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WHAT DRIVES FARMERS TO ADOPT HYBRID MAIZE? AN ANALYSIS OF FARM AND FARMERS SOCIOECONOMIC CHARACTERISTICS IN PUNJAB, PAKISTAN

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ABSTRACT

This study is significant as it provides insights into the factors influencing the adoption of hybrid maize, which is crucial for enhancing agricultural productivity and food security in rural Punjab, Pakistan. Using information from a 400-hybrid maize farmer survey conducted in 2020, the study examined the results with the negative binomial regression model. The findings indicate that characteristics of farms and farmers, including educational level, farming experience, access to credit, interaction with extension agents, and sources of off-farm income, significantly influence the rate of adoption of hybrid maize varieties. Adoption is progressing more rapidly among larger farms, farmers with higher schooling levels, and those with access to credit. In addition, farmers with more farming experience are more likely to adopt hybrid maize earlier. The study also found that access to information and extension services played a critical role in the adoption process. In addition, government policies and regulations, market dynamics, and socio-cultural factors also play important roles in shaping the adoption of hybrid maize. Based on these findings, the study suggests several policy interventions to promote the adoption of hybrid maize in Pakistan, including targeted extension services, subsidies for hybrid seed, and public-private partnerships to improve seed supply chains. These interventions may facilitate the accelerated adoption of hybrid maize in Pakistan, thereby enhancing the agricultural output and ensuring adequate nutrition within Pakistan.

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INTRODUCTION

Maize (*Zea mays L.*) is the third most important cereal crop in Pakistan, following wheat and rice. As a high-yielding cereal crop globally, it holds significant importance for developing nations such as Pakistan, where the population is growing rapidly, and food supplies have already been exceeded. The share of maize in GDP is 0.6% and 3.4% of value added in agriculture, as the area under maize crop rose to 1418 thousand hectares. The production of maize crops has shown an increase of 7 % from the previous year (7.883 to 8.465) million tonnes (GoP, 2023).

The adoption of improved technologies like hybrid seed varieties, fertilizers, and mechanized operations not only enhances the productivity and well-being of rural farmers as well as rural workers and consumers with a greater potential for rural development (Hazell, 2010; Otsuka and Larson, 2014). In today's Punjab province of Pakistan, hybrid maize growers have almost fully adopted this crop, however, this study undertakes the dynamics of hybrid maize varietal adoption by replacing one hybrid variety with a more newly released one, rather than the replacement of traditional maize variety to hybrid maize variety (Abbas et al., 2017; Ashraf et al., 2015). The adoption of technology is typically characterized by a binary classification (adopter and non-adopter) and the rate of adoption, determined by the proportion of cultivated areas utilizing the technology. Nevertheless, limited research has been conducted to assess the adoption gap and the factors that determine the adoption gap of hybrid maize varieties.

Very few scholars conducted research on the speed of adoption in different countries by duration model not by count data model (Adams et al., 2017; Smale and Nazli, 2014) and according to my best knowledge, no one scholar discussed the speed of adoption of new technology by negative Binomial regression model in hybris maize in Pakistan. Earlier literature in developing economies (Langyintuo and Mekuria, 2008; Munasib and Jordan, 2011) fails to ponder the timing of the adoption of an event and does not ostensibly highlight the consequence of descriptive variables on the time-path of adoption. If the adoption of technology is associated with certain events which be fallen in the past then a time of adoption of technology can provide valuable information. Particularly Matuschke (2007) discussed how adoption is related to certain events that happened in the past or if the spell is linked to learning by doing and learning from others. The negative binomial regression model was applied in our research to bridge this study gap. This model describes the decision of the time of adoption of technology and what factors affected the observed time period. The objective of our study is to estimate the adoption gap and to measure the determinants affected by the adoption gap of hybrid maize varieties in Punjab, Pakistan.

Background of study

The Green Revolution delivered significant works on the introduction of agricultural innovations in developing countries, especially in South Asia, primarily based on the seminal research undertaken in the United States by Griliches (1971) and Rogers

(1995). Comprehensive examinations of the early decades of this literature were conducted by Feder et al. (1985) and Feder and Umali (1993). Considering the significance of valuable inputs such as integrated pest management, fertilizers, and adequate moisture, along with farmers' expertise in maximizing the cultivation of initial short-statured, varieties that produce high yields, initial research investigations have examined the characteristics of farmers' educational background, financing, land availability, and irrigation facilities. A primary hypothetical archetype of this period was farmers' decision-making under risk, illustrating a farmer's land allocation between "modern" and "traditional" as a portfolio decision influenced by risk aversion and the stochastic nature of relative output (Just and Zilberman, 1983; Roumasset et al., 1979) It was recorded that safety-first and various stimuli associated with risk were also anticipated. The early literature prominently featured learning mockups, where growers addressed uncertainty by collecting data on high-yielding varieties through testing and practices, frequently illustrated. As a Bayesian approach (Hiebert, 1974; Leathers and Smale, 1991; Lindner et al., 1979) functional this framework in investigating the time between adoptions of agricultural innovations (Feder and Slade, 1984; Foster and Rosenzweig, 1995). Farmers acquire knowledge through experiential learning from their peers. The decision to cultivate a new hybrid maize variety is a process that relies on how growers seek and acquire information. Hazell and Anderson (2012) showed that early adoption of innovative technology enhances productivity and has a better impact on the rate of return on capital investment. Strenuously, endemic adoption of technology is likely to put downhill pressure on output prices and uphill pressure on the input prices and its can depreciatively affect the peripheral farmers who have yet not adopted the technology (Fuglie and Kascak, 2001). Fuglie and Kascak (2001) highlighted that early adoption of innovative technology in agriculture can determine the endurance of farms and improve the efficiency of agriculture. Currently, farmers in Punjab province possess higher levels of schooling and greater access to technological information. Consequently, capital investments are unnecessary for transitioning between high-yielding hybrid varieties. The decision to switch varieties is contingent upon the performance of the new hybrid relative to the previous one, considering specific farming objectives and circumstances (Smale and Nazli, 2014).

METHODOLOGY

Study area and Sampling method

Primary data were collected using a structured questionnaire from 400 hybrid maize growers in the Punjab province of Pakistan. Hybrid maize production in the province and study area is representative of the country. The majority of hybrid maize production is produced from the selected province and the studied districts contribute over 50% of the hybrid maize area in the respective countries (Akhtar et al., 2018). Samples were chosen using a multistage random sampling method. In the initial stage, the province of Punjab was designated as the primary area of study. The 2nd step involved the random selection of four districts for hybrid maize cultivation. Subsequently, from each district, two Tehsil cities were chosen, and from each city, two union councils were randomly picked. In the subsequent phase, a random selection of villages from the designated union councils was conducted, followed by face-to-face interviews with randomly chosen hybrid maize cultivators. Figure 1 illustrates the sampling framework of the investigation. The information gathered from the respondents included, among other factors, farmers' socioeconomic position, sources of risk, attitudes toward risk, selections of risk management techniques, and revenue sources. Figure 1 shows the Sampling stages for selecting farmers in the study area.

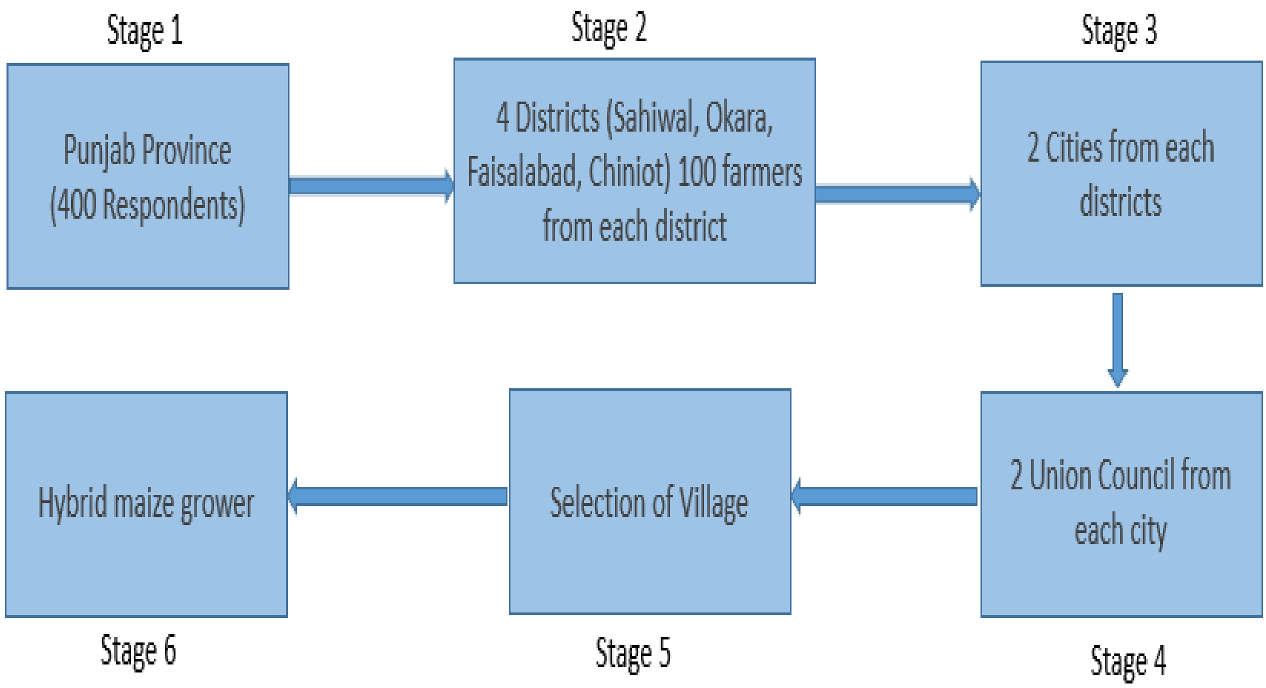

Figure 1. Sample selection stages in the study area.

A total of 400 farmers were systematically selected for the study, with 100 farmers being randomly chosen from each district within the research region (Yamane, 1967).

$$n = \frac{N}{(1+Ne^2)} \quad (1)$$

Where n denotes the sample size; N signifies the total number of farmers within the study area; e represents the error of margin, established at ±15% (0.15).

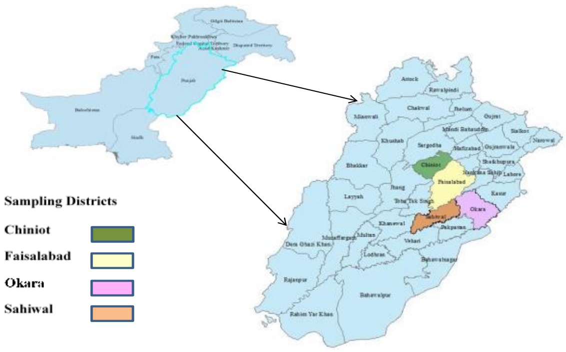

Figure 2. Sample study districts in Punjab province.

Study Area

The study area was located in rural Punjab, positioned geographically at approximately 30º00'N, and 70º00'E within the semi-arid low zone. (Ahmed et al., 2012). This province is the most populous and the second largest in Pakistan. The agricultural area of Punjab is exceptionally fertile and possesses an extensive irrigation infrastructure. It is crucial to the economy of Pakistan (Abid et al., 2011). This represents 56.2% of the total cultivated area, 74% of the whole production of cereals, and 53% of the total GDP from agriculture in the country (Badar et al., 2007). The primary focus of our study was hybrid maize farming due to several key reasons. Faisalabad, Okara, Chiniot, and Sahiwal are primary regions for hybrid maize cultivation and represent the optimal agroecological zones in central Punjab (Naqvi and Ashfaq, 2014). Second, they are fully aware of hybrid maize technology. Figure 2. Shows the sample study districts in Punjab Province.

Econometric Approach

Issues arising when the dependent variable is restricted to non-negative values are examined through count data econometric models. In this study, the dependent variable, referred to as the adoption gap, is classified as a non-negative integer variable. The year of adoption versus release or awareness is evaluated by following Cameron and Trivedi (1998) and Cameron and Trivedi (2009). The pattern of distribution of Y_j is determined by combination of observed externalX_j and unobserved variables U_j. If E is the expected operator and is a vector of k variables to be calculated, the average of the count data model is written as:

$$E(Y_j/x_j, u_j) = \lambda_j(x_j, \beta, U_j) = \lambda \quad (1)$$

In most cases, equation (1) becomes the log-linear description of the average value of count data models on independent variables.:

$$log\lambda = x_j\beta + \mu_j = \sum_{k=1}^{k} x_{jk}\beta_k + U_j \quad (2)$$

$e^{nj}, = 1, 2, 3, \ldots, n$, are chosen by the explanatory and equally distributed with $E(e^{nj}) = 1$, and $var(e^{nj}) = \eta^2$ within the bound of this specification when X_j has constant value. The assumption of unit means value for $E(e^{nj})$ does not lead to loss of generality. The model assumes independence of u_j. In this specification, when the form X_j to obtain:

$$E(Y_j/X_j) = EE(Y_j/x_j, u_j) = e^{xj\beta} = \mu_j \quad (3)$$

And

$$var(Y_j/x_j) = \mu_j + \eta^2\mu^2 \quad (4)$$

The choice of the count data model is based on the assumptions U_j regarding the distribution (Cameron and Trivedi, 1998; Cameron and Trivedi, 2009).

Negative Binomial Regression Model

The Poisson regression model assumes that the mean and variance of the dependent variable in the Poisson distribution are equal, a condition known as equip-dispersion, which is shown by:

$$E(\frac{Y_J}{X_J}) = var(\frac{Y_j}{X_j}). \quad (5)$$

The Poisson distribution's mean and variance are often equal; however, empirical data frequently demonstrate that the conditional variance exceeds the mean.

$$E(\frac{Y_J}{X_J}) < var(\frac{Y_j}{X_j}) \quad (6)$$

Equation 2 indicates the presence of overdispersion, characterized by a discrepancy between the mean and variance. Consequently, the Poisson model is unsuitable for 299odelling the adoption gap of hybrid maize varieties (Cameron and Trivedi, 1998; Cameron and Trivedi, 2009). A generalized model addressing the overdispersion issue is found on the negative binomial probability distribution, as represented in equation 3.

$$f(y/\mu, \alpha) = \frac{\Gamma(y+a^{-1})}{\Gamma(y+10\Gamma(a^{-1})}(\frac{a^{-1}}{a^{-1}+\mu})^{a-1}(\frac{\mu}{a^{-1}+\mu})^{y} \quad (7)$$

Where $\mu = e^{x'\beta}$ $y = 0, 1, 2, \ldots$, and α ≥ 0 Embodies the degree of over-dispersion. Addressing the issue of over-dispersion in the estimation of the Poisson model (Cameron and Trivedi, 1998; Cameron and Trivedi, 2009; Cameron and Trivedi, 2013), A regression-based test for over-dispersion has been discussed, focusing on the significance of the parameter in relation to the Poisson model. The method evaluates the subsequent hypotheses.

$$H_o: Var[Y_j] = E[Y_j] \quad (8)$$

$$H_1: Var[Y_j] = E[Y_j] + ag(E[Y_j]) \quad (9)$$

H_0 The basic Poisson assumption is that the variance equals the mean. However, H_1 it is hypothesized that in cases of over-dispersion, the variance does not equal the mean or exceeds it by some function of the mean $g(E[Y_j])$. The hypothesis test for over-dispersion is conducted through regression analysis.

$$z_j = \frac{y_j - \lambda_j)^2 - y_j}{\lambda_{j\sqrt{2}}} \quad (10)$$

$$w_j = \frac{(\lambda_j)}{\sqrt{2\lambda_j}} \quad (11)$$

Where λ_j is the projected value of y_j from the Poisson regression and $g(\lambda_j)$ is the assumed probability density function of U_j (Cameron and Trivedi, 1998; Cameron and Trivedi, 2009). This test relies on several assumptions, with the primary one being that consistent estimates are obtained under either H_o or H_1 consistent estimates of $E[y_j] = \lambda_j$ are found from the Poisson regression model (Cameron and Trivedi, 1998; Cameron and Trivedi, 2009).

Furthermore, it was demonstrated that the test for over-dispersion, referred to as T_{op}, can be effectively conducted by assessing the significance of the individual coefficient in the Linear Ordinary Least Squares (OLS) regression of Z_j onW_j. The authors proposed an assumption $g(\lambda_j)$ regarding the execution of the test for overdispersion.

$$g(\lambda_j) = \lambda_j \text{ and } g(\lambda_j^2) \quad (11)$$

The chi-square statistics are employed to assess the significance of the regression coefficients in relation to zero when presenting the regressions. Consequently, based on the data's response to the model, if the basic Poisson model is deemed inadequate, a compound Poisson or negative binomial model serves as an alternative due to its capacity to accommodate over-dispersion (Cameron and Trivedi, 1998; Cameron and Trivedi, 2009). In our study over-dispersion problem existed which is why a negative binomial (compound Poisson) models were used to determine what factors affected the adoption gap of hybrid maize verities in Punjab, Pakistan.

Dependent Variable of Study

The adoption gap is the dependent variable in this study: that is, the difference between the year of adoption of a variety and the year of dissemination or awareness of that variety. The analysis is done at the variety level considering those varieties which were farmers grew in the survey year. That's why the challenge with recall data was easy for farmers to remember the year of release and adoption of that variety.

In rural Punjab among hybrid maize farmers, the average adoption gap was 1.73 years. Abdulai and Huffman (2005) and Dadi et al. (2004) assumed that all the growers in the village were aware of the technology at the same time. The main varieties grown in the study area during the survey year are given in Figure 3.

Explanatory variables

It has been reported that older farmers are more likely to adopt new technology due to their greater experience (Abdulai and Huffman, 2005; Dadi et al., 2004; Smale and Nazli, 2014). The age of farmers influences their crop production decisions during a variety of changes. Smale and Nazli (2014) showed that younger farmers have also a positive effect on the technology adoption or replacement of variety. Distance to the main market creates a barrier to accessing inputs and information about technology. In other words, we can say that long distance creates problems for farmers to adopt modern technology due to high transaction costs. Abdulai and Huffman (2005) and Dadi et al. (2004) showed that there is a significant and negative relationship between main market distance and the adoption of modern technology.

Hybrid maize adaptors in rural Punjab are fully adapted due to the influence of multinational companies in hybrid seed production and information. Extension contact can influence the adoption of technology or the replacement of variety from old to new (Dadi et al., 2004; Smale and Nazli, 2014) farmers who acquire information from extension agents (contact with extension workers) can adopt variety more quickly than others.

In developing economies where farmers are riskier due to high production risk, farmers are less likely to adopt technology (Beyene and Kassie, 2015). If risk-reducing strategies such as credit access and off-farm income are available for farmers during the production period. Farmers are more likely to adopt technology or replace varieties that might bring a high profit, even if these are perceived as risky. For off-farm income and credit access take a dummy variable, one for those farmers who have access to credit and off-farm income and otherwise zero. Lastly, take dummies for the district for location-specific differences in the analysis.

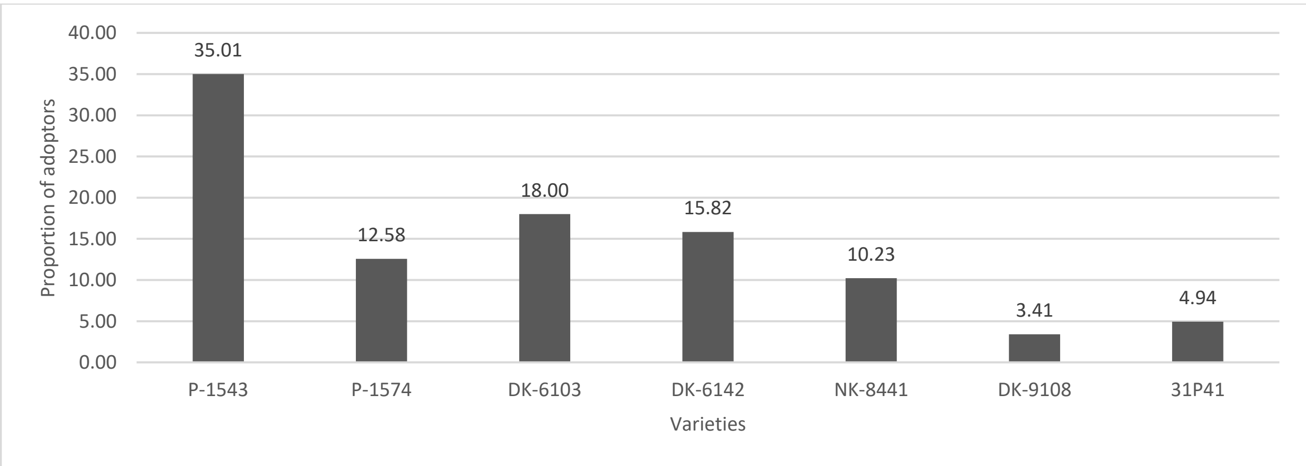

Figure 3. The main varieties grown in the study area during the survey year.

RESULTS AND DISCUSSION

Table 1 presents the summary data of farm and farm households used in negative binomial regression models with regard to socioeconomic traits. With a maximum of 7 years, the average value of adoption difference between hybrid maize types was 1.73 years. With a minimum age of 25 years and a maximum age of 70 years, the average value of age of hybrid maize farmers was 44.77 years. The mean years of education were 6.69. Although some of the hybrid maize farmers were fresh competitors in this farm sector, their experience in this activity was 12.20 years. The area used for cultivating hybrid maize averaged 33.32 acres. The major market's average distance from the farm gate was 15.83 kilometers. For hybrid maize growers, we use extension services, credit access, and areas (Sahiwal, Faisalabad, and Okara) as dummy variables. These were consecutively 0.77, 0.48, 0.25, 0.25, and 0.25.

Negative binomial regression models were employed to estimate the factors influencing the adoption gap among hybrid maize cultivators in rural Punjab, Pakistan. The calculated Poisson regression model was criticized due to the assumption of variance of the dependent variable equal to its meaning and it was tested for over-dispersion. There was an over-dispersion problem existing in the modal, so it was rejected. Thus, the negative binomial model was selected since it allows for over-dispersion (Cameron and Trivedi, 2009; Cameron and Trivedi, 2013). So, we used the negative binomial model for this study.

Table 2 addresses the model's parameter estimates. First, examine the likelihood ratio test of the model which displayed the general goodness of fit of the model and it was statistically significant at a one percent level of significance before straight to the results. With a coefficient of 0.0419, the variable of schooling is statistically significantly one percent level of significance. This implies that the projected log count of the adoption gap of the hybrid maize variety reduces by 0.0419 for every unit increase in education. Coefficients (0.0055) of farmer experience which is statistically significant at a five percent level of significance. This means that for each one-unit increase in farming experience, the expected log count of the adoption gap of hybrid maize variety decreases by 0.0055 and hybrid maize land (-0.0011) is negatively related to the adoption gap. Age and main market distance positive and non-significant impact on the adoption gap, age showed that if farmers are older, then the adoption gap is also greater. Same way, if the main market distance is greater, then farmers have low access to the market so that's why the gap was greater. The predicted justification for this is that farmers far from the main market could pay more for labor and transportation and lack knowledge of the accessibility of the recently published technology supplied by dealers or any other. We use extension contact as a dummy variable; at ten percent, the coefficient of extension contact was significant, indicating that more extension agents interacting with farmers help to close the adoption difference.

Due to risky production, farmers are less likely to adopt modern technology. If risk-reducing strategies such as credit access and off-farm income are available for farmers during the production period. Farmers are more likely to adopt technology or replace varieties that might bring a higher profit, even if these are perceived as risky. Ten and one percent levels of significance allow coefficients of off-farm income and credit availability to be statistically significant. Consequently, the predicted log count of the hybrid maize variety reduces by 0.2273 and 0.1360 for every unit increase in credit access and off-farm income.

The parameter estimates for districts represented as dummy variables indicate that Okara district has a negative sign (p) and is significant at the ten percent level of significance. This finding indicates that farmers residing in the Okara region exhibit a smaller adoption gap compared to those in other districts. Okara district is the primary region for hybrid maize cultivation. Here farmers have more ability to replace the variety because these farmers are more aware of technology. However, the coefficient of Faisalabad district has positive signs. So, its coefficient showed that farmers are less adaptor to new technology or speed of variety replacement is very slow. Table 2 shows that important variables in the negative binomial regression model also have significant marginal effects, ensuring the robustness of the results.

Table 1. Descriptive statistics and definition of variables.

Variables	Descriptive	Units	Min	Max	Mean	Std. D
Dependent Variable						
Adoption Gap	Discrepancy between the year of adoption and the year of release or awareness	Year	0.00	7.00	1.73	1.41
Explanatory Variable						
Age	Age of Household farmer	Year	25.00	70.00	44.77	9.93
Education	Education of Household farmer	Year	0.00	16.00	6.89	4.02
Experience	Experience of maize farmers	Year	2.00	26.00	12.20	5.45
Maize Area	Hybrid maize Area	Acre	2.00	150.00	33.32	33.93
Distance from main market	Distance from farm gate to main market	Km	1.00	36.00	15.83	8.78
Extension	1=extension service; 0 otherwise	dummy	0.00	1.00	0.77	0.42
Off-farm income	1=off-farm income; 0 otherwise	dummy	0.00	1.00	0.36	0.48
Credit Access	1=credit access; 0 otherwise	dummy	0.00	1.00	0.47	0.50
Sahiwal	1=Sahiwal; 0 otherwise	dummy	0.00	1.00	0.25	0.43
Okara	1=Okara; 0 otherwise	dummy	0.00	1.00	0.25	0.43
Faisalabad	1=Faisalabad; 0 otherwise	dummy	0.00	1.00	0.25	0.43

Table 2. Estimates of the negative binomial regression model of hybrid maize varieties adoption gap.

Variables	Negative Binomial regression			
	Coefficient	Standard Error	Marginal Effects	Standard Error
Age	0.0032	0.0047	0.0055	0.0082
Education	0.0419***	0.0105	0.0728	0.0185***
Experience	0.0055**	0.0093	0.0095	0.0162**
Maize Area	-0.0011	0.0014	-0.0020	0.0025
Distance from main market	0.0051	0.0045	0.0088	0.0078
Extension	0.1497*	0.0893	0.2602	0.1555*
Off-farm income	0.1360*	0.0836	0.2362	0.1455*
Credit Access	0.2273***	0.0815	0.3950	0.1424***
Sahiwal	-0.1393	0.1167	-0.2421	0.2029
Okara	-0.1949*	0.1168	-0.3387	0.2033*
Faisalabad	0.1585	0.1058	0.2755	0.1841
Constant	0.9956***	0.2270		
LR chi2(11)	54.35***			
Pseudo R2	0.041			
Log likelihood	-643.075			
Total Observations	400			

Note: * significant at the level 0.10 **Significant at the level 0.05; ***Significant at the level 0.01.

CONCLUSIONS

Nowadays in Punjab, Pakistan time to adoption of new varieties refers to the dissemination of new varieties to their use by a grower. Growers in Punjab, Pakistan have cultivated new varieties for several years, and the adoption of new varieties infers the replacement of one new variety to another. This research indicates the determinants influencing the adoption gap (variety replacement) of the hybrid maize verities in rural Punjab, Pakistan using a negative binomial regression model. The finding based on the primary data collection from four districts of Punjab, reveals that growers who have more education are more adopting behavior toward new verities. Because they have more technology information. The significance of hybrid maize area and maize experience in influencing the adoption gap suggests that the importance of technical training and more learned from previous varieties and modern varieties decrease the adoption gap or help in the quick replacement of new hybrid varieties. Technical information about new hybrid varieties assimilated through extension workers was found to be an important determinant in the variety replacement (decreasing of adoption gap). This represents the significance of strengthening the extension services and enlightening the expertise of extension officers in delivering eminent information that curtails the risk of adoption due to imperfect transfer of information. The significance of off-farm income and credit access during crop failure direct the importance of risk coping/mitigation strategies to hasten the variety replacement. Our study is based on primary data, but variety replacement (adoption gap) is a dynamic and continuing procedure. For further research viewpoint, it is imperative to assemble data over time to recognize the variety replacement process and detention the dynamics of some of the descriptive variables that affect adoption gap/variety replacement.

REFERENCES

Abbas, T., Ali, G., Adil, S.A., Bashir, M.K., Kamran, M.A., 2017. Economic analysis of biogas adoption technology by rural farmers: The case of Faisalabad district in Pakistan. Renew. Energy 107, 431–439.

Abdulai, A., Huffman, W.E., 2005. The diffusion of new agricultural technologies: The case of crossbred-cow technology in Tanzania. Am. J. Agric. Econ. 87, 645–659.

Abid, M., Ashfaq, M., Khalid, I., Ishaq, U., 2011. An economic evaluation of impact of soil quality on Bt (Bacillus thuringiensis) cotton productivity. Soil Env. 30, 78–81.

Adams, P., Farrell, M., Dalgarno, B., Oczkowski, E., 2017. Household adoption of technology: The case of high-speed broadband adoption in Australia. Technol. Soc. 49, 37–47.

Ahmed, H., Khan, M.R., Panadero-Fontan, R., Sandez, C.L., Farooq, M., Naqvi, S.M.S., Qayyum, M., 2012. Geographical distribution of hypodermosis (Hypoderma sp.) in Northern Punjab, Pakistan. Kafkas Univ Vet Fak Derg 18, A215–A219.

Akhtar, S., LI, G., Ullah, R., Nazir, A., Iqbal, M.A., Raza, M.H., Iqbal, N., Faisal, M., 2018. Factors influencing hybrid maize farmers' risk attitudes and their perceptions in Punjab Province, Pakistan. J. Integr. Agric. 17, 1454–1462.

Ashraf, S., Khan, G.A., Ali, S., Iftikhar, M., 2015. Socio-economic determinants of the awareness and adoption of citrus production practices in Pakistan. Ciência Rural 45, 1701–1706.

Badar, H., Ghafoor, A., Adil, S.A., 2007. Factors affecting agricultural production of Punjab (Pakistan). Pak. J. Agri. Sci 44, 3.

Beyene, A.D., Kassie, M., 2015. Speed of adoption of improved maize varieties in Tanzania: An application of duration analysis. Technol. Forecast. Soc. Change 96, 298–307.

Cameron, A.C., Trivedi, P.K., 2009. Microeconometrics using stata (Vol. 5): Stata press College Station, TX.

Cameron, A.C., Trivedi, P.K., 2013. Regression analysis of count data. Cambridge university press.

Dadi, L., Burton, M., Ozanne, A., 2004. Duration analysis of technological adoption in Ethiopian agriculture. J. Agric. Econ. 55, 613–631.

Feder, G., Just, R.E., Zilberman, D., 1985. Adoption of agricultural innovations in developing countries: a survey. Econ. Dev. Cult. Chang. 33, 255–298. https://doi.org/10.1086/451461

Feder, G., Slade, R., 1984. The acquisition of information and the adoption of new technology. Am. J. Agric. Econ. 66, 312–320.

Feder, G., Umali, D.L., 1993. The adoption of agricultural innovations: a review. Technol. Forecast. Soc. Change 43, 215–239.

Foster, A.D., Rosenzweig, M.R., 1995. Learning by doing and learning from others: Human capital and technical change in agriculture. J. Polit. Econ. 103, 1176–1209.

Fuglie, K.O., Kascak, C.A., 2001. Adoption and diffusion of natural-resource-conserving agricultural technology. Rev. Agric. Econ. 386–403.

GoP, 2023. Economic survey of Pakistan. Retrieved from Islamabad, Pakistan. http://www.finance.gov.pk/survey_1617.html.

Griliches, Z., 1971. Hybrid corn and the economics of innovation. The Economics of Technological Change, Penguin Books, London, pp.211-228.

Hazell, P.B., 2010. Asia's Green Revolution: past achievements and future challenges. Rice in the global economy: strategic research and policy issues for food security. International Rice Research Institute, Los Baños, 61-92. https://ageconsearch.umn.edu/record/164488/files/RiceintheGlobal.pdf#page=70.

Hazell, P.B., Anderson, J.R., 2012. Public policy toward technical change in agriculture. https://agris.fao.org/search/en/providers/122566/records/6473920268b4c299a3f9f37c.

Hiebert, L.D., 1974. Risk, learning, and the adoption of fertilizer responsive seed varieties. Am. J. Agric. Econ. 56, 764–768.

Just, R.E., Zilberman, D., 1983. Stochastic structure, farm size and technology adoption in developing agriculture. Oxf. Econ. Pap. 35, 307–328.

Langyintuo, A.S., Mekuria, M., 2008. Assessing the influence of neighborhood effects on the adoption of improved agricultural technologies in developing agriculture. African J. Agric. Resour. Econ. 2, 151-69.

Leathers, H.D., Smale, M., 1991. A Bayesian approach to explaining sequential adoption of components of a technological package. Am. J. Agric. Econ. 73, 734–742.

Lindner, R., Fischer, A., Pardey, P., 1979. The time to adoption. Econ. Lett. 2, 187–190.

Matuschke, I., 2007. Adoption and impact of proprietary seed technologies in staple food crops: The case of hybrid wheat and pearl millet in India: Cuvillier Verlag.

Munasib, A.B.A., Jordan, J.L., 2011. The effect of social capital on the choice to use sustainable agricultural practices. J. Agric. Appl. Econ. 43, 213.

Naqvi, S.A.A., Ashfaq, M., 2014. Estimation of technical efficiency and it's determinants in the hybrid maize production in district Chiniot: a Cobbdouglas model approach. Pakistan J. Agric. Sci. 51, 181–188.

Otsuka, K., Larson, D.F., 2014. An African green revolution: Springer. https://ndl.ethernet.edu.et/bitstream/123456789/71851/1/Keijiro%20Otsuka.pdf.

Rogers, E.M. (1995) Diffusion of Innovations. 4th Edition, the Free Press, New York.

Roumasset, J.A., Boussard, J.M., Singh, I., 1979. Risk, uncertainty and agricultural development. https://www.cabidigitallibrary.org/doi/full/10.5555/19791859615.

Smale, M., Nazli, H., 2014. Time to Variety Change on Wheat Farms of Pakistan's Punjab. Retrieved from: https://cgspace.cgiar.org/items/19589248-beee-4921-97d2-a8923f352378.

Yamane, T., 1967. Problems to Accompany Statistics: An Introduction Analysis: Harper & Row.

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