

Household wealth and adoption of improved maize varieties in Nepal: a double-hurdle approach

Raju Ghimire^{1,2} · Wen-Chi Huang³

Received: 21 November 2014 / Accepted: 6 October 2015 / Published online: 7 November 2015
© Springer Science+Business Media Dordrecht and International Society for Plant Pathology 2015

Abstract In the light of emerging debates about increasing agricultural production and food security for rural farmers in developing countries, this paper examines the effects of household wealth on adoption and use intensity of improved maize varieties (IMVs) in two agro-ecological regions of central Nepal. Using cross-sectional farm-level data from 416 households, we first categorized households into two wealth groups – poorly endowed and well-endowed households – and then estimated Cragg’s double-hurdle model for adoption and use intensity of IMVs for each group. The study found the presence of heterogeneous factors influencing adoption and intensity of adoption between poorly and well-endowed households, suggesting a need for wealth-group-specific policy interventions to increase adoption of IMVs and their subsequent impacts on food security. The results also indicated that the availability of seed in local retail outlets will benefit

especially the poorly endowed farmers because distance to market showed a negative impact on adoption and intensity of adoption of IMVs. Therefore, government should establish a wide seed distribution network in rural areas, preferably by way of a public-private partnership (PPP), if the desired adoption rate and intensity of adoption are to be achieved. Linking farmers to markets by integrating farmers with potential buyers could help reduce transaction costs and make agriculture more profitable.

Keywords Technology adoption · Improved maize varieties · Food security · Double-hurdle model · Nepal

Introduction

Maize (*Zea mays* L.) is the second largest staple crop in Nepal after paddy rice in both area and production, and is a crop of great socioeconomic importance for Nepalese agriculture and food security. It covers one-fourth of the total cropped area, and almost 64 % of agricultural households depend on it for their livelihood. Furthermore, it contributes 26 % of the country’s total edible food production, 3 % of the national gross domestic product (GDP) and 10 % of the agricultural GDP (CBS 2011). Maize is cultivated in a wide range of agro-ecological environments from the Terai¹ to mid-hills (subtropical mild climate) under both irrigated and rain-fed conditions (upland *bari* terraces) across the country (Paudyal and Poudel 2001). Specifically, it is a priority staple food crop for hill people. In the Terai region, on the other hand, maize is largely produced as an income-generating feed crop for livestock

✉ Wen-Chi Huang
wenchi@mail.npust.edu.tw

Raju Ghimire
ghimireraj@hotmail.com

¹ Department of Tropical Agriculture and International Cooperation, National Pingtung University of Science and Technology, 1 Shuefu Road, Neipu, Pingtung 91201, Taiwan

² Department of Agriculture, Ministry of Agricultural Development, Hariharbhavan, Lalitpur, Nepal

³ Department of Agribusiness Management, National Pingtung University of Science and Technology, 1 Shuefu Road, Neipu, Pingtung 91201, Taiwan

¹ Terai is the southernmost part of the country bordering India, which has a flat, fertile landscape and tropical hot climate. This region stretches more than 1000 km from east to west.

(Paudel and Matsuoka 2009). Recently, this crop has become an important source of cash, especially for Terai farmers, either directly through its sale to millers or indirectly through the sale of animals that are fed with maize grain and silage.

Despite this importance, the average productivity of maize in Nepal is the lowest in South Asia (FAOSTAT 2013). Farmers are still growing local cultivars that are low-yielding, prone to lodging and are disease-susceptible. Consequently, the productivity of maize has either remained stagnant or increased at a very slow rate (Paudel and Matsuoka 2009; Thapa et al. 2014). For instance, the yield of maize is as low as 2 t ha⁻¹, far below the potential yield of 8 to 10 t ha⁻¹ (Joshi et al. 2012). Various reports related to agriculture and food security assessments in Nepal have noted that low agricultural productivity is an important constraint on the achievement of productivity growth, food security and poverty reduction. However, there is potential for increasing agricultural productivity as exemplified by the large gap in yield between those of research stations and farmers' fields (Paudel and Matsuoka 2009). For farmers to achieve higher yields, factors responsible for low agricultural productivity need to be assessed.

The process of adopting improved crop varieties has become a challenging constraint to the improvement of agricultural productivity and achievement of sustainable livelihoods for farmers under various socioeconomic conditions. For example, the inconsistent agricultural growth and low yields indicate that technology adoption has not contributed much to the enhancement of sustainable agricultural growth and productivity in Nepal (Pant 2015). Moreover, no improved technology, regardless of access to other inputs and reliable markets, will have significant impacts on productivity, income and poverty reduction unless it is adopted by a significant proportion of farmers (Minten and Barrett 2008; Pant 2015). Although widening adoption of new technologies is an effective way to increase agricultural productivity, technology adoption is a relatively complicated process, from hearing about a technology to actual uptake, that may be influenced by a number of factors, such as socioeconomic characteristics of farmers, their risk-bearing ability, access to and level of resources, inputs, provision of extension, infrastructure and market, and other institutional factors. Farm-level studies with innovative tools can provide insights into key factors affecting farmers' use of new technology and their effects on household livelihood and food security (Doss 2006). Despite considerable research directed to this issue, however, very little attention has been paid to studying adoption intensity, particularly in the Nepalese context. As a result, there has been limited empirical information on why some farmers adopt and intensify use of improved seed varieties and others do not.

Other countries in South Asia with agricultural conditions similar to those of Nepal have addressed the above mentioned adoption problems and challenges by implementing programs and policies at various levels. For example, India has heavily

subsidized agricultural inputs (fertilizers, seeds, electricity for pumping) and made an effort to link farmers to product markets (Shinoj 2015). Similarly, Bangladesh has focused on strengthening research and extension delivery systems, and Sri Lanka implemented breeding programs to develop high-yielding, pest- and disease-resistant varieties, revitalized credit markets, and established crop insurance and an efficient seed supply system (Karim and Haque 2015; Weerahewa et al. 2015). Additionally, available studies indicate that integration of farmers and formal markets offers farmers reasonable prices and higher profits, which ultimately lead to improved access to technology, inputs, credit markets, reduced transaction costs, increased efficiency in production, and increased adoption rates and food and nutrition security (Kumar 2015).

Initially, policymakers and researchers sought simple descriptive statistics about the adoption and diffusion of new seed varieties, but these did not offer much insight into the process of technology adoption and productivity growth (Doss 2006). Correspondingly, the adoption of high-yielding varieties of crops by farmers in developing countries was viewed as the solution to low productivity growth and incomes in agriculture over the years (Besley and Case 1993). To this end, many donor agencies invested substantial resources in agricultural technologies. Most of the new agricultural technologies, however, did not fully achieve the desired goals (Faltermeier and Abdulai 2009). As a result, concerns arose later about the impact of technology adoption on production, poverty and malnutrition, food security and input use in agriculture that need to be reassessed. Therefore, this study has employed an innovative methodological tool to discover deeply embedded problems of adoption challenges in the Nepalese farming systems.

Several examples from the adoption literature (e.g., Becerril and Abdulai 2010; Just and Zilberman 1988; Koundouri et al. 2006; Uaiene et al. 2009) reveal that adoption decisions are based on risk, uncertainty, input rationing, information imperfections, human capital and social networks. Further, resource-poor farmers are often reluctant to invest in any untried technology because of their limited resources (cash, labor, time). As economic theory would predict, relatively wealthier (or more resource-endowed) households are better able to cope with production and price risks and consequently are more willing to adopt new technologies than their poorer (or less resource-endowed) counterparts (Bola et al. 2012; Hardaker et al. 2004; Langyintuo and Mungoma 2008). However, the influence of household wealth status has not been adequately studied in the adoption literature, particularly in South Asia and in relation to maize in Nepal.

Most of the previous studies on agricultural technology adoption have addressed the factors influencing technology adoption other than the intensity of adoption (Feder et al. 1985; Sunding and Zilberman 2001). The adoption alone, however, will neither improve agricultural productivity nor

reduce food insecurity and poverty if barriers to the continued use and intensification of that technology are not identified and overcome (Oladele 2006). Therefore, the objective of this study is to examine the factors influencing adoption of improved maize varieties and the intensity of adoption by poorly endowed and well-endowed households in rural Nepal. To focus on the intensity of adoption, we used the latest methodological tool, Cragg's double-hurdle model, to analyze the data. We expect this study will help to introduce a new dimension to the understanding of adoption and use intensity of IMVs by rural farmers in low-income countries. The study also aims to help policymakers see how policies might be changed to enhance adoption rates, increase production and improve food security, and what policy options can be introduced to improve the ability of small-scale, resource-poor farmers to access and benefit from the new technologies.

Research and development of maize varieties in Nepal

Various organizations and research institutions have been involved in research in Nepal in developing improved maize varieties and improving maize-based cropping systems in order to increase the productivity and food security of rural farmers. The Nepal Agricultural Research Council (NARC), in collaboration with the International Maize and Wheat Improvement Center (CIMMYT), has focused on germplasm exchange and improvement of maize varieties in Nepal. They provide farmers with the best high-yielding maize varieties that withstand infertile soils, drought, pests and diseases. Similarly, the Hill Maize Research Project (HMRP) has been successfully promoting the development and adoption of newly improved maize varieties and crop management practices in Nepal. With the main objective of reducing food insecurity among rural farm families, the HMRP has implemented various programs for increasing the productivity and sustainability of maize-based cropping systems. Additionally, a long-term major initiative has been launched – the Cereal System Initiative for South Asia (CSISA) – with the purpose of decreasing hunger and malnutrition and increasing the food and income security of resource-poor farm families in Nepal and neighboring countries of South Asia. Community based seed production (CBSP) is an approach of the HMRP that empowers farmers to produce high-yielding, improved maize seed, which is locally preferred. Its aims are to provide quality seed to buyers, boost local seed markets, open avenues for people to start seed-trading businesses and offer farmers a “basket” of crop varieties to choose from.

NARC, as a leading research institution in Nepal, works mainly with open-pollinated and inbred varieties of all food crops. For example, it has developed and released more than 20 open-pollinated maize varieties for commercial production

and identified more than 15 promising lines, including four lines of quality protein maize (QPM). Additionally, other high-yielding, disease- and drought-tolerant maize varieties developed through NARC-CIMMYT collaboration (2002–2010) include Manakamana 1, 3, 4, 5, 6, Arun, Posilo makai-1, Deuti and Shitala, which are very popular in the study areas (CIMMYT 2012). However, only one-third of currently released varieties are in demand. Farmers are overwhelmingly growing old local varieties: 75 % of all the foundation seeds demanded for maize in 2010 were for varieties released before 1995 (Joshi et al. 2012). NARC has also developed one hybrid maize variety (Rampur Hybrid-2) that is recommended for the Terai region of Nepal. Along with hybrid varieties, improved open-pollinated varieties (OPVs) released by the public sector (NARC/NMRP) – Rampur Local, Rampur Composite and Rampur Yellow – are popular among farmers in the Terai region. Rampur Local is highly preferred in Chitwan and neighboring districts – almost two-thirds of its output is used for home consumption (Ghimire et al. 2013). Some local varieties are being cultivated because of their specific traits (e.g., taste, color) and farmers hesitate to give them up and switch to new ones. Manakamana-1 and Ganesh-2 continue to be dominant in the Hill region, even though they were introduced over a decade ago (CIMMYT 2012).

Although the government and various projects have made some effort to fulfill the need for adoption of high yielding and better quality seed by linking CBSP to seed markets, the maize seed supply and delivery system imposes constraints on the real adopters. Among others, limited numbers of input suppliers, limited knowledge, demanded inputs not being available on time and in quantity, lack of awareness about improved varieties and technologies, and inadequate education are the foremost constraints in the maize seed industry in Nepal (Khatri-Chhetei 2015). Because NARC has limited capacity and programs to produce competitive hybrid maize varieties, promoting private sector involvement in the hybrid seed and commercial seed business in remote areas and at the community level is urgent (Pant 2015). The government has, over time, launched a number of programs and policy guidelines, including the Agricultural Development Strategy (ADS), Seed Vision and NARC vision, to address these issues. Commitment to effectively implementing these policies to fulfill the seed requirements of farmers, however, is obviously lacking.

Materials and methods

Study area

The study was conducted in four districts of two agroecological regions in central Nepal (Fig. 1). Kavre and Nuwakot districts were selected from the Hill region, and

Fig. 1 Map of Nepal showing study area. *Source:* MoAD 2013



Chitwan and Rautahat districts were selected from the Terai region.

The selected districts represent major maize-producing areas of the country with fertile and productive land and suitable agro-ecology for maize production. Farmers in these areas have begun to adopt improved crop varieties. We selected central Nepal as the study area mainly for three reasons: first, maize production in the central region accounts for about 24 % of the national maize production (MoAD 2013); second, the predominantly rain-fed growing environment in the region is suitable for maize production; and third, the majority of the farmers are smallholders who own nearly or less than 0.5 ha of land, with many parcels, plots and subplots, and are facing adoption challenges. Table 1 presents an agro-ecological profile and the production environment of the study districts in the Hill and Terai regions.

Theoretical and empirical framework

Estimating wealth indices

The households' ability to cope with risks and hence benefit from new technology is directly or indirectly related to its resource endowment or productivity assets (Fischer and Qaim 2012; Langyintuo and Mungoma 2008). Household assets mostly comprise the physical, human, financial and social capital which are used as the key indicators of wealth. Because the levels of asset endowment vary across households, it is difficult to rank households on the basis of their economic status without normalizing (or weighting) the assets in a manner that avoids distortions due to different measurement scales. The weighting procedure involves the identification of the relevant weight for each asset indicator by extracting from a set of variables those few with orthogonal linear

combinations that capture the common information (Langyintuo and Mungoma 2008).

Following Filmer and Pritchett (2001), Langyintuo and Mungoma (2008) and Zeller et al. (2006), this paper used household assets to construct wealth indices by the principal component analysis (PCA)² method. We used data on the ownership of 16 types of farm and consumption assets (see Table 5 for the list of assets and their scoring coefficients). In PCA, the components are ordered so that the first component (PC1) explains the largest possible amount of variation that is common to all of the variables in the original data (Filmer and Pritchett 2001). A common feature of PCA in statistical software packages converts all indicators into standardized variables with the mean of zero and a standard deviation of 1 (Zeller et al. 2006). Hence, the resulting index is also a normally distributed variable with a zero mean and a standard deviation equal to 1. Suppose we have a set of N variables, a_{1j}^* to a_{Nj}^* , representing the ownership of N assets by each household j . PCA starts by specifying each variable normalized by its mean and standard deviation: for example, $a_{1j} = (a_{1j}^* - a_1^*)/s_1^*$, where a_1^* is the mean of a_{1j}^* across households and s_1^* is its standard deviation. These selected variables are expressed as linear combinations of a set of underlying components for each household (j):

$$\begin{aligned} a_{1j} &= \nu_{11}A_{1j} + \nu_{12}A_{2j} + \dots + \nu_{1N}A_{Nj} \\ &\quad \dots \\ a_{Nj} &= \nu_{N1}A_{1j} + \nu_{N2}A_{2j} + \dots + \nu_{NN}A_{Nj} \end{aligned} \quad \forall j = 1, \dots, j \quad (1)$$

where the A 's are the components and the ν 's are the coefficients on each component for each variable (and do not vary across

² The estimated mean value of the Kaiser-Meyer-Olkin (KMO) of sampling adequacy is 0.866, suggesting that performing PCA is appropriate (Hair et al. 2006).

Table 1 Agro-ecological profile and production environment of the study sites

Characteristics	Hill region		Terai region	
	Kavre	Nuwakot	Chitwan	Rautahat
Altitude (meters)	318–3015	457–5144	100–2000	122–244
Climate	Subtropical	Subtropical	Tropical	Tropical
Annual rainfall (mm)	1581	1200	2150	2125
Temperature (°C)	10–32	8–30	10–41	12–43
Cropping system	rice-veg-maize rice-fallow rice-maize	rice-veg-maize rice-fallow rice-maize	rice-wheat-rice rice-wheat-maize rice-veg-maize	rice-wheat-rice rice-wheat-maize rice-veg-maize
Major crops	maize, rice, subtropical fruits and vegetables	maize, rice, subtropical fruits and vegetables	rice, maize, wheat, tropical fruits and vegetables	rice, maize, wheat, tropical fruits and vegetables

Source: Based on author's survey 2013 and CBS (2011)

households). The first principal component, expressed in terms of the original (un-normalized) variables, is therefore an index for each household based on the expression:

$$A_{1j} = f_{11} \left(\frac{a_{1j}^* - a_1^*}{s_1^*} \right) + \dots + f_{1N} \left(\frac{a_{Nj}^* - a_N^*}{s_N^*} \right) \quad (2)$$

where f_{11} is the weight for the first of the N household asset indicator variables identified as significant in the PCA model, a_{1j}^* is the j th household's value for the first variable, and a_1^* and s_1^* are the mean and standard deviations of the first variable over all households. According to Filmer and Pritchett (2001), PCA can be used to compute weights that mark each indicator's relative contribution to the overall asset component. Using these weights, a household-specific asset index can be computed based on each household's indicator values as shown in Eq. (2).

Specification of Cragg's double-hurdle model

Farm households are assumed to maximize their utility function subject to resource constraints (Asfaw et al. 2012). Moreover, viewing adoption through the lens of optimization by rational agents, households should adopt a technology if and only if adoption is actually a choice that can be taken and at the same time adoption is expected to be profitable or otherwise advantageous. Modeling farmers' decision making about whether to adopt or not to adopt a technology constitutes a discrete (whether or not to take up the technology) and continuous (the intensity of use) decision. Asfaw et al. (2012) and Becerril and Abdulai (2010) modelled an adoption decision in a random utility framework:

$$G_i^* = X_i' \gamma + u_i \quad \text{with } G_i = \begin{cases} 1 & \text{if } G_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

where G_i^* is a latent variable denoting the difference between utility from adopting improved varieties (U_{iA}) and the utility

from not adopting the technology (U_{iN}), such that a utility-maximizing farm household, i , will choose to adopt new technology if utility gained from adopting is greater than the utility of not adopting ($G^* = U_{iA} - U_{iN} > 0$). The term $X_i' \gamma$ provides an estimate of the difference in utility from adopting the technology ($U_{iA} - U_{iN}$), using the household and farm-level characteristics, X_i' , as explanatory variables, while the term γ is a vector of parameters to be estimated and u_i is the error term.

The adoption decision is a process that extends over a certain period of time, from hearing about the technology for the first time to actual uptake. This holds true in particular for knowledge-intensive system technologies such as high-yielding maize seed. To allow for the application of the empirical model developed here, we assumed that the adoption process involves two decision stages (Noltze et al. 2012). First, the farmer decides whether to adopt the technology or not to adopt it (a dichotomous choice), and second, decides on the extent of adoption or the proportion of acreage under that particular technology once adopted (a continuous variable – intensity of adoption). Not all the farmers adopted IMVs at the same time (during the survey year), so some observations have zero values for their adoption status. Following Aramyan et al. (2007), Bokusheva et al. (2012), Gao et al. (1995), Langyintuo and Mungoma (2008), Newman et al. (2003), and Yen and Jones (1997), we employed a relatively new and innovative econometric tool, Cragg's double-hurdle model, to analyze the data related to households making two sequential decisions with regard to adopting and using IMVs. In the first hurdle, we estimated the probit model to determine the probability of adopting improved maize varieties by farm households and, in the second hurdle, we used a truncated regression model to determine the extent or intensity of adoption. Each hurdle is conditioned by the household's socioeconomic

characteristics and variety-specific attributes. The model specification is:

$$Y_{i1}^* = \alpha W_i' + u_i \quad \text{decision to adopt an IMV variety} \quad (4)$$

$$Y_{i2}^* = \beta X_i' + u_i \quad \text{extent of adoption} \quad (5)$$

$$Y_i = \beta X_i' + u_i \quad \text{if } Y_{i1}^* > 0 \text{ and } Y_{i2}^* > 0 \quad (6)$$

where, Y_{i1}^* is a latent variable that represents the probability of the household's decision to adopt IMVs, Y_{i2}^* is a latent variable representing the extent of adoption (or area of IMVs cultivation), and Y_i is a dependent variable, the observed proportion of the maize area planted to IMVs. W_i' and X_i' are vectors of variables explaining the adoption decision and use intensity, respectively, α and β are the parameters to be estimated, and u_i and μ_i are the respective error terms assumed to be independent and normally distributed as $u_i \sim N(0,1)$ and $\mu_i \sim N(0,\sigma^2)$. The model is estimated using maximum likelihood estimation procedures. The log likelihood equation for the independent double-hurdle model allowing for heteroscedasticity and a non-normal error structure can be written as follows (Jensen and Yen 1996; Yen and Jones 1997):

$$\begin{aligned} \text{LogL} = \sum_0 \ln \left[1 - \phi \left(X_i' \alpha \right) \phi \left(\frac{W_i' \beta}{\sigma} \right) \right] \\ + \sum \ln \left[\phi \left(X_i' \alpha \right) \frac{1}{\sigma} \phi \left(\frac{y_2 - W_i' \beta}{\sigma} \right) / \sigma \right] \end{aligned} \quad (7)$$

Data and variable specification

The data used for this study originates from a survey conducted on a sample of farm households in central Nepal during the 2013 crop season. A multistage random sampling procedure was used to select districts, villages and farm households. In the first stage, four districts (Kavre, Nuwakot, Chitwan and Rautahat) were selected on the basis of the intensity of maize production (widespread in area), agro-ecology (predominance of rain-fed upland environment) and farmers' field characteristics. In the second stage, eight villages (two from each district) were randomly selected, and then 16 wards³ (two wards from each village) were selected in the third stage. Finally, a random sample of 416 farm households (26 households from each ward) was drawn and surveyed using the standardized survey instrument. The respondents were the household head or household principal male or female members who directly took part in the decisions and managed the farm.

We selected our explanatory variables on the basis of the adoption literature and organized them into three broad

categories: farm and farmers' characteristics, institutional and access-related variables, and technology-specific variables.

1) *Farm and farmers' characteristics*: These variables included age, gender, education, household size and farm size. The age of the household head was incorporated because it is believed that, with age, farmers accumulate personal capital and show a greater likelihood of investing in innovations. However, it may also be that younger farmers are more flexible, interested in trying new things and hence more likely to adopt new technologies than older farmers (Asfaw et al. 2012). Thus, the expected sign of the coefficient on age is indeterminate. We included a dummy variable for the gender of the household head to capture the gender difference. Male farmers are expected to be more likely to adopt and intensify use of new crop varieties because women in Nepal have very limited access to resources such as land, capital and extension (Gartaula et al. 2012). Educated farmers are typically assumed to be better able than uneducated ones to process information and search for appropriate technologies to alleviate their production constraints. The belief is that education gives farmers the ability to perceive, interpret and respond to new information much faster than their less educated counterparts (Uaiene et al. 2009). The expected sign on the coefficient of education is positive. Family labor⁴ is another variable used in the models. A large family often has a large number of working members, and this is expected to have a positive impact on the adoption of improved crop varieties because a larger household can more easily make use of its labor force in farming operations. Also, improved high-yielding varieties may increase the seasonal demand for labor, so that adoption is less attractive for those with limited family labor (Doss 2006). The size of the family farm is often argued as an important factor affecting adoption decisions. Farmers with larger farms are more likely to adopt improved technologies, particularly new varieties of seed, than those with small farms because farmers with large farms can afford to devote part of their land to try out the new technology (Mariano et al. 2012). Therefore the sign on the coefficient on farm size is positive.

2) *Institutional and access-related variables*: Farmers' contact with extension agents is expected to have a positive effect on adoption. According to the innovation-diffusion theory, such contacts, by exposing farmers to information, can be expected to stimulate adoption (Polson and Spencer 1991). Membership of a farmers' group or

³ A Ward is the lowest administrative unit at village level and all the administrative works are performed under the direct supervision of the respective Village Development Committee (VDC).

⁴ Family labor includes the number of family members aged between 15 and 65 years who can work in the field. It excludes those having disabilities and overseas employment (Abebaw and Haile 2013).

cooperative is included because farmers in a group learn from one another how to grow new crops and search for markets for their products. Network effects are important for individual decisions and, particularly in the context of agricultural innovations, farmers share information and learn from one another (Andrew and Rosenzweig 1995; Conley and Udry 2010). The expected sign on the coefficient on membership in farmers' groups and cooperatives is positive. It is expected that the availability of improved seed in the local retail stores will improve the likelihood of a farmer adopting a new variety. Therefore, access to seed is expected to have a positive influence on adoption and use intensity. Distance to market is also assumed to play an important role in technology adoption (Kassie et al. 2011). The hypothesis here is that the farther away a household is from input/output markets, the lower the likelihood that it will adopt new technology. The coefficient on the distance of the household to the nearest markets is expected to be negative. Income from off-farm employment may ease liquidity constraints and increase the likelihood that farm families will adopt new varieties, so the expected sign for off-farm work is positive. The relationship between wealth and adoption of improved crop varieties is expected to be positive because a household's ability to cope with risk increases with its wealth or stock of productive assets.

- 3) *Technology-specific variables*: During the adoption process, farmers compare the available crop varieties' production potential, resistance to pests and diseases, palatability and marketability (demand in market if they intend to grow for sale). Therefore, the expected sign for the technological attributes of selected maize varieties is positive.

Results and discussion

Distribution of respondents by wealth status

Farm households in the rural areas are not equally endowed. They are endowed with varying levels of resources or assets, each of which can potentially contribute to the wealth of the household. The PCA was run⁵ on 16 selected asset indicators that are generally perceived to be important in defining wealth status in the study districts. Among these 16 components extracted in the first stage of the PCA, only the first four components were significant according to the Kaiser criterion⁶ of

⁵ Statistical software package STATA 12.0 was used to construct the wealth indices through the PCA method.

⁶ The Kaiser criterion states that unless a principal component extracts at least as much as one of the original variables (i.e., has a standardized variance equal to or greater than 1), it should be dropped from further analysis (Filmer and Pritchett 2001).

an eigen-value greater than 1. The first four significant components were further extracted in constructing the wealth index, which explained about 63 % of the total variance. The overall standardized composite wealth indices were utilized to rank the households from the lowest to the highest composite wealth index (Filmer and Pritchett 2001; Langyintuo and Mekuria 2005). Households that had wealth indices greater than the sample mean 0 were classified as well-endowed (41 %); those with negative indices were categorized as poorly endowed (59 %), as shown in Fig. 2.

The characteristics of respondents by wealth status are presented in Table 2. As expected, the well-endowed households owned significantly larger farms than their poorly endowed counterparts (0.86 ha versus 0.54 ha). The years of formal education were also found to be higher among wealthy households (9 years versus 7 years). The proportion of farm households that adopted IMVs was 81 % in well-endowed households but only 37 % among poorly endowed households. The average proportion of land under cultivation of IMVs for the latter was considerably less than that of the former.

To support their farm investment (e.g., seeds, fertilizers, pesticides), a majority of the households from both wealth categories participated in nonfarm activities such as teaching, government service, police/army, small businesses, carpentry, labor for cash, machinery repair, local alcohol brewing, firewood collection, sewing and so on. In contrast to the widely held view of educated and rich people having more access to nonfarm employment, households from both wealth groups were found to be involved in off-farm activities in equal proportions. This is possibly because poorer households may want to compensate for their poor agricultural base by working in the off-farm sector. The proportion of farmers having access to seed, extension services and participation in farmers' groups/cooperatives was higher among well-endowed households than among poorly endowed households. It should be noted, however, that the comparison of descriptive statistics may not take into consideration other characteristics of the farmers that may affect the adoption of improved maize varieties and intensity of adoption. It requires additional multivariate analysis to study these effects and evaluate the adoption factors at the farm household level.

Factors influencing the adoption of IMVs

The empirical analysis of the adoption of IMVs involved two sets of estimations: poorly endowed and well-endowed (Table 3). The value of log-likelihood, the Pseudo R² and the LR Chi² (significant at 1 % level) reported in Table 3 indicate that our specification provides a reasonably good fit to the data and that explanatory variables used in the models were collectively able to explain farmers' choice of IMVs in the study area.

Fig. 2 Distribution of households according to wealth. Note: $W_p = -1.7976$ is the mean index of households falling below the sample mean of 0; $W_w = 2.6802$ is the mean index of households above the sample mean

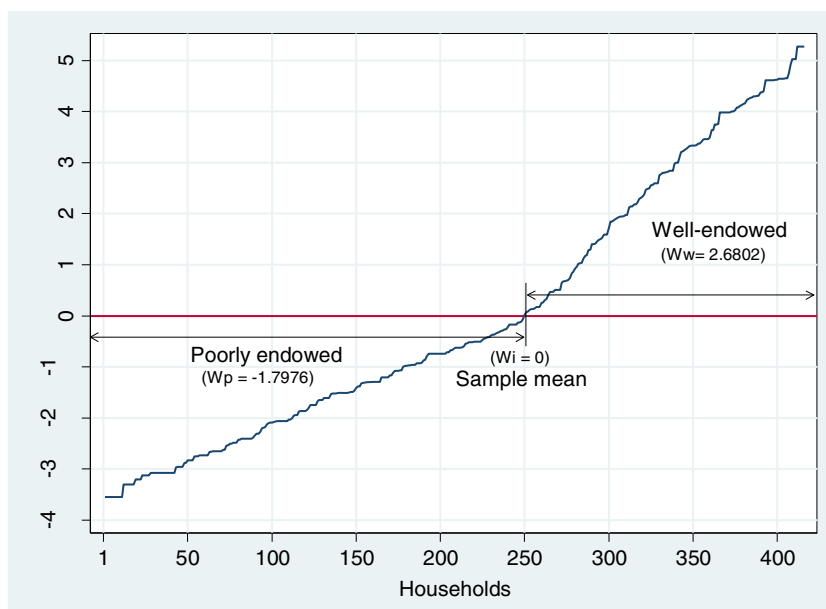


Table 2 Definition of variables and characteristics of respondents by wealth status

Variables	Description	Poorly endowed (n=249) ^a	Well-endowed (n=167) ^a	Expected sign ^b
Dependent variables				
Adopters	Proportion of farmers growing IMVs	37.35 (48.47)	80.83 (39.48)	
IMVs area	Proportion of land area allocated for IMVs	18.29 (25.36)	65.41 (33.74)	
Explanatory variables				
Farms and farmers' characteristics variables				
Age	Age of household head in years	45.21 (11.08)	43.60 (10.33)	-
Gender	=1 if household head is male, 0 otherwise	0.70 (0.45)	0.71 (0.45)	+
Education	Years of formal education of the head	7.08 (3.42)	9.08 (2.67)	+
Family labor	Number of family members (15–65 years)	3.06 (0.94)	3.18 (1.01)	+
Farm size	Total cultivated area in current year (ha)	0.54 (0.16)	0.86 (0.23)	+
Institutional and access-related variables				
Extension	=1 if receives extension services, 0 otherwise	0.34 (0.47)	0.61 (0.48)	+
Member	=1 if member in farmers' group, 0 otherwise	0.57 (0.49)	0.86 (0.34)	+
Seed access	=1 if IMVs are available at local store, 0 otherwise	0.41 (0.49)	0.77 (0.41)	+
Distance	Distance to input/output markets (km)	12.41 (6.11)	13.59 (5.50)	-
Off-farm work	=1 if participate in off-farm work, 0 otherwise	0.76 (0.42)	0.77 (0.42)	+/-
Wealth index	Wealth index of farm household assets	-1.79 (1.01)	2.68 (1.53)	+
Technology-specific variables				
Yield potential	=1 if the adopted variety to yield more than the local one, 0 otherwise	0.68 (0.46)	0.84 (0.36)	+
Pest/disease resistance	=1 if the adopted variety to be more resistant to pest/disease than the local one, 0 otherwise	0.40 (0.49)	0.58 (0.49)	+
Palatability	=1 if the adopted variety perceived to be more palatable than the local one, 0 otherwise	0.19 (0.39)	0.37 (0.48)	+
Marketability	=1 if it is easier to sell grains of IMVs in market than the local one, 0 otherwise	0.43 (0.49)	0.69 (0.46)	+
Region	=1 if household resides in Terai, 0 otherwise	0.43 (0.49)	0.59 (0.49)	+/-

Numbers in parentheses are the standard deviations

^a n = number of households

^b Plus (+) for positive and minus (-) for negative hypothesized effect of independent variables on the dependent variable

Table 3 Probit estimates of the probability of adopting improved maize varieties

Variables	Poorly endowed (<i>n</i> =249)		Well-endowed (<i>n</i> =167)	
	Coefficients	Marginal effects	Coefficients	Marginal effects
Age	-0.022 (0.012)**	-0.005	-0.043 (0.021)**	-0.005
Gender	0.052 (0.262)	0.011	-0.878 (0.517)**	-0.097
Education	0.091 (0.043)**	0.018	0.108 (0.089)	0.012
Family labor	-0.099 (0.124)	-0.019	-0.155 (0.230)	-0.017
Farm size	2.045 (0.941)**	0.410	-1.261 (1.247)	-0.134
Extension	0.359 (0.230)*	0.072	0.227 (0.399)	0.025
Member	0.036 (0.259)	0.007	1.385 (0.519)***	0.154
Seed access	0.412 (0.233)**	0.083	1.662 (0.498)***	0.184
Distance	-0.057 (0.023)***	-0.012	-0.009 (0.039)	-0.001
Off-farm work	-0.178 (0.255)	-0.036	0.613 (0.462)*	0.068
Wealth index	0.359 (0.145)***	0.072	0.554 (0.202)***	0.062
Yield potential	0.857 (0.311)***	0.172	0.704 (0.465)*	0.078
Pest/disease- resistance	0.397 (0.237)**	0.079	0.603 (0.474)	0.067
Palatability	0.259 (0.271)	0.052	-0.004 (0.482)	-0.001
Marketability	0.295 (0.233)	0.059	1.203 (0.473)***	0.133
Region	0.296 (0.269)	0.059	0.258 (0.527)	0.029
Constant	-1.019 (1.070)		-1.414 (2.019)	
Statistical values of the estimated models				
Log likelihood	-89.844039		-32.454512	
LR Chi ² (16)	149.38		98.27	
Prob > Chi2	0.0000		0.0000	
Pseudo R ²	0.4540		0.6022	
Percent correctly predicted	83.13		92.22	

Notes: *** Significant at 1 %, ** significant at 5 %, * significant at 10 % confidence level. Numbers in parentheses are the standard errors

The results reveal that across both wealth groups, age, seed access, wealth index and yield potential significantly influence the probability of adopting IMVs, with age having a negative influence. Consistent with previous findings by Bola et al. (2012), this result shows that older farmers are less likely to adopt IMVs. This is possibly due to the fact that young farmers are more flexible when exposed to new ideas and are likely to bear greater risk than their older counterparts. Furthermore, older farmers usually are reluctant to change varieties, clinging onto the local one that they perceive as more palatable for daily consumption, easier to manage post-harvest and with high flour to grain extraction ratio (Chirwa 2005; Smale 1995).

Gender had a significant and positive impact on the probability of adopting IMVs among well-endowed households – a household headed by a female was 10 % more likely to adopt IMVs. This is possibly because extension programs in Nepal have used a group approach targeted to female farmers. However, policy should be focused on female farmers among poorly endowed households if desired increases in adoption and agricultural production are to be achieved.

The coefficient on education was positive in both models but significant only in the subsample of poorly endowed households. One additional year of education increased the probability of adopting IMVs by 2 %, implying that educated farmers can cope with risk and better process information than less educated ones. This result is supported by previous literature (e.g., Adesina and Zinnah 1993; Doss 2001; Feleke and Zegeye 2006; Langyintuo and Mungoma 2008; Mariano et al. 2012; Mittal and Kumar 2000; Paudel and Matsuoka 2008) suggesting that adoption depends on the decision makers' educational level and access to information because education is thought to create a favorable mental attitude for the acceptance of new practices.

Farm size had a positive and significant influence on the probability of adopting IMVs among poorly endowed households. This indicates that, as cultivated farmland increases by one unit, the likelihood of adopting IMVs also increases by 41 %, confirming our expectation that owning more farmland is correlated with higher adoption rates. Consistent with earlier findings (e.g., Kassie et al. 2011; Mariano et al. 2012; Mendola 2007), this result likely reflects the scarcity of land

among poorly endowed farm households for cultivation of newly developed seed varieties.

The availability of extension services significantly increases the likelihood of adopting IMVs by 7 % among poorly endowed households reflecting the importance of information from extension organizations on the use of new technology, including IMVs. This result is in harmony with the observations of Arslan et al. (2014), Beke (2012), Mignouna et al. (2011), Paudel and Matsuoka (2008) and Ransom et al. (2003) that farmers who have contacts with extension workers are more likely to hear about improved varieties and thus have more incentive to adopt new agricultural technologies.

We found that the greater the participation of farmers in groups/cooperatives, the more likely they were to adopt IMVs. Membership in farmers' groups/cooperatives increased the probability of adopting IMVs by 15 % in the subsample of well-endowed households. Similar to the findings of Bola et al. (2012), Mignouna et al. (2011) and Sharma and Kumar (2000), this result supports the hypothesis that farmers' exposure to various information sources is associated with the ability to analyze the risks and benefits and take advantage of new innovations.

The coefficient of access to seed was positive and significantly influenced the adoption decision of IMVs in both models. If the seeds were available at local stores, the likelihood of adopting IMVs increased by 8 % among poorly endowed households and by 18 % among well-endowed households. This is expected as farming households residing in remote areas have little opportunity to obtain improved seeds from reliable sources, emphasising the importance of the availability of seed in local areas. Seed access, as well as access to other inputs, has mostly been reported to have similar results in previous studies (Langyintuo and Mungoma 2008; Nguetzet et al. 2011).

Distance to the nearest input/output market appeared to have a negative and significant influence on the adoption of IMVs among poorly endowed households but not among their well-endowed counterparts. The probability of adopting IMVs decreases by 1.2 % for every additional kilometer between market and farm. The reason for its significance only in poorer households may be related to their limited means of transportation (e.g., bicycle, motorbike, carts and vans), which makes them reliant on local buyers/sellers. The opposite is true for the well-endowed households. This result is consistent with previous studies (Feleke and Zegeye 2006; Kassie et al. 2011).

As expected, off-farm work had a significant positive effect on the adoption of IMVs among well-endowed households but not among poorly endowed ones. If members of the farm households participated in off-farm work, their probability of adopting IMVs increased by 7 %. Similar to the findings of Langyintuo and Mungoma (2008), this result suggests that the additional income from off-farm activities helps to relieve

liquidity constraints. Participation in off-farm work, however, may reduce the amount of time that farmers can spend on farming and thereby reduce efficiency in agricultural work, which ultimately may lessen the willingness to invest in new crop varieties. This is also not surprising in that the more risk-averse farmers tend to divert their efforts to nonfarm activities that offer higher returns and lower risk than agriculture (Chang and Mishra 2008).

Yield potential had positive and significant impact on farmers' decisions to plant a given variety of maize in both wealth groups, whether farmers were producing for home consumption or the market. This implies that the probability of planting IMVs increases with the farmers' perceptions about IMVs yielding more than local varieties by 17 % among poorly endowed and 8 % among well-endowed households. This result is supported by the findings of Adesina and Zinnah (1993) and Langyintuo and Mungoma (2008). It is, therefore, not surprising that the probability of adopting an IMV will increase once a farmer perceives that the return from the given variety is higher than that of the local one.

Resistance to insects/diseases showed a positive and significant effect on the adoption of IMVs for poor households. If a poorly endowed farm household perceives that an IMV is more resistant to insects/diseases, the probability of planting that particular variety will increase by 8 %. This is possibly because poorer households are less likely than their wealthier counterparts to be able to afford pesticides and other inputs to control insects/diseases.

Marketability had positive and significant impact on the probability of adopting an IMV only among well-endowed households. If it were easier to sell grain from IMVs than grain from the local variety, the likelihood of planting IMVs would increase by 13 %. This implies that, if demand exists in the market, wealthy farmers are willing to adopt and expand the cultivation of IMVs to maximize their returns.

Intensity of adoption

In this section, we present the results of our analysis of the intensity of adoption of IMVs using the second stage of Cragg's double-hurdle model. We performed truncated regression – all the zero values (those who did not adopt IMVs) from the probit model (first-hurdle) were truncated and only positive values (the proportion of land allocated for IMVs) were included in the regression model. The situation after the adoption is different from the adoption stage. The variables that play significant roles in adoption might not play significant roles in adoption intensity as evidenced by the variables age, gender and education from the adoption intensity model (Table 4). Consistent with Langyintuo and Mungoma (2008), age, gender and education no longer play significant

Table 4 Maximum likelihood estimates of adoption intensity

Variables	Poorly-endowed (<i>n</i> =249)	Well-endowed (<i>n</i> =167)
Age	0.178 (0.185)	0.021 (0.091)
Gender	2.555 (2.944)	0.904 (1.906)
Education	0.394 (0.577)	0.479 (0.386)
Family labor	0.155 (1.565)	-0.066 (0.844)
Farm size	1.941 (13.453)	-2.903 (4.098)
Extension	4.117 (2.705)*	0.415 (1.592)
Member	7.721 (3.292)***	3.535 (2.529)*
Seed access	5.411 (2.849)**	3.659 (2.120)**
Distance	-0.587 (0.271)**	-0.090 (0.164)
Off-farm work	0.424 (2.976)	-1.523 (1.968)
Wealth index	6.326 (1.846)***	2.793 (0.735)***
Yield potential	9.547 (6.184)*	10.833 (3.041)***
Pest/disease resistance	0.048 (2.821)	1.012 (1.635)
Palatability	3.512 (2.860)	0.028 (1.709)
Marketability	2.851 (2.823)	2.759 (1.904)*
Region	1.892 (3.068)	9.327 (2.231)***
Constant	23.975 (15.153)*	46.355 (8.814)***
Statistical values of the estimated models		
Censored observations	93	135
Log likelihood	-358.65035	-478.37898
Wald Chi ² (16)	56.19	146.08
Prob > Chi ²	0.0000	0.0000
Sigma	11.481 (0.849)***	8.369 (0.509)***

*** Significant at 1 %, ** significant at 5 %, significant at 10 % confidence level. Numbers in parentheses are the standard errors

roles in determining how much area is put under IMVs once they are adopted.

The analysis of the effects of extension services provides further support to the need for information during the adoption process by signifying the positive role of information in adoption intensity among poorly endowed households. The availability of extension services increases the intensity of adoption of IMVs by 4 %. This suggests that contact with extension agents facilitate technology transfer and promotes adoption at lower cost (Bola et al. 2012; Nkonya et al. 1997; Ojiako et al. 2007; Polson and Spencer 1991).

Access to seed and membership of farmers' groups/cooperatives were significant and positively related to the intensity of IMV use in both models. With membership in farmers' groups/cooperatives, the use intensity among poorly endowed and well-endowed households will increase by 8 and 3.5 % respectively. This result is consistent with the findings of previous studies (Bamire et al. 2002; Bola et al. 2012; Ojiako et al. 2007). Similarly, households will increase their use intensity by 5 % if the improved seeds are available in

local retail stores. This implies that the higher the accessibility of seeds, the larger the proportion of land that is allocated for IMVs, a result supported by the findings of Langyintuo and Mungoma (2008).

Distance to market was significant and negatively related to adoption intensity among poorly endowed households. With every kilometer increase in travel distance to the market, adoption intensity decreased by about 0.6 %, probably owing to limited access to transportation to the market and high transaction costs. Linking farmers to markets by integrating farmers with potential buyers – for example, farmers-traders, farmers-retailers, farmers-agro-processors and cooperatives – could help farmers not only be sure of reliable markets but also reduce price risk and increase economies of scale (Kumar 2015).

Wealth index and yield potential showed positive and significant impact on the intensity of IMVs in both models. Among technology-specific variables, yield potential influenced adoption intensity irrespective of wealth group, and marketability of grains positively influenced adoption intensity among well-endowed households. If the poorly and well-endowed households

perceived that an improved variety gives superior returns, they will expand the area of IMVs by 9.5 and 11 % respectively, and in terms of wealth index, they will increase the intensity by 6 and 3 % respectively. This striking difference between wealth groups may indicate the eagerness of poorer households to intensify IMVs, maximize the returns and shift the household's wealth status to a higher level (well-endowed). Further, it is worth noticing that the wealthy households are more likely to be market-oriented and are willing to trade off palatability for consumer acceptability.

Finally, to reflect unobserved regional (agro-ecological) differences, the location of the farm households was specified as a regional dummy variable and included in the models. The use intensity of IMVs was found to be influenced by region for well-endowed farmers, having positive and significant impact on households in the Terai region. Supported by the findings of Takeshima (2015), this study showed that intensification of input adoption per unit of land has been higher in the Terai region. Farm mechanization, which is associated with the wealth status of households, plays an important role in the intensification of adoption there by reducing the labor cost and making farmers more competitive in the market. It is difficult to mechanize small farms and increase adoption intensity in the hill areas, however. The reasons why farmers in the hills are less willing to intensify their use of IMVs may also be linked to road and market access. In the hills, access to development infrastructure such as roads, markets and irrigation is far more difficult than in the Terai region.

Conclusions and policy implications

The use of improved, high-yielding crop varieties by rural farm households can chart a route to improved livelihoods with food security. Household wealth often plays a vital role in adopting improved agricultural technologies, particularly improved crop varieties, in developing countries. The relationship between household wealth and adoption of improved crop varieties is thought to be positive because households' ability to cope with risk increases with its wealth or stock of productive assets. However, empirical investigation of the effect of household wealth on adoption of IMVs in developing countries is often lacking. In this study, we determined the factors influencing adoption of IMVs and intensity of adoption, and examined whether these factors differed across wealth groups (poorly endowed and well-endowed households) in Nepal by using survey data and Cragg's double-hurdle model.

The results of empirical analysis showed that factors affecting adoption of IMVs and intensity of adoption varied across the two wealth groups. Household wealth index positively influenced the adoption of IMVs, and affected the way in which other variables influenced the adoption decisions. Factors most strongly related to adoption in both groups were access to improved seed, yield potential and farmers' ages, with older farmers being less likely to adopt, possibly because of risk aversion. Availability of seed in local retail outlets would benefit all farmers but particularly the poorly endowed because of the difficulties and costs of transportation and travel to distant markets. If desired adoption rates and intensity of adoption are to be achieved, the government will probably have to establish a wide seed distribution network in rural areas. Furthermore, the involvement of the private sector, preferably under the public-private partnership (PPP) model, in producing and distributing improved seeds and other inputs will have to be addressed. Education and extension services positively influenced adoption among poorly endowed households, implying that increased awareness and information reduced risk aversion and motivated farmers to adopt new technology. Similarly, membership of farmers' groups/cooperatives and off-farm work positively influenced adoption among the subsample of well-endowed households. Because distance to market showed a negative impact on adoption and intensity of adoption, the implication is that high production and transaction costs make farmers less competitive in product markets. To minimize production costs, a farm mechanization policy should be effectively implemented. To reduce transaction costs, farmers need to be linked to markets by integrating farmers with potential buyers – for example, farmers-traders, farmers-retailers, farmers-agro-processors and cooperatives. Because Nepal lacks adequate road networks connecting production pockets to market centers, building agricultural roads may contribute to reduced transportation costs and increased profitability in agriculture.

Overall, given that the factors affecting adoption and intensity of adoption varied across the two wealth groups, there is a need for careful analysis of the problems by wealth categories and for appropriate policies and programs to help farmers overcome the problems of increasing adoption and use intensity of IMVs, and their subsequent impacts on food security and general livelihoods of rural farmers.

Acknowledgments The authors would like to thank the staffs of District Agriculture Development Offices (DADOs) and Agriculture Service Centers (ASCs) in the study areas for their support and advice during the data collection. Similarly, our profound acknowledgement and thanks are

due to the members of farmers' associations in the study districts for their direct and indirect contributions in cooperating and arranging time to conduct interviews.

Appendix A

Table 5 Scoring coefficients (eigen-vectors) of household assets used in wealth index construction

Household assets ($N=16$)	Scoring coefficients
Roof materials	0.3335
Floor and wall materials	0.3304
Cemented toilet	0.3259
Water source / Tapped water	0.2852
Motorcycle	0.2827
Bicycle	0.2754
Television	0.2648
Computer	0.2564
Bathroom	0.2352
Cattle/ Buffalo	0.2240
Sprayer	0.2199
Refrigerator	0.2096
Mobile phone	0.1822
Oxen plow	0.1655
Radio	0.1655
Poultry / fowl	-0.1209

Source: Authors' estimates based on field survey data 2013

References

- Abebaw, D., & Haile, M. G. (2013). The impact of cooperatives on agricultural technology adoption: empirical evidence from Ethiopia. *Food Policy*, 38, 82–91. doi:10.1016/j.foodpol.2012.10.003.
- Adesina, A. A., & Zinnah, M. M. (1993). Technology characteristics, farmers' perceptions and adoption decisions: a Tobit model application in Sierra Leone. *Agricultural Economics*, 9(4), 297–311. doi:10.1016/0169-5150(93)90019-9.
- Andrew, D. F., & Rosenzweig, M. R. (1995). Learning by doing and learning from others: human capital and technical change in agriculture. *Journal of Political Economy*, 103(6), 1176–1209.
- Aramyan, L. H., Lansink, A. G. J. M. O., & Verstegen, J. A. A. M. (2007). Factors underlying the investment decision in energy-saving systems in Dutch horticulture. *Agricultural Systems*, 94(2), 520–527. doi:10.1016/j.agsy.2007.01.005.
- Arslan, A., McCarthy, N., Lipper, L., Asfaw, S., & Cattaneo, A. (2014). Adoption and intensity of adoption of conservation farming practices in Zambia. *Agriculture, Ecosystems & Environment*, 187, 72–86. doi:10.1016/j.agee.2013.08.017.
- Asfaw, S., Shiferaw, B., Simtowe, F., & Lipper, L. (2012). Impact of modern agricultural technologies on smallholder welfare: evidence from Tanzania and Ethiopia. *Food Policy*, 37(3), 283–295. doi:10.1016/j.foodpol.2012.02.013.
- Bamire, A., Fabiyi, Y., & Manyong, V. (2002). Adoption pattern of fertiliser technology among farmers in the ecological zones of south-western Nigeria: a Tobit analysis. *Australian Journal of Agricultural Research*, 53(8), 901–910.
- Becerril, J., & Abdulai, A. (2010). The impact of improved maize varieties on poverty in Mexico: a propensity score-matching approach. *World Development*, 38(7), 1024–1035. doi:10.1016/j.worlddev.2009.11.017.
- Beke, T. E. (2012). Institutional constraints and adoption of improved rice varieties: econometric evidence from Ivory Coast. *Revue d'Études en Agriculture et Environnement*, 92(02), 117–141. doi:10.4074/S1966960711002013.
- Besley, T., & Case, A. (1993). Modeling technology adoption in developing countries. *The American Economic Review*, 83(2), 396–402. doi:10.2307/2117697.
- Bokusheva, R., Finger, R., Fischler, M., Berlin, R., Marín, Y., Pérez, F., & Paiz, F. (2012). Factors determining the adoption and impact of a postharvest storage technology. *Food Security*, 4(2), 279–293. doi:10.1007/s12571-012-0184-1.
- Bola, A. A., Diagne, A., Wiredu, A. N., & Ojehomon, V. E. (2012). Wealth status and agricultural technology adoption among smallholder rice farmers in Nigeria. *International Journal of Sustainable Development*, 05(2), 97–114.
- CBS (Central Bureau of Statistics). (2011). *Nepal living standard survey* (Vol. 3). Kathmandu: National Planning Commission Secretariat, Government of Nepal.
- Chang, H.-H., & Mishra, A. (2008). Impact of off-farm labor supply on food expenditures of the farm household. *Food Policy*, 33(6), 657–664. doi:10.1016/j.foodpol.2008.02.002.
- Chirwa, E. W. (2005). Adoption of fertiliser and hybrid seeds by smallholder maize farmers in southern Malawi. *Development Southern Africa*, 22(1), 1–12.
- CIMMYT. (2012). *Annual progress report* (Hill maize research project, phase IV). Kathmandu: CIMMYT.
- Conley, T. G., & Udry, C. R. (2010). Learning about a new technology: pineapple in Ghana. *The American Economic Review*, 100(1), 35–69.
- Doss, C. R. (2001). Designing agricultural technology for African women farmers: lessons from 25 years of experience. *World Development*, 29(12), 2075–2092. doi:10.1016/S0305-750X(01)00088-2.
- Doss, C. R. (2006). Analyzing technology adoption using microstudies: limitations, challenges, and opportunities for improvement. *Agricultural Economics*, 34(3), 207–219. doi:10.1111/j.1574-0864.2006.00119.x.
- Faltermeier, L., & Abdulai, A. (2009). The impact of water conservation and intensification technologies: empirical evidence for rice farmers in Ghana. *Agricultural Economics*, 40(3), 365–379.
- Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: a survey. *Economic Development and Cultural Change*, 33(2), 255–298.
- Feleke, S., & Zegeye, T. (2006). Adoption of improved maize varieties in Southern Ethiopia: factors and strategy options. *Food Policy*, 31(5), 442–457. doi:10.1016/j.foodpol.2005.12.003.
- Filmer, D., & Pritchett, L. H. (2001). Estimating wealth effects without expenditure data—or tears: an application to educational enrollments in states of India. *Demography*, 38(1), 115–132.
- Fischer, E., & Qaim, M. (2012). Linking smallholders to markets: determinants and impacts of farmer collective action in Kenya. *World Development*, 40(6), 1255–1268. doi:10.1016/j.worlddev.2011.11.018.
- Food and Agriculture Organization of the United Nations. (2013). FAOSTAT database, available at <http://faostat3.fao.org/compare/E>.
- Gao, X., Wailes, E. J., & Cramer, G. L. (1995). Double-hurdle model with bivariate normal errors: an application to US rice

- demand. *Journal of Agricultural and Applied Economics*, 27(2), 363–376.
- Gartaula, H., Niehof, A., & Visser, L. (2012). Shifting perceptions of food security and land in the context of labour out-migration in rural Nepal. *Food Security*, 4(2), 181–194. doi:10.1007/s12571-012-0190-3.
- Ghimire, S., Dhungana, S. M., Krishna, V., Teufel, N., & Sherchan, D. P. (2013). *Biophysical and socio-economic characterization of cereal production systems of Central Nepal* (Socio-Economics Program Working Paper). Mexico: CIMMYT.
- Hair, J. F., Tatham, R. L., Anderson, R. E., & Black, W. (2006). *Multivariate data analysis* (Vol. 6). Upper Saddle River: Pearson Prentice Hall.
- Hardaker, J. B., Huirne, R. B., Anderson, J. R., & Lien, G. (2004). *Coping with risk in agriculture*. United Kingdom: CABI publishing.
- Jensen, H. H., & Yen, S. T. (1996). Food expenditures away from home by type of meal. *Canadian Journal of Agricultural Economics/Revue Canadienne d'Agroeconomie*, 44(1), 67–80.
- Joshi, K. D., Conroy, C., & Witcombe, J. R. (2012). *Agriculture, seed, and innovation in Nepal: Industry and policy issues for the future* (IFPRI Project Paper). Nepal: International Food Policy Research Institute (IFPRI) and Cereal Systems Initiative for South Asia (CSISA).
- Just, R. E., & Zilberman, D. (1988). The effects of agricultural development policies on income distribution and technological change in agriculture. *Journal of Development Economics*, 28(2), 193–216. doi:10.1016/0304-3878(88)90058-2.
- Karim, Z., & Haque, A.K.E. (2015). *Convergence of policies and programs for sustainable and climate resilient agriculture in Bangladesh*. Paper presented at Regional Workshop on Agricultural Transformation: Challenges and Opportunities in South Asia, Kathmandu, Nepal, February 13, 2015.
- Kassie, M., Shiferaw, B., & Muricho, G. (2011). Agricultural technology, crop income, and poverty alleviation in Uganda. *World Development*, 39(10), 1784–1795. doi:10.1016/j.worlddev.2011.04.023.
- Khatri-Chhetee, D. (2015). *Maize seed value chains in the Hills of Nepal- Linking small farmers to markets*. Paper presented at Regional Workshop on Agricultural Transformation: Challenges and Opportunities in South Asia, Kathmandu, Nepal, February 13, 2015.
- Koundouri, P., Nauges, C., & Tzouvelekas, V. (2006). Technology adoption under production uncertainty: theory and application to irrigation technology. *American Journal of Agricultural Economics*, 88(3), 657–670.
- Kumar, A. (2015). *Best practices in contract farming: Challenges and opportunities*. Paper presented at Regional Workshop on Agricultural Transformation: Challenges and Opportunities in South Asia, Kathmandu, Nepal, February 13, 2015.
- Langyintuo, A. S., & Mekuria, M. (2005). *Accounting for neighborhood influence in estimating factors determining the adoption of improved agricultural technologies*. Paper presented at the American Agricultural Economics Association Annual Meeting, Rhode Island, USA, July 24–27, 2005.
- Langyintuo, A. S., & Mungoma, C. (2008). The effect of household wealth on the adoption of improved maize varieties in Zambia. *Food Policy*, 33(6), 550–559. doi:10.1016/j.foodpol.2008.04.002.
- Mariano, M. J., Villano, R., & Fleming, E. (2012). Factors influencing farmers' adoption of modern rice technologies and good management practices in the Philippines. *Agricultural Systems*, 110, 41–53. doi:10.1016/j.agsy.2012.03.010.
- Mendola, M. (2007). Agricultural technology adoption and poverty reduction: a propensity-score matching analysis for rural Bangladesh. *Food Policy*, 32(3), 372–393. doi:10.1016/j.foodpol.2006.07.003.
- Mignouna, D. B., Manyong, V. M., & Rusike, J. (2011). Determinants of adopting imazapyr-resistant maize technologies and its impact on household income in Western Kenya. *AgBioforum*, 14(3), 158–163.
- Minten, B., & Barrett, C. B. (2008). Agricultural technology, productivity, and poverty in Madagascar. *World Development*, 36(5), 797–822. doi:10.1016/j.worlddev.2007.05.004.
- Mittal, S., & Kumar, P. (2000). Literacy, technology adoption, factor demand and productivity: an econometric analysis. *Indian Journal of Agricultural Economics*, 55(3), 490–499.
- MoAD (Ministry of Agricultural Development). (2013). *Statistical information on Nepalese agriculture*. Kathmandu: Ministry of Agricultural Development, Government of Nepal.
- Newman, C., Henschon, M., & Matthews, A. (2003). A double-hurdle model of Irish household expenditure on prepared meals. *Applied Economics*, 35(9), 1053–1061.
- Nguezet, P. M. D., Diagne, A., Okoruwa, V. O., & Ojehomon, V. (2011). Impact of improved rice technology (NERICA varieties) on income and poverty among rice farming households in Nigeria: a local average treatment effect (LATE) approach. *Quarterly Journal of International Agriculture*, 50(3), 267–292.
- Nkonya, E., Schroeder, T., & Norman, D. (1997). Factors affecting adoption of improved maize seed and fertilizer in Northern Tanzania. *Journal of Agricultural Economics*, 48(1–3), 1–12. doi:10.1111/j.1477-9552.1997.tb01126.x.
- Noltze, M., Schwarze, S., & Qaim, M. (2012). Understanding the adoption of system technologies in smallholder agriculture: the system of rice intensification (SRI) in Timor Leste. *Agricultural Systems*, 108, 64–73. doi:10.1016/j.agsy.2012.01.003.
- Ojiako, I. A., Manyong, V. M., & Ikpi, A. E. (2007). Determinants of rural farmers' improved soybean adoption decisions in northern Nigeria. *Journal of Food, Agriculture and Environment*, 5(2), 215–223.
- Oladele, O. (2006). A Tobit analysis of propensity to discontinue adoption of agricultural technology among farmers in Southwestern Nigeria. *Journal of Central European Agriculture*, 6(3), 249–254.
- Pant, B. D. (2015). *Accelerating growth in agricultural productivity and profitability*. Paper presented at Regional Workshop on Agricultural Transformation: Challenges and Opportunities in South Asia, Kathmandu, Nepal, February 13, 2015.
- Paudel, P., & Matsuoka, A. (2008). Factors influencing adoption of improved maize varieties in Nepal: a case study of

- Chitwan District. *Australian Journal of Basic and Applied Sciences*, 2(4), 823–834.
- Paudel, P., & Matsuoka, A. (2009). Cost efficiency estimates of maize production in Nepal: a case study of the Chitwan district. *Agricultural Economics – Czech*, 55(3), 139–148.
- Paudyal, K., & Poudel, S. (2001). Impact of public-and private-sector maize research in Nepal. In R. V. Gerpacio (Ed.), *Impact of public-and private-sector maize breeding research in Asia 1966–1997/98* (pp. 66–80). Mexico: CIMMYT.
- Polson, R. A., & Spencer, D. S. (1991). The technology adoption process in subsistence agriculture: the case of cassava in Southwestern Nigeria. *Agricultural Systems*, 36(1), 65–78. doi:10.1016/0308-521X(91)90108-M.
- Ransom, J., Paudyal, K., & Adhikaric, K. (2003). Adoption of improved maize varieties in the hills of Nepal. *Agricultural Economics*, 29(3), 299–305. doi:10.1016/S0169-5150(03)00057-4.
- Sharma, V. P., & Kumar, A. (2000). Factors influencing adoption of agroforestry programme: a case study from North-West India. *Indian Journal of Agricultural Economics*, 55(3), 500–510.
- Shinoj, P. (2015). *Agriculture development and climate change : A first order assessment of Indian policies*. Paper presented at Regional Workshop on Agricultural Transformation: Challenges and Opportunities in South Asia, Kathmandu, Nepal, February 13, 2015.
- Smale, M. (1995). Maize is life: Malawi's delayed green revolution. *World Development*, 23(5), 819–831. doi:10.1016/0305-750X(95)00013-3.
- Sunding, D., & Zilberman, D. (2001). The agricultural innovation process: research and technology adoption in a changing agricultural sector. *Handbook of Agricultural Economics*, 1, 207–261.
- Takeshima, H. (2015). *Typology of tractor use growths patterns in Terai*. Paper presented at Regional Workshop on Agricultural Transformation: Challenges and Opportunities in South Asia, Kathmandu, Nepal, February 13, 2015.
- Thapa, B., Aoudel, A.P., Subedi, S., Poudel, A.P., Ghimire, K.H., Poudel, H.P. (2014). Varietal development of full season normal maize in the Western hills of Nepal. Pages 129–131 in Vol. 1, Proceeding of the 27th National Summer Crops Workshop, April 18–20, 2013, at National Maize Research Program, Rampur, Chitwan: Nepal Agricultural Research Council (NARC).
- Uaiene, R. N., Arndt, C., & Masters, W. (2009). *Determinants of agricultural technology adoption in Mozambique* (Discussion papers (67E)). Republic of Mozambique: Ministry of Planning and Development.
- Weerahewa, J., Marambe, B., Silva, P., Pushpakumara, G., De Alwis, D. (2015). *Converging policies and programs for climate resilient agriculture in Sri Lanka*. Paper presented at Regional Workshop on Agricultural Transformation: Challenges and Opportunities in South Asia, Kathmandu, Nepal, February 13, 2015.
- Yen, S. T., & Jones, A. M. (1997). Household consumption of cheese: an inverse hyperbolic sine double-hurdle model with dependent errors. *American Journal of Agricultural Economics*, 79(1), 246–251.
- Zeller, M., Sharma, M., Henry, C., & Lapenu, C. (2006). An operational method for assessing the poverty outreach performance of

development policies and projects: results of case studies in Africa, Asia, and Latin America. *World Development*, 34(3), 446–464. doi:10.1016/j.worlddev.2005.07.020.



Raju Ghimire is a Senior Agricultural Development Officer in the Department of Agriculture of the Ministry of Agricultural Development, Government of Nepal. He is also involved in the Michigan State University and USAID/MEAS funded project “Improving agricultural extension: Scaling up organic off-season vegetable production and ensuring food security in Western Nepal”. He is currently a Doctoral candidate at the Department of Tropical Agriculture and International Cooperation, National Pingtung University of Science and Technology, Taiwan. His research areas include agricultural technology adoption, food security and welfare of rural farmers in Nepal. He completed his Masters degree in Environmental Protection and Agricultural Food Production at the University of Hohenheim, Germany.



Dr. Wen-Chi Huang is an Associate Professor in the Department of Agribusiness Management, National Pingtung University of Science and Technology, Taiwan. She studied for her Masters and PhD degrees in Agricultural Economics at Pennsylvania State University, USA and is currently the Director of the International Program on Agribusiness Management, National Pingtung University of Science and Technology, Taiwan. She is also member of the Executive Committee of the Asian Partnership for Human Resource Development in Rural Asia (Asia DHRRA). She has published on topics related to agricultural technology adoption, rural development, organic/sustainable production, food security, and farmers' wellbeing. She has also served as reviewer and editorial board member for numerous international journals.