australia’s grains industry
factors influencing productivity growth

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foreword

The Australian grains industry has faced considerable pressure over the past few decades. A continuous decline in terms of trade means that farmers in this industry have had to make productivity improvements to maintain their profitability and international competitiveness.

For the Australian grains industry to continue making productivity improvements in the future it is essential that the drivers of productivity are well understood. ABARE’s annual farm survey data are an extensive and consistent historical information resource that is widely used for productivity research.

Analysis presented in this report uses ABARE’s farm survey data by investigating the drivers influencing productivity differences between individual grain producing farms as well as over time. The analysis has revealed that the factors likely to influence individual farm productivity performance are diverse and include variables representing human, physical, financial and natural capital.

The work in this report was funded by the Australian Grains Research and Development Corporation. The results of the analysis can assist in determining the allocation of research resources to areas where the most effective productivity improvements can be achieved for the grains industry.

Phillip Glyde
Executive Director
November 2006
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This report draws heavily on data collected in ABARE’s 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 ABARE’s survey staff in collecting these data is also gratefully acknowledged. Without this assistance, the analysis presented in this report would not have been possible.
contents

summary 1
1 introduction 5
2 past research on australia’s grains industry 6
   productivity growth at an aggregate level 6
   productivity growth at an individual farm level 7
   objective in this research 8
3 identifying factors likely to influence productivity growth 9
4 methodology 12
   data sources 13
   selection of explanatory factors for inclusion in model 14
5 factors influencing productivity growth 16
   natural capital 16
   financial capital 18
   human capital 19
   activities 19
   mediating processes 20
   risk factors 21
   industry characterised by heterogeneity 21
   productivity growth trends 22
appendix
A technical notes supporting the analysis 29
references 44
figures
A a framework for analysing rural livelihoods 9
B adoption of direct drill and minimum till on grain farms 21
C average total factor productivity, by GRDC region 23
D average moisture availability index, by GRDC region 23
E distribution of total factor productivity growth rates 25
F derivation and estimation of total livelihood productivity 30

maps
1 GRDC agroecological zones 13
2 GRDC regions 13
3 average annual TFP growth rates, 1988-89 to 2003-04 28

tables
1 potential explanatory factors for inclusion in the regression model 15
2 regression results: model estimates and significance 17
3 total factor productivity growth rates, 1988-89 to 2003-04 23
4 farm average growth rates (excluding moisture effect) from 1988-89 to 2003-04, and share of input or output costs in 2003-04 26
5 farm average TFP growth rates (excluding moisture effect) and sensitivity to moisture availability, 1988-89 to 2003-04 27
summary

> Sustained productivity improvements have long been the engine of growth of Australia's agriculture sector. Farmers have continually pursued more efficient ways to produce more output from less input to offset declining terms of trade and maintain viability. Strategies employed by farmers for making productivity gains in the past have depended on access to a broad range of resource inputs, both market and nonmarket. However, there is a growing realisation that the environment in which farms operate in the future could alter farmers' access to these resource inputs, particularly the nonmarket inputs. Issues such as climate change, vegetation regulation and continued rural migration could have an impact on the effectiveness of past strategies used by grain growers to make productivity gains.

> What is not well known is the relative importance in determining total factor productivity of individual agricultural inputs drawn by growers from the diverse range available.

> In this report, an economic framework for systematically investigating a broad range of factors that potentially influence productivity growth in the grains industry has been used. This framework is based on a rural livelihoods approach that is founded on a diverse range of market and nonmarket capital stocks (physical, natural, financial, human and social) as well as a broad range of factors that modify farmers' access to these agricultural business inputs.

> The innovative statistical approach used here to evaluate factors assembled in the rural livelihood productivity model provides greater model stability and new insights into the factors that influence productivity growth in the grains industry.

> This study reveals that the factors likely to significantly influence individual farm productivity performance are more diverse than has been reported in previous research. These results support Gollop and Swinand’s (1998) claim that total factor productivity is a biased measure of how well society is allocating scarce resources because it fails to take into account changes in both nonmarket inputs and outputs. Taking account of nonmarket agricultural inputs and outputs produces a better measure to capture the technical efficiency with which producers combine all market and nonmarket inputs to produce all market and nonmarket outputs.
Factors from four (physical, natural, financial and human) of the five asset classes were found to have a significant influence on productivity growth in most regions. It was not possible to draw conclusions on the importance of social capital in determining productivity growth.

The implication from this finding is that changes to a wide range of policy settings could affect grains industry productivity. For example, changes to policies that affect land use intensity are all likely to have significant impacts on individual grain growers’ productivity.

Moisture availability is the dominant influence on productivity

Moisture availability was found to be a dominant factor affecting total factor productivity of purchased inputs at any point in time. The moisture effect was considered so dominant and largely beyond farmers’ control that all further analysis was done excluding the effects of moisture availability. This was done to develop a clear understanding of the technical efficiency with which grain producers are combining inputs to produce outputs. However, the efficiency with which available moisture is used by farmers can be dependent on crop husbandry practices. For example, direct drill and minimal till are likely to improve total factor productivity in the southern region during drier years.

Impact of land use intensity and other factors

Land use intensity was the other factor (apart from moisture availability) that had a substantial impact on total factor productivity. Its impact on total factor productivity is largely dependent on natural soil fertility and management practices (for example, double cropping). Other factors that had a significant impact on farm level total factor productivity in some or all regions included finance, land area, education, crop specialisation, investment income and corporate ownership.

Land degradation in the form of depreciated natural capital through wind erosion, water erosion, dryland salinity, soil acidity, soil sodicity and loss of soil structure did not significantly affect total factor productivity in any region according to the model specified in this study. However, it is possible that variations in land degradation effects could have been picked up in ‘land area (adjusted)’ and/or ‘land use intensity’ variables. There is insufficient evidence at this stage to dismiss land degradation factors having an effect on productivity.
results vary across farms, zones and regions

> In this study, it is found that estimates of productivity growth are substantially influenced by the scale at which the analysis is undertaken. The considerable heterogeneity that exists in performance across GRDC agroecological zones can be disguised at a regional and national level.

> There is also considerable variation in productivity growth between and within farms that is not explained by factors explicitly incorporated in the model (such as moisture availability, land area, land use intensity and crop specialisation) that is likely to have a corresponding impact on income distributions. The extent to which such income variations are a consequence of the management decisions made by individual farmers may have important consequences for the design of government policies that are intended to address fluctuations in climatic factors.

results for total factor productivity

> This report confirms earlier research showing that growth in total factor productivity (TFP) is continuing to decline in the Australian grains industry.

- The national average TFP growth rate of 1.9 per cent estimated in this study over a sixteen year period commencing in 1988-89 is considerably less than the rate of 3.8 per cent obtained by Knopke et al. (2000, p. 15) over the seventeen year period ending in 1993-94.

- It has been conventional to take a long run view of changes in productivity because of the effects of moisture availability and other exogenous shocks. However, even after the effects of moisture availability are netted out, the Australian grains industry has realised an underlying productivity improvement of around 2.6 per cent a year on average over the past sixteen years — still less than the productivity gains realised during the late 1970s and 1980s.

- While total factor productivity has continued to increase over the past three decades, it has done so at a declining rate. However, as mentioned earlier, such aggregate performance masks the performance of individual farms. The farm average growth rate at a national level, excluding the effect of moisture availability, was around 2.2 per cent a year over the period 1988-89 to 2003-04.

- On a GRDC region basis, farm average total factor productivity growth, excluding the effect of moisture availability, is more diverse: northern region (2.0 per cent), southern region (2.0 per cent) and western region (2.5 per cent).
On a GRDC agroecological zone basis, the spatial variance is even more profound, ranging from zones exhibiting nonsignificant growth to around 3.4 per cent in Victoria’s high rainfall region.

The move out of wool growing and into cropping has contributed to output growth in the grains industry in many areas. Output growth has been achieved through input growth in the southern and western regions, largely through increases in materials and services and, in particular, through increased use of crop chemicals. While the growth in crop chemical use has been significant in all regions, it has been the largest in the western region, which has the highest adoption of direct drill (57 per cent), compared with the northern region (21 per cent) and southern region (20 per cent).

Further research

Further productivity research would benefit from more biophysical and social data to better understand differences at the agroecological zone level. It was also evident that the number of significant factors in the southern region was much larger than the number identified in the northern and western regions. The southern region had roughly three times as many observations compared with the other regions and the higher number of explanatory factors may be associated with greater variance within the data. This problem may be alleviated by extending the times series component by processing earlier ABARE farm survey data to a form that can be incorporated in the regression model.

The importance of nonmarket natural resource inputs in determining total factor productivity growth on grain properties is highlighted in this report. Furthermore, total factor productivity measures that include only market based inputs and outputs are inadequate for detailed analysis of the growth in technical efficiency necessary for sustainable development in the Australian grains industry. The results from this study demonstrate that changes to the environment (for example, climate change) or to government policies that affect the intensity with which agricultural land is used (for example, vegetation regulation) may affect total factor productivity growth on grain properties in the future.
introduction

It is widely recognised that sustained productivity improvements have long been the engine of growth for Australia’s agriculture sector. Farmers have continually pursued more efficient ways of producing more output from less input. The resulting productivity growth has enabled agricultural producers to offset declining terms of trade and maintain viability. While there is a widespread appreciation of the importance of nonmarket inputs in farm production systems, there is a mounting realisation that farmers’ access to these nonmarket inputs is changing as a result of changes to the biophysical, regulatory and social environments in which they operate. Factors such as global warming, native vegetation regulation and rural migration are all likely to affect agricultural productivity growth in the future.

The problem faced by Australia’s grains industry is how to effectively address the pressures that are likely to affect farmers in the future. What is required by policymakers in the first instance is a robust framework that allows a simultaneous evaluation of the likely importance of these nonmarket factors on individual farm productivity growth over time.

Total factor productivity analysis has long been used as a framework to better understand the forces that affect productivity in the hope of affecting them for the better. Past studies of productivity in the grains industry have typically focused on growth in industry productivity over time. However, as these studies have relied on data aggregated at an industry level, the scope to investigate the factors influencing these productivity changes at an individual farm level has been limited. In a more recent study, productivity estimates were produced at the farm level in two different years. This allowed factors that were important in explaining differences between farms to be investigated, but it was not possible to adequately identify factors that had a significant impact on productivity over time. Indeed, any changes in weather patterns or restrictions that affect land use could be expected to have a major influence on farm productivity both over time and between regions.

The aim in this study is to investigate the importance of a wide range of factors that are likely to influence productivity on individual farms in Australia’s grains industry over time. In particular, this research seeks to establish whether change to climate patterns, environmental regulations, structural adjustment and rural migration trends are likely to have an impact on productivity growth within Australia’s grain growing industry in the future.
past research on Australia’s grains industry

The specific aim in this research is to quantify the importance of factors influencing productivity growth of individual grain growers over time. As such, it builds on recent research by ABARE that describes the productivity growth realised by the grain growing industry in aggregate at a regional and agroecological zone level as well as between individual grain growers in particular years (Knopke, O’Donnell and Shepherd 2000; Alexander and Kokic 2005). These reports also contain useful background information that can further assist readers in contextualising the results from this research. A brief summary of this research is presented below.

productivity growth at an aggregate level

Knopke et al. (2000) focused on growth in productivity in the grains industry in aggregate over the 22 years to 1998-99. Total factor productivity was derived by dividing an index of total outputs produced by grain growers by an index of total inputs used by grain growers. Annual growth rates were derived by fitting a logarithmic trend line, with the annual index data being regressed against a time variable.

Average annual total factor productivity growth of the grains industry (3.2 per cent) was higher than that achieved by other Australian broadacre industries: beef industry (2.1 per cent) and sheep industry (0.6 per cent). Economies of scale were found to exist, with productivity growth on larger grain farms being higher than that on smaller farms. It was also found that annual productivity growth of the grains industry was highest in the western region (3.5 per cent), followed by the southern region (3.2 per cent) and northern region (3.0 per cent). The superior productivity performance of the grains industry in the western region was also matched by higher improvements in wheat yields, higher cash incomes and higher rates of return for grain growers in the western region (Knopke et al. 2000).

Qualitative research by Knopke et al. (2000) also identified the following factors as being responsible for productivity gains: better farm management, advances with plant breeding, improved crop rotations with better pest and weed control, development of new herbicides, more efficient fertiliser use, larger scale farming and advances in tractor and machinery design.
The report by Knopke et al. (2000) provides a detailed breakdown of trends in the output and input components of total factor productivity at an industry level by each GRDC agroecological zone. It also provides summaries of the characteristics of each agroecological zone in terms of productivity growth, climate, grain growing activity and average farm performance.

However, the study pointed to limitations in the interpretation of the results. The importance of moisture availability in influencing productivity measures was noted, but not able to be accommodated. Furthermore, it was noted that while changes to the resource base through land degradation may also be important, they could not be explicitly modeled. Also relevant to this study is that all productivity growth rates pertain to aggregates – that is, at an industry, region or zone level – and not farm average rates – that is, the average of productivity growth rates achieved by individual farms. As such, the distribution and drivers of productivity performance between individual farms was not able to be examined.

Productivity growth at an individual farm level

Alexander and Kokic (2005) were able to address many of the problems identified in Knopke et al. (2000) by producing farm level estimates of productivity at a specific point in time for each GRDC region. Factors that were found to significantly influence total factor productivity growth at an individual farm level included moisture availability, intensity of land use, scale of operation, the proportion of operating area being cropped, cultivation techniques, training and education, dependence on off-farm wages (negative) and land degradation (variable signs), depending on the region and year.

Tree analysis was also used to investigate the characteristics that influence a farm’s total factor productivity and was a complement to their regression model approach. Tree analysis divides farms into groups with similar characteristics, maximising the homogeneity of farms at each branch of the tree according to their productivity index. The tree analysis identified significant heterogeneity within regions that most likely indicated the presence of missing variables that characterise individual GRDC agroecological zones.

The research by Alexander and Kokic (2005) also pointed to some limitations. It was acknowledged that the time dimension to modeling total factor productivity is important and can significantly influence individual farm productivity. One example used was that large capital expenditure in the study year is likely to reduce a farm’s total factor productivity because this measure does not incorporate the benefits in
future years. Knopke et al. (2000) also noted that farmers may defer their input expenditure in low income years. Although the work by Alexander and Kokic (2005) addressed many of the limitations identified in Knopke et al. (2000), the model also lacked a theoretical economic foundation and was affected by statistical stability issues.

**Objective in this research**

The primary aim in this research is to develop a method to analyse and model a broad range of factors likely to influence productivity growth on Australian grain farms. Furthermore, the development of a new methodology will enable limitations experienced in past research to be addressed – such as limited theoretical economic frameworks, model stability issues and inability to investigate changes in farm level productivity growth through time.
identifying factors likely to influence productivity growth

The factors likely to influence productivity growth on Australian grain farms are also likely to be the factors that can influence rural income growth. A rural livelihood framework developed by Ellis (2000) provides a convenient approach to systematically identifying such factors, as shown in figure A. Ellis’s (2000) framework was first applied to Australian agriculture by Nelson et al. (2005).

Rural livelihood strategies are built on a set of five asset classes or stocks of capital with which farmers are able to undertake production (figure A). Farms with access to all these dimensions of capital are likely to be more resilient to external changes and shocks, and consequently better able to remain viable during stressful events and may also be better placed to improve productivity over time. Furthermore, sustainable productivity growth may depend on the range of capital types to which farmers have access and the degree of substitutability between these different types of capital stock. The five types of assets or capital stocks identified by Ellis (2000) are:

- **physical capital**: assets brought into existence by economic production processes (for example, tools, machines, infrastructure and land improvements)

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**fig A**  a framework for analysing rural livelihoods

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Ellis (2000)
> natural capital: natural resource base that yields products used by human populations (for example, land, water and vegetation)

> human capital: factors that influence the productivity of labor (for example, education, skills, health and management capacity)

> financial capital: stocks of cash and other financial assets that can be used to purchase either production or consumption goods, and access to credit

> social capital: relates to the social norms, networks and trust that facilitate cooperation within or between groups.

Physical capital and natural capital need little introduction as they have long been recognised as basic factors determining economic growth. The concept of human capital is also well established in economic growth literature, having been introduced in the 1960s. However, social capital is a relatively new and evolving concept in economic literature. Nevertheless, it is recognised that social capital can potentially contribute to economic growth by ‘reducing transaction costs, promoting cooperative behavior, diffusing knowledge and innovations’ (Productivity Commission 2003, p. viii). The assemblage of this comprehensive set of asset classes gives recognition to the likely range of nonmarket inputs that potentially determine farm productivity growth.

Stocks of capital can diminish as they generate flows of intermediate inputs (or outputs) — for example, trees (natural capital) into fence posts, or cash (financial capital) into fertiliser. Conversely, stocks can increase following a surplus of production over consumption, thus enabling investment in additional productive capacity in the future (Ellis 2000, p. 31).

Access to the five types of capital is mediated by processes that are largely outside an individual farmer’s control (Ellis 2000). It is therefore likely that substitutability between asset classes is affected by imperfect information, transaction costs, externalities and other breakdowns in the competitive market model usually assumed to face farm business units. These include the numerous contextual, social, economic and policy (government and industry) considerations that interpose on a farmer’s access to the abovementioned capital stocks used in income generating activities (known as livelihood strategies). Ellis (2000) identified five types of mediating processes or asset access modifiers (figure A):

> social modifiers: factors inhibiting capabilities and choices or, conversely, enhancing access to the five asset classes, including age and possibly gender
> **institutional modifiers:** formal rules, conventions constraining human interactions, including legal systems over private property rights and the way in which markets operate

> **organisational modifiers:** groups bound by a common purpose, including farmer organisations and government agencies

> **trend modifiers:** exogenous time related changes, including relative price trends, rural migration and technological improvements and

> **shock modifiers:** periodic destruction or loss of capital stocks caused by essentially random exogenous events, including drought, disease and pest incursions as well as unsecured losses incurred following corporate bankruptcies.

Income earning activities generate the means of household survival and collectively form part of a farm’s livelihood strategy. Activities that generate outputs of goods or services either return income, are consumed on-farm or generate social claims (and thereby create social capital through the concept of quid pro quo). Activities are divided between natural resource based activities (for example, cropping, grazing, quarrying or contract harvesting) and non-natural resource based activities (for example, work in a nearby town or financial investment activities). Risk is often considered to be a fundamental driver of diversification and is therefore also included as a factor influencing the suite of activities undertaken by a household (Ellis 2000, p. 60).

Environmental sustainability is explicitly represented in Ellis’s (2000) framework for livelihood analysis and includes the undesirable consequences of some agricultural activities such as erosion, salinity and loss of soil structure. The links between environmental degradation and farm productivity in many instances are not clear. For example, land degradation, such as dryland salinity, can limit farm productivity by negatively affecting access to other natural resource inputs. However, in other instances, it could be argued that environmental degradation is more akin to an undesirable output that may have a minor impact on farm productivity but a large external impact. For example, undesirable herbicide discharge into water courses may accompany the production of desirable agricultural outputs. In this study, undesirable land degradation can be categorised as either an output or an input simply on the basis of the sign of the regression coefficient.
methodology

Total factor productivity (TFP), the conventional index measure of on-farm productivity, is defined as the ratio of the volume index of all marketable outputs, $O_M$, to the volume index of all marketable inputs, $I_M$:

$$\text{TFP} = \frac{O_M}{I_M}$$

The estimated geometric time trend in total factor productivity is the total factor productivity growth rate. It is a measure — over the data period — of the (yearly) proportional rate of improvement in the technical efficiency with which farmers combine marketable inputs to produce marketable outputs.

Previous studies have commonly estimated changes in TFP over time at an aggregate level, such as for a country or industry. However, with detailed panel data it is possible to use the same formulae to estimate TFP across farms as well as over time. This allows TFP comparisons over time and between farms.

However, as Gollop and Swinand (1998) point out, total factor productivity at the aggregate national level is a ‘biased barometer of how well society is allocating scarce resources’ because it fails to take into account changes in nonmarket inputs and outputs. They propose a measure of productivity, which they refer to as total resource productivity, that includes nonmarket inputs and outputs.

Using the rural livelihoods framework developed by Ellis (2000), total factor productivity in the current paper is related to nonmarket socioeconomic inputs and outputs (see appendix A for details). The following regression model is used to determine the significance of those factors for TFP:

$$\ln(\text{TFP}) = \mu + \sum_{i \in N}^{\alpha_i \ln X_i} + \epsilon$$

where $\mu$ is a constant and $X_i$ is the volume of nonmarket factor $i$ out of the set of all nonmarket factors $I_N$. 
productivity in australia’s grains industry  

**data sources**

The farm financial and physical data used in this analysis were obtained from ABARE’s Australian agricultural and grazing industries survey (AAGIS) of broadacre farmers from 1988-89 to 2003-04. For the purposes of this report, grain farms have been defined as those from the cropping and mixed cropping-livestock industries and from the GRDC agroecological zones shown in map 1. For much of the analysis the zones are divided into three broad geographic regions as shown in the lower panel in map 2. A summary of the salient features of each region can be found in Alexander and Kokic (2005).

The moisture availability index data used in this study was obtained from the Queensland Department of Primary Industries (Potgieter, Hammer and Butler 2002). It measures at the shire scale the amount of moisture available for wheat production during the winter growing season, and is based on a soil water balance model that takes into account factors such as rainfall, soil type, sunlight and temperature.

In order to match biophysical data with farm financial data, farms have been spatially represented as a point or point buffer (rather than a farm boundary). Because of the inherent approximations involved, the spatial covariates generated are rough esti-
mates. Future analyses should be able to make use of the more accurate polygon data as these become available. Also, with some biophysical data there is an issue of matching over time (for example, rainfall is recorded daily), and generally it is preferable for these data to be processed through suitable biophysical models so that they match up with the financial year basis of the farm survey data. For example, the moisture availability index corresponds to the winter growing season and hence links in easily with the farm survey data.

**selection of explanatory factors for inclusion in model**

The variables likely to influence TFP and therefore likely to be included in model 1 are listed in table 1. A more detailed description of these potential explanatory factors is given in appendix A. According to the rural livelihoods framework, they include factors representing the capital groups, factors that modify farmer access to these capital groups, livelihood activities, risk factors (future price and moisture availability) and undesirable byproducts. These variables were selected from ABARE’s farm survey database and other sources, according to Ellis’s [2000] rural livelihoods framework. A full description of all variables in the regression model is found in appendix A.

Most of the variables used by Nelson et al. [2005] were also used in the current study, but additional variables were selected on the basis of previous work on productivity [Knopke et al. 2000; Alexander and Kokic 2005] and in consultation with subject matter experts. Physical capital, market based natural capital and other market based inputs are components of the dependent variable (TFP) and do not appear as explanatory variables. The final group of explanatory variables selected for inclusion in the regression model was from the set that had been short listed on the basis of economic theory and whose components were not significantly correlated [to improve model stability]. Some explanatory variables used in earlier studies could not be incorporated in this analysis because there were not sufficient observations through time.

Water is critical for crop development and any unmet demand for water manifests as stress. The annual wheat water stress index is a measure of the relative water stress of the crop accumulated throughout the growing season. It has been simulated by using daily rainfall with average weekly radiation data, maximum and minimum temperatures, location specific soil data and crop specific water requirements. For ease of discussion in this report, the annual wheat water stress index simulated for all wheat producing shires in Australia by Potgieter et al. [2002] is referred to [less precisely] as moisture availability.
The inclusion of household and community features in the factors to be investigated, along with more conventional farm business and environmental characteristics, is appropriate for the grains industry in Australia where the majority of farms are still predominately privately owned family operations located in rural communities. However, there are very few variables from ABARE’s surveys that can be considered as social capital variables. Those that were available as proxy measures were unable to be included for statistical reasons. Accordingly, social capital is underrepresented in this analysis.

<table>
<thead>
<tr>
<th>variable</th>
<th>brief description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>natural capital</strong></td>
<td>operating area of farm in hectares of arable land</td>
</tr>
<tr>
<td>land area (adjusted)</td>
<td>land area (adjusted) divided by area operated</td>
</tr>
<tr>
<td>land use intensity</td>
<td>moisture available for the winter wheat crop</td>
</tr>
<tr>
<td>moisture availability index</td>
<td>average slope of land (percent rise)</td>
</tr>
<tr>
<td>land gradient</td>
<td></td>
</tr>
<tr>
<td><strong>financial capital</strong></td>
<td>access to credit plus liquid assets</td>
</tr>
<tr>
<td>finance</td>
<td></td>
</tr>
<tr>
<td><strong>human capital</strong></td>
<td>highest level of education for operator</td>
</tr>
<tr>
<td>education of operator</td>
<td>highest level of education for spouse</td>
</tr>
<tr>
<td>education of spouse</td>
<td></td>
</tr>
<tr>
<td><strong>social capital</strong></td>
<td>indicates membership of a Landcare group</td>
</tr>
<tr>
<td>landcare membership</td>
<td></td>
</tr>
<tr>
<td><strong>activities</strong></td>
<td>proportion of land area for cropping activities</td>
</tr>
<tr>
<td>crop specialisation</td>
<td>proportion of total income from off-farm wages</td>
</tr>
<tr>
<td>off-farm wages</td>
<td>proportion of income from off-farm investments</td>
</tr>
<tr>
<td>off-farm investment income</td>
<td></td>
</tr>
<tr>
<td><strong>mediating processes</strong></td>
<td>farm’s main cropping method is direct drill</td>
</tr>
<tr>
<td>direct drill</td>
<td>farm’s main cropping method is minimal till</td>
</tr>
<tr>
<td>minimum till</td>
<td>interactive term</td>
</tr>
<tr>
<td>moisture direct drill interactive</td>
<td>interactive term</td>
</tr>
<tr>
<td>moisture minimum till interactive</td>
<td></td>
</tr>
<tr>
<td>corporate farm</td>
<td>farm owned by a publicly-listed company</td>
</tr>
<tr>
<td>trend</td>
<td>generic trend term (time in years)</td>
</tr>
<tr>
<td><strong>risk factors</strong></td>
<td>standard deviation of moisture availability index</td>
</tr>
<tr>
<td>variability of moisture availability</td>
<td>weighted coefficient of variation of output prices</td>
</tr>
<tr>
<td>commodity price variability</td>
<td></td>
</tr>
</tbody>
</table>
5

factors influencing productivity growth

The variables in table 1 were fitted to each GRDC region in order to identify the factors that significantly affect productivity growth (as represented in equation 6 in appendix A). The explanatory factors in the regression model for each GRDC region explained over two-thirds of the annual variability in TFP at the individual farm level. The results of the regression analyses are presented in table 2.

The regression estimates of the model coefficients are reported for the factors that, on the basis of their $P$-value, have been judged most likely to affect productivity growth. The smaller a $P$-value, the more likely it is that a factor does in fact affect productivity growth. The regression coefficients for those factors judged to be nonsignificant (ns) have not been published.

natural capital

Natural capital factors dominated in their influence on total factor productivity. This is not surprising given that the grains industry in Australia is predominately extensive, dryland agriculture. Of the natural capital variables, moisture availability was singularly most important.

At an individual farm level, the degree to which moisture availability affects TFP varies markedly between GRDC regions — it is higher in the southern and western regions than in the northern region. For example, an increase in moisture availability (a reduction in the water stress index) of 10 per cent is likely to increase TFP in the southern and western regions by 8.1 per cent and 7.6 per cent respectively, compared with 5.0 per cent in the northern region, all other factors held constant (table 2). Although increased moisture availability is likely to lead to increased productivity in all regions, it is a factor largely beyond the control of farmers. However, as discussed later, the extent to which farmers are able to make use of available moisture is dependent on the effectiveness of crop husbandry techniques adopted to conserve available moisture.

Land area (adjusted) is also a significant factor driving productivity growth in both the northern and southern regions. The average area of farms has been increasing
over time and is generally considered to be an important expression of structural adjustment. These results suggest that broadacre cropping farms can capture economies of scale by amalgamating properties to realise productivity gains, with these effects being larger in the southern region compared with the western and northern regions. An increase in farm area (adjusted) of 10 per cent is likely to increase average farm TFP by 1.2 per cent in the northern region, 1.9 per cent in the southern region and 1.1 per cent in the western region, all other factors held constant.

Land use intensity is also positively correlated with TFP in all regions and was the second most important factor determining farm level TFP in the model. According to the model estimates, a 10 per cent increase in land use intensity is likely to increase average farm TFP by 2.9 per cent, 2.7 per cent and 3.4 per cent in the northern, southern and western regions respectively, all other factors held constant. The results suggest that, after considering all other factors in the model, there are grain farmers that are able to operate their land more intensively than others and have higher TFP.

Table 2: Regression results: model estimates and significance

<table>
<thead>
<tr>
<th>variable</th>
<th>north (1159 obs.)</th>
<th>south (2893 obs.)</th>
<th>west (947 obs.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>R²</td>
<td>67%</td>
<td>75%</td>
<td>67%</td>
</tr>
<tr>
<td>intercept</td>
<td>-31.7 *</td>
<td>-24.3 *</td>
<td>-37.8 **</td>
</tr>
<tr>
<td>moisture availability index (log)</td>
<td>0.501 **</td>
<td>0.808 **</td>
<td>0.756 **</td>
</tr>
<tr>
<td>land area adjusted (log)</td>
<td>0.117 *</td>
<td>0.188 **</td>
<td>0.109 *</td>
</tr>
<tr>
<td>land use intensity (log)</td>
<td>0.290 **</td>
<td>0.271 **</td>
<td>0.336 **</td>
</tr>
<tr>
<td>land gradient (%)</td>
<td>ns</td>
<td>-0.022 *</td>
<td>ns</td>
</tr>
<tr>
<td>finance (log)</td>
<td>0.070 **</td>
<td>0.042 **</td>
<td>ns</td>
</tr>
<tr>
<td>education of operator (0,1,…,6)</td>
<td>0.035 *</td>
<td>0.020 *</td>
<td>ns</td>
</tr>
<tr>
<td>education of spouse (0,1,…,6)</td>
<td>ns</td>
<td>ns</td>
<td>ns</td>
</tr>
<tr>
<td>age of operator (log)</td>
<td>ns</td>
<td>ns</td>
<td>ns</td>
</tr>
<tr>
<td>crop specialisation (%)</td>
<td>0.002 **</td>
<td>0.001 *</td>
<td>ns</td>
</tr>
<tr>
<td>off-farm wages (%)</td>
<td>ns</td>
<td>-0.002 **</td>
<td>ns</td>
</tr>
<tr>
<td>off-farm investment income (%)</td>
<td>-0.002 *</td>
<td>-0.004 **</td>
<td>-0.004 **</td>
</tr>
<tr>
<td>direct drill (0,1)</td>
<td>ns</td>
<td>0.445 *</td>
<td>ns</td>
</tr>
<tr>
<td>minimum till (0,1)</td>
<td>ns</td>
<td>0.364 **</td>
<td>ns</td>
</tr>
<tr>
<td>moisture direct drill interaction</td>
<td>ns</td>
<td>-0.105 *</td>
<td>ns</td>
</tr>
<tr>
<td>moisture minimum till interaction</td>
<td>ns</td>
<td>-0.089 **</td>
<td>ns</td>
</tr>
<tr>
<td>corporate farm (0,1)</td>
<td>0.284 **</td>
<td>0.119 *</td>
<td>0.153 *</td>
</tr>
<tr>
<td>trend (%)</td>
<td>1.48 *</td>
<td>1.03 *</td>
<td>1.76 **</td>
</tr>
<tr>
<td>variability of moisture availability (log)</td>
<td>ns</td>
<td>ns</td>
<td>ns</td>
</tr>
<tr>
<td>commodity price variability (log)</td>
<td>ns</td>
<td>ns</td>
<td>ns</td>
</tr>
</tbody>
</table>

* significant between the 5 per cent and 0.01 per cent levels. ** significant at less than the 0.01 per cent level. ns nonsignificant.
The degree to which land use intensity affects TFP in this model (in any particular year) is largely dependent on natural soil fertility, rainfall and subsequent management decisions (for example, double cropping), as substitutes for soil fertility such as fertiliser, have already been accounted for in the TFP measure.

Over time, however, any changes to policy settings that affect land use intensity could also have a significant impact on productivity growth. For example, to the extent that native vegetation regulations inhibit growth in land use intensity, there is likely to be a negative productivity impact. Suboptimal levels of vegetation density, type and distribution as a consequence of regulatory control can decrease returns from grazing and limit land use change to cropping, both of which could otherwise lead to higher productivity growth. Australia’s agricultural input markets are showing signs of becoming increasingly subject to regulatory control and the importance of land use intensity in determining productivity growth suggests a need to further develop the representation of natural asset data in the model.

Land gradient was a significant factor in lowering TFP in the southern region only. This would suggest that, all other factors considered, farms on relatively steeper country in the southern region are likely to exhibit lower productivity compared with farms on more level land. The model was unable to ascertain whether lower productivity growth on steeper country was directly linked to land gradient or other factors commonly associated with steeper slopes that prevail in the southern region — for example, soil fertility. Although land gradient is highly significant in the southern region, it explains very little of the variability in TFP. Furthermore, its impact on TFP is also relatively minor compared with some other factors in the model. For example, a 1 percentage point decrease in land gradient is likely to be associated with average farm TFP being around 0.22 per cent higher, all other factors constant.

**financial capital**

Finance availability is a highly significant factor influencing TFP in the northern and southern regions only. The positive coefficient indicates that farms with greater borrowing capacity and liquid assets are also likely to exhibit higher TFP. An increase in availability of finance of 10 per cent is likely to increase average farm TFP by 0.7 per cent in the northern region and 0.42 per cent in the southern region. Data on access to finance could not be collected directly and therefore the variable ‘finance’ used in this study is a proxy that has been constructed using likely determinants of credit worthiness. It was not possible to explain the cause and effect relationships between availability of finance and TFP. Further research would be required to understand the way in which access to finance emanates from higher TFP or could lead to higher productivity growth.
human capital

The number of years of formal education achieved by the farm operator is a significant and positive determinant of TFP in the northern and southern grain growing regions, but is not significant in the western region. Human capital can be increased through both formal education and ‘learning by doing’. These results suggest that, for each additional level of education (as defined in appendix A) an operator is able to attain (all other factors constant), average farm TFP is likely to increase by 3.5 per cent in the northern region and 2.0 per cent in the southern region. No measurement of experience attained through ‘learning by doing’ was available for this study.

An operator’s spouse is generally considered to be a contributor to the the human capital of a farm business and many spouses are intimately involved in management and decision making roles on grain properties. However, the education level of the operator’s spouse in the model was not a significant factor determining TFP in all regions.

activities

Crop specialisation — that is, the proportion of land area (adjusted) that is used for cropping purposes — is a significant determinant of TFP in both the northern and southern regions. A 10 percentage point increase in crop specialisation is likely to result in an increase in TFP of 2 per cent and 1 per cent respectively, all other factors constant. This is broadly consistent with past productivity research that indicates that productivity in the broadacre agricultural industries has been generally higher in cropping than in the livestock industries.

Off-farm wages as a proportion of the farm’s total cash receipts has a highly significant negative relationship with TFP in the southern region only. The results suggest that a 10 percentage point increase in the proportion of wages earned off-farm in the southern region is likely to reduce average TFP by 2 per cent, all other factors constant. This might be interpreted to imply that landholders who work off-farm may not be investing as much effort into improving the productivity of the farming operation as landholders who do not work off-farm. However, as grain farmers are assumed to be profit maximising rather than productivity maximising, diversifying income sources is a well documented livelihood strategy for minimising the risk associated with deriving income solely from agricultural production, which is substantially influenced by the vagaries of weather.
Off-farm investment income as a proportion of a farm’s total cash receipts has a highly significant negative relationship with TFP across all regions. A 10 percentage point increase in off-farm investment income is likely to lower TFP in the northern region by 2 per cent in the southern region and by 4 per cent in the western region, all other factors constant. This may indicate that some farmers are investing capital off-farm as part of a portfolio approach to investment thus reducing the capital available for on-farm productivity improvements, or due to the limited potential to improve productivity on-farm.

**mediating processes**

The choice of cultivation practices is a significant determinant of TFP in the southern region. Grain producers in the southern region who employed either direct drill (zero till) or minimal till practices were likely to exhibit, on average, higher TFP levels by around 44 per cent and 36 per cent respectively than producers using traditional cultivation methods. The choice of cultivation practices was not a significant factor influencing TFP in the northern or western regions.

There is a range of possible explanations for this result, including substitution away from traditional mechanical cultivation to chemical cultivation to minimise input costs, improve soil structure and/or conserve moisture.

Examination of the interaction between cultivation practices and moisture availability indicates that direct drill improves TFP in drier years in the northern region, as shown by the highly significant negative relationship. Direct drill is likely to be particularly important in determining the yield of winter crops in northern regions, which are dependent to a large extent on summer rainfall stored in heavier soils. Traditional mechanical cultivation for weed control and stubble management results in the loss of moisture vital for crops that might be sown up to six months later. The adoption of planters able to handle large volumes of trash and fast, GPS guided chemical cultivation rigs (up to 48 metres in width) are likely to have contributed to strong productivity growth in northern regions in particular (figure B).

The interaction between moisture availability and nontraditional cultivation practices is highly significant in the southern region. Further adoption of both minimum and zero till practices is therefore likely to improve TFP in drier years in the southern region. There are no significant improvements in TFP from using moisture conserving technology in drier years in the western region. Corporate farms are significantly more productive than noncorporate farms in all regions and were 28, 12 and 15 percentage points higher in the northern, southern and western regions respec-
tively, as derived from the corporate farm indicator variable. Corporate or publicly listed companies are likely to have greater access to financial, informational and managerial resources.

In the model, the generic trend term captures any trends in TFP that are not explained by other time related factors in the model and is significant in all regions. This suggests that productivity is increasing significantly as a consequence of factors not specified in the model in the northern, southern and western regions by 1.5 per cent, 1.0 per cent and 1.8 per cent a year. Further research is required to identify and quantify these unknown contributors to productivity growth.

**risk factors**

The risks associated with variability in the moisture availability index is not significant in any region. This implies that regions subject to greater variability in moisture availability are not likely to be less productive. As such, it can be concluded that farms in all regions may have developed agricultural systems that enable them to cope effectively with the variability in moisture availability.

The risks associated with variability in commodity output prices is significant in the southern region only; for example, an increase in price variability of 10 per cent is likely to be associated with a decrease in TFP of around –7.8 per cent, all other factors constant.

**industry characterised by heterogeneity**

Although moisture availability is a crucial factor in determining total factor productivity in the grains industry and has the largest explanatory power of any factor included in the model, TFP varies substantially not only between farms, but also within farms over time. When modeling panel data, variation of the dependent variable (TFP) occurs in both the temporal and cross-sectional dimensions. The cross-sectional variation in TFP corresponds with the variation that occurs between

---

fig B  adoption of direct drill and minimum till on grain farms

<table>
<thead>
<tr>
<th></th>
<th>1995-96</th>
<th>1998-99</th>
<th>2001-02</th>
</tr>
</thead>
<tbody>
<tr>
<td>northern region</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>southern region</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>western region</td>
<td>80</td>
<td>60</td>
<td>40</td>
</tr>
</tbody>
</table>

%
sample farms and the temporal variation corresponds with variation in TFP within
an individual farm over time. Accordingly, when modeling TFP, the aim is to explain
the total variation in TFP, which is the sum of temporal and cross-sectional variation.

The proportion of total variation of TFP explained by moisture availability is
approximately 20 per cent at the farm level. This means that 80 per cent of the
variation in TFP is explained by other factors, some of which are explicitly incor-
porated in the model as real effects and others that are not. Furthermore, the 80
per cent of variation in TFP not explained by moisture availability is comprised of
variation between farms and variation within farms.

In the model the unexplained variation between farms is captured by the random
effect term. The random effects term explains between 20 and 30 per cent of the
variation of TFP and is independent of all other covariates in the model. This means
that it explains a greater proportion of variation than moisture availability and its
inclusion in the model enables the accurate estimation of all other parameters in
the model. This means that farms that are identical to each other according to all
other factors in the model, including moisture availability, could still have substan-
tially different levels of productivity.

However, not only do significant differences exist between farms (as one would
expect), there are substantial differences in productivity over time on individual
farms (within farm variation) that cannot be explained by moisture availability
alone. The proportion of within farm variation of TFP explained by moisture
availability is approximately 35 per cent. In other words, around 65 per cent of
the variability in TFP is explained by numerous other factors, some of which are
included in the model but others that have not been included, such as the timing of
critical farm management and marketing decisions.

productivity growth trends

The total factor productivity of Australia’s grains industry increased at an average
growth rate of 1.86 per cent over the sixteen year period from 1988-89 to 2003-
04 (table 3). For the purposes of this study, Australian grains producers have been
defined as farmers in the specialist grains industry and the mixed livestock–crops
industry. Knopke et al.’s (2000, p. 13) results indicated that productivity growth
rates realised by specialist croppers (3.6 per cent) were noticeably higher than the
average rate achieved by mixed livestock–croppers (2.6 per cent) over the period
1977-78 to 1998-99. However, the results from this study suggest that the gap has
narrowed and that the productivity growth rates for specialist croppers and mixed
farms are roughly equal at 1.8 per cent and 1.9 per cent respectively.
The TFP growth rate for all regions of 1.86 per cent estimated in this study is considerably less than the rate of 3.8 per cent obtained by Knopke et al. (2000, p.15) over the period 1977-78 to 1993-94. Knopke et al. (2000) observed a decline in productivity growth rates in the mid to late 1990s and the estimate in this study provides further evidence that total factor productivity growth in Australia’s grains industry has continued to decline in recent years.

Part of the reason that the TFP growth rates presented here are lower than those reported by Knopke et al. (2000) is because of the severe drought toward the end of the sixteen year analysis period. Moisture availability effects are the largest single factor affecting TFP as mentioned earlier. Time series plots of TFP and an index of moisture availability show that the peaks and lows of TFP in each region coincide with the peaks and lows in the moisture availability index (figure C and D). It is therefore appropriate to measure the underlying TFP growth rate excluding

### Table 3  Total factor productivity growth rates, 1988-89 to 2003-04

<table>
<thead>
<tr>
<th>GRDC region</th>
<th>region growth rate excl. moisture effect</th>
<th>region growth rate excl. moisture effect</th>
<th>farm average growth rate excl. moisture effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>all</td>
<td>2.58 *</td>
<td>2.19 *</td>
<td></td>
</tr>
<tr>
<td>north</td>
<td>1.26</td>
<td>2.03 *</td>
<td></td>
</tr>
<tr>
<td>south</td>
<td>2.81 *</td>
<td>2.03 *</td>
<td></td>
</tr>
<tr>
<td>west</td>
<td>2.67 *</td>
<td>2.47 *</td>
<td></td>
</tr>
</tbody>
</table>

* Estimate is statistically significant at the 5 per cent level.
the effect of moisture availability (table 3) to better understand how efficiently farmers are combining market inputs to produce market outputs because moisture availability is such a larger driver of productivity beyond farmers’ control.

However, even after allowing for affects of moisture availability, including the recent drought, the TFP growth rate adjusted for moisture availability at a national level of 2.58 per cent remains considerably less than the growth rates obtained by Knopke et al. over the period 1977-78 to 1993-94 of 3.8 per cent. This fact suggests that productivity growth rates for farms in the grains industry may be on the decline.

The growth rates referred to so far and presented in the first two columns of table 3, and also those produced previously by ABARE (Knopke et al. 2000), are for a given industry or aggregate region as a whole. These are useful for comparison with other sectors of the economy or for international comparisons where individual farm level data are not available or where productivity estimates have been estimated using incompatible methodologies. However, such aggregate growth estimates conceal the distribution of productivity growth occurring on component farms.

Any industry or particular region is typically dominated by a small proportion of large farms. Accordingly, the growth rates computed at an aggregate level will underweight the contribution of smaller enterprises. Furthermore, the analysis in the previous section examined factors that influence the productivity of individual grain producers. Thus to be consistent and reflect a more accurate picture for all producers comprising the grains industry, farm average productivity growth rates were produced and used as a basis for all subsequent analysis in this report.

The farm average TFP growth rate excluding the effect of moisture availability of Australian grain producers from 1988-89 to 2003-04 is 2.19 per cent, which is considerably less than the industry aggregate growth rate of 2.58 per cent in table 3. This suggests that the TFP growth rate of smaller producers in the grains industry was less than that of larger producers over the sixteen year period. The farm average TFP growth rate (excluding the effect of moisture availability) trended upwards in all three GRDC regions (north, south and west) in the sixteen year period from 1988-89 to 2003-04 (table 3). However, TFP growth rates in the western region were the largest over the sixteen years.

Further analysis of the distribution of farm average TFP growth rates being achieved within each GRDC region (excluding the effect of moisture availability) is illustrated using the box and whisker plots in figure E. The box is drawn so that its lower and upper boundaries correspond to the 25th and 75th percentiles, while a line at the
value of the median is drawn in the interior of the box. The 5th and 95th percentiles are marked by the limits of the whiskers. The small '+' sign in the box marks the mean.

Figure E clearly illustrates that each GRDC region has a unique distribution of TFP growth rates among component farms. The western region is characterised by farms displaying relatively similar TFP growth rates; 50 per cent of the farms have TFP growth rates that differ by only 0.30 per cent a year and 90 per cent of the farms differ by only 1.32 per cent a year. This is likely to indicate that grain farms in the western region are relatively homogeneous in terms of farm enterprise structure and management. Interestingly, the box and whisker plot is skewed downwards. This could suggest that practices that improve productivity may be adopted rapidly and that the usual leader-follower gap is quite narrow.

The distribution of TFP growth rates in the southern region is highly peaked, which is characterised by 50 per cent of the farms being tightly clumped around the median, but large heterogeneity of the remaining farms — rates for 90 per cent of the farms in the southern region vary by up to 3 per cent a year. The distribution is also upwardly skewed, consistent with the expected leader-follower lagged behavior of adoption of innovation. TFP growth is most heterogeneous on grain farms in the northern region, with the TFP growth rates differing by 0.40 per cent a year for 50 per cent of the farms and by up to 2.24 per cent a year for 90 per cent of the farms (figure E).

The key components of total factor productivity have been separated in table 4 in order to identify where the main changes are occurring. On average, total output from grain farms has grown annually in all three GRDC regions over the past sixteen years: western region (4.8 per cent), southern region (3.8 per cent) and northern region (1.1 per cent). The strongest output growth occurred in the western region, largely due to the significant increase in cropping. Although the downward trend in wool growing is not statistically significant in the northern region, it is likely that the importance of the wool industry is contracting. In 1988-89, grain and wool production in the

![distribution of total factor productivity growth rates](image-url)
western region accounted for around 60 per cent and 28 per cent of total output respectively. In 2003-04, however, these proportions had shifted to 74 per cent and 9 per cent respectively. The shift from wool to cropping was most dramatic in the southern region, where average farm wool output was declining at around 13 per cent a year over the sixteen years, to the extent that wool’s share of average farm output was around 6 per cent in 2003-04. Wool production in the northern region trended in the same direction. All three GRDC regions exhibited significant increases in income from other nonagricultural sources.

The quantity of total inputs used on grain properties in the northern region remained roughly constant between 1988-89 and 2003-04. However, there has been a significant decline in capital, fuel and labor inputs, concurrent with a significant increase in consumption of chemicals. Increased chemical use is consistent with greater adoption of low tillage crop husbandry practices that can deliver higher yields through greater moisture retention. The decline in the levels of farm capital inputs used on grain farms is largely explained by the decline in buildings and other farm improvements as well as the reduction in the sheep flock.

**Table 4**  
Farm average growth rates (excluding moisture effect) from 1988-89 to 2003-04, and share of input or output costs in 2003-04 
cropping and mixed cropping–livestock industries, by GRDC region

<table>
<thead>
<tr>
<th>variable</th>
<th>north</th>
<th>south</th>
<th>west</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>growth share</td>
<td>growth share</td>
<td>growth share</td>
</tr>
<tr>
<td></td>
<td>% pa</td>
<td>%</td>
<td>% pa</td>
</tr>
<tr>
<td>TFP</td>
<td>2.0 *</td>
<td>2.0 *</td>
<td>2.5 *</td>
</tr>
<tr>
<td>all outputs</td>
<td>1.1</td>
<td>100</td>
<td>3.8 *</td>
</tr>
<tr>
<td>crops</td>
<td>1.3</td>
<td>61</td>
<td>3.7 *</td>
</tr>
<tr>
<td>livestock</td>
<td>2.6</td>
<td>28</td>
<td>-2.9 *</td>
</tr>
<tr>
<td>wool</td>
<td>-6.1 *</td>
<td>5</td>
<td>-13.1 *</td>
</tr>
<tr>
<td>other</td>
<td>79 *</td>
<td>5</td>
<td>73 *</td>
</tr>
<tr>
<td>all inputs</td>
<td>-0.9</td>
<td>100</td>
<td>1.8 *</td>
</tr>
<tr>
<td>land</td>
<td>-0.9</td>
<td>11</td>
<td>1.2 *</td>
</tr>
<tr>
<td>capital</td>
<td>-3.8 *</td>
<td>25</td>
<td>-0.8 *</td>
</tr>
<tr>
<td>labor</td>
<td>-1.7 *</td>
<td>17</td>
<td>0.4</td>
</tr>
<tr>
<td>all materials</td>
<td>0.4</td>
<td>23</td>
<td>3.4 *</td>
</tr>
<tr>
<td>- crop chemicals</td>
<td>6.1 *</td>
<td>11</td>
<td>9.0 *</td>
</tr>
<tr>
<td>- fuel</td>
<td>-1.9 *</td>
<td>7</td>
<td>1.3 *</td>
</tr>
<tr>
<td>all services</td>
<td>-1.1</td>
<td>24</td>
<td>2.1 *</td>
</tr>
<tr>
<td>- contracts</td>
<td>-7.6</td>
<td>4</td>
<td>0.6</td>
</tr>
</tbody>
</table>

* Estimate is statistically significant at the 5 per cent level.
In contrast to the northern region there was significant average annual growth in total input use in the southern region (1.8 per cent) and the western region (2.3 per cent) over the sixteen year period (table 4). The growth in the quantities of inputs used was largely a consequence of the growth in material and services used. In 2003-04, these inputs accounted for roughly half of all inputs used in both of these regions. A significant proportion of the growth in total inputs used also resulted from a substantial increase in the use of crop chemicals – 9 per cent a year in the southern region and 18 per cent a year in the western region. Crop chemicals accounted for at least 10 per cent of all input use in all regions in 2003-04 – more than the farm average input share for fuel in all regions. At the same time, there was a slight reduction in capital inputs, consistent with the greater adoption of minimum tillage techniques.

Even at a regional level, farm average TFP growth rates conceal marked subregional performance variation, reinforcing the need to disaggregate further to the level of a GRDC agroecological zones (table 5 and map 3). The average farm TFP growth rates (excluding the effect of moisture availability) ranged from 0.68 per cent in

<table>
<thead>
<tr>
<th>GRDC agroecological zone</th>
<th>TFP growth rate excl. moisture effect</th>
<th>sensitivity to moisture availability</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>northern region</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Queensland Central</td>
<td>0.68</td>
<td>0.96 *</td>
</tr>
<tr>
<td>NSW North East and Queensland South East</td>
<td>1.70 *</td>
<td>0.49 *</td>
</tr>
<tr>
<td>NSW North West and Queensland South West</td>
<td>3.30 *</td>
<td>1.47 *</td>
</tr>
<tr>
<td><strong>southern region</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NSW Victoria Slopes</td>
<td>2.87 *</td>
<td>0.83 *</td>
</tr>
<tr>
<td>NSW Central</td>
<td>1.06</td>
<td>0.90 *</td>
</tr>
<tr>
<td>Victoria High Rainfall</td>
<td>3.36 *</td>
<td>0.59</td>
</tr>
<tr>
<td>South Australia Victoria Mallee</td>
<td>2.57 *</td>
<td>0.92 *</td>
</tr>
<tr>
<td>South Australia Victoria Bordertown-Wimmera</td>
<td>2.25 *</td>
<td>1.27 *</td>
</tr>
<tr>
<td>South Australia Midnorth-Lower Yorke, Eyre</td>
<td>1.54 *</td>
<td>0.58 *</td>
</tr>
<tr>
<td><strong>western region</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Western Australia Mallee and Sandplain</td>
<td>2.28 *</td>
<td>1.62 *</td>
</tr>
<tr>
<td>Western Australia Eastern</td>
<td>0.89</td>
<td>1.09 *</td>
</tr>
<tr>
<td>Western Australia Central</td>
<td>2.60 *</td>
<td>0.78 *</td>
</tr>
<tr>
<td>Western Australia Northern</td>
<td>3.13 *</td>
<td>1.12 *</td>
</tr>
</tbody>
</table>

* Estimate is statistically significant at the 5 per cent level.
Queensland’s central zone (although not significantly different from zero) to 3.36 per cent in the Victorian high rainfall zone. Given that farm average TFP growth rates for the northern, southern and western regions are 2.03, 2.03 and 2.47 per cent respectively (table 3) and the range of TFP growth rates at the zonal level within each region is of the same order of magnitude, 2.62, 2.30 and 2.24 per cent respectively (table 5), there is evidently considerable variation in farm average TFP growth rates within regions and loss of information when relying on national aggregate measures.

Productivity growth rates in the GRDC agroecological zones also vary in their degree of sensitivity to moisture availability as shown in map 3 (data in table 5).

It is unclear whether there is a direct relationship between productivity growth and sensitivity to moisture availability. However, it is evident from comparing the upper and lower panels of map 3 that some agroecological zones that are highly sensitive to moisture availability also have higher than average farm TFP growth (excluding the effect of moisture availability), in particular, the NSW North West and Queensland South West zone in the northern region and Western Australia’s northern zone.

Previous work by Nelson et al. (2005) suggests that farms in these zones may have fewer livelihood options than farms in other parts of the country, which may be the reason why moisture availability has such a large impact on their productivity levels.
In this appendix, a framework is specified for systematically assembling the set of factors that potentially influence productivity growth in the Australian grains industry. The benefit of this framework — rather than selecting potential factors on an ad hoc basis — is that it may lower the likelihood of overlooking important determinants.

The statistical model used in this report to identify key factors likely to influence productivity growth is also more stable than models used in past research (Alexander and Kokic 2005) because the number of observations is substantially higher when using temporal and cross-sectional data in mixed models with a correlated error structure. This is possible by using a Laird–Ware model that accommodates the 'tattered panel' nature of ABARE’s farm survey data. The farm survey data forms a tattered panel because the same farms are not surveyed every year.

Heuristic explanation of the residual nature of productivity growth

This section provides a brief overview of the residual nature of productivity growth, common at whatever level of definition productivity is measured. The following explanations will enable a better understanding of the evolution of productivity measures summarised in figure F, with more in-depth definitions and detail following.

Total factor productivity growth is the additional growth in the volume index of all market outputs above the one-for-one growth that could be expected from the growth in the volume index of all market factor inputs. Total factor productivity growth is therefore considered to be a residual growth.

‘As I understand it, we are interested in “productivity” because we are interested in understanding ... the forces that affect “output” because we hope, ultimately, to be able to affect them for the better. We approach this task first by trying to take into account the “obvious” factors: changes in labor and capital (and other materials if our output measures are gross).
We measure these factors as best we can, aggregate them using some sensible weighting procedure and get a "total input" index. We compare this index with our output index and call any discrepancy "productivity". Crudely speaking then, the "productivity" indexes measure those changes in output that have not been accounted for by the analyst's input measures. It is a measure of our ignorance, and of the magnitude of the task that is still ahead of us.' (Griliches 1961, p. 446)

Total factor productivity (TFP), the conventional index measure of on-farm productivity, is defined as the ratio of the volume index of all marketable outputs, $O_M$, to the volume index of all marketable inputs, $I_M$:

$$ TFP = \frac{O_M}{I_M} $$

The estimated geometric time trend in total factor productivity is the total factor productivity growth rate. It is a measure — over the data period — of the (yearly) proportional rate of improvement in the technical efficiency with which farmers combine marketable inputs to produce marketable outputs.
Previous studies have commonly estimated changes in TFP over time at an aggregate level, such as for a country or industry. However, with detailed panel data it is possible to use the same formulae to estimate TFP across farms, as well as over time. This allows TFP comparisons over time and between farms.

However, as Gollop and Swinand (1998) point out, total factor productivity at the aggregate national level is a ‘biased barometer of how well society is allocating scarce resources’ because it fails to take into account changes in nonmarket inputs and outputs. They propose a measure of productivity, which they refer to as total resource productivity, that includes nonmarket inputs and outputs.

Using the rural livelihoods framework developed by Ellis (2000), total factor productivity in the current paper is related to nonmarket socioeconomic inputs and outputs. The following regression model is used to determine the significance of those factors for TFP:

$$\ln(\text{TFP}) = \mu + \sum_{i \in N} \alpha_i \ln x_i + \epsilon$$

where $\mu$ is a constant and $x_i$ is the volume of nonmarket factor $i$ out of the set of all nonmarket factors $I_{N}$.

**Definition of total factor productivity**

The calculation of TFP is straightforward when the production process involves only one input and output. However, simpler partial measures of productivity (such as yield per hectare) can be misleading, as they tend to attribute all productivity change to a single factor and fail to capture changes in the intensity of the use of other inputs. When there is more than one input (or output) it is necessary to use an indexing procedure to aggregate these diverse inputs (or outputs). There is some debate about the most appropriate indexing procedure (Christensen 1975). The different ways of calculating index numbers correspond to the different functional forms of the underlying production function.

Coelli et al. (1998) identify four of the more commonly used index approaches, including the Laspeyres, Paasche, Tornqvist and Fisher indexes. The Laspeyres and Paasche indexes are used by national statistical agencies to compute both price and volume/quantity indexes, including the consumer price index. These two indexes are popular because they are easy to compute and provide ‘bounds’ for the true index defined using economic theory. The two approaches differ,
however, as the Laspeyres quantity index uses base period prices as weights, while the Paasche index uses current period prices when calculating TFP. The Fisher index (used in this study) is the geometric mean of the Laspeyres and Paasche indexes and is an approach that lies between these two extremes.

The Fisher and Tornqvist indexes are preferred for TFP studies as they have a number of desirable statistical and theoretical economic properties (Christensen 1975; Diewert 1992; Coelli et al. 1998). Although the Tornqvist index is commonly used to calculate TFP, there are equally strong economic justifications for using the Fisher index. Furthermore, the Fisher index may be preferred because it is the only index that satisfies all twenty-one mathematical properties expected of indexes (Diewert 1992). The Fisher index satisfies properties identified by Fisher (1922) as desirable for index formulae, including positivity, continuity, proportionality, commensurability, time reversal, mean value and factor reversal tests. Mullen and Cox (1995) and Islam (2000) also recommended the Fisher index in their studies measuring productivity growth of broadacre agriculture in Australia. Importantly for this study, the Fisher index can handle zero quantities (Coelli et al. 1998). Zeros were common in the data used in this analysis because not all farms had the same range of inputs and outputs.

The Fisher index does not, however, satisfy the transitivity test, which is required for an index to be used to make comparisons between farms (Coelli et al. 1998). Internal consistency is preserved if this condition is satisfied. This test requires that for any three farms or time periods, s, t and r, a direct comparison between s and t produces the same index as an indirect comparison through r. For this study the Fisher index was transformed to make it transitive — see the following section.

Total factor productivity is a ratio of an output quantity index relative to an input quantity index. Each index represents the change in combined inputs or combined outputs relative to a chosen farm or time. The input or output quantities are aggregated using corresponding market prices. The groups of variables making up the inputs and outputs in the present report are described below.

**inputs**

Inputs consist of 28 items that can be split into five major groups: land, capital, livestock purchases, labor, material and services.

**Land** — the value variable for land is the opportunity cost of investing funds in this capital item. This is calculated as the average capital value (that is, the average
of the opening and closing values) multiplied by a real interest rate. The quantity variable used for land is the area operated.

**Capital** is divided into plant and machinery, structures and livestock. The value variable for livestock is the opportunity cost of investing funds in this item. This is calculated as the average capital value (that is, the average of the opening and closing values) multiplied by a real interest rate. The value variables for structures, plant and machinery are the opportunity costs plus depreciation. For beef cattle, sheep and other livestock, the quantity variable is the average of opening and closing numbers. For buildings and plant capital, it is the average value of capital stock deflated by the respective prices paid indexes for each.

**Livestock purchases** are split into beef, sheep and other livestock purchases. Their value equals purchases plus the value of natural changes (births and deaths) and transfers out provided together these are negative. The quantity variables for sheep and beef are derived from the respective value variables and respective prices received indexes for sheep meats and slaughtered beef. For the relatively small category of other livestock, the quantity variable is derived from the value of purchases and a prices received index for livestock products.

**Labor** consists of four items — owner operator and family labor, hired labor, shearing costs, and stores and rations. The value of the owner operator and family labor input is imputed using weeks worked (collected as part of the survey) and an award wage. The value of hired labor is wages paid, and the values of shearing and stores and rations are expenditure on these items. The quantity variables for owner operator and family labor and hired labor are weeks worked. Expenditure on shearing was deflated by a shearing prices paid index to obtain the quantity variable for shearing.

There are seven items in the materials and services group — fertiliser, fuel, crop chemicals, livestock materials, seed, fodder and other materials. And there are eight items in the services group — rates and taxes, administrative costs, repairs and maintenance, veterinarian expenses, motor vehicle expenses, insurance, contracts and other services. The value for each item is expenditure. The quantity variables are derived by deflating the expenditure on each by the appropriate prices paid index.

**outputs**

Output consists of twelve items that can be divided into four major groups: crops, livestock sales, wool and other farm income.
Crops are split into wheat, barley, oats, grain sorghum, oilseeds and other crops. The value variable for wheat is the quantity harvested multiplied by the Australian Wheat Board’s average net return for that year’s pool. For other grains and other crops, the value variable is net receipts in that year. The quantity variable for each of the grains is the quantity harvested. For the other crops, it is receipts deflated by the prices received index for crops.

For livestock sales of beef, sheep and lambs, the value is sales plus the value of natural changes (births and deaths) and transfers in provided together these are positive. For the minor category of other livestock, the value variable is sales. The quantity variables for beef, sheep and lambs are derived from the respective value variables and the prices received indexes for slaughtered beef, sheep and lamb meats. For the category of other livestock, the quantity variable is derived from the value of sales and a prices received index for livestock products.

For wool the value variable is net receipts. The quantity variable is the amount of wool shorn in kilograms.

And finally for other farm income the value variable is receipts and the quantity variable is receipts deflated by the sector prices received index.

Fisher’s ideal index

Index numbers are usually computed over time, but they can also be evaluated between farms and between time points. In the following let the subscripts \( s \) and \( t \) represent two farms at two, possibly different, time points.

The Fisher ideal quantity index is defined in terms of the Laspeyres and Paasche quantity indexes:

\[
Q^L_{st} = \frac{\sum_{i=1}^{N} P_{si} q_{si}}{\sum_{i=1}^{N} P_{si} q_{is}} \quad \text{and} \quad Q^P_{st} = \frac{\sum_{i=1}^{N} P_{si} q_{is}}{\sum_{i=1}^{N} P_{si} q_{is}}
\]

respectively, where \( i, 1 \leq i \leq N \) represents the input (output) \( i \) used (produced) on the farm, \( N \) is the total number of inputs (outputs), \( p_{si} \) is the price for input (output) \( i \) for \( s \) and \( q_{is} \) is the quantity used (produced) of \( i \).

Fisher’s ideal index is the geometric mean of the Laspeyres and Paasche indexes:

\[
Q^F_{st} = \sqrt{Q^L_{st} Q^P_{st}}
\]
When applying the formulae above, a farm at a given time point is chosen as the base and given an index value of 1. The index values of all other farms at all other time points are then relative to this base farm. If an index number is transitive, any two farms at any two time points can be compared with each other by simply dividing their respective index numbers. In other words, if the index is transitive, the estimates from a regression analysis will not depend on which farm is chosen as the base. This is critical when working with farm level data.

To ensure that Fisher’s index is transitive the following transformation is applied:

\[ Q_{sr}^f = \left( \prod_{t=1}^{n} Q_{st}^f Q_{rt}^f \right)^{1/n} \]

where \( 1 \leq r \leq n \) and \( n \) is the number of sample points, including repeated observations of the same farm at different time points.

**derivation of total livelihood productivity**

Total livelihood productivity is a holistic measure of the way in which farm businesses combine all market and nonmarket inputs to produce all market and nonmarket outputs, including both farm based and non-farm based inputs and outputs. The following derivation commences by formulating the rural livelihood framework at the individual household level for subsequent inclusion into Gollop and Swindand’s (1998) derivation of total resource productivity from the constrained maximisation of aggregate output in a competitive economy.

A comprehensive explanation of the terms used in the framework for livelihood analysis is found in the main body of this report.

A livelihood is defined as comprising ‘the assets, activities, and access to these [mediated by institutions and social relations] that together determine the living gained by an individual or household’ (Ellis 2000, p. 10). Thus,

\[ \text{livelihood} = f(\text{assets, activities, access}) \]

where assets comprise five types of capital accessed by farm households to produce flows of outputs (financial, human, natural, physical and social); activities are the various enterprises that generate the means of household existence (for example, cropping, grazing or contract harvesting); and access represents other socioeconomic, natural, policy and other external factors that impact on farmers livelihood strategies (see chapter 4). According to Ellis (2000, p. 10), the most
direct and measurable annual outcome of the livelihood process is household annual income. Therefore,

\[ \text{income} = \text{livelihood} = f(\text{assets, activities, access}). \]

Income is defined as being net of purchased input costs and can therefore be treated as ‘profit’:

\[ \text{profit} = P \cdot Q \equiv \text{income} = \text{livelihood} = f(\text{assets, activities, access}) \]

where \( P \) is a vector of output prices, \( q \), and input prices, \( w \) (some of which are nonmarket prices), \( Q \) is a vector of output quantities, \( Y \), and input quantities, \( X \) (including negative externalities such as pollution), equals farm income (agricultural output produced net of input costs — for example, crops, livestock, other natural resources) plus off-farm income (for example, contract harvesting) plus non-farm income (for example, investment income).

Assuming that farm households aim to improve their livelihoods (maximise their wealth) and therefore farm businesses aim to maximise their profits, then in the absence of market distortions and externalities their individual supply behavior is consistent with maximisation of aggregate profits in a competitive economy [Mas-Colell, Whinston and Green 1995]. It is assumed that individual grain producers maximise productivity given competitively determined market prices, nonmarket resource endowments, existing regulations and technologies associated with each activity. It is also assumed that grain producers are working at full capacity with all capital stocks fully utilised, except access to finance.

Adopting the notation of Gollop and Swinand (1998), production conditions can be expressed as a function, \( H \), of outputs, \( Y \), inputs, \( X \), and a time-index, \( T \), representing technology:

\[ H(Y, X, T) = 1 \]

where \( X \) includes purchased materials, labor and other services, as well as assets, activities and access as defined in the framework of Ellis (2000). Under the assumption of a Walrasian competitive market equilibrium, it follows that:

\[ \sum_{j \in J} q_j Y_j = \sum_{i \in I} w_i X_i \]

where \( q_j \) is the price of the output \( j \), \( w_i \) the price (or shadow price) of the input \( i \), \( J \) is the set of outputs and \( I \) is the set of inputs. Note that there is a subset of inputs...
that at any point in time is given to the farmer. For such inputs, the profit maximisation objective simplifies to maximisation of the combined returns to these fixed inputs, thus yielding their shadow prices. This group of inputs consists of land, owner/operator’s labor and skill level, labor of other family members, fences, some farm owned plant and equipment, etc.

Following Gollop and Swinard (1998), the growth rate of TLP may be written as:

\[
E_{\text{TLP}} = \frac{\partial \ln H}{\partial T} = \sum_{j \in J} q_j Y_j \frac{\partial \ln Y_j}{\partial T} - \sum_{i \in I} w_i X_i \frac{\partial \ln X_i}{\partial T}
\]

where \( M = \sum_{j \in J} q_j Y_j \) is the budget constraint from (2). Let the input subscripts \( I = I_1 \cup I_2 \), where \( I_1 \) represents the market based inputs (that is, inputs for which there exists market prices) and \( I_2 \) represents the nonmarket fixed inputs for which the farmer’s profit maximisation results in shadow prices. It follows from (3) that:

\[
E_{\text{TLP}} = \sum_{i \in I_1} w_i X_i \frac{\partial \ln X_i}{\partial T}
\]

where \( E_{\text{TFP}} \) is the growth rate of total factor productivity. As \( \frac{\partial \ln X_i}{\partial T} = 0 \) for the fixed inputs, it follows that \( E_{\text{TFP}} = E_{\text{TLP}} \).

We now put forward the linear regression:

\[
\ln(\text{TFP}) = \mu + \sum_{i \in I_2} \alpha_i \ln X_i + \epsilon
\]

Since there are no boundary constraints, \( \mu \) may be chosen arbitrarily and so without loss of generality it can be assumed that \( E(\epsilon) = 0 \).

Equation (5) can be used to determine whether between farm variation in fixed inputs, such as education levels can explain variations in TFP.
the Laird–Ware model

When using ABARE’s agricultural survey data it is important to note that these data have an incomplete ‘tattered panel’ structure. That is, some farms stay in the survey for the complete sixteen year period, some stay for part of the period and some stay for a shorter period, drop out from the survey and then come back in. This is partly caused by the design of the survey, which aims to reduce response burden while maximising the accuracy of estimates subject to cost constraints. These type of data can be modeled successfully using linear mixed models for which the residuals are temporally correlated.

Because of missing variables, when fitting equation (5) to real data, not all the variation between individual farms will be accounted for. However, by accounting for these differences in the modeling process, the overall fit of the model and consequently the accuracy of parameter estimates should improve. This is achieved by including a farm level ‘random effect’ term that effectively separates the unexplained variation between farms in the model from the within farm variability over time.

Missing variables may also create differences in the response over time, which can be accounted for in the model by assuming that the residuals are correlated over time within each farm. Failing to include this term when it exists produces an underestimate of the variance that in some cases leads to the false inclusion of unimportant factors in the model.

A very flexible form of mixed model that meets all the requirements above is the Laird–Ware model (Laird and Ware 1982). Most generally the Laird–Ware model is of the form:

\[ y_i = X_i \beta + Z_i \gamma_i + \epsilon_i \]

where \( y_i \) is an \( n_i \times 1 \) column vector of response variable for subject \( i \), \( X_i \) is an \( n_i \times p \) design matrix, \( \beta \) is a \( p \times 1 \) column vector of regression coefficients assumed to be fixed, \( Z_i \) is an \( n_i \times q \) design matrix for the random effects and \( \gamma_i \), which are assumed to be normally distributed with mean zero and variance \( \sigma^2 B \), and are independently distributed across subjects. The matrix \( B \) is an arbitrary covariance matrix. The within subject errors, \( \epsilon_i \), are assumed to be normally distributed with mean zero and variance \( \sigma^2 W_i \), where \( W_i \) is a covariance matrix. The \( \epsilon \) are also independent from subject to subject and independent of \( \gamma_i \).
The Laird–Ware model is very general since different subjects can have different numbers of observations as well as different observation times. Even though the Laird–Ware model is much more general than a simple linear mixed model, it has a very similar likelihood function. When there are several groups of subjects, this is incorporated into the design matrix $X_i$, and the mean vector for subject $i$ is $X_i \beta$. Since the two random components have zero means, $\gamma_i$ is uncorrelated with $\varepsilon_i$. The two covariance matrices are $\text{cov}(\gamma_i) = \sigma^2 B$ and $\text{cov}(\varepsilon_i) = \sigma^2 W_i$, and the total covariance matrix for subject $i$ is:

$$\sigma^2 G_i = \sigma^2 (Z_i B Z_i^T + W_i)$$

Assuming that there are $n_i$ observations for subject $i$, $-2\ln$ of the likelihood is:

$$l = \sum_i n_i \log(2\pi) + \log(\sigma^2 G_i) + (\gamma_i - X_i \beta)^T (\sigma^2 G_i)^{-1} (\gamma_i - X_i \beta)$$

Differentiating $l$ with respect to $\sigma^2$ and setting the result to zero gives:

$$\hat{\sigma}^2 = \frac{1}{n} \sum_i (\gamma_i - X_i \beta)^T G_i (\gamma_i - X_i \beta)$$

Also, for given values of the $B$ and $W_i$, the value of $\beta$ that minimises $l$ is:

$$\hat{\beta} = \left( \sum_i X_i^T G_i^{-1} X_i \right)^{-1} \left( \sum_i X_i^T G_i^{-1} \gamma_i \right)$$

which is the generalised least squares estimator.

Weighting was not used when fitting the Laird–Ware model because the variables used to stratify and select the sample are covariates or are highly correlated with certain covariates in the model. This implies that the design of the survey can be ignored when estimating parameters of the model. See, for example, Breckling, Chambers, Dorfman, Tam and Welsch (1994).

It is possible to adapt (5) to a Laird-Ware form so that it includes a farm level random effect term and temporally correlated errors as follows:

$$\ln(TFP_{ij}) = \mu_i + \sum_{i \in j} \alpha_{ij} \ln X_{ij} + \varepsilon_{ij}$$

where $\mu_i = \alpha_{o} + \gamma_{o,j}$ is the mean effect for farm $j$ of all variables omitted from the regression model, $\alpha_{o}$ is the overall mean effect and $\gamma_{o,j}$ is random effect for farm $j$. The $\varepsilon_{ij}$ term in the equation above is the within farm error, which is assumed to
be independent across subjects, independent of the random effect and normally distributed, but is assumed to be correlated over time according to a continuous autoregressive 1 process:

$$e_{jt} = e^{-\alpha t} e_{j(t-\Delta t)} + \eta_{jt}$$

where $\eta_{jt}$ is a random error term that is distributed normally with mean 0 and variance $\sigma_{\eta}^2$.

**Treatment of data entering the regression model**

For a variety of reasons, it was not considered appropriate for all covariates to enter the model in a logarithmic format. Accordingly, the standard approach to taking logs has been followed, as discussed in Wooldridge (2000).

Variables that are proportions or expressed as a percentages remain in their original form. This enables the regression coefficient to have a percentage point change interpretation. For example, if a proportional variable $X_i$ were to increase from 69 to 70 per cent and the regression coefficient is $\alpha_i = 0.2$, the proportional change in TFP would be 0.2 per cent, all other factors held constant.

Indicator variables, such as the land degradation variables, could not be logged because $\log(0)$ is undefined and accordingly remained in their original form. Regarding interpretation of the estimate for indicator variables, if the condition is true (that is, $X_i = 1$) and the regression coefficient is $\alpha_i = 0.2$, TFP is likely to be 22.1 per cent higher ($\exp(0.2) - 1$) compared with the base case $X_i = 0$. Ordinal variables, such as ‘education of operator’, are treated similarly.

All other variables were logged and have been labelled as such (table 2). In the case of logged explanatory variables, the estimate $\alpha_i$ is often referred to the ‘elasticity’ pertaining to individual explanatory factors. An elasticity is the ratio of the incremental percentage change in TFP with respect to an incremental percentage change in one of the explanatory factors, all other factors held constant. For example, an elasticity of 0.07 per cent [i.e. $\alpha_i = 0.07$] means that if the explanatory factor was increased by 10 per cent, TFP is likely to increase by 0.7 per cent, all other factors held constant. The proportional impacts on TFP for each type of explanatory variable are shown in equation:

$$\frac{\partial TFP}{\partial X_i} = \begin{cases} \alpha_i \frac{\partial X_i}{X_i} & \text{if the explanator is logged} \\ \frac{\partial X_i}{X_i} & \text{if the explanator is linear} \\ e^{\alpha_i} - 1 & \text{if the explanator is an indicator variable} \end{cases}$$
where $\alpha_i$ is the estimate of the coefficient.

Correctly identifying the factors likely to influence productivity growth from among a set of potential or theoretically justifiable factors is the primary aim of this project. Stability means that the parameter estimates and their significance do not change much if minor alterations are made to the data. In practice, regression models using farm survey data are susceptible to instability.

The main cause of instability in farm productivity models is the presence of outliers and significant correlation between explanatory variables. Outliers can have a high influence on parameter estimates, particularly if they lie a long way from the mean of the data. The best approach is to obtain more data. This has been achieved in this study by the use of more sophisticated statistical modeling that uses data both over time as well as cross-sectionally.

Model instability caused by excessive correlation between pairs of explanatory variables can be dealt with by excluding one of the correlated variables. The choice of which variable to retain is based primarily on how closely it represents the underlying theoretical causal factors. The downside of doing this is that some variables will incorporate effects from more than one causal factor – that is, the omitted variable bias. This means that the regression estimates for the included variable may be too large because it partly incorporates the effect of the excluded variable. However, the expansion of the data set mentioned previously greatly assisted in the reduction of significantly correlated explanatory variables compared with earlier studies.

**regression variables**

<table>
<thead>
<tr>
<th>variable</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>natural capital</strong></td>
<td></td>
</tr>
<tr>
<td>land area (adjusted)</td>
<td>Operating area of farm in hectares of arable land – that is, the number of sheep divided by 12 plus the number of beef cattle times 8 and divided by 12, plus the number of hectares cropped. This measures the total productive capacity of the farm. Its purpose is to capture scale economies while allowing for and quality variation.</td>
</tr>
<tr>
<td>land use intensity</td>
<td>The land area (adjusted) divided by total area operated. This variable acts as a crude proxy for land quality and management intensity.</td>
</tr>
<tr>
<td>moisture availability index</td>
<td>A shire-scale measurement of moisture available for the winter wheat crop (Potgieter et al. 2002).</td>
</tr>
</tbody>
</table>


continued...
### Regression Variables (continued)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land gradient</td>
<td>Average slope of land (percentage rise). Data were derived from NASA’s SRTM-3 3-second DEM.</td>
</tr>
<tr>
<td>Financial capital</td>
<td></td>
</tr>
<tr>
<td>Finance</td>
<td>Access to credit plus liquid assets per unit of land area (adjusted). This metric has been constructed by summing borrowing capacity and liquid assets and dividing by land area (adjusted). Borrowing capacity has been derived according to each farms’ equity ratio. Where the equity ratio is less than 70 per cent borrowing capacity is zero, otherwise borrowing capacity = (equity ratio − 0.70) × capital invested (excluding leased assets). Although it is acknowledged that corporate farms are likely to have different financing facilities, it was not possible to model these effects separately and therefore all farms had these finance data constructed in the same manner.</td>
</tr>
<tr>
<td>Human capital</td>
<td></td>
</tr>
<tr>
<td>Education of operator</td>
<td>Ordinal variable with the following values: (1) primary school completed or attended; (2) 1–4 years high school completed; (3) 5–6 years high school completed; (4) trade apprenticeship or technical completed; and (5) university or other tertiary qualification completed.</td>
</tr>
<tr>
<td>Education of spouse</td>
<td>Same as above but for the operator’s spouse</td>
</tr>
<tr>
<td>Social capital</td>
<td></td>
</tr>
<tr>
<td>Landcare membership</td>
<td>Indicator of whether the farmer is a member of a Landcare group</td>
</tr>
<tr>
<td>Activities</td>
<td></td>
</tr>
<tr>
<td>Crop specialisation</td>
<td>Proportion of land area used for cropping activities. This measures how land is being divided between competing cropping and livestock activities.</td>
</tr>
<tr>
<td>Off-farm wages</td>
<td>Off-farm wages and salaries of the operator and spouse as a proportion of total farm income.</td>
</tr>
<tr>
<td>Off-farm investment income</td>
<td>Income from off-farm investments expressed as a proportion of total income.</td>
</tr>
<tr>
<td>Mediation processes</td>
<td></td>
</tr>
<tr>
<td>Direct drill</td>
<td>Indicator for the main planting method on the farm being direct drill (zero till). This is a natural capital (moisture) access modifier.</td>
</tr>
<tr>
<td>Minimum till</td>
<td>Indicator for the main cultivation method on the farm being minimum till. This is a natural capital (moisture) access modifier.</td>
</tr>
</tbody>
</table>

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42
<table>
<thead>
<tr>
<th>variable</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>mediation processes</strong></td>
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<tr>
<td>moisture direct drill interaction</td>
<td>Interaction between moisture availability index and direct drill indicator. A negative coefficient indicates that the moisture conserving benefits of direct drill diminish with increasing moisture availability at planting time. This is a natural capital (moisture) access modifier.</td>
</tr>
<tr>
<td>moisture minimum till interaction</td>
<td>Same as above but for minimum till.</td>
</tr>
<tr>
<td>corporate farm</td>
<td>Indicator of whether the farm is owned by a publicly listed company and therefore may have better access to financial and other resources. Corporate farms = 1 if the farm is corporate and is 0 otherwise.</td>
</tr>
<tr>
<td>trend</td>
<td>Time in years. This captures trends not covered by other variables – for example, technology improvements, rural migration and other relevant price trends.</td>
</tr>
<tr>
<td><strong>risk factors</strong></td>
<td></td>
</tr>
<tr>
<td>variability of moisture availability</td>
<td>Standard deviation of the moisture availability index.</td>
</tr>
<tr>
<td>commodity price variability</td>
<td>Coefficient of variation of the sum of livestock and crop output prices weighted by the area of each.</td>
</tr>
</tbody>
</table>
references


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Fisheries Resources Research Fund  
Forest and Wood Products Research and Development Corporation  
Grains Research and Development Corporation  
Grape and Wine Research and Development Corporation  
GHD Services