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Analysis of Adoption and Impacts of Improved Maize Varieties in Eastern Zambia

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Summary. — This paper analyzes the adoption and welfare impacts of improved maize varieties in eastern Zambia using data obtained from a sample of over 800 farm households. Using both propensity score matching and endogenous switching regression models, the paper shows that adoption of improved maize leads to significant gains in crop incomes, consumption expenditure, and food security. Results further show that improved maize varieties have significant poverty-reducing impacts in eastern Zambia. The paper concludes with implications for policies to promote adoption and impacts of modern varieties in Zambia.

Key words — adoption, Africa, endogenous switching regression, propensity score matching, welfare, Zambia

1. INTRODUCTION

In Zambia, agriculture is vital for attaining the development goals of alleviating poverty and improving food security. Stimulating agricultural growth, and thus reducing poverty and improving food security, primarily depends on the adoption of improved agricultural technologies, including improved maize varieties.

Maize is the main staple food crop grown in Zambia and is a vital crop for food security. It is estimated that over 55% of the daily caloric intake is derived from maize, with an average consumption of about 85–140 kg per year (Sitko *et al.*, 2011). Research investment by national and international research institutions has led to the development and diffusion of improved maize varieties, and this represents a major scientific and policy achievement in African agriculture (Smale & Mason, 2014). By 2006, the adoption rate of improved maize varieties was estimated to be 36.8% (Smale & Mason, 2013). By 2010, 203 maize varieties had been released to farmers, over 100 of which were subsequently grown by farmers in the 2010–11 growing season (De Groote *et al.*, 2012). However, efforts aimed at enhancing the impact of maize technologies on smallholder agricultural productivity and incomes require understanding and identifying the constraints and incentives which influence the adoption of improved maize varieties.

There is limited empirical evidence on the impacts of modern technologies such as improved maize varieties in Africa. Several studies on the impacts of improved varieties (e.g., Amare, Asfaw, & Shiferaw, 2012; Becerril & Abdulai, 2010; Carletto, Kilic, & Kirk, 2011; Crost, Shankar, Bennett, & Morse, 2007; Hossain, Bose, & Mustafi, 2006; Kassie, Shiferaw, & Muricho, 2011; Maredia & Raitzer, 2010; Mathenge, Smale, & Olwande, 2014; Mendola, 2007) have assumed that the characteristics and resources of adopters and non-adopters have the same impact on outcome variables (i.e., homogenous returns to their characteristics and resources). Many of these studies have looked at crops such as maize, groundnuts, and pigeon peas (Asfaw, Shiferaw, Simtowe, & Lipper, 2012; Crost *et al.*, 2007; Kassie *et al.*, 2011).

Most previous studies used single econometric models of adoption and impact. In East Africa, recent analysis of the impact of the adoption of hybrid seed on Kenyan smallholders (Mathenge *et al.*, 2014), builds on in-depth adoption research conducted by Suri (2011), and finds the influence of hybrid seed on income and assets to be favorable for smallholder maize growers. In Zambia, Smale and Mason (2013, 2014) applied panel data regression methods to assess the impact of the adoption of hybrid maize on the income and equality status of maize-growing smallholder farmers, using panel data for the 2002–03 and 2006–07 growing seasons. They found that growing hybrids increased gross nominal income of smallholder maize growers by an average of 29%. However, like many other studies, Smale and Mason (2013, 2014) used a regression approach that assumes that the characteristics of adopters and non-adopters have the same impact on outcome variables.

This paper attempts to address this gap in the existing knowledge by providing a micro perspective on the adoption of maize technology and its impact on household welfare, using an endogenous switching regression (ESR) technique. The ESR results are also compared with the results based on the most commonly used propensity score matching (PSM) technique. Overall, the paper aims to provide empirical evidence on the adoption and impact of improved maize varieties on crop income, consumption expenditure, poverty, and food security in eastern Zambia. This will help us to estimate the true welfare effects of technology adoption by controlling for selection biases on production and adoption decisions.

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The rest of the paper is organized as follows: the next section discusses survey design and data collection in three districts in eastern Zambia; the conceptual framework and estimation technique are presented in Section 3; Section 4 presents and discusses the empirical results; and Section 5 draws conclusion and implications.

2. SURVEY DESIGN AND DATA COLLECTION

The data used in this paper come from a survey of 810 sample households conducted in January and February 2012 in eastern Zambia. This was a baseline survey conducted by the International Institute of Tropical Agriculture (IITA) and the International Maize and Wheat Improvement Center (CIMMYT) in collaboration with the Zambia Agricultural Research Institute (ZARI) for the project entitled Sustainable Intensification of Maize–Legume Systems for the Eastern Province of Zambia (SIMLEZA). A survey questionnaire was prepared and administered by trained enumerators who collected data from households through personal interviews. The survey was conducted in the same SIMLEZA project districts in eastern Zambia—Chipata, Katete, and Lundazi—which were targeted by the project as the major maize and legume growing areas. In the first stage, each district was stratified into agricultural blocks (eight in Chipata, five in Katete, and five in Lundazi) as primary sampling units. In the second stage, 40 agricultural camps [1] were randomly selected, with the camps allocated proportionally to the selected blocks, and the camps selected with probability of selection proportional to size. Overall, 17 camps were selected in Chipata, 9 in Katete, and 14 in Lundazi. The distribution of the sample households by district and gender is presented in Table 1.

A total sample of 810 households was selected randomly from the three districts with the number of households from each selected camp being proportional to the size of the camp. The survey collected valuable information on several issues at household level. Data were collected on the farmers' patterns of resource use, production practices, technology choices and preferences, constraints to market participation, improvements to maize–legume systems, socioeconomic profiles, input markets, access to services, and markets for maize and other farm outputs.

3. CONCEPTUAL FRAMEWORK AND ESTIMATION TECHNIQUE

(a) *Technology adoption decision and household welfare*

Following Becerril and Abdulai (2010) and Crost *et al.* (2007), the decision to adopt technology is modeled in a random utility framework. Let P^* denote the difference between the utility from adoption (U_{iA}) and the utility from non-adoption (U_{iN}) of improved maize varieties, such that a household i will choose to adopt the technology if $P^* = U_{iA} - U_{iN} > 0$. The fact is that the two utilities are unobservable; they can be expressed as a function of observable components in the latent variable model below:

$$P_i^* = Z_i\alpha + \varepsilon_i \text{ with } P_i = \begin{cases} 1 & \text{if } P_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \qquad (1)$$

where P is a binary 0 or 1 dummy variable for the use of the new technology; $P = 1$ if the technology is adopted and $P = 0$ otherwise. α is a vector of parameters to be estimated; Z is a vector that represents household- and farm-level characteristics; and ε is the random error term.

The adoption of new agricultural technologies can help to increase productivity, farm incomes, and food security, and help to reduce poverty levels, thus improving household welfare. Assuming that the variable of interest here—crop income, consumption expenditure, poverty status, and food security—is a linear function of a dummy variable for improved maize variety use, along with a vector of other explanatory variables (X) leads to the following equation:

$$Y_h = \gamma X_h + \delta P_h + \mu_h \qquad (2)$$

where Y_h represents the outcome variables, P is an indicator variable for adoption as defined above, γ and δ are vectors of parameters to be estimated, and μ is an error term. The impact of adoption on the outcome variable is measured by the estimations of the parameter δ. However, if δ is to accurately measure the impact of adoption of improved maize varieties on outcome variables, farmers should be randomly assigned to adoption or non-adoption groups (Faltermeier & Abdulai, 2009).

(b) *Impact evaluation of technology adoption*

Estimation of the impact of technology adoption on household welfare outcome variables based on non-experimental observations is not trivial. What we cannot observe is the outcome variable for adopters, in the case that they did not adopt. That is, we do not observe the outcome variables of households that adopt, had they not adopted (or the converse). In experimental studies, this problem is addressed by randomly assigning adoption to treatment and control status, which assures that the outcome variables observed on the control households without adoption are statistically representative of what would have occurred without adoption. However, adoption is not randomly distributed to the two groups of households (as adopters and non-adopters), but rather to the household itself deciding to adopt given the information it has, therefore adopters and non-adopters may be systematically different (Amare *et al.*, 2012).

Most studies (Hamazakaza, Smale, & Kasalu, 2013; Kalinda *et al.*, 2010; Langyintuo & Mungoma, 2008; Mason,

Table 1. *Distribution of the sample households by district and gender*

District	Number of blocks	Number of camps	Number of households		
			Gender of household head		All
			Female-headed	Male-headed	
Chipata	8	17	129	205	334
Katete	5	9	63	117	180
Lundazi	5	14	98	198	296
All	18	40	290	520	810

Source: Author's calculations using the survey data.