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Information acquisition, learning and the adoption of conservation agriculture in Malawi: A discrete-time duration analysis☆

Robertson R.B. Khataza[a,b,*], Graeme J. Doole[c], Marit E. Kragt[a], Atakelty Hailu[a]

[a] School of Agriculture and Resource Economics, University of Western Australia, 35 Stirling Highway, Crawley, WA 6009, Australia
[b] Lilongwe University of Agriculture and Natural Resources, Bunda Campus, P.O. Box 219, Lilongwe, Malawi
[c] Department of Economics, University of Waikato, New Zealand

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ABSTRACT

Understanding factors that influence the adoption of agricultural innovations is imperative to stakeholders promoting such technologies as well as farmers who are the potential users of the same. Using a discrete-time duration model, this study identifies factors that determine the timing of adoption of conservation agriculture (CA) in Malawi. We establish that social learning through a network of peers, and access to extension advisors facilitates quick adoption of conservation agriculture technologies. Further, our results show that farmers who became aware of the existence of conservation agriculture during years of drought-hazards were highly likely to adopt these practices. The results highlight the need for strengthening and targeting social networks as conduits for information about new technologies. (JEL C41, O33, Q12, Q24).

1. Introduction

Recent efforts to improve agricultural productivity in Africa have focused on the promotion of low-cost sustainable land-care strategies such as conservation agriculture or CA (Andersson and D'Souza, 2014; Giller et al., 2009; Manda et al., 2016; Teklewold et al., 2013). Despite the widespread promotion of CA technologies, the adoption of these practices has been slow and modest in Africa and elsewhere (Andersson and D'Souza, 2014; Giller et al., 2009; Manda et al., 2016; Pannell et al., 2014; Teklewold et al., 2013). The low rate of adoption for these technologies is a result of a diverse range of factors. Notable factors include: 1) farmer's behaviour and attitude towards risk (Ghadim et al., 2005); 2) limited availability of key farm resources such as land and labour, and competing uses of crop residues (Pannell et al., 2014); 3) imperfections in the capital markets and liquidity constraints, especially when herbicides are part of the CA package (Pannell et al., 2014; Parks et al., 2015; Teklewold et al., 2013); 4) weak property rights to land and tenure insecurity (Parks et al., 2015; Teklewold et al., 2013) and 5) imperfect information and uncertainty regarding CA's benefits (Giller et al., 2009; Pannell et al., 2014).

Farmers' lack of information related to the performance of CA technologies is one of the key reasons responsible for their slow adoption in different geographic regions (Andersson and D'Souza, 2014; Pannell et al., 2014; Parks et al., 2015). As a result, the role of information acquisition on adoption decisions has been frequently studied, albeit, using static binary-choice models such as logit or probit (D'Emden et al., 2006; Teklewold et al., 2013). These dichotomous-choice models evaluate adoption as a one-shot decision occurring at some date. Yet, such an approach conceals important policy information regarding the timing and speed of technology adoption (Abdulai and Huffman, 2005; Besley and Case, 1993; Foster and Rosenzweig, 2010; Moser and Barrett, 2006; Sunding and Zilberman, 2001).

Investigating the timing of technology adoption provides insights in two ways. First, earliness of adoption partly reflects a farmer's level of innovativeness or receptiveness to new technologies (Rogers, 1995, 2002). Second, rapid adoption of a new technology implies that the technology is perceived to possess inherently-beneficial features that could potentially address the challenges experienced by its intended users (Rogers, 1995, 2002). Therefore, an analysis of the time-to-adoption for a technology or technologies can contribute to a clearer understanding of the factors that influence their diffusion, and thus guide policy interventions that promote these practices.

The objective of the present study is to investigate the role of information acquisition on the timing of technology adoption, using minimum tillage and crop residue-retention as examples of CA practices. Unlike crop association or rotation that farmers widely perceive as part of the typical integrated maize-legume farming system, these two CA principles are regarded as relatively new management practices

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* Corresponding author at: School of Agriculture and Resource Economics, University of Western Australia, 35 Stirling Highway, Crawley, WA 6009, Australia.
E-mail addresses: Robertson.Khataza@research.uwa.edu.au, rkhataza@bunda.luanar.mw (R.R.B. Khataza).

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in the study area (Andersson and D'Souza, 2014; Ito et al., 2007; Mloza-Banda, 2003; Ngwira et al., 2014). Thus, the two practices are ideal for an adoption study. We hypothesise that delayed investment or under-investment in CA technologies could arise from insufficient information for two reasons:

1. Even if farmers are aware about the existence of a new technology, they could still be uncertain about how best to use such a technology from a technical perspective (Foster and Rosenzweig, 2010; Genius et al., 2014).
2. New technologies can be perceived as riskier than conventional ones given that uncertainty exists with respect to their performance across both space and time (Foster and Rosenzweig, 2010; Pannell et al., 2014; Rogers, 1995).

Imperfect information and uncertainty regarding CA's benefits will then delay its adoption. Where farmers do not have access to researcher-coordinated experiments, social learning through peers (homophily exchange) becomes a vital source of information about new technologies (Foster and Rosenzweig, 2010; Genius et al., 2014; Krishnan and Patnam, 2014; Rogers, 1995). For example, farmers can learn about CA's performance by observing the plots of early adopters or through interaction with their acquaintances who are familiar with such technologies (Krishnan and Patnam, 2014; Maertens and Barrett, 2013; Moser and Barrett, 2006).

We contribute to the literature by providing empirical evidence on the determinants of time-to-adoption for sustainable land-care technologies, using a discrete-time duration analysis framework (DT-DA). To the best of our knowledge, this is the first application of the DT-DA approach to assess the timing of adoption of these sustainable land-care technologies. With a few exceptions (e.g. An and Butler, 2012; Bontemps et al., 2013; Burton et al., 2003; Goncharova et al., 2008; Porterfield, 2001; Tiller et al., 2010), the DT-DA approach has been less widely applied in the agricultural and resource economics literature, yet this method has considerable theoretical and empirical convenience (Jenkins, 1995; Rabe-Hesketh and Skrondal, 2012; Singer and Willett, 1993). The DT-DA framework is suitable for modelling the occurrence of continuous-time events where data have been recorded at discrete-time intervals (Box-Steffensmeier and Jones, 2004; Jenkins, 1995; Rabe-Hesketh and Skrondal, 2012). In practice, it is fairly common to record continuous-time adoption data as grouped or interval data. For example, due to the unavailability of reliable panel data, the majority of microstudies examining the timing of adoption of agricultural technologies tend to rely on recall data (An and Butler, 2012; Besley and Case, 1993; Burton et al., 2003; Fuglie and Kascak, 2001; Moser and Barrett, 2006). Such retrospective data are usually reported on interval-censored scales such as months or years (An and Butler, 2012; Burton et al., 2003; Jenkins, 2005). Thus, it is reasonable to use discrete-time duration models rather than the continuous-time specifications that have been broadly applied in previous studies investigating the timing of adoption of resource-conserving technologies (e.g. D'Emden et al., 2006; Fuglie and Kascak, 2001; Genius et al., 2014). Besides their suitability to handle interval-censored data, DT-DA models can also accommodate other forms of data censoring, which include left-censoring and right-censoring. Given that some households will not have adopted the technology by the end of the study period, right censoring is inevitable. On the other hand, left-censoring is applicable where some farmers may report having adopted agricultural technologies earlier than the anticipated entry date. A naïve approach could involve deleting right-censored observations from the sample. However, such an approach leads to sample-selection bias, which could yield inefficient parameter estimates (Rabe-Hesketh and Skrondal, 2012). Furthermore, exclusion of censored data involves discarding useful information that can help explain the phenomenon under study (Rabe-Hesketh and Skrondal, 2012; Singer and Willett, 1993). Fortunately, discrete-duration analysis can easily handle all the three forms of data censoring described above (Bontemps et al., 2013; Burton et al., 2003; Jenkins, 2005; Porterfield, 2001; Rabe-Hesketh and Skrondal, 2012).

The rest of the paper is organised as follows. In the next section, we present a theoretical framework underlying optimal learning and the timing of adoption decisions. This is followed by an empirical model for our analysis. In Section 3 we give a brief description of the study area and data. Empirical results and presented and discussed in Section 4. Finally, Section 5 presents the study conclusions.

2. Theoretical framework

Consider a farmer who, in the present cropping season (s_0), has the technology choice set consisting of two mutually exclusive land-care alternatives represented by $L_j \in (CA, CT)$, where CA is a green technology and CT is a conventional (brown) technology. By adopting one or both of the two land-care technologies, a farmer derives some economic and environmental benefits denoted by $\pi_j(s_t); s_t \in \{(s_0 + t)\, t = 0, 1, 2, \ldots\ldots\ldots, T\}$.[1] Accordingly, the expected net present value (NPV) of a stream of discounted benefits for the i^{th} farmer is given by $V_i[\pi_{CA}(s_t), \pi_{CT}(s_t)]$. There is an incentive for the farmer to adopt the green technology if its benefits are greater than those derived from the conventional technology. Thus, the farmer's propensity to invest in any CA technology follows the standard NPV criterion given as $V^* = V_{CA}[\pi_{CA}(s_t)] - V_{CT}[\pi_{CT}(s_t)] > 0$ (Abdulai and Huffman, 2005; Genius et al., 2014; Goncharova et al., 2008; Song et al., 2011; Sunding and Zilberman, 2001). We assume, as in real option theory, that investments are uncertain and irreversible. The irreversibility characteristic implies the importance of sunk costs, such that it is costly for a farmer to recover investments already committed in a cropping season (Dixit and Pindyck, 1994; Genius et al., 2014; Song et al., 2011). Therefore, the farmer's problem concerns whether to adopt and, if so, when to adopt the available CA technology and optimise the investment benefits (V^*) associated with this decision. There are two options to consider: adopt CA in the current season (s_1), if the technology is worthwhile, or wait for more information and adopt it in the future, $\{s_t \in [(s_1 + t) \quad t = 2, 3, \ldots\ldots\ldots, T]\}$, after validating its prospects.

A farmer reduces the uncertainty about the technology by gathering more information from at least three channels: extension agents, early adopters (peers or social network members) and self-learning or learning-by-doing (Genius et al., 2014; Ghadim et al., 2005; Rogers, 1995). In each subsequent cropping season(s), potential adopters update their expectation about the new technology (V^*), given the information gathered up to that time. The optimal time of terminating this information-search coincides with the time when a farmer builds a favourable perception of the new technology, hence the farmer adopts the technology at this point. Otherwise, the adoption decision is postponed while the farmer continues to look for extra information in favour of this technology (Genius et al., 2014; Sunding and Zilberman, 2001).

Since sustainable land-care technologies supply multiple benefits, including non-marketable services that may be difficult to value (e.g. carbon sequestration, soil organic matter content, and water infiltration capabilities), the complete benefit function, $\{V^* = (.)\}$, is considered as a latent function. Thus, the V^* which the landowner aspires to optimise is obscure to the analyst. However, the occurrence of an adoption decision within the study time ($t = 1, 2, \ldots, T$) acts as a proxy indicator revealing the optimal length of learning or information acquisition, as well as the likelihood that the new technology is perceived to be

[1] s_0 denotes the inception period for the new technology, i.e. the time when farmers start learning about the existence of the new technology within their proximity, whereas t and T represent the adoption date and end of the study period, respectively. It is likely that some farmers will not have adopted the new technology up to time T, hence such farmers are liable to right-censoring. In retrospective data, adoption time t is recorded discretely, usually in years.