AARES 55th Annual Conference, Melbourne, February 2011

Risk, uncertainty and pasture investment decisions

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Abstract

The private decisions of farmers to invest in new technologies interest economists because these decisions influence the rate of farm productivity growth and the returns to public investment in agricultural research and development.

Economic analysis of decisions to invest in new technologies on farms involves considering the effects of these decisions on the profitability and risk of the farm business. This is done routinely using whole-farm economic models and techniques such as stochastic simulation. Such analysis can be used to predict the extent to which a technology is likely to be adopted in equilibrium, when the consequences of adoption are known to all potential adopters.

Until this equilibrium is reached, however, potential adopters of new technologies face uncertainty about the consequences of adoption. This alters expectations about the effects on profitability and risk of adoption, and hence alters investment decisions. The resolution of uncertainty over time through learning is therefore a key determinant of the rate at which new technologies are adopted, and hence should be represented in dynamic economic models which seek to explain these decisions.

Introduction

One limitation of using whole-farm economic models to analyse the decisions of farmers to invest in new technologies is that these models are usually constructed assuming the consequences of these decisions are known with certainty. Specifically, deterministic, "objectively true" values are often used to represent variables which are actually uncertain to potential adopters. This includes the parameters of probability distributions which characterise risky variables.

This is a flaw because farmers face considerable uncertainty when investing in new technologies and this alters their subjective expectations about the relative merit of the technology, and hence alters their investment decisions. Furthermore, farmers typically engage in learning to reduce uncertainty prior to investing and this causes their subjective expectations and their investment decisions to change over time.

A representation of the process of uncertainty resolution should therefore be included in dynamic models which seek to explain these investment decisions in the (potentially long) period prior to reaching a state of full information, where there is no uncertainty about the consequences of adoption. Constructing such a representation is the objective of this research.

The particular technologies considered in this paper are perennial pastures primarily intended for use on sheep farms in southern Australia. Most economic analyses find the rate of return on such investments is sufficiently high for widespread, rapid adoption to occur. Nonetheless, the observed rate of adoption of these technologies in Australia is relatively slow. There are many possible explanations for this apparent deficiency of the economic analyses, and the effect of uncertainty on the subjective expectations of farmers is one.

Definitions

Before proceeding any further it is important to explain what is meant by the term uncertainty and how it is different to risk. The meaning of these terms varies widely depending on the context in which they are used, and the definitions proposed here are specific to this paper.

The objective of this work is to represent the pasture investment decisions of individual farmers in an economic model. Farmers make these decisions on the basis of the subjectively perceived risk and return of the investment. Hence, “risk” is defined here as the overall perceived variation in the rate of return on investments in new pastures.

The ultimate source of this risk is imperfect information. In particular, risk is caused by imperfect information about the future values to be taken by variables which determine the outcome of interest. There are two kinds of these variables: risky and uncertain.

In the context of pasture investments, risky variables include seasonal conditions and commodity prices. The future values of these stochastic variables are unknown, but the variation in these variables is known to farmers through previous experience. Uncertain variables include the yield of new pastures, or the probability of successfully establishing the new pastures on a particular farm. The future values of these variables are unknown, and because farmers have no experience with these specific pastures, the extent of possible variation in these variables is also unknown.

Both of these forms of imperfect information contribute to the total perceived possible variation in the rate of return which may be generated by an investment in new pastures. The contribution of risky variables to this total perceived variation is often represented in economic models using techniques such as stochastic simulation. However, the contribution of uncertain variables is usually ignored, as it is assumed that farmers know the true value of variables which are actually uncertain to them. This includes assuming the parameters of the probability distributions which characterise risky variables are known to farmers with certainty.

There are varying degrees of uncertainty. The most extreme form is Knightian uncertainty, where agents have no information whatsoever about the type or parameters of the probability distribution underlying the variable of interest. This situation may arise when agents are confronted with an entirely novel innovation. A less extreme version of uncertainty is where agents have some knowledge about the underlying distribution but it is incomplete or unreliable. For example, agents considering investing in a new pasture know the yield of this pasture is a stochastic variable, and from past experience with other pastures they have some information about the parameters of the underlying stochastic process, but this information is imperfect. This is how “uncertainty” is defined in this paper.

Here, it is assumed that agents facing uncertainty about a stochastic variable form subjective expectations about the parameters of the underlying distribution and revise these expectations over time as learning occurs. Specifically, as learning occurs the subjective distribution of beliefs about the uncertain variable is revised until it is characterised by the ‘true’ parameter values of the underlying stochastic process, and hence becomes a risky variable. If the uncertain variable is deterministic, the subjective distribution will contain only the ‘true’ value of this variable once all uncertainty is resolved.

In the case of risky variables, because the parameters of the probability distribution are already known to agents with certainty, learning does not change subjective expectations of these parameters. This means that while the contribution to the perceived variation in the outcome of interest (ie risk) caused by risky variables is constant, the contribution to risk caused by uncertain variables may change over time as learning occurs. Because investment decisions are made on the basis of perceived risk and return, these decisions may change as uncertainty is resolved and these perceptions are revised.

Purpose of the paper

The purpose of this paper is to describe a method for representing the process of uncertainty resolution over time through learning. This process will be incorporated into an economic model of the decision to invest in new pastures. It is hoped this research will increase the extent to which economic models can be used to make predictions about decisions to invest in new technologies which concord with those observed in reality.

In particular, it is commonly observed that decisions to invest in new technologies on farms are made after a period of delay. One explanation for this is that farmers wait before making investment decisions to obtain more information (ie learn), and hence reduce exposure to unfavourable outcomes. As explained above, learning does not reduce exposure to variation in returns generated by risky variables – this is simply a characteristic of the investment. However, it does reduce exposure to variation caused by uncertain variables. Hence, it is hoped that representing the process of uncertainty resolution will help to explain the length of this delay.

If the model of uncertainty resolution is to be useful for explaining the timing of investment decisions, the dependent variable needs to be an uncertain variable about which farmers have decided to learn more about before making an investment decision. A pilot study conducted in 2010 indicated that in the case of new pastures this variable is the probability of successfully establishing and managing the pastures on individual farms.

In the model developed here, uncertainty about this uncertain variable will be resolved over time through learning. This process will be represented by revisions to the parameters of the subjective probability distributions which embody the beliefs of farmers about this variable.

Background to the model

Lindner (1986, p 145) characterises adoption decisions as involving “two universal components, namely risky choice and the acquisition of knowledge (i.e., learning).” The risky choice component exists because the consequences of adopting new technologies are unknown in an environment of imperfect information, hence potential adopters of new technologies must make these decisions on the basis of subjective beliefs about the consequences. Learning is the process by which these beliefs are revised over time, and is therefore critical to dynamic explanations of these decisions.

Linder argues that cross-sectional studies which fail to consider the dynamic component have generally added little to the understanding of adoption decisions. In an environment of imperfect information this will clearly be the case. If subjective beliefs about a technology are being revised over time then each individual in the cross-section may have a different perception of the likely consequences of adoption. Analysing the decisions of these individuals is therefore unlikely to provide much insight into the relative merit of the new technology.

Lindner proposes two solutions to this problem. The first is to wait until the adoption process is complete before conducting cross-sectional studies. The second is to construct dynamic models of adoption in which the perceived consequences of adoption change over time as learning occurs. Because the purpose of this research is to examine the adoption of a new technology which is in the early stages of release the second approach is used here.

The general theme of other studies of this kind is that potential adopters of new technologies hold subjective probability distributions about the likely consequences of adoption. As learning occurs, the parameters of these distributions are updated and adoption decisions are made once some threshold mean or variance of the distribution is obtained.

An example of this is the study of Lindner and Gibbs (1990) in which a Bayesian learning model was constructed to analyse the decision to adopt a new cultivar of wheat. Potential adopters were found to revise their expectations of the yield to be obtained with the new cultivar in response to observations of trial outcomes. The authors also tested the proposition that farmers revised the mean and variance of their beliefs over time in a manner consistent with Bayesian learning, although the results were inconclusive.

Abadi Ghadim and Pannell (1999) constructed a dynamic model of the decision to adopt a new crop species. In this model, trialling the technology caused the subjective distribution of expected yield to be revised over time. These authors also incorporated skill development into the model by allowing the productivity of the innovation to increase over time as the technical skill of the operator increased through learning by doing.

Foster and Rosenzweig (1995) also incorporated learning into a dynamic model of the adoption of high-yielding varieties of rice and wheat. In this target-input model, the source of uncertainty was not the potential payoff from adoption of the innovation, but rather the correct level of inputs to use. Potential adopters learned about these optimal input levels through use of the innovation.

While these studies provide useful background to the current work, they all relate to annual crop innovations. Perennial pastures differ from annual crops in some relevant ways, and as discussed below, these have important impacts on the model developed in this study.

Difference 1: the importance of successful establishment of pastures

Farmers who produce annual crops generally have the technical skills required to establish and manage these crops. Hence, when considering the adoption of an annual crop innovation (such as a new cultivar or variety) the main source of uncertainty is whether or not the innovation will be more profitable than an alternative, assuming the crop is successfully grown.

As such, in economic models which seek to explain the timing of these decisions, the dependent variable of the uncertainty resolution process should be the distribution of the expected change in profit achieved by using the innovation, or some determinant of the change in profit, such as the change in yield. This is precisely what we observe in the studies of Lindner and Gibbs (1990) and Abadi Ghadim and Pannell (1999).

However, this approach does not appear to apply in the case of investing in new perennial pastures. In a pilot study conducted for this project in November 2010, the main source of uncertainty associated with adopting this technology was found to be the probability of successfully establishing the new pastures and effectively managing them in the farm system.

Participants in this study were able to provide distributions of the expected benefits of adopting new pastures, conditional on successful establishment and management. Furthermore, participants indicated that the mean and variance of these distributions were currently sufficient for them to be confident that investing in new pastures would be profitable if they could be successfully established and managed.

However, the participants had delayed making these investments because they did not believe they currently had the required technical skills. These farmers were waiting to invest not because they wanted more information about the likely magnitude of the increase in profitability to be achieved by adopting the new technology, but to give themselves time to obtain the skills necessary to make the investment work.

In light of this, the dependent variable of the uncertainty resolution process developed in this paper is the probability of successfully establishing the new pastures and incorporating them into the farm system. It is important to be clear about the sense in which this is an uncertain variable. In an environment of no uncertainty, this would be a risky variable because the actual value take by this probability depends on (known) variation in seasonal conditions at the time of sowing. However, in reality, this probability is an uncertain variable to farmers because the effect of farm and farmer-specific characteristics on the distribution of possible values of this probability are unknown.

The use of this variable represents a fairly significant departure from previous models of innovation adoption; however it is consistent with the work of Pannell et al. (2006), Rogers (2003) and Kaine (2008). Each of these authors highlight the importance of compatibility between an innovation and the skills, experience and objectives of potential adopters if investment is to occur.

Difference 2: the learning process

Another way in which the adoption of new perennial pasture technologies is different to that of new annual crops is that there is limited scope for conducting trials to learn about the probability of successfully establishing and managing new pastures or for learning by doing to gain the skills required to increase this probability over time.

This is mainly because perennial pastures must be planted on some scale and for some time for trial outcomes to be observable, but conducting such trials may be too great a risk for potential adopters to take. Furthermore, the outcomes of pasture trials are inherently difficult to observe because these outcomes depend very much on the livestock system which utilises the pastures. A change in the livestock system is usually required to utilise new pastures, and hence the effects on farm profitability caused by the new pastures is often impossible to distinguish from the effects caused by the change in the livestock system.

Rather than learning from a series of small trials (learning by doing), farmers appear to learn about new pastures using a process described by Pisano (1996) as “learning before doing”. This means that information about the probability of successfully establishing and managing new pastures and the technical skills required to increase this probability are mainly obtained prior to sowing. This is done in a variety of ways, including gathering information from research providers or peers, attending training or experimenting with different management practices.

Pisano argues that learning before doing is most likely to occur when theoretical understanding of the new technology is relatively high, so that the results of experiments are informative about the likely success or otherwise of using the new technology at a commercial scale. By contrast, learning by doing is most likely to occur when the new technology is not well understood, so the extent to which inference can be drawn from experiments or to which useful experiments can even be designed is limited.

This may help to explain the relatively slow rate of pasture improvement observed in Australia. The limited triallability of new perennial pastures limits the scope for learning by doing, while the relatively low level of theoretical understanding about their likely performance on particular farms limits the scope for learning before doing. This means that uncertainty about the likely consequences of adoption of new pastures is resolved only slowly over time. This hypothesis is broadly supported by Pannell et al. (2006), who argue that triallability and observability are determinants of the extent and rate of adoption of new technologies.

Because learning about new pastures occurs in this way, the techniques used in previous studies to represent the process of learning over time are not applicable. In particular, Lindner and Gibbs (1990) used Bayesian learning from a series of trials to calibrate the revision of subjective beliefs about crop yields with a new wheat variety over time. Here, there are no such trials.

Similarly, Abadi Ghadim and Pannell (1999) and Foster and Rosenzweig (1995) used learning by doing to represent increases in technical skill. This approach requires a variable such as cumulative hectares planted with the new species to calibrate the rate at which skill increases over time. Because there is no such variable in the case of perennial pastures, a different approach must be used to represent the acquisition of knowledge and skill over time.

Measuring the rate of learning

Delavande (2008) has developed an approach which allows the amount of information received by individuals in a given period to be derived from subjective probability distributions. This approach vastly simplifies the task of representing the uncertainty resolution process, because it provides a direct measure of the amount of learning which has occurred in a given period and hence eliminates the need to have an observable trial outcome or proxy variable such as cumulative experience.

To construct this measure, Delavande elicited distributions describing the beliefs of individuals about the probability of an event occurring before and after a period of learning. The implied quantity of information received by the individuals in this period was then derived from the observed change from the prior to posterior distribution using Bayes' rule.

Delavande calls this measure of information received the "equivalent random sample" (ERS). The ERS comprises two numbers: the number of successful trials; and the number of unsuccessful trials that the observed revision of probabilities implies the agent observed, assuming Bayes' rule was used to combine new information with prior beliefs to form posterior beliefs.

The model:

Consider an outcome B that is experienced by agent *i* with probability P_i: $\Pr(b_i = 1) = P_i$

Where $\{b_i = 1\}$ is the binary event "*i* experiences outcome B"

Suppose the objective probability P_i is not known with certainty, and hence the agent holds subjective expectations about it.

Let $f_{i,1} \in \Gamma$ denote *i*'s prior subjective distribution of beliefs about the probability P_i, where Γ denotes the set of all probability distribution functions in $[0,1]$

And, let $f_{i,2} \in \Gamma$ denote *i*'s posterior subjective distribution of beliefs about the probability P_i after *i* has received a new piece of information $o_i \in I$ about the binary outcome B, where I represents the set of all pieces of information that an agent can receive.

The revision process, or learning, is modelled by positing that agent *i* has an updating function $U_i(.,.): \Gamma \times I \rightarrow \Gamma$, which specifies a posterior subjective distribution about P_i given any prior subjective distribution $f_{i,1}$ and any new information received o_i. Thus, we can write $f_{i,2} = U_i(f_{i,1}, o_i)$.

Definition 1:

The *Equivalent Random Sample* $\pi_i(o_i)$ of individual *i* to the data o_i is the random sample of binary events drawn from P_i that would have generated the Bayesian updating from $f_{i,1}$ to $f_{i,2} = U_i(f_{i,1}, o_i)$.

Delavande (2008 pp 47-48)

The ERS characterises both the perceived content of the new information received and the quality of this information. The implied content of the information is the proportion of positive trials in the ERS. The quality of this information is represented by the total number of trials.

In the case of investing in perennial pastures, the event of interest is successfully establishing and managing the new pastures. Potential adopters of this technology learn about this probability in a variety of idiosyncratic ways, and the ERS simplifies all the information generated into a single measure. It is not necessary for these learning activities to be a series of independent trials for this method to work: the ERS is simply the equivalent amount of information received in this form.

It is also not actually necessary for individuals to use Bayes' rule when combining new information with prior beliefs for the ERS to be useful. In constructing the ERS, Bayes' rule is simply used as a normalising device to obtain an estimate of the information received during the relevant period. If a particular farmer uses something other than Bayes' rule, for example attaching a weight to new information that is less than the inverse of the variance of that information, then the ERS derived for this farmer will suggest that relatively little new information was received during the period.

As Delavande (2008, p 44) notes "an observed revision of subjective expectations can be generated by many alternative combinations of interpretation of the data and updating rules." Because we cannot observe the new information received and the mechanism used to update beliefs is unknown, our measure must allow for variation in both and this is precisely what the ERS does.

To clarify the reason for taking this approach it is useful to ask two questions. First, what is the value of knowing that in a given period of time, farmer x revised the probability of successfully establishing the new pastures from p = a to p = b? Secondly, what value is there in knowing that the ERS which corresponds to this revision is { . }?

The answer to the first question is that knowing the rate at which learning is occurring over time is useful for explaining the timing of pasture investment decisions. This could be done by observing or eliciting the mean value of p required for investment to occur, and using regression analysis to determine the length of time required for this value to be obtained. Alternatively, the criterion for investment to occur may be for the standard deviation of the distribution of beliefs about p to reach a threshold value. The time likely to be taken for this value to be reached could also be derived from the elicited probability distributions.

In either case, the threshold will be reached when the marginal cost of learning is equal to the marginal value of the extra information generated. Combining this condition with observations of the amount of learning particular farmers have engaged in may help to answer the question of how much learning is enough?

However, while useful, the analysis described above does not require the ERS. The reason this output is valuable (and hence the answer to the second question) is that the ERS is a measure of the quantity and quality of information received in a period of learning, and therefore can be used to investigate the otherwise unobservable process of learning about new pastures.

In doing this, ERS must be used carefully. As noted above, because both the information received and the updating rule used by farmers are unknown, the ERS will reflect variation in both these variables. However, this does not mean the ERS is too flexible to be useful. On the contrary, because it does not depend on potentially restrictive assumptions about either of these variables, it is potentially very useful.

For example, the subjective value of p may be found to be increasing at a very slow rate. This could be occurring because the new information being received about p is highly precise but similar to the prior belief, or because the new information suggests p is much higher than the prior belief but the precision of this information is so low that it does not contribute strongly to the posterior belief. The ERS could be used to establish which of these explanations is most likely to be correct.

In answering this question we are interested in the subjective perception of new information which has arrived in a particular period. It is irrelevant whether the implied quality of this information is low because it is actually low-quality or because agents are sceptical of all new information: in either case we have gained some insight into the subjectively-perceived new information received in the period of learning.

The ERS will also provide some indication of the variation in information processing rules used by farmers. If the main source of information identified by a group of farmers is a particular research provider, then the information received by these farmers in a given period is likely to be approximately the same. As such, variation in the ERS within this group is likely to be caused by individuals deviating from Bayes' rule when combining new information with prior beliefs. If the degree of variation is large then the use of a single updating rule in economic models should be questioned.

Additionally, the ERS may be used to identify learning activities which produce high-quality information. For example, particular sources of information may be found to be associated with high-precision ERS values. This would provide information about the relative effectiveness of alternative extension strategies, information which could be useful for refining and choosing between these strategies.

The model of uncertainty resolution described above requires eliciting the subjective beliefs of potential adopters of new pastures about an uncertain variable over time. The method used to do this is described in the following section.

Eliciting subjective probability distributions

In economics it is commonly assumed that people hold beliefs about uncertain variables in the form of subjective probability distributions (Manksi 2004). There is a well-established body of work on eliciting these probability distributions from individuals.

> *... from the point of view of modern decision theory, the information that is most relevant to decisions made by individuals in the face of risk is the subjective set which encapsulates their beliefs about uncertain states of nature. The techniques of elicitation of subjective probabilities are well*

developed (Raiffa 1968; Savage 1971) and have found extensive application in the field of agricultural decision analysis (Anderson, Dillon and Hardaker 1977).

Griffiths et al. (1987)

Here, the objective is to elicit sufficient data for prior and posterior probability distributions to be constructed which represent the beliefs of potential adopters about the variable of interest. The method used by Delavande (2008) to do this will also be used in this study. In particular, the first moment of the subjective distribution and several points on the cumulative distribution function will be elicited and used to fit the prior and posterior distributions.

The first moment of the distribution is the agent's subjective probability of the event occurring. To elicit this value, a relatively simple question can be asked, such as "what do you think is the per cent chance of successfully establishing the new pastures and incorporating them into your farm system?"

As Delavande (2008, p 52) notes, eliciting points in the cumulative density function without introducing the difficult concept of a probability's probability is not easy: "the respondent's task is more abstract than providing quantiles or points in the cumulative distribution of beliefs concerning a continuous variable like income, since the quantity of interest is itself a probability."

To resolve this difficulty, Delavande uses a new technique which is based on asking for an individual's "strength of belief" about an outcome. The objective is to ascertain the subjective probability that the objective probability P_i is greater than x, where x is a threshold probability. Three points on the CDF are elicited by asking respondents: "on a scale of 0 to 100, how strongly do you believe the per cent chance of the event occurring is greater than x?"

Delavande performs several tests to establish whether the responses to this question can be considered to be probabilities, and finds this is the case. In fact, the strength of belief method appears well-suited to this purpose, and is now being used in other surveys to elicit perceptions of uncertainty (Delavande 2008 p 61).

Empirical application

In future work this method will be used to elicit subjective probability distributions from a sample of 50 farmers in south west Victoria before and after half-yearly periods of learning. This data will be used for two purposes: first, the rate at which beliefs are being revised over time will be calculated and used to incorporate the dynamic process of uncertainty resolution in a whole farm economic analysis of pasture investment decisions.

Secondly, the implied quantity and quality of information received in the period will be derived from these distributions in the form of individual-specific ERS values. Specifically, for each elicited prior distribution possible combinations of n successful trials and r unsuccessful trials will be used to generate posterior distributions using Bayes' rule, and the combination which provides the best fit to the elicited posterior distribution will be identified using a least-squares criterion.

The ERS values obtained from this sample of farmers will be used to investigate the observed revision in the subjective probability distributions over time. The ERS values will also be related to data elicited from the participants about the type of learning activities they have engaged in.

Concluding comments

A method for representing the process of uncertainty resolution over time through learning is described in this paper. The method is designed to reflect two important characteristics of pasture investment decisions. First, the main source of uncertainty is the probability of successfully establishing and managing the new pastures. Secondly, the new information about this probability received by farmers in a given period cannot be observed, hence an alternative mechanism for observing this rate is required.

Future work will involve the empirical application of this model and its combination with a discounted cash flow analysis of the investment decision using a whole-farm economic model. It is hoped this work will increase understanding of the timing of pasture investment decisions, and – more broadly – increase the extent to which economic models can be used to explain the timing of technology adoption decisions on farms.

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