laxmi-8812**	
Female (Yes=1)	0.371 (97.08)	−0.925 (253.6)	0.554 (156.5)
Education (in year)	0.00191 (0.00563)	−0.00656 (0.00465)	0.00465 (0.00579)
Age (in year)	0.000634 (0.00814)	−0.0102 (0.00685)	0.00956 (0.00840)
Age square (in year)	0.00000213 (0.0000843)	0.000104 (0.0000726)	−0.000106 (0.0000889)
SC/ST (Yes=1)	−0.123** (0.0585)	0.0175 (0.0353)	0.105* (0.0590)
BPL (Yes=1)	−0.0318 (0.0597)	0.0787** (0.0391)	−0.0470 (0.0627)
Family members in farming (#)	0.0157 (0.0159)	−0.0208 (0.0134)	0.00503 (0.0167)
Experience in farming (year)	−0.00188 (0.00302)	−0.00102 (0.00241)	0.00290 (0.00333)
Smartphone (Yes=1)	0.0337 (0.0694)	0.0937** (0.0450)	−0.127* (0.0764)
KCC (Yes=1)	0.106** (0.0515)	−0.00229 (0.0331)	−0.104* (0.0539)
Extension intensity	0.551* (0.312)	0.289*** (0.0977)	−0.840** (0.328)
First land quintile, base category			
Second land quintile	0.0370 (0.0594)	0.0863** (0.0394)	−0.123** (0.0595)
Third land quintile	−0.0673 (0.0656)	0.0447 (0.0379)	0.0226 (0.0669)
Asset index	−0.00939 (0.0107)	0.00123 (0.00602)	0.00816 (0.0109)
Cultivar attributes			
Higher yield	0.0573 (0.0660)	−0.0263 (0.0504)	−0.0310 (0.0711)
Better marketability	0.0578 (0.0672)	−0.00500 (0.0465)	−0.0528 (0.0685)
Better by product	0.104 (0.139)	−0.0439 (0.0914)	−0.0600 (0.146)
Pest and disease resistance	−0.0174 (0.0567)	0.00355 (0.0423)	0.0139 (0.0583)
Weather-related risk tolerance	−0.0834 (0.0542)	0.0745* (0.0392)	0.00890 (0.0571)
Better behavioral choice (e.g., taste, smell)	−0.149** (0.0611)	0.0237 (0.0400)	0.126** (0.0606)
Low input requirements	−0.148** (0.0610)	0.00620 (0.0538)	0.142** (0.0678)
Shorter duration	1.355 (1219.6)	1.127 (349.4)	−2.482 (1554.8)
Better for storage	−0.0523 (25.98)	0.699 (67.89)	−0.647 (41.90)
Other perceptions	−0.0330 (0.0627)	−0.00103 (0.0388)	0.0341 (0.0643)
Drought constraints (Yes=1)	0.117** (0.0586)	0.0819* (0.0484)	−0.198*** (0.0626)
Number of observations	319	319	319

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors in parentheses. Other independent variables used in the regressions are plot location (e.g., surrounded by other farmers' plots, command area, near river/pond), soil type (sandy loam, sandy, clay and loam), soil color (e.g., brown, black, yellow), and district dummies.

Column 1 presents the marginal effects for the adoption of Pioneer-45s42. SC/ST farmers are less likely to adopt Pioneer-45s42. Given that the modern cultivar is more expensive than the old cultivar, poorer and more vulnerable farmers may not be able to afford Pioneer-45s42 because of the higher fixed cost involved in its adoption.[22] However, farmers with KCC access are more likely to adopt Pioneer-45s42, and extension intensity also is positively associated with its adoption. With regard to cultivar traits, farmers that are concerned with drought constraints are more likely to adopt this cultivar. Because most of Rajasthan's cultivated area is rainfed, this cultivar is particularly suited to the climate, and hence it is the state's most planted mustard cultivar, covering more than 30% of the total mustard area. However, farmers who are concerned about high input requirements and behavioral constraints such as taste or smell are less likely to adopt this cultivar.

Column 2 presents the marginal effects for the adoption of Laxmi-8812. Poorer farmers are more likely to adopt Laxmi-8812, a finding consistent with the fact that Laxmi-8812 was developed by the public sector and its seed costs are about half those of the privately developed Pioneer-45s42. Extension intensity also is positively associated with the adoption of Laxmi-8812. Interestingly, farmers that have smartphone access also are more likely to adopt Laxmi-8812. This finding suggests that smartphones are the information channel used to disseminate the cultivar. With regard to land size, the second quintile result shows a higher likelihood for adopting Laxmi-8812. In terms of cultivar traits, weather-related risk tolerance and drought constraints increase the likelihood of adopting Laxmi-8812. Notably, the coefficient of drought constraints is higher in terms of magnitude for Pioneer-45s42 than for Laxmi-8812, which suggests the greater relative importance of this driver is higher for the former variety.

In sum, the result for Pioneer45s42 is effective for drought constraints in the region, the main driver for its adoption. For Laxmi-8812, the main drivers are weather-related risk tolerance and drought constraints. We also found that the poorer farmers are more likely to adopt old cultivars and less likely to adopt modern cultivars.

Pearl Millet

Table 5 presents the marginal effects of top pearl millet cultivars adopted by study farmers. The top cultivars are Proagro-9444 (modern), HHB-67 (modern), and Pioneer-86M84 (modern)—the only surveyed crop in which all three top cultivars were modern.[23] The base category comprises a group of older cultivars.

[22] See Figure 5.

[23] Proagro-9444, HHB-67, and Pioneer-86m84 were released in 2001, 2005, and 2011, respectively. All three cultivars were developed by the private sector. For more details, see Appendix Table A3.

Table 5: Marginal effects for the top cultivars of pearl millet, multinomial logistics framework

	Top cultivars			Old cultivars, base category
Independent variables	**Proagro-9444**	**HHB-67**	**Pioneer-86M84**	
Female (Yes=1)	−0.227 (1.049)	0.458 (5.638)	0.00429 (0.438)	−0.235 (4.165)
Education (in year)	−0.000484 (0.00389)	−0.000550 (0.00310)	0.00186 (0.00280)	−0.000823 (0.00417)
Age (in year)	0.00184 (0.00704)	0.00327 (0.00504)	−0.00136 (0.00521)	−0.00374 (0.00709)
Age square (in year)	−0.0000186 (0.0000739)	−0.0000045 (0.0000506)	−0.000000318 (0.0000533)	0.0000235 (0.0000732)
SC/ST (Yes=1)	0.0432 (0.0426)	0.00252 (0.0327)	−0.0201 (0.0330)	−0.0256 (0.0459)
BPL (Yes=1)	0.151*** (0.0463)	−0.0388 (0.0374)	−0.0317 (0.0320)	−0.0804 (0.0554)
Family members in farming (#)	−0.0231** (0.0117)	−0.00521 (0.00757)	0.00787 (0.00847)	0.0205* (0.0117)
Experience in farming (year)	−0.00179 (0.00230)	−0.00266 (0.00203)	0.00169 (0.00164)	0.00276 (0.00252)
Smartphone (Yes=1)	0.0453 (0.0618)	0.0419 (0.0560)	−0.0390 (0.0534)	−0.0482 (0.0745)
KCC (Yes=1)	0.00372 (0.0386)	−0.0594** (0.0298)	0.0603** (0.0285)	−0.00467 (0.0418)
Extension intensity	−0.0492 (0.196)	0.273 (0.259)	−0.343 (0.221)	0.118 (0.239)
First land quintile, base category	–	–	–	–
Second land quintile	0.0265 (0.0418)	0.0460 (0.0300)	−0.0543 (0.0344)	−0.0182 (0.0436)
Third land quintile	0.0333 (0.0473)	0.0169 (0.0290)	−0.0662* (0.0340)	0.0160 (0.0487)
Asset index	−0.00384 (0.00780)	0.00184 (0.00781)	−0.00197 (0.00636)	0.00398 (0.00888)
Cultivar attributes				
Higher yield	0.121*** (0.0440)	0.0673*** (0.0249)	−0.0121 (0.0302)	−0.177*** (0.0391)
Better marketability	0.114** (0.0461)	−0.0483 (0.0341)	−0.106*** (0.0406)	0.0397 (0.0503)
Better by product	−0.00512 (0.0791)	−0.0420 (0.0314)	0.0244 (0.0563)	0.0228 (0.0704)
Pest and disease resistance	−0.0508 (0.0437)	0.0159 (0.0328)	0.0366 (0.0284)	−0.00178 (0.0471)
Weather-related risk tolerance	−0.0576 (0.0378)	0.0134 (0.0251)	−0.0205 (0.0266)	0.0647* (0.0386)
Better behavioral choice (e.g., taste, smell)	−0.0547 (0.0368)	−0.0647** (0.0256)	−0.0557** (0.0276)	0.175*** (0.0356)
Low input requirements	−0.0969** (0.0481)	0.0118 (0.0343)	0.0267 (0.0336)	0.0584 (0.0469)
Shorter duration	0.0769 (8.085)	−0.363 (43.66)	0.231 (3.334)	0.0551 (32.25)
Better for storage	−0.146* (0.0770)	−0.0693* (0.0398)	0.127** (0.0540)	0.0880 (0.0797)
Other perceptions	0.167* (0.0861)	0.0229 (0.0609)	0.0821* (0.0447)	−0.272** (0.129)
Drought constraints (Yes=1)	−0.0276 (0.0452)	−0.00987 (0.0290)	−0.0502 (0.0340)	0.0876* (0.0487)
Number of observations	482	482	482	482

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors in parentheses. Other independent variables used in the regressions are plot location (e.g., surrounded by other farmers' plots, command area, near river/pond), soil type (sandy loam, sandy, clay and loam), soil color (e.g., brown, black, yellow), and district dummies.

Column 1 presents the marginal effects for the adoption of Proagro-9444. BPL farmers are more likely to adopt Proagro-9444—an unusual result that needs further investigation. Farms with a greater number of members involved in farming are negatively associated with the adoption of Proagro-9444. With regard to cultivar traits, farmers with concerns related to higher yield and better marketability are more likely to adopt Proagro-9444, whereas farmers with concerns about low input requirement and storage traits are less likely to adopt it.

Column 2 presents the marginal effects for the adoption of HHB-67. KCC access is negatively associated with the adoption probability of HHB-67. Given that HHB-67 is older than Pioneer-86m84, at least in terms of year of release, it may be that farmers with better access to credit facilities are more likely to adopt Pioneer-86m84. Farmers with higher yield constraints also are more likely to adopt this cultivar, whereas farmers that are looking for better storage traits and are concerned about behavioral attributes such as taste are less likely to adopt this cultivar.

Column 3 presents the marginal effects of Pioneer-86m84. Farmers with KCC access are more likely to adopt this variety. Given that Pioneer-86m84 is the most recently developed cultivar, the findings are consistent with the previous paragraph. Farmers who are looking for better marketability, taste, and better storage traits are less likely to adopt this cultivar.

To identify the drivers of the old cultivars, we also interpret the marginal effects of old cultivars presented in column 4. Farmers with concerns about higher yield are less likely to adopt older cultivars, but, farmers with taste concerns are more likely to adopt older cultivars.

In sum, the main adoption drivers of modern cultivars are higher yield, marketability, and better storage traits, and the main adoption drivers of old cultivars are taste attributes. As mentioned earlier, farmers that are concerned about taste attributes are more likely to adopt older cultivars in case of wheat as well.

Gram

Table 6 presents the marginal effects of the top gram cultivar adopted by study farmers. The top cultivar is GNG-1581 (modern).[24] The base category comprises a group of older cultivars.

[24] GNG-1581 was developed by the public sector and released in 2008. For more details, see Appendix Table A4.

Table 6: Marginal effects for the top cultivars of gram, logistics framework

Independent variables	Top cultivar GNG-1581	Old cultivars, base category
Female (Yes=1)	−2.005 (637.3)	2.005 (637.3)
Education (in year)	−0.0177* (0.0106)	0.0177* (0.0106)
Age (in year)	0.00754 (0.0250)	−0.00754 (0.0250)
Age square (in year)	0.0000321 (0.000291)	−0.0000321 (0.000291)
SC/ST (Yes=1)	−0.166 (0.131)	0.166 (0.131)
BPL (Yes=1)	0.0859 (0.123)	−0.0859 (0.123)
Family members in farming (#)	−0.188*** (0.0471)	0.188*** (0.0471)
Experience in farming (year)	−0.00848 (0.00803)	0.00848 (0.00803)
Smartphone (Yes=1)	0.697*** (0.183)	−0.697*** (0.183)
KCC (Yes=1)	−0.0624 (0.115)	0.0624 (0.115)
Extension intensity	1.088** (0.433)	−1.088** (0.433)
First land quintile, base category		
Second land quintile	0.285*** (0.107)	−0.285*** (0.107)
Third land quintile	0.198** (0.0791)	−0.198** (0.0791)
Asset index	−0.0144 (0.0241)	0.0144 (0.0241)
Cultivar attributes		
Higher yield	0.00912 (0.0930)	−0.00912 (0.0930)
Better marketability	0.277** (0.109)	−0.277** (0.109)
Better by product	−1.164 (637.3)	1.164 (637.3)
Pest and disease resistance	−0.460*** (0.169)	0.460*** (0.169)
Weather-related risk tolerance	0.248*** (0.0947)	−0.248*** (0.0947)
Better behavioral choice (e.g., taste, smell)	−0.348*** (0.113)	0.348*** (0.113)
Low input requirements	−0.332** (0.134)	0.332** (0.134)
Shorter duration		
Better for storage	0.574** (0.224)	−0.574** (0.224)
Other perceptions	−0.119 (0.143)	0.119 (0.143)
Drought constraints (Yes=1)	0.325** (0.138)	−0.325** (0.138)
Number of observations	100	100

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors in parentheses. Other independent variables used in the regressions are plot location (e.g., surrounded by other farmers' plots, command area, near river/pond), soil type (sandy loam, sandy, clay and loam), soil color (e.g., brown, black, yellow), and agro-ecological dummies. Agro-ecological dummies are used here because of the sample size.

The table presents the marginal effect for the adoption of GNG-1581.[25] Years of education and number of family members involved in farming activities are both negatively associated with the adoption of GNG-1581. The second and third quintile of land is positively associated with the adoption of this cultivar. Extension activity also is positively associated with the adoption probability of GNG-1581. With regard to cultivar traits, farmers who are concerned with better marketability, weather-related risk tolerance, drought constraints, and better storage traits are more likely to adopt this cultivar. The farmers with pest and disease tolerance, taste attributes, and low input requirements are less likely to adopt it.

[25] The results presented here come from the logistic regression but not from the multinomial regressions, as the number of observations restrict us from implementing the multinomial framework.

6. SUMMARY AND CONCLUSIONS

This paper had two main objectives. The first was to identify farmer-level constraints in the adoption of modern cultivars, and to explore the role of these constraints by decomposing the overall elasticity into the elasticity of adoption probability and use intensity. The second objective was to present a cultivar-specific analysis for each of the top cultivars, whether old or modern, to identify the role of its characteristics separately for each crop.

The findings showed that KCC access and extension intensity were the key drivers of modern cultivars. In case of credit facilities, the findings confirm that farmers are utilizing credit facilities for the purchases of agricultural inputs which was the intended objective of KCC. Samantra (2010) also shows that more than 80% of farmers have applied for renewal of their KCC accounts that also suggests a continuous demand of credit from the farmers. In the context of extension intensity, the finding has an implication to strengthen the outreach of extension by targeting more remote villages. Focus should be made especially on introducing the modern agricultural inputs, and their appropriate implementation.

Our estimated elasticities show that the role of both KCC access and extension intensity is more important for the adoption probability than for the use intensity. In turn, this has implications to provide more focus at places where there is low adoption in terms of number of adopters.

With regard to the studied traits, the main drivers for the use of modern cultivars were drought constraints (all crops), weather-related risk tolerance (all crops), higher yield (wheat and pearl millet), better marketability and storage traits (pearl millet and gram), and pest and disease tolerance (wheat). The main driver for old cultivars was taste attributes (wheat, pearl millet, and gram). A number of studies examines these factors in the context of agricultural productivity, and its implication for farmer's income. For example, the study by Tack et al. (2014) in the context of the effect of warming and drought shows that both these factors are strongly related to the yield risk, Kalra et al. (2008) showed that rise in per degree temperature will result in declining the agricultural productivity, and Joshi et al. (2007) highlights the role of the pest and disease risk to reduce the yield gap. Better marketability and storage traits are related to the higher output price and post-harvest losses, respectively, and have implications for the profitability of farmers. Consequently, cultivar developers should take into account the identified traits when designing innovations in agricultural technology.

Moreover, there is a need to strengthen credit facilities for poor farmers in particular and expand extension services to all farmers to encourage them to adopt modern cultivars.

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Appendix Tables

Appendix Table A1: Wheat cultivars adopted by farmers in Rajasthan, 2015–2016

Name of cultivar	Cultivar type	Developers	Year of release	Area (ha)	Share in total area (%)	No. of farmers	Share in total farmers (%)
Raj-1482	OPV	Public	1983	259	28.8	321	32
HD-2967	OPV	Public	2011	177	19.7	103	10
Raj-4037	OPV	Public	2004	141	15.7	178	18
Raj-3077	OPV	Public	1989	107	11.9	101	10
Lok-1	OPV	Public	1982	87	9.7	128	13
Raj-3765	OPV	Public	1996	42	4.7	86	9
HD-2851	OPV	Public	2005	15	1.7	15	1
PBW-343	OPV	Public	1996	15	1.7	15	1
HD-3086	OPV	Public	2014	11	1.2	5	1
Land race	Land race	–	–	7	0.8	9	1
Other cultivars	OPV	Public/Private	–	37	4.1	43	4
Total	–	–	–	898	100	1,004	100

Source: ICAR-IFPRI survey, 2017

Note: There is no hybrid in wheat.

Appendix Table A2: Mustard cultivars adopted by farmers in Rajasthan, 2015–2016

Name of cultivar	Cultivar type	Developers	Year of release	Area (ha)	Share in total area (%)	No. of farmers	Share in total farmers (%)
Pioneer-45s42	Hybrid	Private	2005	149	34.1	200	37
Laxmi-8812	OPV	Public	1997	84	19.2	75	14
Parasmani-2	OPV	Private	2011	15	3.4	10	2
Pioneer-45s19	Hybrid	Private	2010	14	3.2	30	6
Pioneer-21	Hybrid	Private	2012	14	3.2	27	5
Progro-5222	Hybrid	Private	2009	14	3.2	17	3
Pusa-26	OPV	Public	2011	14	3.2	18	3
RH-749	OPV	Public	2014	13	3.0	10	2
SVJ-314	OPV	Private	2013	11	2.5	9	2
Pioneer-45s46	Hybrid	Private	2010	10	2.3	19	4
Pusa-30	OPV	Public	2013	10	2.3	12	2
Pusabold	OPV	Public	1985	10	2.3	8	1
Urmi-2121	OPV	Private	2013	9	2.1	7	1
Varuna(T-59)	OPV	Public	1976	9	2.1	10	2
Other cultivars	Hybrid/OPV/Land race	–	–	62	14.2	85	16
Total	–	–	–	438	100.2	537	100

Source: ICAR- IFPRI survey, 2017

Appendix Table A3: Pearl millet cultivars adopted by farmers in Rajasthan, 2015–2016

Name of cultivar	Cultivar type	Developers	Year of release	Area (ha)	Share in total area (%)	No. of farmers	Share in total farmers (%)
Pragro-9444	Hybrid	Private	2001	264	28.3	257	24.57
HHB-67	Hybrid	Public	2005	95	10.2	88	8.41
Pioneer-86m84	Hybrid	Private	2011	64	6.9	76	7.27
Pioneer-86m86	Hybrid	Private	2012	58	6.2	90	8.6
Pioneer-86m88	Hybrid	Private	2015	43	4.6	39	3.73
Dhanya MP-7792	Hybrid	Private	2015	28	3.0	34	3.25
JK26	Hybrid	Private	2012	25	2.7	47	4.49
Nandi-65(MH-1549)	Hybrid	Private	1997	11	1.2	8	0.76
JK36	Hybrid	Private	2010	6	0.6	9	0.86
Land race	–	–	–	293	31.4	292	27.92
Other cultivars	Hybrid	Private/Public	–	45	4.8	106	10.14
Total	–	–	–	933	100	1,046	100

Source: ICAR- IFPRI survey, 2017

Appendix Table A4: Gram cultivars adopted by farmers in Rajasthan, 2015–2016

Name of cultivar	Cultivar type	Developers	Year of release	Area (ha)	Share in total area (%)	No. of farmers	Share in total farmers (%)
GNG-1581	OPV	Public	2008	36	32.1	43	30.71
C-235	OPV	Public	1975	7	6.3	9	6.43
Vardan (GNG-663)	OPV	Public	1995	6	5.4	4	2.86
Samrat (GNG-469)	OPV	Public	1997	4	3.6	5	3.57
CSJD-884 (ADASH)	OPV	Public	2003	2	1.8	1	0.71
Vishal Phule (G-87207)	OPV	Public	1997	2	1.8	6	4.29
Land race	Land race	–	–	55	49.1	72	51.43
Total	–	–	–	112	100	140	100

Source: ICAR-IFPRI survey, 2017

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