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Using Returns, Risks and Learning to Understand Innovation Adoption [1]

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Abstract

Adopting innovations is the key to improving production and productivity on farms and maintaining their long-run competitiveness and profitability. However, some innovations are adopted widely and rapidly while others are adopted slowly or not at all, and our understanding of the reasons for this remains limited. In this paper we seek to establish if explicitly accounting for the value of risk and the process of learning improves our understanding of decisions to adopt an innovation. The key finding from this case study is that an observed delay in adopting an apparently profitable innovation reflects the learning time it takes to resolve uncertainty regarding the implementation of the new technology.

Key words: investment analysis, risk, real options, Bayesian learning, innovation adoption

Introduction

Comprehensive economic analysis of decisions to adopt an innovation on a farm incorporates (i) *static analysis* that quantifies the costs, benefits and risk (defined as variation in possible outcomes) of incorporating a new technology into a farm production system in the steady state and (ii) *dynamic analysis* that considers how uncertainty (defined as incomplete knowledge) about the consequences of adoption is reduced to the level where a decision is able to be made to adopt or reject the innovation (Lindner, 1986).

Three aspects of pasture investment decisions have been investigated in this study: returns, risk and time for learning. First, the distributions of returns associated with several investments in pasture on farms in south-west Victoria were estimated. The returns and risk generated by the investments were analysed using both the net present value and real options methods of investment analysis. In addition, the role of time in enabling learning to inform and make these decisions was analysed using a Bayesian learning model. Considering how decision-makers' beliefs about the likelihood of success when investing in an innovation change over time helps to explain adoption of new pasture technology

[1] This research was undertaken while Tom Jackson was a PhD student at the University of Melbourne, 2010-2013.

by farmers. In particular, dynamic aspects of decision processes help to explain behaviour that appears inconsistent with the results of static analysis, such as the non-adoption by some farmers of apparently profitable technologies.

Why Study Pasture Investment Decisions?

Decisions to invest in pasture have been much studied in Australia. The classical economic approach in these studies is to treat farmers as profit-maximisers. If an investment is considered sufficiently likely to increase profit, it should be included in the feasible set of choices. Typically, it is found that the option of investing in improving pasture meets this criterion.

The main reason that justifies further consideration of pasture investment decisions is that pasture investments are inherently risky, yet relatively few studies of these decisions have included an explicit analysis of risk and uncertainty. For example, while Saul *et al.* (2011) found that pasture improvements on farms in south-west Victoria generated an internal rate of return of 27 per cent (in real terms), they did not consider risk, and instead assumed that average gross margins per head and the increase in the stocking rate associated with pasture improvement were constant over the life of the pasture. Similarly, studies by Warn (2004), Scott *et al.* (2000), Vere *et al.* (2001) and Lewis *et al.* (2012) focussed mainly on the expected returns associated with pasture investments.

Furthermore, while some authors have considered risk when analysing investments in pasture, there remain gaps in our understanding of these decisions. For example, Jones *et al.* (2000) measured the risk and return associated with alternative pasture systems using a simulation model. The sources of variation represented were pasture type and seasonal conditions; commodity price variation was not included. Moreover, the risk analysis was performed using the method of stochastic dominance. This approach has some theoretical limitations, which also apply to other expected-utility based methods of risk analysis (Starmer, 2000). Thus, it is useful to examine pasture investments using other methods.

Behrendt *et al.* (2006) analysed pasture improvement scenarios in the New England region of New South Wales. The authors used stochastic simulation to construct risk-efficient frontiers which allow scenarios that are unlikely to be preferred by farmers to be identified, i.e. choices with a relatively high degree of risk relative to returns. However, Behrendt *et al.* note this approach does not allow the particular scenario on the frontier to be identified which represents the combination of risk and return most likely to be preferred by farmers. This is because it does not include a systematic method for trading-off differences in risk and return between alternatives. Instead, this method leaves decision-makers with the problem of choosing between a set of alternatives which vary in terms of mean and variance — which can be challenging when differences in these two values are not worth the same amount.

Tozer and Stokes (2009) used simulation to measure the risk and return of two pasture investments in Western Australia, using real options to analyse investment decisions. The real options method facilitates valuing risk in the same units as returns (in dollars), allowing differences in risk and return between alternatives to be ‘traded off’ directly. A similar approach to that of Tozer and Stokes is used in this paper, although there are some differences. In particular, the analysis of pasture improvement by Tozer and Stokes involved a significant change to the enterprise mix of the farm, which influences estimated risk and return in addition to the effects of changing pasture species. In the present study, it is assumed that no changes to the enterprise mix of the farm occur when the pasture investment is made, which is a closer representation of the pasture investment problem faced by farmers in south-west Victoria.

A further reason for more pasture investment analysis is that there is a perceived problem with pastures in Australia. This is evident from the significant funds which continue to be invested in pasture-related research and development in Australia, for example by organisations such as Meat and Livestock Australia (MLA, 2011). The perceived problem is that desirable, perennial pasture species are being replaced with undesirable, annual species because the rate at which desirable perennial species are being resown appears to be lower than the rate required to maintain the existing pasture area (McRobert and McGuckian, 2012). Undesirable annual species lower the productivity of grazing enterprises by producing less and lower quality feed for livestock than improved perennial species, and they contribute to environmental problems such as erosion and salinity (Kemp and Dowling, 2000).

Method

The subject of this analysis was decisions by farmers to sow pastures they had not previously used. Stochastic simulation of a whole-farm bio-economic model was used to construct distributions of possible returns for a range of pasture improvement scenarios, and a suite of tools were used to analyse the static and dynamic aspects of these decisions. Data used to calibrate this analysis were obtained from a survey of farmers in south-west Victoria (described below). The methods and results associated with the static and dynamic analytical tools are largely distinct, and as such are described separately below.

Farmers interviewed for this project were randomly selected from a database of participants in extension activities conducted for the EverGraze project (Friend *et al.*, 2007) between 2007 and 2010. The database contains approximately 300 farmers from the Southern Grampians Shire in Victoria, Australia. From this total, 40 farmers were interviewed in this project. Approximately half the farms were clustered around the town of Hamilton and the other half were clustered around the town of Dunkeld. The number of farmers interviewed for this project is the maximum number that could feasibly be interviewed by the author within the time and budget constraints of this project. All interviews were conducted by the author at the home of the participants. Each interview took between one and two hours to complete.

The first round of interviews was conducted in March and April 2011. The second round was conducted in May 2012. All participants except one were interviewed in both rounds. A longitudinal approach was taken to allow the dynamic aspects of pasture investment decisions to be investigated. The interviews were structured and followed a written questionnaire. In the first round, questions were asked about the pasture(s) currently being considered for sowing, the length of time during which the pasture(s) had been under consideration, and the expected benefits from the new pasture. The survey also elicited farmers' beliefs about the probability of successfully establishing the pasture(s) under consideration, as establishment was identified by many farmers to be the key source of risk associated with these investments.

In the second round, beliefs about the probability of successfully establishing the pasture(s) being considered were again elicited, as was the outcome (success or failure) of any trials conducted in the past year. Key findings were that the learning process took on average four years, and that 50 per cent of all trials were successful. The second survey also included a number of questions about the characteristics of commonly sown pasture species. These questions related to persistence, establishment costs, expected dry matter production, and the timing of pasture growth throughout the year. Responses to these questions were incorporated into the whole-farm model.

Method for the static analysis

Two methods were used to analyse the static aspect of pasture improvement. One was the traditional or 'Marshallian' approach to capital budgeting in which investments are considered to be beneficial if the present value of benefits exceeds the value of costs at the required discount rate (Chatfield and Vangermeersch, 1996). Second, real options analysis was conducted, which also involves comparing the present value of benefits with the value of costs, but where the value of risk is measured explicitly as the value of the 'real option' to delay investing while more information about likely returns is obtained (Dixit and Pindyck, 1994).

The value of benefits generated by an investment in pasture improvement is the amount of farm profit earned with the improved pasture, minus the amount that would have been earned without the improved pasture. Distributions of benefits associated with various pasture improvement scenarios were constructed using stochastic simulation of a bio-economic model. Key characteristics of the farm system represented in this analysis are as follows.

- The base case farm system was replicated in two locations in south-west Victoria, Hamilton and Dunkeld, to illustrate the effects of changes in soil type and seasonal conditions on the performance of particular pasture species;
- The representative farm (designed based on practices commonly-used by the farmers interviewed for this project) was a 1,000 hectare prime lamb and wool operation in south west Victoria, with an average stocking rate throughout the year of 13.8 DSE (or 7 ewes) per hectare in Hamilton, and 12.5 DSE per hectare (6.4 ewes) per hectare in Dunkeld;
- The farm is assumed to comprise 950 hectares of improved pastures (the 'rest of farm' paddock) and 50 hectares of degraded pasture (the 'weed patch' paddock, comprised of early-maturing annual grasses);
- The period over which the operation of this farm system was simulated was 1972-1973 to 2011-2012. The model was simulated using financial years because this provides a good match between the production cycle and the reporting period; and
- Average annual rainfall over the simulation period is 680mm in Hamilton, and 657mm in Dunkeld.

In each investment scenario the weed patch paddock is sown with an improved pasture species and/or receives a capital application of lime and fertiliser. In all scenarios the stocking rate of the weed patch paddock is increased from 11.7 to 15.6 DSE per hectare (6 to 8 ewes per hectare), reflecting the practices of the case-study participants. Key characteristics of the pasture improvement scenarios are summarised in Table 1.

Table 1: Pasture improvement scenarios

Scenario name	**Establishment cost per hectare**	**Expected persistence**	**% of peak production year 1**	**% of peak production year 2**	**% of peak production year 3**
Fertiliser	$150.0	9.0 years	100%	100%	100%
Ryegrass	$415.0	6.8 years	60%	80%	100%
Phalaris	$367.5	9.0 years	40%	60%	100%
Lucerne	$430.0	6.2 years	40%	60%	100%
Cocksfoot	$346.4	9.0 years	40%	60%	100%
Tall fescue	$435.0	9.0 years	30%	50%	100%

Source: author's calculation

The quantities of dry matter produced by pastures once they are fully established on the rest of farm and weed patch paddocks are presented in Table 2.

Table 2: Average dry matter produced (DM/ha/year) 1972-73 to 2011-12

	Location	
Pasture	**Hamilton**	**Dunkeld**
Base case scenario: 'heavy soil'		
Rest of farm	8,031	7,176
Weed patch	6,836	5,924
Base case scenario: 'light soil'		
Rest of farm	8,016	7,160
Weed patch	6,742	6,690
Pasture improvement scenarios: 'heavy soil' Weed patch paddock*		
Fertiliser	8,911	7,762
Ryegrass	8,918	7,262
Phalaris	7,366	6,464
Tall Fescue	8,164	7,029
Pasture improvement scenarios: 'light soil' Weed patch paddock*		
Fertiliser	9,049	8,778
Ryegrass	8,662	8,624
Lucerne	6,202	6,581
Cocksfoot	7,864	8,430

Source: GrassGro simulation

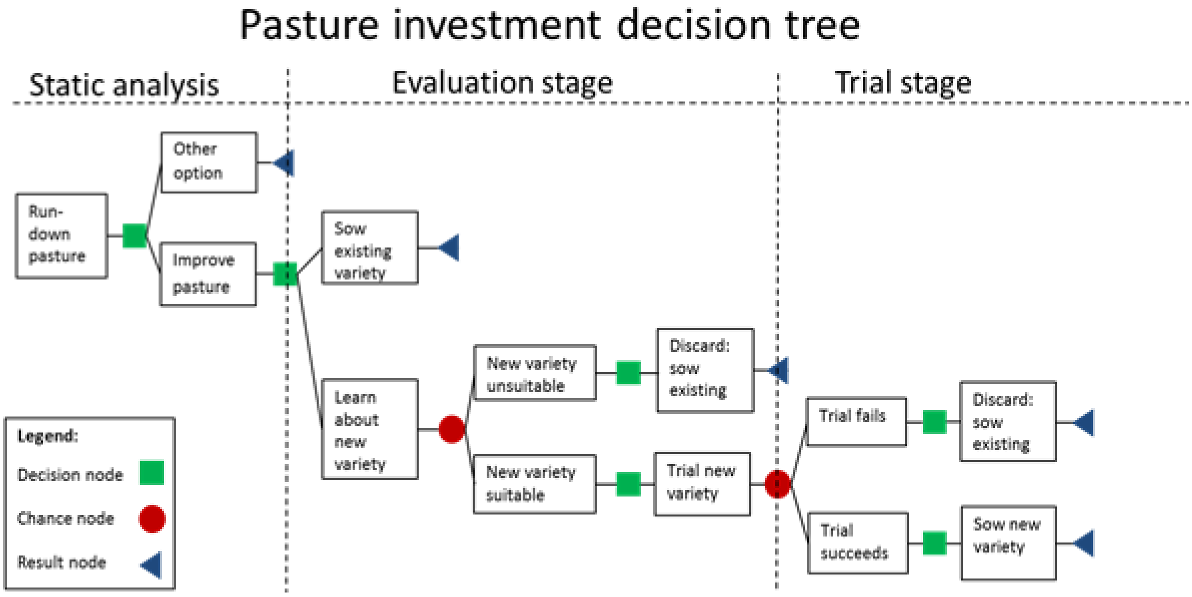
Distributions of the changes in pasture production associated with each pasture improvement scenario and the resulting effects on the output of lamb and wool and the amount of supplementary feed required were calculated using the bio-physical model GrassGro (Donnelly *et al.*, 2002). These quantities were multiplied by distributions of relevant commodity prices (specifically lamb, mutton, wool, skins, replacement ewes, supplementary feed and fertiliser) using the MS Excel-based simulation software @Risk to generate distributions of possible annual benefits for each scenario. The present value of benefits over a ten-year period were then estimated and compared to the total value of costs for each scenario.

Method for dynamic analysis

The dynamic component of this analysis involved constructing a Bayesian learning model (Raiffa and Schlaifer, 1961) that represented the revision of farmers' expectations about the probability of successfully establishing the pasture on their farm. This variable was identified as the key source of uncertainty regarding pasture investments by the farmers interviewed for this project. These interviews revealed that, when forming expectations about the costs and benefits associated with investing in new pasture, the farmers expected establishment would be successful on the first attempt, and that a dynamic process of learning was engaged in prior to undertaking the investment to ensure this expectation would in practice be met (maybe).

Figure 1 contains a simplified representation of the learning process used by farmers when deciding whether or not to sow a new pasture species. In the evaluation stage, low-cost sources of information such as field days and marketing material were used over a period of approximately three years to learn about the probability of successful establishment. If the content of this information was sufficiently positive, the mean probability held by the farmers about the likelihood of successful establishment was revised upwards, and the trial stage of the learning process commenced. This stage typically involved a one-year, on-farm trial. If the trial was successful, beliefs about the probability of successful establishment were revised upwards again, and the investment proceeded. If the trial was unsuccessful, the pasture species was typically discarded.

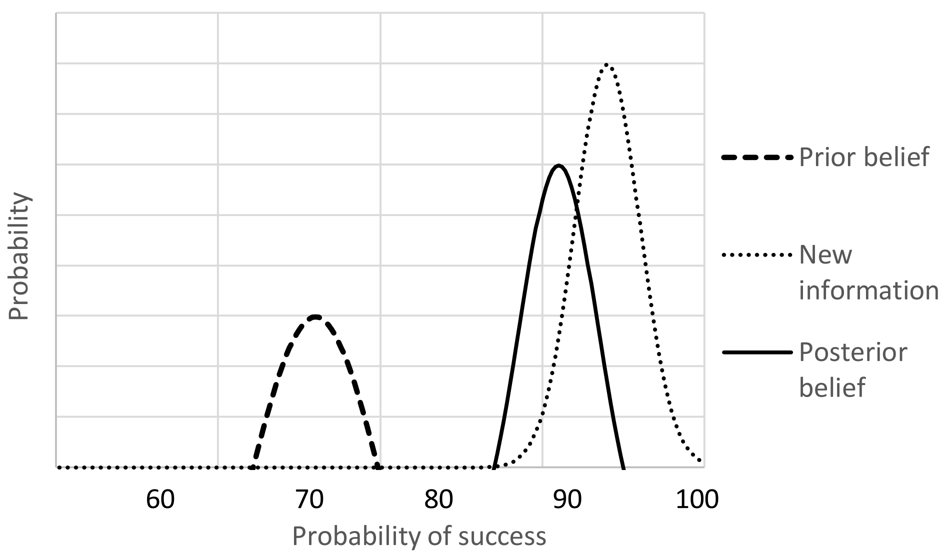
Figure 1: Pasture investment decision tree



Source: author

As an example, Figure 2 illustrates the trial stage of the learning process for a pasture species that was suitable for a particular farm.

Figure 2: Trial stage learning model for a suitable species



Source: author

At the start of this stage, prior beliefs (the dashed line) about the probability of successful establishment among the case-study farmers were centred on 70 per cent. At the end of this stage (the solid line) farmers generally held a posterior belief about the probability of success with a mean of 90 per cent. This implies that a successful trial yields new information (the dotted line) with a mean of 95 per cent.

In this analysis, the content and quality of new information obtained in each stage of the learning process was derived using methods described by Raiffa and Schlaifer (1961), using information obtained through the survey that quantified the prior and posterior beliefs of farmers (i.e. their beliefs at the start and end of each stage of the learning process). Specifically, the implied mean and variance of new information is proportional to those of the prior and posterior distributions, and can therefore be derived from the functions that define these distributions.

Theoretically, if the (uncertain) probability of successfully establishing a pasture (p) follows a Bernoulli process, then the prior distribution of beliefs about this variable are defined by the statistic (*r', n'*), and the sample data are defined by the statistic (*r, n*), then the posterior distribution of beliefs about *p* will be a beta distribution with the parameters:

$$r'' = r' + r\,, \quad n'' = n' + n$$

In this case, the mean belief about *p* in the sample data is defined by Raiffa and Schlaifer (1961, p.263) as:

$$E(p|r,n) \equiv \acute{p} = \frac{r}{n}$$

And the variance of these beliefs is defined as:

$$V(p|r,n) = \frac{r(n-r)}{n^2(n+1)} = \frac{\acute{p}(1-\acute{p})}{n+1}$$

Accordingly, given prior values of *n'* and *r'*, and a target posterior value of *r'' / n''* (obtained from the surveys), these formulas can be used to identify the smallest quantity of new information (*n, r*) which gives rise to the target posterior belief. This was done using the 'goal seek' function in MS Excel. Since information is costly, it is assumed that farmers collect the smallest quantity necessary to make a decision.

Results

Results from the static analysis

Results from the Marshallian and real options analyses of the pasture investment scenarios that were investigated for a heavy soil in Hamilton are shown in Table 3. Results from the other location and soil type analyses show somewhat different rankings of the pasture investment scenarios. As these differences are of limited relevance to general readers these results are not shown here.

Table 3: Marshallian and real options-adjusted (ROA) net present values – Hamilton heavy soil

Scenario	Marshallian discount rate	Marshallian net present value	Marshallian rank	ROA-adjusted discount rate	ROA-adjusted NPV	ROA-adjusted rank
Fertiliser	4.0%	$39,514	2	5.7%	$35,945	2
Ryegrass	6.9%	$45,176	1	8.5%	$40,587	1
Phalaris	4.0%	$26,404	4	6.1%	$21,524	4
Tall Fescue	4.0%	$36,111	3	5.5%	$31,826	3

Source: author's calculation

The first key finding is that the estimated net present values of the various pasture investments considered are positive and generally similar to one another. This occurred mainly because the increase in the stocking rate achieved with all new pastures was assumed to be the same, and this variable is the main determinant of the value of returns generated by pasture improvement. That is, each improved pasture generally produced enough extra feed to allow the additional stock to be run, while keeping yields per head fairly constant and reducing supplementary feed costs to a similar extent.

Although the amount of extra profit earned with each improved pasture species varied from year to year depending on realised seasonal conditions, the cumulative effect of these differences over the expected life of the pastures was relatively small. This reflects the relatively favourable conditions for pasture growth which exist in south-west Victoria and the relatively conservative initial stocking rates used in the analysis, which in turn reflect the experience of the farmers in south-west Victoria who were surveyed to calibrate this analysis.

The second key finding is that the ranking of projects by net present value was the same regardless of whether the real option to delay investing was included as a cost or not. This occurred because the real option values (i.e. the value of risk) associated with all pasture investments were relatively small, and — more importantly — of a similar magnitude between the different pastures. In addition, the most significant risk associated with these decisions is that a pasture may not persist for the entire investment period, a risk that was represented identically in both the Marshallian and real options analyses using the exponential decay depreciation method described by McDonald and Siegal (1986). In particular, a Poisson parameter (λ) that represented the probability of the pasture failing in any given year was added to the discount rate used to estimate the net present value of each investment.

While the risks other than non-persistence that were captured in the real options analysis (i.e. variation in seasonal conditions and prices) were not found to be key influences on investment decisions in this case, risks such as these that cannot be usually represented in the discount rate of a Marshallian analysis may be highly important in other cases. For example, if the variability of returns generated by the different pasture improvements had been more diverse, then using the real options method would have resulted in greater differences in the risk-adjusted discount rates, and this may have resulted in different rankings of the projects using the Marshallian and real options methods. In such cases, tools such as real options analysis may be required to understand whether an investment is worthwhile or not.

In addition to being profitable when evaluated at the expected value (or mean) of possible net present values, the distributions of returns associated with these investments revealed there were few circumstances in which they were not profitable. The conclusion that follows is that many farmers wishing to increase profit ought to invest regularly in pasture improvement and do so with little delay. However, this expectation was not observed in the surveys conducted for this project, where (i) only a small proportion of farmers sow new pastures in any given year, (ii) these investments are often delayed for some time, and (iii) farmers facing apparently similar conditions choose to sow quite different pasture species. Explaining these behaviours requires further analysis.

Results from the dynamic analysis

Application of the Bayesian learning model to aggregated prior and posterior distributions elicited from survey participants produced estimates of the average quantity of information obtained while learning, in the form of n values. While of little direct interest in themselves, these values provide valuable insight into the quality of the information obtained while engaged in different types of learning.

For a suitable pasture species, the mean posterior belief at the end of the trial stage was 0.9 (i.e. the probability of successful establishment is thought to be 90 per cent), up from either 0.7 or 0.8 at the start of the trial stage (depending on the individual). Based on these means, and two possible variances of prior beliefs, Table 4 summarises the relative quantity of information obtained in these two stages of the learning process.

Table 4: The relative quantity of information in trial data and prior beliefs

	Prior variance	
Prior mean	0.0014	0.0054
0.7	3.6	3.6
	Prior variance	
Prior mean	0.0005	0.0021
0.8	1.8	1.8

Source: author's calculation

Table 4 shows that the implied quantity of data received in the trial stage is 1.8 to 3.6 times greater than the quantity of information present in the prior beliefs at the start of the trial stage. Prior beliefs at the start of the trial stage are almost completely defined by the new information which is received in the evaluation stage. Therefore, the data indicate that the effective quantity of new information received in the trial stage is between 1.8 and 3.6 times greater than that received in the evaluation stage. Given that farmers interviewed for this project typically took 3 years to complete the evaluation stage, while only one year to complete the trial stage, in annual terms, the difference in the quantity of information obtained is three times larger than the values shown in the table above. Table 4 also shows that the relative quantity of information obtained in the evaluation and trial stages does not depend on the variance of prior beliefs. This is important because estimates of the variance of prior beliefs were more difficult to obtain than estimates of the mean.

Estimates of the quantity of information obtained while learning are otherwise difficult to obtain. Particularly in the evaluation stage, when multiple sources of information are being used, the information being obtained cannot be measured directly, and each source has an unknown relevance or credibility weight. The method used to quantify the information obtained while learning could be applied to other learning processes to identify forms of learning or information dissemination which are more or less effective for making decisions.

The finding that an on-farm trial contains substantially more new information than other sources reflects the fact that the context in which information is generated during the trial stage is very similar to that in which the new pasture is to be used. Accordingly, a trial outcome (positive or negative) is perceived to be highly informative of the true probability of success associated with a particular new pasture. Conversely, in the evaluation stage, information is necessarily collected from off-farm sources, and the context in which this information is generated is less well-known, and different to that in which the new pasture is to be used; this means that such information is perceived to be less informative than the result of an on-farm trial. This finding suggests that more rapid adoption of new pasture species could be achieved by shifting the focus of extension from providing general information to facilitating on-farm trials.

These results are consistent with the theoretical arguments of Lindner and Fischer (1982, pp. 16-22), who suggested that information obtained from external (i.e., non-trial) sources will be of less use for learning about a particular innovation than the same quantity of information obtained from internal sources. This argument reflects two possible quality problems associated with external information: bias and reliability. Bias reflects systematic error on behalf of the decision-maker in converting the external information into a signal about the true value of the variable of interest in his or her firm. Reliability reflects uncertainty about the actual signal being provided by the external source. Both of these quality problems appear to be relevant for farmers in the evaluation stage of learning about the probability of successfully establishing a new pasture. This finding is also in accordance with the following observation of Lindner (1986, p.150), that

> recent theoretical research suggests that improving the quality of innovation-specific information is more important for rapid diffusion than increasing its quantity. This raises the possibility that the efficacy of extension expenditure could be improved considerably by facilitating self-learning activities rather than attempting to substitute for them by bombarding potential adopters with so-called facts.

The learning model also helps us to understand why only some pastures are adopted by particular farmers, and why only some farmers adopt particular pasture species. Specifically, given plausible assumptions about the new information obtained while learning, the learning model can generate posterior distributions of beliefs about the probability of successful establishment with mean values that are too low for investment to occur. The fact that not all species are suitable for all farms means that this will be the case for some proportion of the pastures evaluated or trialled. Furthermore, the fact that trials are imperfect means that some farmers will incorrectly form a view that a particular species cannot be successfully established on their farm and hence not adopt it.

Discussion

Representing explicitly the learning process in decisions about whether to invest in improving pasture allowed some commonly-observed aspects of pasture investment decisions to be understood better. In particular, this analysis explains to a considerable extent why the farmers in the study delayed adopting new pasture species and/or cultivars, and changed their views about investing in a new pasture after some years passed. This reflects the substantial time and effort required to collect the quantity of information needed to shift the beliefs of farmers about the probability of success of a new pasture to a ‘strength of belief’ (probability value) that was high enough for them to proceed with the investment.

Overall, the application of the standard tools of investment analysis — NPV and real options allied to a learning model to comprehensively evaluate expected returns, risk and learning — generates a more complete understanding of the decision to invest in new pasture. Although not always possible, performing ex-ante analysis along the lines of returns, risk *and* learning could help developers of new technologies and others seeking to increase the rate of adoption in innovation in agriculture. Similarly, insights from the learning model could be used to improve the efficiency of extension efforts for technologies that can be trialled by individual farmers.

There are two main contributions of this study. The first is the contribution to the discipline of farm management economics. Discussed below, this contribution is a demonstration of how existing methods for analysing farm investments can be used to evaluate the key characteristics of such investments, namely returns, risk and time. In addition, economic consequences apply to various 'end-users' of improved pastures, including farmers and their advisors, farm input suppliers, and policy makers. These consequences are also discussed below.

Implications

For farm management economics

The academic contribution of this work is to show that existing methods for analysing farm investments are sufficient to systematically evaluate the key economic variables which determine technology adoption decisions on farms. As identified by Lindner (1986), analysis of these decisions must answer two key questions. The first is the static question: is the value of benefits greater than the value of costs? In this study, answering this question was extended to include an allowance for the value of risk associated with the investments. The second question is dynamic: how long does it take to make the investment decision, and what causes it to change over time? This second question was investigated here using a Bayesian learning model and data collected from farmers while they were engaged in the process of making a pasture investment decision.

As argued by Lindner (1986), analysis of a decision to invest in new technology on farms must answer both of these questions, because they are both essential components of the decision. Specifically, Lindner argued convincingly that studies of adoption which only consider the static question are unlikely to explain adequately the decisions to adopt technology by an individual farmer at a given point in time, and are also unlikely to explain adequately the diffusion of a new technology through a population of farmers over time.

Although diffusion of information about innovation was not considered in this study, the first of Lindner's predictions was borne out comprehensively. Specifically, the static analysis of risk and return found that all pasture investments considered were profitable, even when the value of risk was taken into account. Accordingly, the investment decision that follows directly from this analysis is for farmers to invest in new pastures immediately. By contrast, the 40 farmers interviewed for this project typically sowed new pastures only after a four-year process of learning, and sowed only half of all the species they evaluated. Application of the learning model also provided an insight into why only some pastures are sown by individual farmers, and why only some farmers sow particular pastures: *if the outcome of the learning process is that the pasture species being considered cannot be successfully established, investment in that species will never occur.*

Similarly, the real options tool was found to be an effective method for systematically valuing the risk associated with pasture investments. An important advantage of this approach is that it does not require an explicit representation of the investor's utility function to value risk. While assumptions about risk preferences must be made to use the real options approach, these preferences are expressed solely in the discount rate, and sensitivity analysis (available from the authors on request) showed that in this case, representing different risk preferences had relatively little impact on the outcome of the analysis.

For farmers

For farmers, economic consequences follow from both the static and dynamic components of the investment analysis. The most important economic consequence of the static analysis was the finding that pasture investments can be profitable under a range of circumstances, and that accounting for the value of the risk associated with these investments does not change this result. Furthermore, it was shown that improved pastures did not need to persist for more than ten years for investments in such pastures to be profitable. In fact, although ryegrass had the shortest expected persistence of all the scenarios considered here (less than seven years) this species was found to be the most profitable pasture investment on heavy soils.

The main determinant of the annual returns generated by investments in pasture improvement was the increase in the stocking rate achieved. This finding is consistent with previous studies of pasture investments, for example Warn (2004). The choice of species sown was found to be less important than the extra stock carried. In addition, although fertilising relatively low-quality annual grasses generated the smallest annual returns of all scenarios considered, once differences in establishment costs and expected persistence were taken into account, this form of pasture improvement had a net present value comparable to that of the scenarios in which an improved pasture species was sown.

In terms of risk, the similar ranking of preferred pasture investments that was obtained from the Marshallian and real options analyses indicated that, once differences in the risk of shortened persistence between species are taken into account, other differences in risk between species (i.e., those relating to the quantity and quality of pasture produced under different seasonal conditions) are relatively unimportant. For farmers, this provides support for the widely-held view that the possibility of shortened persistence is the most important risk to consider when making pasture investment decisions. Nonetheless, in contrast with the views of many farmers, it was also shown that pastures which persist for less than ten years represent profitable investment opportunities. These findings highlight the importance of obtaining good information about persistence when making pasture investment decisions.

From the dynamic component of this study, the main economic consequence for farmers was the finding that *on-farm trials provided the most information* about whether or not a new pasture species is suitable for a particular farm. Furthermore, gathering information from off-farm sources prior to conducting an on-farm trial was not necessarily an effective use of learning time, because the amount of new information obtained was relatively small. The surveys conducted for this project revealed that even after an average of three years collecting information from off-farm sources, only one in every two trials was successful. It is not known what the failure rate of trials would be if extra information was not collected first from off-farm sources. However, given that it took the farmers an average of three years to collect this information (and even then the failure rate was still 50 per cent), it may be beneficial to perform low-cost pasture trials sooner in the learning process.

For farm input suppliers and developers of new pastures

For rural merchandise sellers and seed developers, the economic consequences of this work follow mainly from the dynamic part of the analysis. In particular, it may be useful for these organisations to know that the farmers did not attach high credibility to the information they provide about the suitability of new pastures to particular farms. This was demonstrated by the small amount of information obtained from these sources in the evaluation stage of the learning process, and also emerged anecdotally from discussions with farmers. This low credibility reflected the perceived incentive of these organisations to disseminate relatively positive information about new pastures in order to increase sales, as well as a lack of transparency about how the information being provided was obtained, such as the fertiliser and grazing regime used in commercial pasture trials. This study showed that on-farm trials were by far the most effective form of learning as they possessed the key characteristics of being local and credible. Accordingly, these organisations could increase the rate of learning about their products by facilitating on-farm trials. This could be done by providing farmers with 'trial' seed samples.

Another economic consequence of this study for seed and other merchandise sellers relates to a reason for not re-sowing pastures that was given often by the farmers interviewed. This reason was that they did not believe new cultivars were sufficiently superior (if at all) to existing ones to warrant sowing them. In other words, these farmers did not believe valuable genetic gain was being made in the pasture species of interest. Although there is trial and experimental information that this is not the case, and genetic gain is occurring through the efforts of plant breeders, significant development may not be occurring in relation to the traits which are of most interest, such as persistence, to farmers operating relatively extensive farm systems.

For rural policy-makers

For policy-makers, the major economic consequence of the static component of this analysis is that there is little to suggest there is anything wrong with the pasture investment decisions currently being made by the sample of farmers studied in south-west Victoria, and, by inference, to many of the wider population of farmers making decisions about investing in new pasture. Although pasture investments (as pure private goods) have been found to be profitable under a range of circumstances, the learning process farmers typically engage in prior to sowing a new pasture takes some time to complete, and in many cases, the outcome is that new pastures are deemed not suitable to sow. Farmers appear to be acting in their best interests in making these decisions.

The dynamic analysis also revealed that the *farmers attached little credibility to information obtained from off-farm sources* (such as government departments and seed sellers) when learning about the probability of establishing a new pasture species successfully. If this lack of credibility is also attached to external sources of information when learning about characteristics of pastures (or other innovations) that cannot be learned about on-farm, then improvements in these characteristics that may be occurring will be only slowly incorporated into farmers' beliefs. For example, if the persistence of a particular species had been significantly improved, given that the only possible sources of this information are off-farm, this improvement would likely be incorporated into the beliefs of farmers only slowly.

For future research

The dynamic learning process used by farmers when making pasture investment decisions appears worthy of further analysis. In particular, further analysis into differences in the rate of learning between individual farmers and pasture species could provide some additional insight into the learning process, including how it could be altered or improved. For example, differences in the rate of learning between individuals may be associated with the sources of information used by these individuals (and in particular the trust placed in these sources), and/or broader determinants of human capital such as education, age and experience.

Another area in which more research may be beneficial is valuing individual characteristics of pastures, such as growth rates throughout the year, energy content, and persistence. This research would be useful for guiding pasture improvement research. This study has shown that, given current growth rates, energy content and persistence, sowing improved perennial pasture species is profitable, but the marginal value of improvement in each of these traits is not currently known. Given that the value of pasture varies throughout the year depending on relative scarcity, this analysis will not be at all straightforward. Similarly, valuing an increase in persistence would need to account for the value of foregone genetic gain in other traits.

Limitations of the Study

One limitation of this study was the constrained nature of the pasture investments that were analysed. In particular, to obtain reliable estimates of the biological consequences of pasture improvement, the biophysical simulation model GrassGro was used. Although a concerted effort was made in the analysis to represent a range of different pasture species, soil types, seasonal conditions and locations, the pasture investments which were constructed were nonetheless specific to a fairly narrow range of circumstances, and the applicability of the findings from this analysis to other circumstances is correspondingly limited.

Another limitation of this study is the treatment of risk preferences. Specifically, potential investors in improved pastures have been assumed to be risk-neutral throughout the analysis. In reality, farmers have a variety of risk preferences, of which neutrality is only one, and not even a particularly likely one. Previous studies have concluded that Australian farmers are typically risk-averse, at least to some extent (Bond and Wonder, 1980; Bardsley and Harris, 1987). As discussed by Dixit and Pindyck (1994), representing risk-aversion will alter real option values, since the ability to avoid negative outcomes will be more valuable to a risk-averse individual than to a risk-neutral individual. Potential investors were assumed to be risk neutral in this analysis because representing any other risk preference would have required assumptions to be made about the utility functions of these investors which are no less restrictive than the assumption of risk-neutrality. Furthermore, sensitivity analysis showed that while real option values changed somewhat when risk-averse preferences were represented by increasing the investor's discount rate, they remained small compared with the cash flows of the investments considered, and did not change the ranking of pasture investments.

The main limitation of the dynamic analysis is the quality of the data which could be obtained to calibrate the learning model. Specifically, only the expected values of the probability distribution of successfully establishing a new pasture in each stage of the learning process could be accurately obtained from the farmers interviewed for this project. By contrast, to fully calibrate the learning model, it is necessary to obtain estimates of the mean and variance of the subjective probability distributions in each stage of the learning process. In the absence of specific data about these distributions other than the expected value, the variance of these distributions was estimated using other, more general data which were obtained in the interviews. These estimates of variance are not specific to individual farmers, or to individual pasture species, and as a consequence the findings of the learning model are also generic.

Perhaps the most significant consequence of aggregating the data obtained from individual farmers is that only a single learning process was effectively represented in the model, and hence the estimates of how much information is obtained while learning are deterministic. In reality, the content of information obtained by individual farmers in a period of learning is stochastic – the signal received in a given period of learning will vary between farmers depending on which sources of information they consult and the true suitability of the pasture to their farm. As noted by Lindner and Fischer (1982, p. 7) this stochastic content of information means that even individuals with the same prior beliefs 'generally will require different amounts of information to be persuaded to adopt a particular innovation purely because the information collected is likely to differ in its content from decision maker to decision maker'. Here, because only one learning process has been represented in the model, this stochastic variation in the content of new information is not represented.

Conclusion

This research has shown that pasture investments on farms in south-west Victoria are profitable under a range of circumstances, and that this conclusion is unchanged when an allowance is made for the value of risk associated with these investments. In addition, analysis of the dynamic learning process that farmers engage in prior to sowing a new pasture helps to explain why these decisions can change over time, and reveals there are significant differences in the quantity of information obtained from different types of learning.

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