Australian Government

Australian Bureau of Agricultural and Resource Economics and Sciences

Innovation and productivity in the Australian grains industry

Katarina Nossal and Kee Lim

ABARES research report 11.06

July 2011

www.abares.gov.au

Science and economics for decision-makers

Nossal, K and Lim, K 2011 *Innovation and productivity in the Australian grains industry,* ABARES research report 11.06, Canberra, July.

ISSN 1447-8358
ISBN 978-1-921192-95-1

Australian Bureau of Agricultural and Resource Economics and Sciences
Postal address GPO Box 1563 Canberra ACT 2601 Australia
Switchboard +61 2 6272 2010
Facsimile +61 2 6272 2001
Email info@abares.gov.au
Web abares.gov.au

ABARES project 43071

From 1 July 2011, responsibility for resources and energy data and research was transferred from ABARES to the Bureau of Resources and Energy Economics (BREE).
Please visit **www.bree.gov.au** for access to BREE publications and information.

Acknowledgments

This research was funded by the Grains Research and Development Corporation and is part of the Harvesting Productivity Initiative.

The authors thank Yu Sheng, Alistair Davidson, Clara Cuevas, Astrid Dahl, Peter Gooday and Terry Sheales of ABARES for their contributions to the report, as well as Shiji Zhao and Prem Thapa, previously of ABARES. They also gratefully acknowledge the feedback provided by Zoltan Lukacs, Professor Chris O'Donnell and other participants at the Harvesting Productivity Initiative Working Group meeting in Canberra in 2009.

This report draws heavily on data collected in ABARES surveys of broadacre industries. The success of these surveys depends on the voluntary cooperation of farmers, their accountants and marketing organisations in providing data. The dedication of ABARES survey staff in collecting these data is also gratefully acknowledged. Without this assistance, the analysis presented in this report would not have been possible.

Foreword

Productivity growth is fundamental to the long-term success of the Australian grains industry. Yet recent evidence suggests cropping productivity growth rates have slowed over the past 10 or 15 years. Among other drivers, farmers' capacity to adapt, adopt and apply innovations is increasingly important for reviving productivity gains to retain industry competitiveness on global markets and help meet future food supply needs.

ABARES has undertaken significant work to estimate and analyse productivity growth and its determinants in Australian broadacre agricultural industries. This study, funded by the Grains Research and Development Corporation, expands the scope of ABARES analysis to the role of innovation at the farm level. The study empirically evaluates the characteristics of grain growers that determine their capacity to harness the knowledge and technologies that result from R&D to achieve productivity improvements. Further development of some characteristics, such as human capital, has the potential to enhance growers' capacity to effectively integrate innovations within their existing farming systems to deliver productivity gains.

This project is one of a series of projects under the Harvesting Productivity Initiative ABARES is undertaking for the Grains Research and Development Corporation. The initiative aims to build a greater understanding of the drivers of productivity to help the grains industry achieve its full potential.

P Glyde

Philip Glyde
Executive Director
July 2011

Contents

Foreword iii

Summary 1

1 Introduction 2

2 A framework of innovation at the farm level 4

What makes a farmer innovative? (Stage 1) 4

How does innovation adoption by farmers influence their productivity? (Stage 2) 7

3 Innovation in the grains industry 8

Measuring farm innovation 8

Grains industry innovation adoption 10

Estimating innovative effort 13

4 Estimating the role of innovative capacity 15

Factors that determine innovative capacity 15

How do these factors influence farmers' innovative effort? 18

Discussion 22

5 Farm innovation and productivity 23

How does innovation by farmers influence their productivity? 23

Discussion 24

6 Conclusions 26

Policy implications 26

Further research 27

Appendixes

A Ordered probit model 29

B Regression analysis 33

References 36

Tables

1	Proportion of growers adopting innovations, by industry type and region, 2006–07 and 2007–08	12
2	Method for ranking farm innovative effort	13
3	Distribution of grains farms by innovation ranking	14
4	Variables selected for the ordered probit analysis	19
5	Change in the probability of high, moderate and low innovative effort	20
6	Effect of innovation on farm productivity	24
7	Ordered probit results	31
8	Marginal effects	32
9	Dependent and independent variables in the regression model	34
10	Total factor productivity regression results	35

Figures

1	A simplified framework of innovation at the farm level	5
2	Proportion of grain growers adopting innovations, 2006–07 and 2007–08	11

Boxes

1	National Innovation Surveys and the agriculture sector	9
2	ABARES farm business innovation survey	10
3	ABARES broadacre farm survey data: physical and financial characteristics	17
4	Model selection for empirical estimation	18

Summary

To lift productivity growth, grain growers must effectively adopt and integrate innovations into their existing farm production systems. While off-farm R&D is a dominant source of knowledge and technologies for the grains industry, it is the adoption of these innovations by growers that leads to productivity gains. Recent analysis suggests that growers have not undertaken sufficient innovation to maintain past rates of productivity growth, and productivity growth in the grains industry has been slowing over the past decade. This slowdown has escalated interest in opportunities to strengthen productivity growth rates.

Improving growers' capacity to innovate is one potential mechanism for lifting productivity growth. The innovative capacity of growers—that is, their ability to successfully innovate to improve farm performance—depends on a host of characteristics inherent to the farmer, their farm and their broader operating environment. These characteristics influence the adoption of innovations and outcomes for productivity. The supply of innovations and whether growers are willing to innovate also have a bearing on likely adoption patterns and productivity growth.

The objective of this study was to test the influence of growers' innovative capacity on their adoption of innovations, and, in turn, their productivity. An ordered probit model was used to empirically analyse the influence of farm-level factors on the likely effort allocated to innovation (measured by the extent of adoption of a range of innovative activities). Then, a regression model was employed to test the impact of innovation adoption and other determinants of innovative capacity, on farm-level productivity. Both stages of the analysis used ABARES farm-level data for 2006–07 and 2007–08.

The results suggest that improving innovative capacity among growers is likely to increase efforts toward innovation adoption and enhance the ability of growers to realise productivity gains. The first-stage results found that innovative effort increases among growers with a greater innovative capacity, as measured in terms of their education, farm size, land use intensity, profits, use of contract services, and other farm-level characteristics. The results from the second stage suggest that higher innovative effort, as well as a greater ability to effectively integrate innovations into farming systems, leads to higher productivity. This suggests that farmers with higher innovative capacity are, on average, better decision makers with a greater ability to source and effectively use innovations to achieve productivity gains.

While innovative capacity is largely determined by growers' characteristics (such as education, business acumen, financial resources, skilled labour and access to public and private extension services) such characteristics are often influenced by policy and investment decisions. The findings of this study support the need for a greater emphasis on education, skills and training in the agriculture sector along with improved information accessibility through efficient public and private extension. Human capital is likely to become even more relevant to maintaining and improving grower productivity given a tightening labour market, increasingly sophisticated farm technologies and the growing importance of integrated farm management practices. In addition, agricultural policies that inhibit innovative capacity and reduce farmers' decision-making flexibility could constrain long-term productivity growth among grain growers and the agriculture sector more broadly.

1 Introduction

From a policy perspective, much of the analytical work investigating agricultural productivity trends has, in recent times, sought to understand the implications of stagnating public investment in rural research and development (R&D). Such studies have found that public investment in R&D explains a substantial share of agricultural productivity growth (Alston et al. 2010; Sheng et al. 2011a). It is widely accepted that R&D plays a significant role in driving productivity improvements.

Notwithstanding that R&D is a large source of innovations, productivity improvements rely on their adoption by farmers. Although Australian farmers are renowned for their willingness to pursue, adopt and adapt new innovations, the innovative effort of the grains industry as a whole has not been sufficient to maintain past rates of productivity growth. Recent ABARES analysis suggests a slowing of technological change and a decline in the rate at which average farms catch up to best practice over the past decade (Hughes et al. 2011).

The slowdown in agricultural productivity growth (Sheng et al. 2011b), along with pressures to reform rural R&D policy in Australia (Productivity Commission 2010), has escalated interest in finding ways to improve productivity, including through enhancing farmers' innovative capacity. Despite the seemingly simple link, the successful translation of R&D to improved farm productivity depends on many factors. In particular, much relies on farmers' capacity to adopt suitable innovations and successfully integrate them into existing farming systems.

Innovative capacity and its measurement have become a national priority for Australia following the Cutler review which concluded that while innovation policy has strongly focused on R&D, less attention has been paid to improving the capacity of firms to adapt and apply innovations (Australian Government 2009; Cutler and Company 2008). For agriculture, a broader understanding of innovative capacity and its contribution to farm innovation adoption and productivity growth can also aid in evaluating policies and investment decisions aimed at improving productivity growth.

This study develops a framework of the innovation process at the farm level to evaluate:

- the factors that make a farmer innovative
- how innovation adoption by farmers influences productivity.

A discrete choice model is used to analyse the effect of various farm-level factors on the innovation adoption of grain growers. Then, a regression model is used to evaluate the relationship between innovation adoption and growers' productivity. This approach to agricultural innovation analysis, which captures farm behaviour in relation to a range of innovative activities, results in a deeper understanding of how diverse grain growers engage in the innovation processes and outcomes.

The report is structured as follows. In chapter 2, a framework for considering the innovation process at the farm level is developed. Innovation adoption in the grains industry, and measures of the innovative effort of grain growers, are examined using farm level data in chapter 3. The role of innovative capacity in determining the extent to which a grain grower might innovate is investigated in chapter 4, and the influence of innovative effort on farm productivity is estimated in chapter 5. Potential implications and directions for further research are discussed in the final chapter.

2 A framework of innovation at the farm level

Farm innovation adoption is the introduction of any new or significantly improved technologies or management practices. These include new products, processes, and organisational or marketing systems that have not previously been used on the farm, although they might not be new to the sector or to the world (OECD 2005; Schumpeter 1942). Ongoing innovation adoption by growers fundamentally drives productivity growth in the grains industry.

In agriculture, a useful way to conceptualise the pathways through which R&D contributes to productivity is through an innovation systems framework (Nossal 2011; Spielman and Birner 2008). Put simply, R&D is undertaken on and off-farm with the expectation of developing new innovations to be diffused to the farm sector (for example, through extension and social networks) and ultimately adopted by farmers. However, the system is far from linear and there is a complex set of interrelated factors that can shape the innovation process.

While most empirical analyses have focused on the early stages of the innovation system, most notably the impacts of R&D investment (Alston et al. 2010; Mullen and Crean 2007; Sheng et al. 2011a), few have considered innovation at the farm level. Further empirical analysis is warranted to better understand farmers' decisions to innovate, the effort allocated to innovation adoption and the impacts of these decisions on farm productivity.

In this chapter, a two-stage approach for considering the innovation process at the farm level is developed. In the first stage, factors likely to determine whether a farm is innovative or not and the extent of their innovative effort is discussed. Then, the contribution of innovation adoption to productivity performance at the farm level is considered in the second stage.

What makes a farmer innovative? (Stage 1)

Farm innovativeness can be measured by 'innovative effort', that is, the extent to which a farmer adopts a set of innovations. Innovative effort is determined by farmers' capacity and willingness to innovate, and the supply of innovations available to them (figure 1). Characteristics of a farmer, their farm and their operating environment influence whether they have the capacity to adapt and integrate innovations on their farm, and whether they are willing to do so. Given a supply of appropriate innovations 'on-the-shelf', these farm-level factors determine the likely effort a farm will contribute to innovation.

The contribution of innovative capacity, willingness to innovate, and the supply of innovations to a farms' innovative effort is conceptualised in the first part of this chapter.

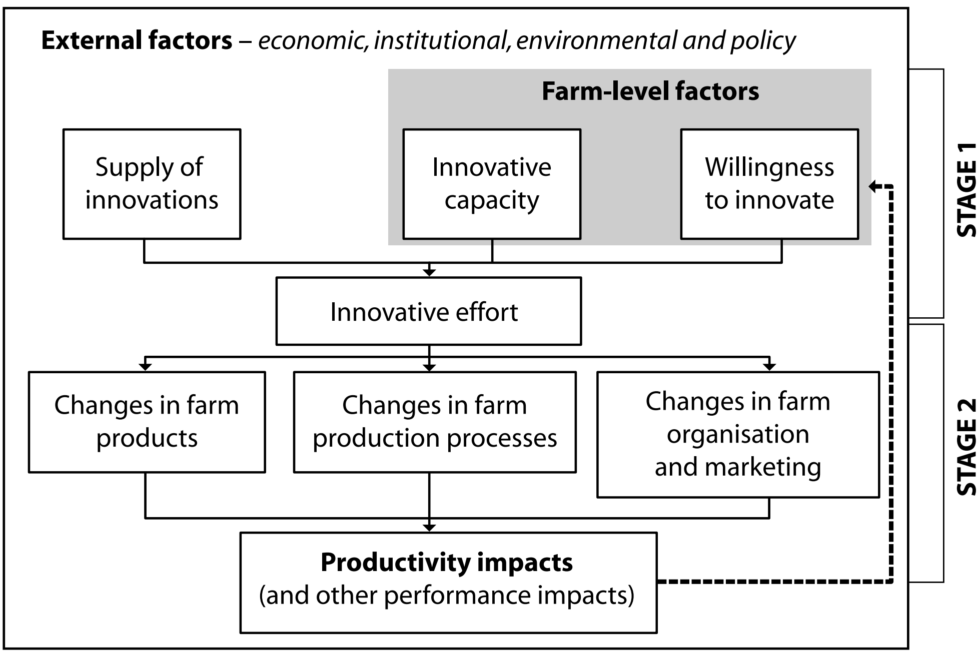
Innovative capacity

Innovative capacity can constrain or facilitate innovation adoption by farmers. It is defined as the ability to effectively adopt innovations. As such, innovative capacity reflects a farmer's potential for innovation. Farmers with high innovative capacity can better source the outputs of R&D and use them effectively to improve their farm business.

A host of farm-level factors can influence innovative capacity in agriculture. Factors such as education, income and farming experience are widely considered to positively affect innovative capacity (Prokopy et al. 2008). These, and other characteristics, give farmers the inherent abilities, information and skills needed for innovation adoption. Conversely, small farm size and limited access to credit are often highlighted as constraints to innovation adoption (Feder et al. 1985).

Factors external to farms can also influence innovative capacity, primarily: economic, institutional, environmental and policy factors. For example, rural extension initiatives can enhance innovative capacity by providing farmers with the requisite knowledge for innovation. Economic factors, such as exchange rates or interest rates, can also improve or inhibit a farmer's capacity to invest in new technologies by directly impinging on their financial means.

1 A simplified framework of the innovation process at the farm level



However, while innovative capacity is necessary it is not sufficient for innovation adoption to occur. Willingness to innovate also plays an essential role in farm decision-making (Pannell et al. 2006).

Willingness to innovate

A farmer's willingness to innovate also determines their innovation adoption. Willingness relates to a wide range of sociological and psychological factors that can deter (or entice) individual farmers from being innovative or adopting suitable innovations even if they have the capacity to do so. For example, farmers' attitudes to learning and innovation, risk aversion, awareness of innovations, personal goals, values and motivations, and past experiences with innovation adoption can affect whether farmers are willing to innovate.

Like innovative capacity, these sociological or psychological characteristics of farmers can be influenced by farm-level factors (including those of the farmer, their farm and their external operating environment). For example, various demographic (such as age, level of education, family circumstances, attitude to risk, personality) and situational factors (such as farm size, access to credit, participation in off-farm work) can affect farmers' goals and interest in adopting innovations (Marsh 2010; Pannell et al. 2006).

In addition, a farmers' institutional environment can affect the information or incentives they face. Information contributes to the learning process and allows farmers to adjust their perceptions about an innovation to make adoption decisions (Marsh 2010). Incentives can be moral, social or economic and can encourage or discourage farmers to innovate. Financial incentives can be a strong motivator for innovation adoption, although they are not the only consideration.

Supply of innovations

The third factor determining farmers' innovative effort is supply of innovations. Adoption relies on the supply of innovations available that are suitable to the farm and have an observable relative advantage.

Innovation suitability is an important determinant of innovation adoption. While new technologies are expected to be superior to existing technologies, they are unlikely to be well suited to all farms. The suitability of innovations, and hence the benefits of adoption, vary widely according to characteristics of the innovation, the potential adopter and their existing production technology. The incompatibility of an innovation with current farming systems is often highlighted as a reason that farmers do not adopt some innovations (Feder et al. 1985).

The innovations available to the farmer must also have an observable relative advantage to entice adoption. The relative advantage of an innovation relates to its expected benefits in terms of productivity, risk reduction and economic viability. However, farmers also weigh these benefits against other innovation characteristics such as cost, complexity, compatibility and impact on lifestyle. The ability to observe the relative advantage of an innovation, through reliable information, trials or adoption by peers, is important to reducing the complexity and risks associated with innovation adoption (Pannell et al. 2006).

How does innovation adoption by farmers influence productivity? (Stage 2)

The rate and extent of innovation adoption by farmers (their innovative effort) is a core driver of productivity growth. More than any other factor, productivity growth is a reflection of farm-level decisions and the underlying willingness and capacity of farmers to take advantage of technological opportunities. It is only when new technology is used and dispersed widely across a population that any real welfare gains can arise (Stoneman 2002).

The relationship between innovative effort and productivity growth is shown in the second stage of the farm-level innovation process (figure 1). This framework has been applied to firms within the broader economy (Crepon et al. 1998; Wong et al. 2007), and in this example is adapted to agricultural industries.

Farm innovation adoption 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 marketing systems (such as developing a new farm business partnership, increasing on-farm storage capacity or using futures contracts to sell grain). The aggregate of these changes determines changes in productivity and other performance indicators, such as profitability. While farmers are unlikely to innovate without some payoff (including improvements to the environment or to their wellbeing), productivity improvements are not realised unless changes in total farm output exceed changes in total input use (Nossal 2011).

Increasing innovative effort, through adoption of more innovations to a greater extent, would be expected to increase a farm's productivity. However, these benefits are often not direct or immediate. In some cases, several innovations are adopted together, in order to generate productivity improvements. For example, farms might introduce a new disease-tolerant variety and simultaneously adapt soil management practices to suit its growing cycle. In other cases, there may be a short-term fall in productivity as a result of innovation adoption, for example, following a switch to a no-till regime. Such effects can lead to lags between innovation adoption and productivity growth.

While innovative effort is necessary for changes in productivity, productivity can also influence a farmer's innovative effort (figure 1). Improvements in productivity can enhance a farmer's capacity or willingness to innovate, eventuating in greater innovation adoption in the future. For example, highly productive farms might have a greater financial capacity to invest in innovation adoption. These feedback relationships are inherent within the innovation process.

3 Innovation in the grains industry

A broad conceptual framework for considering the process of innovation at the farm level and, in particular, for identifying the range of factors that can influence farmers' innovative effort, and the subsequent impacts on their productivity was proposed in chapter 2. More than any other factor, productivity growth reflects farmers' efforts in adopting innovation, as it is through innovating that farmers can increase outputs or reduce input requirements (Nossal 2011).

In this chapter, the importance of various farm characteristics that can influence grain growers' innovative effort is investigated. A background to farm innovation measurement and its limitations is provided and the nature and extent of innovation adoption undertaken by grain growers during the study period (2006–07 to 2007–08) is analysed. Data on the nature and extent of innovation adoption is used to construct a measure of innovative effort for each grower; this measure will provide a means for comparing innovativeness among grain growers.

Measuring farm innovation

Measurement of innovation in agricultural industries is deficient compared with other industries (box 1). Most studies of agricultural innovation adoption are narrow in scope, using a case study approach and focusing on individual innovations or a small set of innovative activities (D'Emden et al. 2008; Fernandez-Cornejo 2007; Marsh et al. 2000; Pannell et al. 2006). These studies provide insight into specific innovations, yet often cannot be generalised to describe farm innovation behaviour to any great extent. As a result, there is little information on the overall extent of innovation in the agricultural sector and the implications of changes in innovation adoption for productivity and other performance indicators.

The adoption of innovations, in agriculture and other sectors, is measured using survey data. Surveys are typically used to assess farmers' behaviour in adopting innovations and the extent of adoption. This approach, particularly where farmers are required to rank answers, is highly subjective and open to interpretation by respondents (Evangelista et al. 1998; Rogers 2003).

The complex nature of innovation processes, coupled with measurement difficulties, has focused attention on R&D expenditure as an indicator of innovative effort in agriculture. However, other aspects of the innovation process remain necessary to improve productivity, notably the extension of R&D to farmers, and the capacity of farmers to identify, adapt and adopt innovations generated through off-farm R&D (Marsh 2010; Nossal 2011).

This study uses survey data to estimate a 'snapshot' of innovation in the grains industry. The survey was designed using the definitions and methods set out in the Oslo Manual (OECD 2005), but adapted to suit Australian broadacre industries (Liao and Martin 2009). The data provide a broad overview of the innovations adopted by the grains industry and enable a measure of innovative effort to be developed.

box 1 National Innovation Surveys and the agriculture sector

The important role of innovation in driving growth in output and productivity is recognised by economists internationally. However, understanding of innovation processes and their economic impacts is limited. In response, the OECD (1992, 2005) developed a set of standards for collecting and analysing data on innovation and, over the past two decades, there has been an increased effort by Australia and other economies to measure business innovation using this approach. Part of the motivation for the OECD's Oslo Manual, and subsequent innovation surveys, has been to better understand aspects of the innovation process other than R&D (OECD 2005).

However, most surveys of innovation in Australia and overseas have excluded the agriculture sector (as well as the government and services sectors); see for example ABS (2010) and Wong et al. (2007). Consequently, agriculture risks being left behind in the development of initiatives directed at improving innovation under the National Innovation Strategy. Many objectives of the National Innovation Strategy apply equally to the agriculture sector, including ensuring:

– productivity growth is above the average of high income countries
– people and workplaces are equipped with the skills to innovate
– businesses are investing in innovation to secure ongoing competitiveness
– businesses are actively involved in international collaboration (Cutler and Company 2008).

Agriculture has been excluded from National Innovation Surveys because agricultural innovation processes differ from innovation in other sectors; consequently such standard surveys cannot adequately measure agricultural innovation. Specifically:

– agriculture consists of many small firms which are generally too small to undertake significant research internally
– innovation in agriculture is considered to be supplier-dominated with most innovations created through off-farm R&D
– in Australia, funding of research is often by rural R&D corporations which are co-funded by the public and private sector; this differs from other industries where public and private sector research are separated
– many agricultural innovations are sequential and build upon the outcomes of past R&D; business innovation surveys are not well suited to capturing incremental innovation that occurs on and off-farm
– many agricultural innovations are not patentable; for example, new production practices (such as changing rotations or tillage techniques) have large productivity benefits, but cannot be patented by the farm manager. Standard patent-based measures of innovation are therefore less applicable in agriculture.

ABARES farm innovation survey was first conducted in 2008 using the definitions and methods set out by the Oslo Manual, adapted to suit Australian broadacre industries. Data from the survey can be used to monitor trends in farm innovation, evaluate impacts on agricultural productivity and improve the linkages between public R&D and rural industries. Furthermore, the data can allow the sector to develop its own benchmarks for innovation to ensure agriculture does not lag behind the national push to develop the skills and capacity needed for innovation.

Grains industry innovation adoption

Data on the nature and extent of innovation adoption by Australian grain growers was sourced from the farm business innovation survey conducted by ABARES (box 2). The survey covered a wide range of innovation types, namely: new products, changes in production practices (including natural resource management practices), changes in business management and labour use, and changes in marketing, such as forward selling and contracted sales. Farm managers ranked each innovation adopted by the extent of their adoption over the two years ending 2007–08: 'not at all or very little', 'to some extent' and 'to a great extent'.

While the survey is a snapshot at a point in time, it nevertheless points to innovation adoption being a common undertaking for most farmers. During the 2-year study period, the vast majority (90 per cent) of grain growers adopted at least one type of innovation. Of these, 88 per cent had adopted at least one innovation to 'some extent' and 45 per cent adopted at least one innovation to 'a great extent'. Comparatively, around 39 per cent of businesses in the national economy (excluding agriculture) reported implementing an innovation in 2007–08 (ABS 2010).

box 2 ABARES farm business innovation survey

ABARES conducted the farm business innovation survey in 2008 to collect data on the nature and extent of innovation adoption on broadacre farms over the two financial years ending June 2008. Following international standards, innovation adoption 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 (OECD 2005).

Given the vast number of management practices and technologies available to farmers, their adoption behaviour was considered under broad innovation types. For example, farms reporting new soil management practices may have been referring to any within a spectrum of innovations, including new tillage practices, sowing practices or crop rotations. They may also have adopted a number of innovations related to soil management.

The innovation data were collected in conjunction with ABARES annual survey of broadacre farms and can therefore be linked to farm physical and financial performance. A description of ABARES broadacre farm survey is in box 3. ABARES has previously summarised the innovation survey results against measures of farm performance in Liao and Martin (2009).

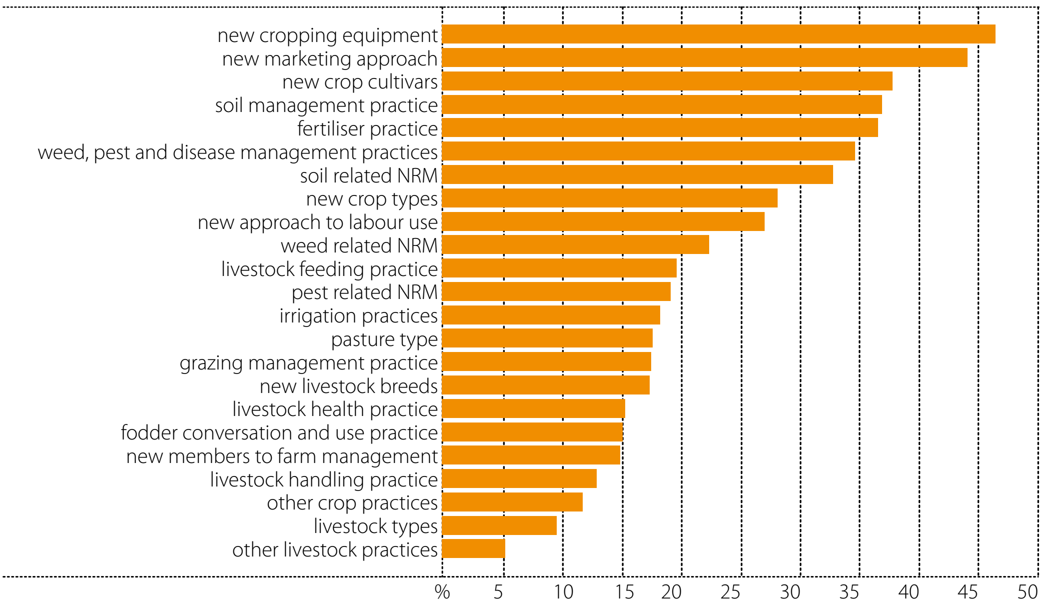
The results presented and used in this analysis are based on the nature and extent of adoption by around 920 Australian grain growers, either specialist cropping or mixed crop–livestock farms.

The most common type of innovation grain growers (47 per cent) reported was new cropping equipment (figure 2). A high Australian exchange rate, particularly in 2007–08, is likely to have contributed to strong demand for imported machinery, including cultivation, planting, fertilising, spraying and harvesting equipment (Liao and Martin 2009).

Many grain growers (44 per cent) also reported adopting new marketing approaches (figure 2). This development may, in part, reflect the increased array of options for marketing grain which have become available in recent years (Liao and Martin 2009). Growers can now sell grain directly to a broader range of traders and end users using a wider variety of payment and delivery options.

The types of innovations adopted varied between specialist cropping and mixed crop–livestock farms, reflecting different farm production systems (table 1). Cropping specialists were more likely than mixed crop–livestock farmers to introduce new crop husbandry practices, including new cultivars (44 per cent to 32 per cent), fertiliser practices (43 per cent to 32 per cent) and weed, pest and disease management practices (41 per cent to 29 per cent). In contrast, mixed crop–livestock farmers were more likely to adopt innovations relating to livestock feeding practices (15 per cent to 23 per cent), livestock breeds (12 per cent to 22 per cent) and pasture types (13 per cent to 22 per cent).

2 Proportion of grain growers adopting innovations, 2006–07 and 2007–08



Note: Includes both specialist cropping and mixed crop–livestock farms. NRM = Natural resource management.

The types of innovations adopted differed markedly between GRDC agro-ecological regions (table 1). In particular:

- farmers in the southern (43 per cent) and western regions (39 per cent) were more likely to have adopted new crop cultivars, compared with those in the northern region (28 per cent)
- farmers in the southern region were more likely to have adopted new weed, pest and disease management practices (40 per cent) compared with those in the western (30 per cent) and northern (31 per cent) regions.
- farmers in the northern (40 per cent) and southern (38 per cent) regions were more likely to have changed soil management practices compared with the western region (26 per cent)
- more than half the farmers in the southern region (51 per cent) had adopted a new marketing approach compared with 36 per cent in the western region and 39 per cent in the northern region.

In part, the variations in innovation adoption between regions reflect differences in farm operating environments, including seasonal, environmental and market conditions. For example, higher adjustment pressures associated with dry conditions that prevailed around the time of the survey are likely to have motivated many of the farms in the northern and southern regions to change soil management and irrigation and water management practices.

1 Proportion of growers adopting innovations, by industry type and region, 2006–07 and 2007–08

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

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

Estimating innovative effort

As outlined in chapter 2, the productivity of grain growers is determined by their innovative effort. This section uses the farm business innovation survey data (described in box 1 and figure 2) to develop a measure of innovative effort for each farm. The measure is then used in chapters 4 and 5 to empirically evaluate innovation processes at the farm level, as described in the conceptual framework.

The measure of innovative effort developed for each farm was based on the number and extent of innovations that each grower had adopted (in the two years to June 2008). Given that nearly all grain growers had adopted at least one innovation, they were grouped into three categories of innovativeness: low innovators, moderate innovators and high innovators. The most innovative farms had adopted at least six innovations to 'some extent' (and up to three innovations to a 'great extent') or at least three innovations to a 'great extent' (table 2).

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

Compared to quantitative data, responses, and consequently rankings, are likely to be subjectively influenced by growers' perceptions (Evangelista et al. 1998; Rogers 2003). Were they available, data on the expenditure associated with innovation adoption might provide a more accurate indicator of innovative effort.

Also, the measure may not be stable over time. While it provides a 'snapshot' of innovative effort in the grains industry, this is likely to vary from year-to-year. As additional data become available, further refinements to the measure may be warranted.

Nevertheless, this method produces a robust measure of innovative effort insofar as it was based on a wide range of innovations, rather than individual technologies or practices. This provides a useful basis for empirical analysis of the underlying factors that might contribute to a grower's innovative capacity or willingness to innovate (as in Stage 1 of the suggested framework of innovation at the farm-level).

3 Distribution of grains farms by innovation ranking

	frequency	percent
Low	419	45
Moderate	273	30
High	228	25
Total	920	100

Under the selected categories: 45 per cent of farms were classified as low innovators, 30 per cent as moderate innovators and 25 per cent as high innovators (table 3). The skewed distribution suggests significant potential for average growers to become more innovative. Improving innovative effort could require an increase in growers' capacity and/or willingness to innovate, but could also reflect a lack of 'suitable' innovations that have an observable relative advantage and that are available for farmers to adopt.

4 Estimating the role of innovative capacity

The framework developed in chapter 2 outlined two farm-level determinants of innovative effort: innovative capacity and willingness to innovate. (The supply of suitable innovations is also relevant, but mostly relies on off-farm processes). This chapter focuses on grain growers' innovative capacity. Compared to 'willingness', innovative capacity is more easily measured using farm survey data and is relevant to stakeholders seeking to improve the capabilities necessary for ongoing innovation among grain growers. The farm-level factors likely to influence innovative capacity among growers are assessed, and the effect of these factors on innovative effort is empirically evaluated.

Factors that determine innovative capacity

The capacity of farm businesses to innovate is a key factor influencing innovation adoption. Characteristics such as a farm operator's age, education and experience, as well as the profitability of the farm business, are widely considered to positively affect innovative capacity. Some characteristics of the farm operating environment can also have an effect.

The factors discussed below were selected for analysis based on their standing in the literature and data availability. These farm-level factors can constrain or enhance the capacity of farms to adopt innovations.

Characteristics of the farm and the farm manager

- **Education** – Higher levels of education attainment are expected to positively influence innovativeness. Education increases knowledge, decision-making skills and the ability to apply information effectively in new situations (Abadi Ghadim et al. 2005). Therefore, education is fundamental to building human capital to allow farmers to take advantage of new technologies and practices.
- **Age** – Similarly, age is expected to increase experience and build human capital, with positive implications for innovation adoption. However, the positive impacts of age may weaken as farmers grow older. Some older farmers may have a shorter planning horizon (time to retirement) and hence may be less inclined to risk change. In contrast, younger farmers are often more willing to take risks and invest in new ideas. Existing research has found mixed results about the impact of age on farmer decision-making (Guerin and Guerin 1994; Pannell et al. 2006). In this study, innovation was measured using a quadratic relationship, presupposing that innovativeness first increases and then falls with age.
- **Profits** – Higher profits are expected to enhance financial capacity to invest in new technologies and practices, to the extent that profitable farms have more financial assets available for innovation, and greater access to credit.

- **Farm size** – Larger farm businesses are expected to be more innovative (Pannell et al. 2006). Larger farms typically have more resources available for innovation (including human, financial, social, natural resource and physical capital) and more opportunities to profitably innovate (Schumpeter 1943). In addition, farms with higher output can often lever larger overall benefits from adopting innovations. In particular, larger farms are better suited to adopting innovations with large fixed transaction or information costs (Fernandez-Cornejo 2007). In this study, farm size is measured in terms of aggregate output, expressed in dry sheep equivalents (DSE). DSE is a standard unit for measuring the carrying capacity or operating size of a farm. This study follows convention and assumes beef cattle to be equivalent to 8 DSE and a hectare of cropped land to be 12 DSE.
- **Land use intensity** – For similar reasons, farms with more intensive businesses are expected to be more innovative. Land use intensity is measured as output (in DSE) per hectare.
- **Labour availability** – Farms with a larger supply of labour (measured as the total weeks worked by family and non-family labour) are more likely to adopt innovations (Diederen et al. 2003b) insofar as they can allocate sufficient time to implement new technologies and management practices (Prokopy et al. 2008). In addition, there is greater labour specialisation on larger farms, including labour allocated to long-term business development and technological change (Diederen et al. 2003b).
- **Off-farm income** – The hypothesis in this study is that farms with greater access to off-farm income are more likely to be innovative. Off-farm income supplements on-farm income to improve financial capital and hence innovative capacity, especially among smaller farms, despite scale disadvantages. While Zhao et al. (2009) found off-farm income to be associated with lower productivity growth in the grains industry in Australia, analysis of the US agriculture sector found off-farm income to be associated with significantly higher adoption of management-saving technologies, (for example, herbicide-tolerant crops and conservation tillage) (Fernandez-Cornejo 2007).
- **Contract services** – Use of contract services is expected to positively relate to innovativeness. Past studies suggest that farm managers often innovate in response to ideas from others (Sunding and Zilberman 2001). In this study, use of contract services serves as proxy for formal networks and information-sharing. Contract services include consultant agronomists and agricultural contractors (such as harvesting and spraying contractors). Informal networks, including relationships with farm groups or members of the local community, could also be useful indicators of social networking and exposure to innovative opportunities (Pannell et al. 2006), but have not been included in this analysis due to data limitations.

Various other characteristics are also likely to influence farmers' willingness to innovate, but were not included here because of lack of data availability. These include attitudes to learning and innovation, risk aversion, awareness of innovations, personal goals and motivations, innovations adopted in the past, and the technologies currently in use. For example, attitudes and awareness can influence farm managers' perceptions of innovations and their likely benefits. The nature of existing technologies is also likely to affect the usefulness and compatibility of new technologies being considered (Rogers 2003). Data on these factors have not been collected, but would make useful additions to future surveys of farm business innovation, where measureable.

Characteristics of the operating environment

Characteristics of the operating environment that influence innovativeness are often shared by groups of farms (Diederen et al. 2003b). For example, farms belonging to a particular industry, market, region or state face common factors that can influence innovative effort, such as market access constraints, consumer preferences, technology availability, regional infrastructure, property rights and agro-climatic conditions.

In this study, two variables were used as proxy measures to capture the influence of characteristics that might be common among some groups of farms:

- **Industry** – Farms were grouped according to enterprise mix to determine the relative innovativeness of specialist cropping and mixed crop–livestock farms. These groups operate different farming systems and face differences in market and regulatory conditions that may influence their innovative capacity. The nature and extent of opportunities to improve productivity are also likely to differ significantly between these two industry groups.
- **Region** – Location is also likely to influence innovative effort among growers. Farms in different agro-ecological regions are likely to face different operating circumstances, particularly in terms of climate. In this study, innovative effort was analysed by the northern, southern and western agro-ecological regions, as defined by the GRDC. The northern region is subtropical and summer rainfall dominant. The southern region is temperate with uniform to winter-dominant rainfall. The western region is characterised by a Mediterranean climate with strong winter rainfall dominance (GRDC 2008).

box 3 ABARES broadacre farm survey data: physical and financial characteristics

ABARES collects production, financial and socioeconomic data from farm businesses annually as part of its broadacre farm survey program. The survey design is a stratified random sample that is representative of Australian broadacre agriculture (including dryland cropping, mixed crop–livestock, beef, sheep and beef–sheep industries). Broadacre farms account for around 62 per cent of Australian agriculture (in terms of gross value of production).

The sample closely reflects the operation of commercial enterprises because small farms are excluded from the survey. These small farms account for less than 2 per cent of the gross value of agricultural production.

This study used data from the 2007–08 broadacre industry survey. The sample was restricted to grain growers (specialist cropping plus mixed crop–livestock farms) and excluded farms with incomplete information to yield a final sample of 920 farms.

How do these factors influence farmers' innovative effort? An ordered probit model

A discrete choice model was used to test the likelihood that a particular farm would be a low, moderate or high innovator, according to its individual characteristics and operating environment (box 4).

A combination of continuous and dummy variables was selected based on data available through ABARES farm surveys and factors found to be significant determinants of innovativeness in the literature, as discussed in the previous section (table 4). Labour (measured in total weeks worked), farm size and land use intensity (output per unit area) were included as continuous variables. Age and age squared were included to account for the potential quadratic relationship between age and innovation (whereby age initially contributes to increased and then decreased innovative effort). The remaining variables (education, profit, off-farm income, use of contract services, industry and region) were included as dummy variables to represent different sub-groups of growers and to ease interpretation.

box 4 Model selection for empirical estimation

The probit model is the preferred empirical model that relates innovation adoption behaviour to variability in influencing factors. Several agricultural adoption studies (Breustedt and Glauben 2007; Diederen et al. 2003a; Fernandez-Cornejo 2007) have used this model and its variants.

In this study, an ordered probit model specification was chosen to cater for three categories of innovativeness. Although the categories are inherently ordered (low, moderate or high), the distances between adjacent categories are unknown.

The ordered probit model is used to indicate the likelihood of a farm being a high, moderate or low innovator based on its characteristics. That is, the impact of certain explanatory variables on a farmer's propensity to adopt more or less innovations (higher/lower innovative effort) is estimated.

Appendix 1 contains technical details on the estimation methodology and results from the analysis.

The estimated influence of various farm characteristics on innovative effort largely conformed to expectations, with positive coefficients indicating greater innovativeness. Increases in education, labour availability, farm size, land use intensity, use of contract services and off-farm income were associated with more innovative farmers. Age had a varying effect on innovativeness, with increasing age initially leading to a rise in innovativeness, but then to a flattening. However, contrary to expectations, higher profits were seemingly associated with less innovative farmers, a result discussed in more detail below. The full estimation results are in appendix 1.

The marginal effects between the three innovator categories were also estimated to better understand how changes in various characteristics influence innovative effort (table 5). The marginal effects reflect the expected change in the probability of each outcome (high, moderate or low innovator) in response to a small (unit) change in the value of a particular characteristic, while keeping all other variables constant (at their means). For logged variables (labour, farm size, land use intensity), the marginal effect is the expected change in probability from a 1 per cent change in that variable, while for dummy variables it is the expected change in probability from a shift from 0 to 1. For example, university education is expected to increase the probability of high or moderate innovative effort by 29 per cent and 5 per cent respectively, and reduce the probability of low innovation by 34 per cent, relative to a farmer with no or primary school education. All marginal effects had the expected sign.

4 Variables selected for the ordered probit analysis

variable	explanation	mean/value (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 (1,0); including:	
	– Primary **d**	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 **a**	18 867 (22 724)
Land use intensity **b**	Farm size (DSE) divided by area operated	7.46 (2.98)
Profit **c**	Dummy (5 percentile categories, with the lowest 20% as the base case), total farm profit	20%
Contract	Dummy (1,0); 1 if farm uses contract services	79%
Off-farm income	Dummy (1,0); 1 if farm has other income sources	38%
Operating environment (market and environmental conditions)		
Industry	Dummy variables (1,0); including:	
	– Cropping (if major activity is cropping)	47%
	– Mixed crop–livestock (if major in both crop and livestock) **d**	53%
Region	Dummy variables (1,0); including:	
	– Southern **d**	56%
	– Northern	20%
	– Western	18%
	– No region	6%

a 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. **b** Natural logarithms for labour, farm size and land use 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** Farm business profit: farm cash income + changes in trading stocks – depreciation – imputed labour costs. **d** Base case.

The results reveal a number of factors relevant to a grower's innovative capacity, particularly education. Increasing education through university studies increases the probability of being a high innovator by almost twice as much as high school education (28 per cent compared with a 16 per cent increase), when compared to a grower with only primary school education. This implies that knowledge acquired through education has a strong influence on grain growers' capacity to research and integrate new technologies and management practices into farming systems. Age, which can also be a measure of knowledge and farming experience, increased the likelihood of high innovative effort by 0.7 per cent for every additional year, although this gain in innovativeness diminished past a certain age.

Labour availability, farm size and land use intensity all contributed to an increased probability of innovation adoption among grain growers. These variables are all indicative of the scale of farming operations, with larger farms typically having more labour available and greater output. Broadly speaking, the marginal effects for these variables suggest that farm scale increases the likelihood that a farm will be a high innovator and reduces the likelihood it will be a low innovator. These results are consistent with other studies of innovativeness in agriculture and other industries (Diederen et al. 2003b; Liao and Martin 2009; Schumpeter 1942).

Larger farms can appear more innovative for a variety of reasons. From a financial perspective, larger farms can be expected to have greater access to financial resources with which to invest in innovation and, in turn, to manage the associated risks. In addition, they are more likely to have access to a larger workforce, often with specialised skills and an intimate knowledge of the farm, that is better placed to implement (or suggest) long-term business development opportunities. Further, innovation activities are also likely to be more profitable for larger enterprises, particularly where there are large fixed costs associated with innovating (Feder 1980).

5 Change in the probability of high, moderate and low innovative effort

	high innovator	moderate innovator	low innovator
	%	%	%
Age	0.7	0.4	–1.0
Age squared	0.0	0.0	0.0
Education			
High school	16.2	11.8	–28.0
TAFE	20.4	5.1	–25.6
University	28.7	5.1	–33.8
Labour availability (log)	5.5	3.1	–8.6
Farm size (log)	4.2	2.3	–6.6
Land use intensity (log)	5.5	3.0	–8.5
Profit			
Lower middle (20–40%)	–7.2	–4.7	11.9
Middle (40–60%)	–7.3	–4.6	11.9
Upper middle (60–80%)	–8.1	–5.6	13.7
Highest (top 20%)	–8.8	–6.6	15.4
Contract	3.2	1.9	–5.1
Off-farm income	3.6	1.9	–5.5
Industry			
Cropping	–0.6	–0.3	0.9
Region			
Northern	3.4	1.7	–5.0
Western	–6.4	–4.3	10.7

Note interpretation: For age, the results suggest the expected change in probability resulting from an additional year of age, holding all other variables constant. For logged variables (labour, farm size, land use intensity), the results suggest the expected change in probability resulting from a 1 per cent change in that variable, holding all others constant. For education, profit, contract, off-farm income, industry and region, the results are the expected change in probability relative to the base case (that is, the change resulting from a shift in the dummy variable from 0 to 1).

Higher farm profits were associated with lower innovative effort, although the marginal effects between innovation categories were minimal. At first glance, this result could seem counterintuitive. However, while the expected benefits from innovating accrue in the longer term, the associated investment costs are likely to reduce short-term profits. While not possible in this study, including lagged farm cash income in the model might produce a better indicator of capacity to invest in new technologies.

Off-farm income had a positive influence on innovation adoption. This lends weight to the hypothesis that additional income, or income sources, enhance adoptive capacity by improving financial capacity or, as suggested earlier, in responding to an increasing opportunity cost of labour. That is, innovation adoption can often lead to labour being freed-up for higher value uses either on or off-farm.

Grain growers using contract services were more likely to innovate. Although farms were not differentiated by the type of services engaged, greater access to information through some contracted services (such as consultancy or extension services) would be expected to lead to increased innovation. In addition, outsourcing activities that were once considered standard on some grain farms (such as sowing and spraying) has helped disseminate latest technologies and possibly freed capacity for farmers to innovate in other areas.

The innovativeness of grain growers was found to vary among the three GRDC agro-ecological regions. Relative to the 'reference' southern region, growers in the northern region were more likely to be high innovators whereas those in the western region were less likely. Possible reasons for these differences include:

- Western growers may face relatively fewer occasions for innovation because homogenous cropping systems are more widespread.
- Below average farm cash incomes among western growers in the study period may have contributed to reduced innovative effort.
- The northern and southern region may have responded to relatively greater incentives for innovation due to seasonal pressures during the survey period.

Comparing innovation adoption across a number of periods is likely to yield greater insights about these hypotheses.

There were no significant differences in the innovative effort observed between specialist cropping and mixed crop–livestock farms. This result suggests that other factors have a substantially greater influence on innovation adoption decisions than whether income is earned from multiple enterprises or whether these additional enterprises offer greater scope for innovation.

Discussion

The analysis in this section evaluated the importance of various characteristics in explaining the innovative efforts of grain growers, through a comparison of low, moderate and high innovators.

The key finding from this part of the analysis was the importance of human capital and, in particular, tertiary education, in explaining innovation adoption behaviour. Education had a substantial effect on the number and extent of innovations adopted by grain growers. It is likely that skills, training and education will become increasingly important to agriculture against a backdrop of a tightening labour market, increasingly sophisticated farm technologies and the emerging importance of integrated management practices, including those related to managing weeds, diseases and pests.

The results are robust to the extent they are statistically significant and consistent with previous ABARES research into the relationships between farm characteristics and innovation (Jackson 2010; Knopke et al. 2000). For example, during workshops on grain industry productivity, grain growers indicated that farms with a larger capital base are often better placed to finance new innovations (Jackson 2010). Moreover, despite the survey period (2006–07 and 2007–08) being characterised by below average seasonal conditions and reduced crop outputs (particularly in the northern and southern regions) (ABARE 2009), it is expected that the importance of education in explaining innovation adoption would remain under more favourable seasonal conditions.

Nevertheless, this analysis revealed several areas that would benefit from further research:

- The effects of poor seasonal conditions or other unexpected events on farm innovative effort are not well understood and are likely to differ among innovation types. Some farms may defer adoption decisions in periods of financial uncertainty (such as large machinery investments), while others may face additional incentives to innovate in order to adapt to emerging pressures (such as innovations to improve water conservation or reduce input costs).
- While the factors selected for analysis are similar to those in past analyses of innovation adoption, there is a wider set of variables that are also likely to affect innovative effort, but are more difficult to measure. For example, a farmer's attitude to risk and uncertainty is likely to have a substantial influence over their willingness to innovate (Abadi Ghadim and Pannell 1999). Although the extent of omitted variable bias present in this analysis is unknown, the findings are, nevertheless, broadly consistent with past analyses elsewhere (Diederen et al. 2003b; Guerin and Guerin 1994; Prokopy et al. 2008). Further research into the influence of risk and uncertainty in innovation adoption decisions is likely to be important given the susceptibility of the grains industry to changes in climate, pests, diseases, water and labour availability as well as global economic conditions.
- Innovative effort could vary over time in response to changes in innovation availability or suitability (Pannell et al. 2006). It is possible that low levels of innovativeness reflect inherent farm characteristics, but also indicate a shortage of additional productivity-enhancing innovations suitable for the farm to adopt. Innovation data collected over a number of years would enable more reliable estimates of the determinants of innovativeness.

5 Farm innovation and productivity

Following the empirical estimation of the determinants of innovation among grain growers, this chapter provides a preliminary analysis of Stage 2 of the innovation framework – 'how does innovation adoption influence productivity?' As outlined in chapter 3, innovation among grain growers, through adoption of new technologies and management practices, is fundamental to improving productivity over time. The contribution of innovation to the productivity level of grain growers is evaluated in this chapter.

How does innovation adoption by farmers influence their productivity?

A cross-sectional, log-linear regression model was used to test the influence of innovative effort on total factor productivity. For the purposes of this study, the measure of total factor productivity for each farm related to 2007–08 while the three measures of innovative effort (measured as high, moderate or low innovation adoption) related to aggregate innovation adoption between 2006–07 and 2007–08. Appendix 2 contains details on the data sources and methodology used in this chapter.

While innovative effort is the main factor of interest, other farm-specific factors were included in the regression model due to their previously identified influence on productivity growth among grain growers (see, for example Kokic et al. 2006; Zhao et al. 2009). These factors were age, education, crop-specialisation, off-farm income, profit, agro-ecological region and land use intensity (appendix 2).

A significant positive relationship was found between innovativeness and farm productivity among grain growers (table 6). The results suggest that farms with greater innovative effort (in terms of both the number of innovations and their extent of adoption) are likely to exhibit higher productivity, as suggested in the conceptual framework. Compared to a farm with low innovative effort, high innovative effort increases productivity by 3.4 per cent, all other factors constant.

However, the significance of other explanatory variables suggests that productivity relies on factors beyond innovative effort. Education, land-use intensity and profitability were all strongly associated with higher farm-level productivity. For example, a 10 per cent increase in land use intensity is likely to improve productivity by 3.2 per cent on average. Furthermore, a grower with university education exhibited average productivity 36.6 per cent higher than growers with little education (no formal education or primary schooling only). Even after controlling for age, all formal education contributed substantially to grower productivity relative to those growers without education beyond primary school.

6 Effect of innovation on farm productivity

variable	coefficient sign
High innovator	+
Moderate innovator	+
Age	–
Age squared	+
Education	
High school	+
TAFE	+
University	+
Crop specialisation	+
Land use intensity (log)	+
Profit	
Lower middle (20–40%)	+
Middle (40–60%)	+
Upper middle (60–80%)	+
Highest (top 20%)	+
Contract	+
Off-farm income	–
Region	
Northern region	+
Western region	+
Intercept	–

Notes: All coefficients are significant at the 1 per cent level.
R2 = 0.68

These factors highlight the contribution of innovative capacity, not only to innovation adoption, but also to growers' ability to effectively integrate innovations into farming systems. As discussed in chapter 5, innovative capacity also depends on various factors included in the regression model, including education, land use intensity and profitability. Education, along with other aspects of human capital, is vital in developing the knowledge and skills needed for effective innovation. Profitability improves a farm's ability to invest in innovation and could improve the effectiveness of innovation adoption where finance assists in attaining the information needed to effectively integrate new innovations. Profitable farms could also achieve higher productivity through the types of innovations they are adopting.

Discussion

The second stage analysis presented in this chapter suggests innovation adoption is a significant driver of farm productivity growth. That is, farms that adopt more innovations, to a greater extent, are likely to exhibit higher productivity relative to their peers.

In addition, farmers with a greater ability to effectively integrate innovations into farming systems—measured using farm-level indicators of innovative capacity—are also more productive, on average.

Several relevant implications emerge from these results, particularly with regard to the role of innovative capacity as a driver of productivity growth. While grain growers are highly innovative (and vast majority undertook some innovative activity during the survey period), considerable variability remains in the level of productivity growers achieved. The results imply that increasing the extent of innovation adoption and the ability of farmers to effectively integrate innovations into production systems are critical for improving productivity at the farm level.

While the results are empirically robust (R2 = 68 per cent), they may underestimate the importance of innovativeness for farm performance because of constraints to both the analytical approach and the underlying data:

- Cause and effect relationships are inherently difficult to capture in cross-sectional analysis. In theory, innovation drives productivity performance, but causality may be bidirectional given that farms with higher productivity could be in a better position to innovate. Further data would be required to understand the extent to which higher productivity increases innovative effort.
- Innovation adoption is expected to have substantial long-run impacts on productivity and it is less likely that innovation will have a large influence on productivity levels within the one-year period considered. Invariably there are lags between adopting an innovation and its impact on farm performance. The adoption of some innovations may even lead to a short-term fall in productivity given the input costs often associated with introducing new technologies and changing farm production systems. The use of panel data, if available, would better capture the nature of the relationship between innovative effort and farm performance over time.
- Measured productivity growth captures other external impacts not directly related to the ability of the farm to convert inputs into outputs. The most obvious of these is seasonal conditions which can cause estimated productivity levels to fluctuate significantly from year to year (Gray et al. 2011). The impact of innovation adoption on productivity could be underestimated in this study as seasonal effects have not been netted out.
- Lack of data on innovation expenditure limits the explanatory power of the innovative effort measure. Expenditure data are typically used to measure innovation effort or intensity. The ABS collects these data for other market sector industries, yet excludes agriculture (Wong et al. 2007). Data on innovation expenditure would substantially improve analyses of farm innovation and productivity. For example, innovation expenditure data could provide a basis for comparison between major and minor innovative changes (where major innovations are expected to contribute significantly more to productivity) (Stoneman 2002). In this study, aggregating innovations with different benefits and costs may lead to an overestimate or underestimate of the impact of innovation on productivity growth (Diederen et al. 2003a).

6 Conclusions

Two research objectives motivated this study: to analyse the effect of various farm-level factors on innovation adoption by grain growers; and, in turn, to evaluate the relationship between innovation adoption and growers' productivity. A conceptual framework was developed to analyse these links, the range of factors that could potentially influence them and their role in the innovation system more broadly. Then, empirical methods were used to apply the framework to Australian grain growers to better understand the processes through which innovation drives grower productivity.

The results indicate that various farm-specific factors can contribute significantly to the number of innovations adopted and the extent of their adoption, given a supply of innovations 'on-the-shelf'. Specifically, higher innovative effort is more likely among grain growers with higher education, greater labour availability, larger farm sizes and more intense land use, that is, growers with higher innovative capacity.

While innovative effort promotes productivity, innovative capacity is key to maximising productivity payoffs to any given level of innovative effort. This is because farmers with a higher innovative capacity are more often better decision-makers with a greater ability to source and use innovations to greater effect. In this regard, components of innovative capacity, in particular education, land use intensity and profits, were identified as important determinants of productivity among grain growers.

Policy implications

Several policy areas have a direct bearing on the innovative capacity of farmers. These include policies that affect the quality of human capital (including education, skills and research extension policies), and policies specific to the agriculture sector (including access to natural resources and business support measures).

A number of training issues limit the supply of skilled labour in rural industries, including low participation in vocational education and training (VET) and tertiary courses. Although other factors also play a role, such as competition from other industries, declining rural populations and poor perceptions of agriculture as a career path (DAFF 2009), further collaboration between government and industry may help meet the sector's diverse education and training needs. For example, the Regional AgriFood Skills and Workforce Development Strategy (currently being developed by AgriFood Skills Australia and the Department of Education, Employment and Workplace Relations) is one recent initiative aimed at taking a coordinated approach to agricultural education policy, funding, design and delivery.

Further investment in education and training should be supplemented by improving farmer access to new information and technologies (Nossal and Gooday 2009). Public and private extension services remain important to dispersing information to farmers. Improving the efficiency of these services is likely to improve innovative capacity and, in turn, productivity. However, such initiatives should recognise diversity within the industry in terms of farming landscapes, production systems and managerial approaches. For example, the Regional Development and Extension Networks proposed by the GRDC is one initiative designed to expand expertise and innovativeness at the regional level through partnerships between grower groups, agribusinesses and consultants (PISC 2011).

Broader agricultural policies targeted toward other objectives can also pose a disincentive to innovation adoption or constrain innovative capacity among some growers. Two notable examples are native vegetation and drought assistance policies.

- Native vegetation policies can constrain innovative capacity to the extent that they limit farmers' ability to increase land use intensity or spatially adjust their activities to improve efficiency. They may also constrain adoption of productivity-enhancing innovations for some growers. In contrast, more flexible policy approaches—for example, market-based instruments (such as environmental auctions and biodiversity tenders) may provide a given level of ecosystem services at lower cost.
- Business support provided through drought assistance programs can be a disincentive for some growers to pursue opportunities for innovation, particularly those that allow farmers to better cope with climate variability. As an alternative, policies that focus on self-reliance and risk management can improve incentives for growers to develop innovative capacity.

A wide range of policy settings within the broader economy can also influence innovative capacity. For example, ongoing microeconomic reform in areas such as education, financial markets, labour and skills and competition policy can all serve to improve the innovative capacity of individual growers.

Further research

This study has contributed to increased understanding of the characteristics that build innovative capacity among grain growers, and the relevance of these factors for increasing the extent and effectiveness of innovation, with a view to improving productivity. However, further research in this area would assist policy makers in prioritising initiatives directed at improving productivity growth.

A more precise measure of grain growers' innovative effort could be achieved by collecting expenditure data for innovative activities. These data, combined with existing data on the number and extent of innovative activities, would allow researchers to more accurately identify innovations that are likely to deliver relatively higher productivity gains.

In addition, if time series data were available, developing a dynamic model would better capture lagged relationships between innovative effort and productivity. ABARES capacity to investigate long run relationships between R&D, innovation and productivity will be significantly constrained if a lack of time series data limits future research in this area. Consideration should therefore be given to establishing a regular survey of a known panel of growers with provision to handle inevitable respondent attrition.

There are also likely to be benefits from research into other farm-level drivers of innovation and productivity (as outlined in the framework in chapter 2), including:

- the determinants of farmers' willingness to innovate (including motivations, attitudes and approach to risk management)
- the effectiveness of the R&D system in supplying innovations suitable to the diverse growers comprising Australia's grain industry.

Research into these areas could build a greater understanding of how different groups of farmers approach innovation and improve the effectiveness of R&D in delivering productivity gains.

For example, ABARES data on the factors that motivate grower innovation adoption decisions could be analysed across a range of innovative activities. The research could evaluate the relevance of financial, personal and environmental factors to growers' willingness to innovate. It could also evaluate whether motivations are common across innovations or across groups of growers (such as those with higher capacity to innovate). Further, the impact of motivations on the productivity achieved by growers could be analysed and the findings used to identify opportunities for increasing productivity through improved design and targeting of extension.

Research into the supply of innovations, and specifically, whether these innovations offer the level of productivity growth needed to maintain profitability and competitiveness could be evaluated. While innovations are increasingly targeted toward grower demands, innovation adoption has not been sufficient to maintain productivity growth in recent years. Also, there have been suggestions that the productivity gains from innovations have not been as large as those offered previously. The source of innovations used by Australian growers, the costs associated with adoption (including costs of adapting the technology or gaining skills to effectively implement the technology), and the expected productivity impacts of adoption could be evaluated. A potential mismatch between the innovations supplied and those demanded by the sector could be investigated with a view to improving research, development and extension.

appendix

A Ordered probit model

This appendix describes the statistical model used in chapter 4 to evaluate the importance of various factors likely to influence innovativeness among grain growers.

Model selection and estimation

An ordered probit model was used to evaluate factors likely to influence farm innovation adoption behaviour. The dependent variable was based on farmers' rankings as low, moderate or high innovators (as determined by their innovative effort measured in chapter 3).

In the ordered probit model, Y_i is a proxy for the unobserved continuous variable Y_i*, where Y_i* in this study is innovative effort. The unobserved outcomes $Y*$ can be modelled as:

$$Y*_i = B'X_i + e_i$$

where X_i is the vector of explanatory variables and e_i is the error term with standard normal distribution.

Each farm's innovative effort depends on both observed and unobservable factors. The observed variables (table 4) were identified and were 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).

Given three ordinal categories, the relationship between the observed categories of Y_i and the values of Y_i* was specified as:

$$Y_i = 0 \text{ if } Y_i* \leq u_1,$$

$$Y_i = 1 \text{ if } u_1 < Y_i* \leq u_2$$

$$Y_i = 2 \text{ if } u_2 \leq Y_i*$$

where u_1 and u_2 are the unobservable threshold parameters that were estimated with the other parameters in the model. The likelihood that the ordered variable Y takes each specific value (0, 1, 2) is given by:

$$Prob\ (Y = 0) = P(\ Y^{*} \leq u_1\ ) = P(`B'X + e_i) \leq u_1 = \text{Ø}\ (u_1 - B'X)$$

$$Prob\ (Y = 1) = ø(u_2 - B'X) - ø(u_1 - B'X)$$

$$Prob\ (Y = 2) = 1 - ø(u_2 - B'X)$$

where $ø$ is a cumulative standard normal distribution such that the sum of the probabilities equals one. The results were estimated using STATA.

The ordered probit results are presented in table 7. The model was found to be statistically significant at the 1 per cent level based on a likelihood ratio test. Given the inherent difficulties with interpretation of coefficients (Greene 2003), the marginal effects were also estimated (table 8; summarised in table 5). These are the marginal effects of a one unit change of a variable on the probability of being a low $(Y = 0)$, moderate $(Y = 1)$ or high $(Y = 2)$ innovator, all other variables held at their mean. For dummy (binary) variables, the marginal effect is the difference in the probability of the farm being a low, moderate or high innovator. For example, a farmer with university education is 29 per cent more likely to be a high innovator than a farmer with only primary education (or no formal education) (table 8).

7 Ordered probit results

exogenous variable	coefficient	standard error	z statistic	prob>|z|
Age	0.026	0.006	4.770	0.000
Age squared	0.000	0.000	–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	2 254.02			
Pseudo R2	0.0547			
LR test	Chi2 (17)	= 2254.02	Pr > Chi2	= 0.000

Notes: Base comparison is a farmer 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 (see appendix 1 for further discussion). As a result, the weighted sample size increases from 920 to 20 544.

8 Marginal effects

	high innovator	standard error	moderate innovator	standard error	low innovator	standard error
Age	0.007	0.00	0.004	0.00	–0.010	0.00
Age squared	0.000	0.00	0.000	0.00	0.000	0.00
Education						
High school	0.162	0.01	0.118	0.01	–0.280	0.03
TAFE	0.204	0.03	0.051	0.00	–0.256	0.03
University	0.287	0.03	0.051	0.00	–0.338	0.03
Labour availability (log)	0.055	0.01	0.031	0.00	–0.086	0.01
Farm size (log)	0.042	0.00	0.023	0.00	–0.066	0.00
Land use intensity (log)	0.055	0.00	0.030	0.00	–0.085	0.01
Profit						
Lower middle (20–40%)	–0.072	0.01	–0.047	0.01	0.119	0.01
Middle (40–60%)	–0.073	0.01	–0.046	0.00	0.119	0.01
Upper middle (60–80%)	–0.081	0.01	–0.056	0.01	0.137	0.01
Highest (top 20%)	–0.088	0.01	–0.066	0.01	0.154	0.01
Contract	0.032	0.00	0.019	0.00	–0.051	0.01
Off-farm income	0.036	0.00	0.019	0.00	–0.055	0.01
Industry						
Cropping	–0.006	0.00	–0.003	0.00	0.009	0.01
Region						
Northern	0.034	0.01	0.017	0.00	–0.050	0.01
Western	–0.064	0.01	–0.043	0.00	0.107	0.01

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

appendix

B Regression analysis

This appendix discusses the method used in chapter 5 to estimate the influence of innovative effort and other farm-level factors on productivity.

Construction of the total factor productivity index

Total factor productivity is the conventional measure of on-farm productivity used by many research agencies, including ABARES. It is calculated as the ratio of the quantity of all market outputs to the quantity of all market inputs. Price indexes were used as weights to aggregate diverse inputs and outputs.

Total factor productivity indexes were calculated for each farm using the Fisher ideal quantity index (Q^F), which is the geometric mean of the Laspeyres (Q^L) and Paasche (Q^P) indexes:

$$Q_{st}^F = \sqrt{Q_{st}^L Q_{st}^P}$$

where

$$Q_{st}^L = \frac{\sum_{i=1}^N p_{is} q_{it}}{\sum_{i=1}^N p_{is} q_{is}} \qquad \text{and} \qquad Q_{st}^P = \frac{\sum_{i=1}^N p_{it} q_{it}}{\sum_{i=1}^N p_{it} q_{is}}$$

and where i, $1 \leq i \leq N$, represents the input (output) used (produced) on the farm, N is the total number of inputs (outputs), p_{it} is the price for input (output) i for farm t, q_{it} is the quantity used (produced) of i and the subscript s denotes the base or reference farm.

To ensure consistency between farms, a transitivity transformation is applied. Transitivity ensures that any transformation applied from farm A to farm B and from farm B to farm C, is equivalent to applying the same transformation from farm A to farm C. This means the total factor productivity between any two farms can be compared to each other by simply dividing their respective index numbers. The EKS transformation applied to ensure transitivity of the Fisher index is:

$$Q_{st}^{EKS} = \left(\prod_{r=1}^{N} Q_{sr}^F Q_{rt}^F\right)^{\frac{1}{N}}$$

where N is the number of farms and Q_{it}^{EKS} is the transitive Fisher index between farms s and t. A full explanation of ABARES productivity estimation approach is found in Gray et al. (2011).

Data used to estimate total factor productivity

ABARES uses data from its annual farm surveys program to estimate total factor productivity. There are 12 output types, which can be aggregated into four major groups: crops, livestock sales, wool and other farm income. Input data are also split into four categories: land, labour, capital and materials and services. A complete summary of the data used to estimate the productivity of individual grain growers is found in Gray et al. (2011).

Model selection and estimation

The model used to determine the significance of innovation adoption in influencing total factor productivity was:

$$\ln(TFP) = \mu + \sum_i \alpha \ln X_i + \beta \mathrm{I}_i + \varepsilon_i$$

where μ is a constant incorporating all unexplained factors shared between individual farms, X_i represents the set of farm-level factors that are likely to influence total factor productivity, I_i represents the innovation ranking for a farm, and ε_i is a random disturbance term incorporating all unexplained differences between farms.

Variables considered to be significant determinants of productivity from earlier ABARES research, along with innovative effort, were included in the productivity regression model (table 9) (Kokic et al. 2006; Zhao et al. 2009). Farm size and labour were not included as these variables are captured in the measure of total factor productivity (the dependent variable). Crop specialisation was included to estimate the influence of enterprise mix on productivity.

9 Dependent and independent variables in the regression model

dependent variable	brief description
Total factor productivity	Farm-level total factor productivity index, measured in natural log
Independent variables	
Innovative effort **a**	Dummy: High, moderate or low innovator
Age	Age of farm owner/operator
Age squared	Age of farm owner/operator squared
Education of operator	Dummy: highest level of education for owner/operator
Labour	Aggregate weeks worked by total farm labour, measured in natural log
Land use intensity	Scale of operations (in DSE) divided by total area operated (in hectares), measured in natural log
Crop specialisation	Proportion of area used for cropping (%)
Profit	Dummy: farm profit (5 percentile categories)
Off-farm income	Dummy: income from off-farm sources
Contract	Dummy: use of contract services
Region	Dummy: southern, northern, western

a Categories of innovative effort are defined in chapter 4.

Treatment of data in the estimation

While a log-linear specification was assumed in the regression model, not all variables could enter the model in logarithmic format. Specifically:

- variables that are proportions or expressed in percentage terms were not logged and remained in their original form
- indicator variables (0,1) cannot be logged, because log (0) is undefined, and hence remained in their original form

The interpretations of each explanatory variable on total factor productivity (TFP) are shown in the following equation:

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

where α_i is the estimated coefficient.

10 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	0.000	(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% level.
$R_2 = 0.68$

Results

The regression model explained 68 per cent of the variation in data between farms (table 10). This level of explanatory power is consistent with other models based on farm-level data. All variables had the expected signs and were statistically significant.

Innovation adoption is a significant determinant of total factor productivity in the grains industry. Once accounting for the other factors in the model, including characteristics of the farm and farm manager, farms that do not innovate are likely to be associated with lower total factor productivity.

References

Abadi Ghadim, AK and Pannell, DJ 1999, 'A conceptual framework of adoption of an agricultural innovation', *Agricultural Economics*, vol. 21, no. 2, pp. 145–54.

Abadi Ghadim, AK, Pannell, DJ and Burton, MP 2005, 'Risk, uncertainty, and learning in adoption of a crop innovation', *Agricultural Economics*, vol. 33, no. 1, pp. 1–9.

ABARE 2009, *Australian grains 09.1*, Australian Bureau of Agricultural Resource Economics, Canberra.

ABS 2008, *Research and Experimental Development, All Sector Summary, Australia, 2006–07*, cat. no. 8112.0, Australian Bureau of Statistics, Canberra.

—— 2010, *Innovation in Australian Business, 2008–09*, cat. no. 8158.0, Australian Bureau of Statistics, Canberra.

Alston, JM, Anderson, JR, James, J and Pardey, PG 2010, *Persistence pays: US agricultural productivity growth and the benefits from public R&D spending*, Springer, New York.

Australian Government 2009, *Powering Ideas: An Innovation Agenda for the 21st Century*, Canberra.

Breustedt, G and Glauben, T 2007, 'Driving Forces behind Exiting from Farming in Western Europe', *Journal of Agricultural Economics*, vol. 58, no. 1, pp. 115–27.

Crepon, B, Duguet, E and Mairesse, J 1998, *Research, Innovation, and Productivity: An Econometric Analysis at the Firm Level*, NBER Working Paper No. 6696, August 1998.

Cutler and Company 2008, *Venturous Australia: building strength in innovation*, Cutler and Company, Melbourne.

D'Emden, FH, Llewellyn, RS and Burton, MP 2008, 'Factors influencing adoption of conservation tillage in Australian cropping regions', *Australian Journal of Agricultural and Resource Economics*, vol. 52, no. 169–182.

DAFF 2009, *Workforce, Training and Skills Issues in Agriculture, A report to the Primary Industries Ministerial Council by the Industries Development Committee Workforce*, Training and Skills Working Group, October.

Diederen, P, Meijl, H, Wolters, A and Bijak, K 2003a, *Innovation Adoption in Agriculture: Innovators*, Early Adopters and Laggards, Cahiers d'économie et sociologie rurales, n° 67, 2003.

Diederen, P, van Meijl, H and Wolters, A 2003b, 'Modernisation in agriculture: what makes a farmer adopt an innovation?' *International Journal of Agricultural Resources*, *Governance and Ecology*, vol. 2, no. 3, pp. 328–42.

Evangelista, R, Sandven, T, Sirilli, G and Smith, K 1998, 'Measuring innovation in European industry', *International Journal of the Economics of Business*, vol. 5, no. 3, pp. 311–33.

Feder, G 1980, 'Farm Size, *Risk Aversion and the Adoption of New Technology under Uncertainty*', Oxford Economic Papers, vol. 32, no. 2, pp. 263–83.

Feder, G, Just, RE and Zilberman, D 1985, 'Adoption of agricultural innovations in developing countries: a survey', *Economic Development and Cultural Change,* vol. 33, pp. 255–98.

Fernandez-Cornejo, J 2007, *Off-Farm Income, Technology Adoption, and Farm Economic Performance*, Economic Research Report No. 36, ERS USDA.

Gray, EM, Jackson, T and Zhao, S 2011, *Agricultural productivity: concepts, measurement and factors driving it*, ABARE report for the Rural Industries Research and Development Corporation, Canberra.

GRDC 2008, *Annual Report, 2007–08*, Grains Research and Development Corporation, Canberra.

Greene, W 2003, *Econometric Analysis,* 5th edition, Pearson Education, New Jersey.

Guerin, LJ and Guerin, TF 1994, 'Constraints to the adoption of innovations in agricultural research and environmental management: a review', *Australian Journal of Experimental Agriculture*, vol. 34, pp. 549–71.

Hughes, N, Lawson, K, Davidson, A, Jackson, T and Sheng, Y 2011, *Climate adjusted production frontiers for the Australian broadacre cropping industry*, ABARES report for the Grains Research and Development Corporation, Canberra.

Jackson, T 2010, *Harvesting productivity: ABARE–GRDC workshops on grains productivity growth*, ABARE research report 10.6 to the Grains Research and Development Corporation, Canberra.

Knopke, P, O'Donnell, V and Shepherd, A 2000, *Productivity growth in the Australian grains industry*, ABARE research report 2000.1, Canberra.

Kokic, P, Davidson, A and Boero Rodriguez, V 2006, *Australia's Grains Industry: Factors Influencing Productivity Growth*, ABARE Research Report 06.22 prepared for the Grains Research and Development Corporation, Canberra.

Liao, B and Martin, P 2009, *Farm innovation in the broadacre and dairy industries, 2006–07 to 2007–08,* ABARE report to the Australian Government Department of Agriculture, Fisheries and Forestry, Canberra.

Marsh, SP 2010, *Adopting innovations in agricultural industries*, paper presented at the ABARE Outlook Conference, Canberra.

Marsh, SP, Pannell, DJ and Lindner, RK 2000, 'The impact of agricultural extension on adoption and diffusion of lupins as a new crop in Western Australia', *Australian Journal of Experimental Agriculture*, vol. 40, pp. 571–83.

Mullen, JD and Crean, J 2007, *Productivity growth in Australian agriculture: Trends, sources and performance*, Research Report, Australian Farm Institute, Canberra.

Nossal, K 2011, *From R&D to productivity growth: Investigating the role of innovation adoption in Australian agriculture*, ABARES report for the Rural Industries Research and Development Corporation, Canberra.

Nossal, K and Gooday, P 2009, *Raising productivity growth in Australian agriculture*, ABARE Issues and Insights 09.7, November.

OECD 2005, *Oslo Manual*, OECD/Eurostat, Paris.

OECD 1992, *Oslo Manual*, 1st edition, Paris.

Pannell, DJ, Marshall, GR, Barr, N, Curtis, A, Vanclay, F and Wilkinson, R 2006, 'Understanding and promoting adoption of conservation practices by rural landholders', *Australian Journal of Experimental Agriculture*, vol. 46, no. 11, pp. 1407–24.

PISC 2011, *Grains industry National research, development and extension strategy*, Primary Industries Standing Committee— R&D sub-committee, April 2011.

Productivity Commission 2010, *Rural Research and Development Corporations*, Draft Inquiry Report, Canberra.

Prokopy, LS, Floress, K, Klotthor-Weinkauf, D and Baumgart-Getz, A 2008, 'Determinants of agricultural best management practice adoption: Evidence from the literature', *Journal of Soil and Water Conservation*, vol. 63, pp. 300–11.

Rogers, E 2003, *Diffusion of Innovations*, Free Press, New York.

Schumpeter, J 1942, *Capitalism, Socialism, and Democracy*, Harper and Brothers, New York.

—— 1943, *Capitalism, Socialism and Democracy*, Harper, New York.

Sheng, Y, Gray, E and Mullen, JD 2011a, *'Public investment in R&D and extension and productivity in Australian broadacre agriculture',* paper presented to ABARES conference paper 11.08, presented to the Australian Agricultural and Resource Economics Society, Melbourne, 9–11 February.

Sheng, Y, Mullen, JD and Zhao, S 2011b, *'Has growth in productivity in Australian broadacre agriculture slowed?'* paper 10.1 presented at the Australian Agricultural and Resource Economics Society Conference, Adelaide, 10–12 February 2010.

Spielman, DJ and Birner, R 2008, *How innovative is your agriculture? Using innovation indicators and benchmarks to strengthen national agricultural innovation systems*, Agriculture and Rural Development Discussion Paper no. 41, World Bank, Washington, D.C.

Stoneman, P 2002, *The economics of technological diffusion*, Blackwell Publishers, Malden, Massachusetts.

Sunding, D and Zilberman, D 2001, 'The Agricultural Innovation Process: Research and Technology Adoption in a Changing Agricultural Sector', in Gardner, BL and Rausser, GC (eds), *Handbook of Agricultural Economics*, 1st edition, Elsevier, pp. 207–61.

Wong, M, Page, D, Abello, R and Pang, KP 2007, *Explorations of Innovation and Business Performance Using Linked Firm-Level Data*, Research Paper, ABS cat. no. 1351.0.55.020, September 2007.

Zhao, S, Sheng, EY and Kee, HJ 2009, *Determinants of total factor productivity in the Australian grains industry*, Conference paper 09.16.

RESEARCH FUNDING ABARES relies on financial support from external organisations to complete its research program. As at the date of this publication, the following organisations had provided financial support for Bureau research in 2009–10 and 2010–11. We gratefully acknowledge this assistance.

AusAID

Australia Indonesia Governance Research Partnership (ANU)

Australian Competition & Consumer Commission

Australian Fisheries Management Authority

Australian Government Department of Innovation, Industry, Science and Research

Australian Government Department of Climate Change and Energy Efficiency

Australian Government Department of Resources, Energy and Tourism

Australian Government Department of Sustainability, Environment, Water, Population & Communities

Australian Government Department of the Treasury

Australian National University

Cooperative Research Centre for National Plant Biosecurity

CSIRO

Dairy Australia

Department of Primary Industries, parks, Water and Environment, Tasmania

Ensis (joint venture between the CSIRO (Aust) and Scion (NZ))

Environment ACT

Environmental Hydrology Associates

Fisheries Research & Development Corporation

Food Standards Australia New Zealand

Forest & Wood Products Australia

Goulburn-Murray Water

Grains Research & Development Corporation

Grape & Wine Research & Development Corporation

Horticulture Australia Limited

Industry & Investment NSW

Inovact Consulting Pty Ltd

Korea Rural Economics Institute

Meat & Livestock Australia

Murray–Darling Basin Authority

National Water Commission

New Zealand Institute of Veterinary, Animal & Biomedical Sciences

Peel Harvey Catchment Council

Plant Health Australia

Queensland Competition Authority

Queensland Department of Employment, Economic Development & Innovation

Rural Industries Research & Development Corporation

Sinclair Knight Mertz

South Australian Research & Development Institute

Southern Cross University

University of Melbourne