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# Technology adoption and risk exposure among smallholder farmers: Panel data evidence from Tanzania and Uganda

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ABSTRACT

This paper investigates the empirical linkages between production risks and the adoption of modern inputs among smallholder farmers in Tanzania and Uganda using household panel LSMS-ISA datasets. Applying a moment-based approach and a Mundlak-Chamberlain IV fixed effects model to control for unobserved heterogeneity and endogeneity, the paper uses a translog production function to estimate the mean, variance, skewness, and kurtosis of production. These estimated moments of production are then included in a multivariate adoption model to assess their effects on input adoption decisions. Results reveal that the first four moments of production significantly explain changes in the probability of adopting chemical fertilizer, improved seeds, and pesticides. While the use of these modern inputs is found to be risk decreasing, estimates suggest that the higher their purchasing costs, the greater the cost of farmers' private risk bearing. Under the assumption of a moderate risk aversion, the risk premium amounts to 8.7% and 13.7% of the expected production revenues in Tanzania and Uganda, respectively. This willingness-to-pay is largely explained by production volatility and downside risk aversion and to a small extent by kurtosis aversion. The findings underscore the need to account for farmers' preferences towards higher order moments when designing and implementing modern inputs' adoption policies in developing countries.



## 1. Introduction

In many developing countries, increasing agricultural productivity is one of the primary goals of policymakers and their development partners. In sub-Saharan African (SSA) countries where half of the population lives in poverty, agricultural technological changes are often seen as one of the key pathways for fighting food insecurity, spurring economic growth, and overcoming extreme poverty. Indeed, in many of these countries, most households still live in rural areas and depend on agricultural activities for their livelihoods. In Tanzania and Uganda for example where around 80% of the population live in rural areas, the agricultural sector contributes at least 25% of the Gross Domestic Product, provides about 45% of earning sources and employs over 65% of the total labor force (World Bank, 2017).

Notwithstanding the contribution of agriculture to economic growth in SSA countries, land productivity remains very low. This underperformance of the agricultural sector is likely to jeopardize the food security of African farmers and increase the risks of poverty traps. Among the reasons generally advanced for low productivity levels in Africa, we often find land degradation due to nutrient depletion and soil erosion, population pressure, extreme temperature, inadequate rainfall, inappropriately applied agricultural technologies and mismatched agricultural policies (Duflo, Kremer, & Robinson, 2008).

As a result, SSA governments and their development partners have allocated considerable resources to enhance environmental conditions, stimulate economic growth, and increase agricultural productivity. Various agricultural extension services such as the National Agricultural Advisory Services (NAADS) in Uganda, soil and water conservation programs in Kenya, or agricultural marketing and irrigation programs in Tanzania have thus been geared towards improving agricultural productivity and sustaining farmers' wellbeing. In those programs, a clear emphasis has been put on the adoption of modern agricultural technologies such as high-yielding maize varieties, improved seeds, inorganic fertilizer, and pesticides. These modern inputs are expected to increase agricultural productivity, stimulate the transition from subsistence farming to agro-industry, lower per unit production costs, increase revenues of adopters and, subsequently, enhance their wellbeing (de Janvry & Sadoulet, 2001; Kassie, Shiferaw, & Muricho, 2011; Mendola, 2007; Kijima, Otsuka, & Sserunkuuma, 2008).

Despite the expected benefits farmers can get from the application of these modern inputs, their welfare effects are, however, hampered in many SSA countries by low adoption rates (Bandiera & Rasul, 2006; Croppenstedt, Demeke, & Meschi, 2003).

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For instance, on average, SSA farmers applied in 2014 16 kg of fertilizer per hectare of arable land compared to the world average of 138 kg (World Bank, 2017). There are different theoretical and empirical explanations of these paltry application rates. They include the lack of sufficient resources to purchase modern inputs and their relatively low profitability (Duflo et al., 2008), pervasive labor and credit constraints (Croppenstedt et al., 2003; Moser & Barrett, 2006; Ndjeunga & Bantilan, 2005), high transaction and transportation costs (Minten, Koru, & Stifel, 2013), insufficient knowledge about new agricultural technologies or their availability (Krishnan & Patnam, 2014), and high production, climatic, or price risks (Dercon & Christiaensen, 2011; Giné & Yang, 2009; Koundouri, Nauges, & Tzouvelekas, 2006).

In this paper, I build on the existing rich literature on technology adoption to analyze the role of risk exposure in farm production decisions, especially in the uptake of modern inputs. Interest in risks stems from the empirical evidence that most farmers are indeed risk averse (Antle, 1983, 1987; Binswanger, 1981). Risk-averse farmers will often be reluctant to adopt new technologies and may consistently apply low productivity technologies with low profitability (Dercon & Christiaensen, 2011; Rosenzweig & Binswanger, 1993). Furthermore, the extra caution due to risk aversion and the lack of both *ex ante* and *ex post* coping mechanisms such as formal and/or informal credit and insurance schemes may prevent farmers from undertaking profitable capital investments and earning sufficient revenues to move permanently out of poverty.

A number of authors have documented the role of production risks in agriculture and their effects on adoption of modern technologies (Groom, Koundouri, Nauges, & Thomas, 2008; Kassie et al., 2011; Koundouri et al., 2006; Lamb, 2003). However, despite the profusion of studies, there are often mixed conclusions regarding the identification and relative importance of risk factors in driving technology adoption decisions. This may be attributed not only to structural differences in agricultural practices across regions of the world but also to the complex dynamics of the technology adoption process itself (Moser & Barrett, 2006) and to important shortcomings in the methodological approaches of prior studies. First, with notable exceptions of Lamb (2003) and Dercon and Christiaensen (2011), previous studies used cross-sectional data and econometric methods that do not account for farmers' unobserved heterogeneity which, if not controlled for, may lead to inconsistent and biased estimates. Second, existing adoption studies have focused on either a single new technology (improved water and irrigation system, modern fertilizer, or improved seeds) or a set of modern technologies treated as a unique bundle (Dorfman, 1996). In the real world, farmers often combine different new technologies to maximize their potential spillover effects. In other words, the adoption decision may be described more as a multivariate adoption than a univariate process.

In this paper, I address the above issues by using farm- and household-level panel datasets and extend the moment-based approach of Antle (1983, 1987), derive production risk variables and control for unobserved heterogeneity. To address potential endogeneity problems during the estimation, a two-stage Instrument Variables (IV) approach is employed. Moreover, the possibility of interdependent and simultaneous technology adoption decisions is also accounted for by applying a multivariate approach to model adoption decisions (Dorfman, 1996; Teklewold, Kassie, & Shiferaw, 2013). The empirical approach is applied to smallholder farmers in Tanzania and Uganda, two SSA countries with the longest panel household datasets from the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA). Findings from these countries may also provide useful insights to the understanding of agricultural technology adoption in other SSA countries with relatively similar agricultural profiles.

The rest of the paper is organized as follows. Section 2 presents the conceptual framework used to analyze farmers' adoption decisions in the presence of production risks. Section 3 details the empirical approach and discusses the main econometric issues. Data sources and descriptive statistics of key variables of interest are presented in Section 4. Empirical results and their analysis are presented in Section 5. Main findings and their policy implications are summarized in Section 6.

## 2. Conceptual framework

Consider a risk-averse multi-product farm household utilizing a vector of $M$ conventional inputs $\mathbf{X_c}$ and $(M-S)$ modern inputs $\mathbf{X_a}$ to produce $N$ outputs $\boldsymbol{y} = (y_1, y_2, \ldots, y_n, \ldots, y_N)$. We then have $\mathbf{x} = \left(\underbrace{x_1, x_2, \ldots, x_m, \ldots, x_M}_{\mathbf{X_c}}, \underbrace{x_{M+1}, x_{M+2}, \ldots, x_S}_{\mathbf{X_a}}\right)$. The farmer uses a production technology described by a continuous, at least twice differentiable, and concave production function $y = f(\mathbf{x}, \boldsymbol{e})$, where $\boldsymbol{e}$ is a vector of stochastic factors unknown to the farmer when production decisions are made. This vector is treated as a random variable, whose distribution $G(.)$ is exogenous to the farmer's actions (Kim & Chavas, 2003; Koundouri et al., 2006). In this paper, $\boldsymbol{e}$ captures production risks incurred by the farmer given the imperfect predictability of output quantities to be harvested due to factors beyond the farmer's control (such as rainfall variability, extreme temperatures, and production loss due to pest infestations or diseases). For simplicity, $\boldsymbol{e}$ represents the only source of risks for the farmer while output prices $\boldsymbol{p} = (p_1, p_2, \ldots, p_n, \ldots, p_N)$ and the price of conventional inputs $\mathbf{w_c} = (w_1, w_2, \ldots, w_m, \ldots, w_M)$ and modern inputs $\mathbf{w_a} = (w_{M+1}, w_{M+2}, \ldots, w_S)$ are assumed to be non-random and known to the farmer when production decisions are made[1].

Under risk aversion, the farmer's problem is to maximize the expected utility of profit, $E[U(\pi)]$, i.e.,

$$Max_x E[U(\pi)] = Max_x E\left\{U\left[\left(\sum_{n=1}^{N} p_n y_n(\mathbf{x_a}, \mathbf{x_c}, \boldsymbol{e})\right) - \mathbf{w}'_\mathbf{c}\mathbf{x_c} - \mathbf{w}'_\mathbf{a}\mathbf{x_a}\right]\right\} \tag{1}$$

where $U(.)$ is the *von Neumann-Morgenstern* utility function and $\frac{\partial U(.)}{\partial \pi} > 0$. $E$ is the expectation operator and $\pi$ is the total farm profit.

Denote $\mathbf{x}^1$ and $\mathbf{x}^0$, the optimal input choices under adoption and non-adoption of modern inputs, respectively. A risk-averse profit-maximizing farmer will adopt modern inputs (such as fertilizer, improved seeds, and pesticides) if the expected utility of profit with adoption $E[U(\pi^1)]$ is greater than the expected utility of profit without adoption $E[U(\pi^0)]$, i.e.,

$$E[U(\pi^1)] - E[U(\pi^0)] > 0 \tag{2}$$

The first-order condition under the adoption of the modern inputs, $\mathbf{x_a}$, associated with this problem is:

$$\frac{w_a^1}{p} = E\left[\frac{\partial y_n^1(\mathbf{x}_\mathbf{c}^1, \mathbf{x}_\mathbf{a}^1, \boldsymbol{e})}{\partial x_a^1}\right] + \frac{cov[\partial y_n^1(.)/\partial x_a^1; \partial U(\pi^1)/\partial \pi^1]}{E[\partial U(.)/\partial \pi^1]} \tag{3}$$

[1] The vector $\mathbf{e}$ incorporates all types of production risks (unpredictable weather conditions, effects of pest and diseases,...) as well as crop-specific production risks. Furthermore, the assumption of a vector of stochastic factors (treated as a vector $\mathbf{e}$) to capture production risks is very common in the literature on farm risks (see, for instance, Chavas & Shi, 2015; Groom et al., 2008; Kim & Chavas, 2003; Koundouri et al., 2006). Moreover, as long as farmers are price takers (which is likely to be the case in the short-run), the assumption of non-randomness of output and input prices is not critical (Groom et al., 2008). Finally, while other risks are more or less important in farming (such as price risks, labor and health risks, or policy and political risks), depending on the country, this paper focuses only on production risks which are known to be the most important in sub-Saharan Africa where most farms are exclusively rainfed and highly dependent on climatic vagaries (Lamb, 2003).