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Innovative capacity and productivity: an empirical analysis of Australian grain growers

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Abstract

Slowing productivity growth in the Australian grains industry has led to calls for increasing investment in rural R&D to advance agricultural technology. However, recent research also suggests there is strong potential to increase productivity by enhancing uptake of existing innovations. The productivity gains from innovation adoption are likely to depend on the capacity of farmers to effectively select, adapt and integrate innovations into existing farming systems.

In this paper, the innovative capacity of grain growers is characterised by variables related to the farm, the farmer and their operating environment. The influence of these factors on on-farm innovation adoption is tested using an ordered probit model. The relationship between innovative capacity, innovation adoption and productivity is then evaluated. The results suggest that building innovative capacity is effective in increasing agricultural productivity.

Keywords: innovation, grain growers, ordered probit, productivity

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1 Introduction

Innovation adoption plays an influential role in the productivity achieved by farmers. As most innovations are developed through off-farm R&D, the diffusion and uptake of these innovations by farmers is critical to improving industry performance. Although Australian farmers are renowned for their innovativeness, the extent of innovation has not been sufficient to maintain past rates of productivity growth. Productivity in the grains industry has experienced the most notable slowdown, with annual total factor productivity gains in the 2000s nearly half those achieved in the 1980s and 1990s (Nossal & Sheng 2010).

Recent research by ABARES suggests that both technical change and technical efficiency change have slowed in the grains industry (Hughes et al. 2011). Technical change relates to an outward shift of the production frontier, or an improvement in best practice. Technical efficiency relates to the performance of growers relative to this frontier. A declining rate of technical efficiency change suggests a growing gap between best practice and average grain farms. This indicates significant potential for grain growers to improve productivity by 'catching up' to their peers through adoption of innovations already on-the-shelf.

Several analyses have focused on the role of R&D investment in improving agricultural productivity. This research has confirmed R&D as a significant driver of productivity improvements over the long term (Alston at al. 2010; Sheng et al. 2011). Nevertheless, successful translation of R&D to productivity is indirect and depends on many factors. In particular, productivity outcomes are likely to rely on the capacity of farmers to adopt suitable innovations and successfully integrate them into existing farming systems.

In this paper, a conceptual framework for assessing the drivers and impacts of farm innovation is presented. Several frameworks have been used previously to evaluate innovation adoption by farmers (Abadi Ghadim & Pannell 1999; D'Emden et al. 2008; Sunding & Zilberman 2001). This framework contributes further to the literature by considering farm innovativeness in terms of a range of innovative activities, as opposed to a specific innovation. The framework also extends past analyses by linking innovation adoption to productivity outcomes. This approach provides insights into the relationship between a farmer's capacity to innovate, their innovative effort and their productivity outcomes. Understanding on-farm innovation processes is relevant for industry and policy-makers seeking new mechanisms for lifting productivity in the agriculture sector.

2 Framework

Farm innovation drives productivity. More than any other factor, productivity growth reflects farmers' efforts to adopt innovations, as it is through innovating that farms can increase outputs or reduce input requirements (Nossal 2011).

In this paper, farm innovation is defined as the introduction of any new or significantly improved technology or management practice. These include new products, processes, organisational or marketing systems not previously used on the farm, although they may not be new to the sector or the world (OECD 2005; Schumpeter 1942).

The relationship between innovation and productivity has typically been analysed using R&D investment as a proxy for innovative effort. In Australia, public R&D expenditure has been the indicator most commonly used, given lack of alternative data (for example, Sheng et al. 2011). Yet, as most rural R&D occurs off farm, these studies offer limited understanding of the innovativeness of farm businesses and opportunities at the farm level for increasing productivity growth. For example, little research has evaluated the link from R&D expenditure to develop innovations to other aspects of the innovation process such as extension and adoption by farmers (Nossal 2011; Spielman & Birner 2008). The outcomes of R&D are measureable, at least in terms of productivity growth, but are also indirect and depend on the capacity of farmers to adapt, adopt and integrate innovations into their existing farm systems.

The following framework has been designed to better understand farmers' decisions to innovate, the effort allocated to innovation and the influence of these decisions on farm productivity. It is structured around two key questions:

- What makes a farmer innovative?
- How does innovation affect productivity?

What makes a farmer innovative?

The innovativeness of farmers can be measured in terms of 'innovative effort'; that is, the extent to which a farmer adopts a set of innovations. By considering innovativeness in relation to a set of innovations, the underlying determinants of innovation behaviour can be better evaluated.

Innovative effort depends on three key components: the supply of innovations, the farmer's willingness or desire to innovate and the farmer's capacity to innovate. External incentives such as economic and environmental circumstances can also influence behaviour. Figure 1 outlines a simplified framework of innovation at the farm level.

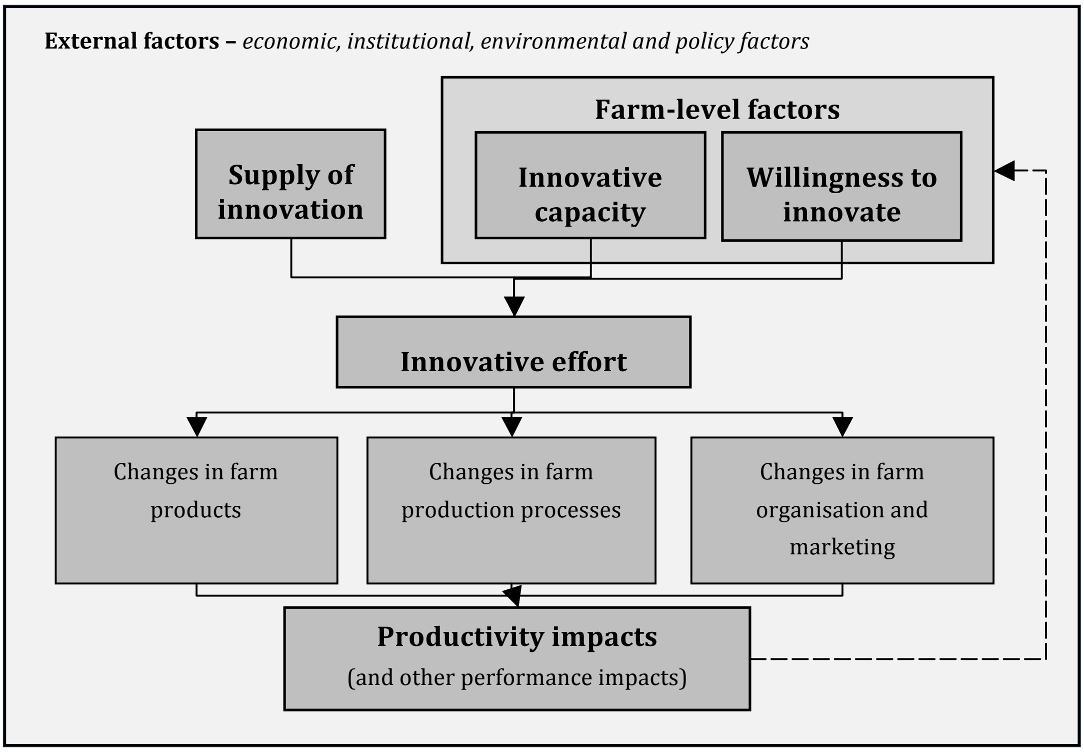
Adoption depends on a supply of innovations that are suitable to the farm and have an observable relative advantage. The relative advantage relates to the perceived benefits of adoption relative to the cost, complexity, compatibility and impact on lifestyle. The suitability of an innovation, and hence the benefits of adopting, vary widely according to characteristics of the innovation and the potential adopter. Incompatibility between the two is often highlighted as the reason behind low adoption rates (Feder et al. 1985; Pannell et al. 2006). For farmers facing a set of suitable innovations 'on-the-shelf', farm-level characteristics then become the main drivers of adoption. These characteristics determine a farmer's willingness to innovate and their capacity to do so.

A wide range of sociological and psychological factors can deter (or encourage) farmers from innovating, even if they have the economic and financial capacity to do so. For example, attitudes to learning, risk aversion, awareness of innovations, personal goals and values and past experiences can influence farmers' willingness to innovate. Various demographic and situational factors (such as education, size, and access to credit) can affect farmers' goals and motivations toward innovating (Marsh 2010). External incentives, be they moral, social or economic, can also encourage innovation adoption.

The focus for the rest of the paper is on farmers' capacity to innovate. Compared with individual perceptions and motivations, characteristics of a farmer's innovative capacity are more easily measured using farm survey data. Building innovative capacity could also offer greater opportunities for productivity growth compared with other policy measures, particularly because it requires no presumptions about which innovations comprise 'best-practice' or generate the greatest on-farm benefits.

Innovative capacity is defined here as the ability to effectively adopt innovations. Strong innovative capacity characterises a farm with the ability to source, select, adapt and integrate the innovations into their existing farming system to improve their productivity. As such, innovative capacity reflects a farmer's potential for innovation.

Figure 1 Simplified framework of innovation at the farm level



The characteristics of farmers that influence their propensity to innovate have been widely studied. Factors such as education, income and farming experience are widely considered to positively affect innovative capacity (Prokopy et al. 2008), while small farm size and limited access to credit are often raised as constraints to farmers' capacity to innovate (Feder & Umali 1993).

In this paper, farm-level characteristics relevant to innovation and productivity outcomes are investigated for Australian grain growers using a cross-sectional dataset.

How does farm innovation affect productivity?

The relationship between farm innovation and productivity is complex. The effect of innovation decisions will depend on the innovation adopted, its integration and the extent of its impact on productivity (that is, in changing farm output relative to input use). These relationships have been difficult to evaluate because of a lack of suitable data. However, both the rate and extent of innovation adoption (innovative effort), and the capacity of farmers to take advantage of technological opportunities are likely to affect productivity outcomes.

Following the framework in Figure 1, innovative effort leads to changes in farm products (such as higher yielding varieties), changes in production processes (such as using rotations or minimum till), or changes in organisational and/or marketing systems (such as forming new business partnerships or using futures contracts to sell grain). The aggregate effect of these changes on inputs and outputs will determine changes in total factor productivity (TFP) and other performance indicators such as profitability. Since, in this paper, the term productivity refers to total factor productivity, the productivity gains discussed capture any change in output that exceeds changes in measured inputs.

3 Data collection

Data on the innovation activities of Australian broadacre farms were collected in the ABARES 2008 survey of farm innovation (Liao and Martin 2009). The survey asked respondents about the innovation activities adopted during 2006–07 and 2007–08. The survey was conducted alongside the ABARES annual broadacre industry survey (the Australian Agricultural and Grazing Industry Survey), which collects physical and financial data across a stratified random sample of farm businesses. The sample used in the analysis contained 920 grain growers, defined to include specialist cropping and mixed crop–livestock farms (under the Australian and New Zealand Standard Industrial Classification 2006). This sample was representative, at a national level, of the Australian grains industry.

The innovation survey followed the Oslo Manual (OECD 2005) definitions and methods for collecting innovation data, adapted where necessary to suit Australian broadacre industries. Following standard practice, innovation was defined as 'the implementation of new practices or technologies that a farm business had not previously used, and was likely to use on an ongoing basis'. Data were collected for a broad range of innovative activities including product, process/production practices (including natural resource management practices), organisational and marketing innovations. Respondents indicated whether they had adopted each innovation 'not at all or very little', 'to some extent' or 'to a great extent'.

Despite the short time period, the vast majority of grain growers had adopted at least one innovation (90 per cent). Of these, 88 per cent had adopted at least one innovation to some extent and 45 per cent had adopted at least one innovation to a great extent. In comparison, around 39 per cent of businesses in the national economy (excluding agriculture) reported implementing an innovation in 2007–08 (ABS 2010).

Most commonly, growers adopted new cropping equipment (47 per cent) and new marketing approaches (44 per cent) (Table 1). However, innovation activities differed between crop specialists and mixed crop–livestock farms and between the northern, southern and western agro-ecological regions. These differences reflect, in part, differences in operating environments, including seasonal, environmental and marketing conditions. For example, dry conditions in the northern and southern regions over the survey period could have prompted farmers in these areas to change soil management, irrigation or water management practices (Liao and Martin 2009).

Variable definitions

As the innovation types remained broad, the intensity of innovative effort among growers was difficult to measure. Each innovation 'activity' could refer to one or numerous innovations. Also, the scale, cost and relevance of these activities could vary substantially between farms. For example, farms reporting new soil management practices could be referring to a spectrum of activities such as a change in tillage practices, sowing practices or crop rotations. Changes may have been a major endeavour for some farms yet only a minor adjustment for others.

Given this limitation, a categorical measure of innovative effort was developed based on the number of innovations adopted and the extent of their adoption. Given that nearly all grain growers had adopted at least one innovation, the categories were low, moderate and high innovators. The high innovators had adopted at least three innovations 'to a great extent' or had adopted less than three innovations 'to a great extent' as well as more than six innovations 'to some extent' (Table 2).

Table 1 Summary of innovations adopted, by industry and region

Type of innovation	Industry			Region		
	Cropping %	Mixed %	All %	Western %	Northern %	Southern %
Product innovations						
New crop types	27	30	28	26	26	27
New crop cultivars	44	32	38	39	28	43
New livestock types	8	11	10	11	5	9
New livestock breeds	13	22	18	26	11	16
Process innovations						
Cropping equipment	53	41	47	43	42	49
Fertiliser practices	43	32	37	35	35	38
Weed, pest and disease management practices	41	29	35	30	31	40
Soil management practices	40	35	37	26	40	38
Weed-related natural resource management	24	21	23	20	21	23
Pest-related natural resource management	19	19	19	18	14	20
Soil-related natural resource management	32	34	33	37	25	33
Other crop practices	12	11	12	7	15	12
Livestock feeding practices	15	24	20	21	9	19
Fodder conversation and use practices	12	18	15	16	9	16
Livestock handling practices	9	17	13	19	9	11
Livestock health practices	10	20	15	26	11	13
Grazing management practices	13	21	18	18	17	15
Other livestock practices	4	6	5	5	3	6
Pasture type	13	22	18	23	13	17
Irrigation and water management practices	14	10	18	3	19	12
Organisational innovations						
New approach to labour use	29	26	27	26	24	27
New members to farm management	18	12	15	15	7	19
Marketing innovations						
New approach to marketing farm production	51	39	44	36	39	51
Sample size	429	491	920	153	151	377

Note: Includes both specialist cropping and mixed crop–livestock farms. Percentages include those farms adopting innovations at least 'to some extent'.

Table 2 Method for ranking farm innovative effort

Innovations adopted 'to some extent' \ Innovations adopted 'to a great extent'	None	Less than 3	3 or more
None	low	moderate	high
Less than 6	low	moderate	high
6 or more	moderate	high	high

Explanatory variables were selected from the AAGIS survey (2008) for their hypothesised relevance to farm innovative capacity. The means and coefficients of variation for the sample are included in Table 3. Given their categorical nature, many of the variables are included as sets of dummy variables. In each dummy set, one category is omitted as the base category. Other variables are continuous.

Age and education are included as they build human capital, through adding the knowledge, skills and experience required for effective innovation. An age squared term is included to determine whether older farms are less likely to innovate given their shorter planning horizon, among other factors (Guerin & Guerin 1994; Pannell et al. 2006).

Labour, measured in weeks worked by family and non-family labour, reflects greater access to resources and knowledge. Farms with a larger labour supply may be able to afford more time to implement new technologies and management practices (Prokopy et al. 2008) and have greater specialisation of labour resources (Diederen et al. 2003b).

Farm size and intensity, measured in dry sheep equivalents (DSE) and in DSE per hectare, respectively, reflect scale economies. Larger, more intensively run farms are expected to have more resources for innovation and have greater opportunities for innovation (Schumpeter 1943). In particular, innovations with large transaction or information costs are more likely to be adopted by larger farms (Fernandez-Cornejo 2007).

Profit, measured using five percentile categories, is used to reflect financial capabilities. Off-farm income also supports farm financial capability, but can affect the priority allocated to farming activities. In previous studies, Zhao et al. (2009) found off-farm income negatively associated with farm productivity in Australia, while Fernandez-Cornejo (2007) found off-farm income associated with significantly higher adoption of management-saving technologies.

Table 3 Descriptive statistics of explanatory variables

Variable	Description	Mean or proportion	Std. dev
Farm business characteristics			
Age	Age of farm owner/operator	54	11.12
Age squared	Age of farm owner/operator squared	–	–
Education	Highest education level of owner/operator, dummy variables including:		
	Primary school[a]	1%	–
	High school	70%	–
	TAFE	11%	–
	University	18%	–
Labour[b]	Aggregate weeks worked by total farm labour	137	98.57
Farm size[b]	Scale of operations measured DSE[c]	18867	22724
Intensity[b]	Farm size (DSE) divided by area operated	7.46	2.98
Profit	Dummy (5 percentile categories, with bottom 20% set as the base case), farm business profit[d]	20%	
Off farm income	Dummy = 1 if farm has other income sources	38%	
Contract	Dummy = 1 if farm uses contract services	79%	
Operating environment (market and environmental conditions)			
Industry	Dummy variables including:		
	Cropping (if major activity is cropping)	47%	–
	Mixed crop-livestock (if major in both crop and livestock)[a]	53%	–
Region	Dummy variables including:		
	Southern [a]	56%	–
	Northern	20%	–
	Western	18%	–
	No region	6%	–

a Base case. **b** Natural logarithms for labour, farm size and intensity are used in the model; age squared is also included as a separate variable to account for a possible quadratic relationship between age and innovativeness. **c** DSE (dry sheep equivalent) measures the carrying capacity of a given farm. It is calculated as the number of sheep plus eight times the number of beef cattle and 12 times the number of hectares cropped and the number of dairy cows. **d** Farm business profit: farm cash income + changes in trading stocks – depreciation – imputed labour costs.

Note: All descriptive statistics are unweighted.

Contract services, a dummy for farms engaging contract services, is included to reflect the benefits of networks, external advice and knowledge spillovers (Zhao et al. 2009). Contract services may include consultants, agronomists or contractors employed by the farm.

Industry and region dummies are included to capture the innovative opportunities arising from certain operating environments. Different industry groups operate different farming systems and face differences in market and regulatory conditions that may influence their innovative effort. Similarly, growers are likely to face different operating circumstances based on their location, particularly in terms of climate. Two industry groups—specialist cropping and mixed crop–livestock—were defined based on enterprise mix. Three regions (southern, northern and western) were defined following the three agro-ecological regions specified by the Grains Research and Development Corporation (GRDC 2008).

4 Analytical method and model specifications

There were two stages to the empirical analysis. In the first stage, factors relating to farm innovative capacity were used to determine the likely innovative effort of a grain grower using an ordered probit model. In the second stage, the relationship of innovative effort, along with farm innovative capacity, to farm-level productivity was estimated using a log–linear regression model.

Determining likely innovative effort (Stage 1)

An ordered probit model was used to evaluate factors that influence the overall innovative effort of grain growers. The probit model and its variants have been used widely in relating observed innovation adoption to various determinants, including the agriculture sector (Feder et al. 1985). Given the dependent variable takes more than two values that are naturally ordered, the use of an ordered probit model (estimated using maximum likelihood) is indicated (Greene 2003). The dependent variable is the innovative effort of each grower, where growers are categorised as low, moderate or high innovators based on their extent and intensity of innovation adoption. These classifications were recorded as zero, one and two, respectively.

To explain the model, Y_i is defined as a proxy for the unobserved continuous variable Y_i^*, where Y_i^* is, in this study, innovative effort. If Y_i^* were observed, a standard regression would be used such as:

$$Y_i^* = B'X_i + \varepsilon_i$$

where X_i is a vector of explanatory variables for innovative capacity and ε_i is an error term with standard normal distribution. Instead, Y_i is used to represent the three ordinal categories, and the relationship between the Y_i and Y_i^* is given by:

$Y_i = 0$ if $Y_i^* \leq \mu_1$,
$Y_i = 1$ if $\mu_1 < Y_i^* \leq \mu_2$
$Y_i = 2$ if $\mu_2 \leq Y_i^*$

where μ_1 and μ_2 are unobserved threshold parameters estimated with the other model parameters.

While innovative effort varies with measurable factors relating to innovative capacity, other characteristics of innovative capacity cannot be observed. Other unobservable factors in this study include the willingness of growers to innovate and the supply of innovations (generated through off-farm R&D).

The likelihood that Y_i takes each value (0, 1, 2) is given by:

$$\text{Prob}\ (Y = 0) = P(\ Y^* \leq u_1) = P('B'X + e_i) \leq u_1 = \emptyset(u_1 - B'X)$$
$$\text{Prob}\ (Y = 1) = \emptyset(u_2 - B'X) - \emptyset(u_1 - B'X)$$
$$\text{Prob}\ (Y = 2) = 1 - \emptyset(u_2 - B'X)$$

where ø is a cumulative standard normal distribution such that the sum of the probabilities equals one.

In applying the model, each explanatory variable (Table 3) was weighted to derive population estimates. The weighting procedure reflected the stratified random survey design. Generally, larger farms are given small weights and smaller farms are given large weights, reflecting the strategy of sampling a higher fraction of the larger farms than of smaller farms (the former having a wider range of variability of key characteristics). Insignificant variables were excluded from the final models and those variables remaining exhibited weak correlation (less than 27 per cent).

Assessing effect of innovativeness on farm productivity (Stage 2)

A log–linear regression model was then used to evaluate the relationship between productivity and innovative capacity. In the model, total factor productivity (in 2008) was related to innovative effort and characteristics of innovative effort described above. This cross-sectional analysis identified the innovation factors important in explaining the differences in productivity between farms.

Farm-level estimates of total factor productivity were calculated using the Fisher index to aggregate diverse inputs and outputs. A ratio of the resulting output index and input index generated the resulting total factor productivity measure. The specific output and input variables used in estimating total factor productivity were derived from AAGIS farm surveys data following the methods employed in previous ABARES studies on broadacre productivity (see Gray et al. 2010).

Selection of explanatory factors for inclusion in model

The farm total factor productivity index was the dependent variable, while the explanatory variables included the innovative effort of each farm, along with factors representing their innovative capacity. A description of these variables is included in Table 4. These factors have often been employed in past analyses of grains productivity (Kokic et al. 2006; Zhao et al. 2009) and, as in Stage 1, include characteristics of the farm, the farmer and their operating environment.

The regression model was then specified, and estimated, as:

$$\ln(\text{TFP}) = \mu + \textstyle\sum_i \alpha_i \ln X_i + \beta I_i + \varepsilon_i$$

where μ is a constant incorporating all unexplained factors shared between individual farms, X_i is the weighted set of farm-level factors representing innovative capacity and ε_i is a random disturbance term incorporating all unexplained differences between farms.

By using farm-level productivity estimates, as opposed to industry-level estimates, the factors important in explaining differences between farms can be investigated (Kokic et al. 2006). However, it was not possible to identify factors with a significant impact over time. For example, weather and policy changes are two factors expected to influence farm productivity from year to year.

Table 4 Explanatory variables

Variable	Description
Dependent variable	
TFP	Farm-level total factor productivity index, measured in natural logarithm
Explanatory variables	
Innovative effort	Dummy for the extent of innovation adoption
	Low [a]
	Moderate
	High
Age	Age of farm owner/operator
Age squared	Age of farm owner/operator squared
Education	Highest education level of owner/operator, dummy variables including:
	Primary school[a]
	High school
	TAFE
	University
Intensity	Scale of operations (in dry sheep equivalent) divided by area operated, in natural logarithm
Crop specialisation	Proportion of farm area used for cropping (%)
Profit	Dummy (5 percentile categories, with bottom 20% set as the base case), farm business profit
Off-farm income	Dummy = 1 if farm has other income sources
Contract	Dummy = 1 if farm employed contract services
Region	Dummy variables including:
	Southern [a]
	Northern
	Western

a Base case.

Treatment of data entering the regression model

As it was not appropriate for all explanatory variables to enter the model in a logarithmic format, a standard approach was followed, as discussed in Wooldridge (2000). Specifically, variables that are proportions or indicator variables (0,1) remain in their original form. The proportional impacts on total factor productivity for each explanatory variable type are shown in the following equation:

$$\frac{\delta TFP}{TFP} = \begin{cases} e^{\alpha_i} - 1 & \text{if the explanatory is an indicator variable} \\ \alpha_i . \delta X_i & \text{if the explanatory is linear} \\ \alpha_i . \delta X_i / X_i & \text{if the explanatory is logged} \end{cases}$$

where α_i is the estimated coefficient.

Both stages of the empirical analysis were estimated using STATA (version 10) data analysis software.

5 Results and discussion

Stage 1

Stage 1 employed an ordered probit model to test the likelihood of high, moderate or low innovativeness for a grain grower according to their inherent characteristics (Table 5). However, estimated coefficients from the ordered probit have no direct quantitative interpretation (Greene 2003). As is typical for ordered probit results, the marginal effects are presented to better understand how changes in various characteristics influence innovative effort (Table 6). The marginal effects reflect the expected change in the probability of each outcome (high, moderate or low) given a unit change in a variable, ceteris paribus. For logged variables (labour, farm size and intensity), the marginal effect is the expected change in probability from a 1 per cent change in a variable, while for dummy variables it is the expected change in probability for a shift from 0 to 1. All marginal effects conformed to expectations and were statistically significant (at 0.1 or less), except industry dummies. The Chi squared test statistic shows the model as a whole is statistically significant, compared to a model with no predictors.

Human capital variables

Increasing education through university studies increased the probability of high innovativeness by 28 per cent (compared with 16 per cent for a high school education), when compared with a grower with only primary schooling. Among the variables, education had the most influence on innovative effort. Age increased the propensity for high innovative effort by 0.7 per cent for each additional year, although this gain flattened past a certain age (as indicated by the age squared term).

Scale variables

Several variables relating to operating scale contributed to an increased probability of innovative effort, including farm size, intensity and labour availability. These factors have moderate impact on likely adoption among grain growers, consistent with other studies (Abadi Ghadim & Pannell 2005; Diederen et al. 2003b). Larger farming operations typically have greater access to financial resources, and a greater ability to manage risks associated with innovating. Also, larger farms more often have access to a larger workforce, often with specialised skills, such that they are better placed to implement opportunities for business development.

Financial and managerial capacity variables

Against prior expectations, farms with higher farm profits were associated with lower innovative effort. This could be a consequence of the short-term costs associated with innovating, with the expected benefits to farm profits accruing in the long term. A lagged indicator might provide a better indication of financial capacity in future research.

Off-farm income had a positive, but relatively small, influence on innovative effort. This lends weight to the hypothesis that additional income enhances financial capacity for innovation. Alternatively, innovation adoption could lead to labour being released for higher value uses, either on or off-farm.

Farmers employing contract services were 3.2 per cent more likely to be high innovators than farmers not engaging in contract services. Engaging services such as consultants or extension officers is an acknowledged source of new information. In addition, outsourcing activities such as sowing, spraying and harvesting have helped incorporate modern technologies in the farm production process.

Operating environment

There were no significant differences in the likely innovative effort of specialist cropping and mixed crop–livestock farms. On the other hand, regional differences were a significant predictor of innovative effort. Relative to the southern region, growers in the northern region were more likely to be high innovators, whereas those in the western region were less likely. These differences could reflect the particular economic and environmental conditions during the study period. Then again, the behaviour may be consistent over time with western growers facing fewer opportunities for innovation because homogenous cropping systems are more widespread. Comparing innovative effort over a longer time frame is likely to provide greater insights.

Table 5 Results of the weighted ordered probit model

Explanatory variable	Coefficient	Standard error	z statistic	Prob>|z|
Age	0.026	0.006	4.770	0.000
Age squared	–0.0003	0.00004	–6.160	0.000
Education				
High school	0.743	0.077	9.700	0.000
TAFE	0.659	0.080	8.260	0.000
University	0.894	0.079	11.300	0.000
Labour availability (log)	0.217	0.022	10.060	0.000
Farm size (log)	0.166	0.012	13.430	0.000
Land use intensity (log)	0.214	0.019	11.410	0.000
Profit				
Lower middle (20–40%)	–0.305	0.030	–10.050	0.000
Middle (40–60%)	–0.304	0.031	–9.950	0.000
Upper middle (60–80%)	–0.352	0.030	–11.820	0.000
Highest (top 20%)	–0.403	0.032	–12.750	0.000
Contract	0.130	0.019	6.730	0.000
Off-farm income	0.140	0.018	7.660	0.000
Industry				
Cropping	–0.022	0.018	–1.280	0.202
Region				
Northern	0.127	0.023	5.510	0.000
Western	–0.274	0.023	–11.700	0.000
μ 1	4.033	0.206		
μ 2	4.870	0.206		
Number of observations	20 544			
Log likelihood	–19 469			
LR test	Chi2(17)	= 2254.02	Pr > Chi2	= 0.000

Note: Base comparison is a farm with primary or no schooling, located in the southern region, running a mixed crop–livestock enterprise and in the bottom 20 per cent of farms ranked by profit level. Weights are used in the model such that the sample represents the industry population. As a result, the weighted sample size increases from 920 to 20 544.

Table 6 Marginal effects

	High innovator	Standard error	Moderate innovator	Standard error	Low innovator	Standard error
Age	**0.007**	0.001	**0.004**	0.001	**–0.010**	0.002
Age squared	**0.000**	0.000	**0.000**	0.000	**0.000**	0.000
Education						
High school	**0.162**	0.014	**0.118**	0.013	**–0.280**	0.026
TAFE	**0.204**	0.028	**0.051**	0.002	**–0.256**	0.029
University	**0.287**	0.029	**0.051**	0.004	**–0.338**	0.026
Labour availability (log)	**0.055**	0.006	**0.031**	0.003	**–0.086**	0.009
Farm size (log)	**0.042**	0.003	**0.023**	0.002	**–0.066**	0.005
Land use intensity (log)	**0.055**	0.005	**0.030**	0.003	**–0.085**	0.007
Profit						
Lower middle (20–40%)	**–0.072**	0.007	**–0.047**	0.005	**0.119**	0.012
Middle (40–60%)	**–0.073**	0.007	**–0.046**	0.005	**0.119**	0.012
Upper middle (60–80%)	**–0.081**	0.006	**–0.056**	0.005	**0.137**	0.011
Highest (top 20%)	**–0.088**	0.006	**–0.066**	0.006	**0.154**	0.012
Contract	**0.032**	0.005	**0.019**	0.003	**–0.051**	0.008
Off-farm income	**0.036**	0.005	**0.019**	0.003	**–0.055**	0.007
Industry						
Cropping	**–0.006**	0.004	**–0.003**	0.002	**0.009**	0.007
Region						
Northern	**0.034**	0.006	**0.017**	0.003	**–0.050**	0.009
Western	**–0.064**	0.005	**–0.043**	0.004	**0.107**	0.009

Note: All marginal effects at the mean (except 'cropping') were significant at the 1 per cent confidence level.

Stage 2

Stage 2 aimed to evaluate the influence of innovation on cross-sectional differences in productivity between farms. The results are in Table 7.

All variables were of the expected sign and showed a statistically significant relationship (at the 1 per cent level). The R-squared values were reasonably high, indicating that the variables included in the models explained most of the variation in total factor productivity between farms.

The results support the linkage between innovative effort and productivity. More innovative farms (in terms of both the number of innovations and the extent of their adoption) are likely to exhibit higher productivity. Compared with a farm with low innovative effort, a farm with high innovative effort increased productivity by 3.4 per cent, given all other factors.

However, the significance of other explanatory variables suggests that productivity relies on factors beyond innovative effort. For example, education, land use intensity and profitability were strongly associated with higher farm productivity. A 10 per cent increase in land use intensity was associated with a 3.2 per cent increase in productivity, on average. For education, a dummy variable, growers with university education exhibited productivity, on average, 44 per cent higher than growers with only primary schooling (or less). Age was statistically significant, but had only a small non-linear relationship to productivity.

Table 7 Total factor productivity regression results

Variable	Coefficient	(t-stat)
High innovator	0.034	(3.97)
Moderate innovator	0.028	(3.91)
Age	–0.010	(–4.97)
Age squared	0.00004	(3.33)
Education		
High school	0.238	(12.25)
TAFE	0.209	(10.01)
University	0.366	(17.54)
Crop specialisation	0.137	(7.06)
Land use intensity (log)	0.324	(33.99)
Profit		
Lower middle (20–40%)	0.048	(4.60)
Middle (40–60%)	0.485	(44.74)
Upper middle (60–80%)	0.777	(72.34)
Highest (top 20%)	1.016	(84.92)
Contract	0.077	(11.24)
Off-farm income	–0.062	(–9.74)
Region		
Northern region	0.084	(9.28)
Western region	0.216	(25.12)
Intercept	–0.602	(–9.74)

Note: All coefficients are significant at the 1 per cent level. R^2 = 0.68.

Limitations

While the results are empirically robust, they may underestimate the importance of innovativeness for productivity because of constraints within the analytical approach and the underlying data. For example, cause and effect relationships are inherently difficult to capture in cross-sectional analysis. While innovation drives productivity, the causality is likely to be bidirectional, given that farms with higher productivity could be in a better position to innovate. Further data are required to understand the influence of higher productivity on innovative effort.

Long-run impacts are also beyond the scope of this analysis. Innovation is expected to influence productivity over the longer term and it is less likely innovation adoption will substantially affect productivity within the one-year period considered. Invariably, there are lags between innovation adoption and performance impacts. Innovation adoption can even lead to a short-term decline in productivity, given associated initial input costs.

Further studies could begin to address these limitations if ongoing surveys were introduced to collect time series data.

6 Conclusions

Stage 1 of the analysis highlighted the importance of various farm-level characteristics in explaining the innovative effort of grain growers. In particular, education had a substantial effect on the number and extent of innovations adopted. Human capital is likely to become increasingly relevant to agricultural productivity given sophisticated farm technologies and integrated management practices, such as those related to weed, pest and disease management.

The Stage 2 analysis suggests that innovative effort is a significant driver of productivity growth. Those grain growers adopting more innovations to a greater extent exhibit, on average, higher productivity relative to their peers.

In addition, innovative capacity is important for enabling productivity payoffs from any given level of innovative effort. Farmers with a greater ability to effectively integrate innovations into their existing farming systems—as measured using farm-level indicators of innovative capacity—also achieve higher productivity, on average. This could be because farmers with higher innovative capacity are more often better decision-makers with a greater ability to source and use innovations to greater effect. As well as education, scale and financial capacity were important drivers of productivity among grain growers.

The results provide relevant insights for lifting productivity growth in the grains industry. While grain growers are highly innovative (with the vast majority undertaking some innovative activity in the survey period), there remains wide variability in the productivity outcomes achieved. Increasing the extent of innovation adoption is one way to improve productivity. In addition, building innovative capacity, such that growers can access and use technologies and production systems effectively, is also likely to yield productivity improvements at the farm level.

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