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How training and innovation link to farm performance: a structural equation analysis

Vilaphonh Xayavong, Ross Kingwell and Nazrul Islam[†]

The complexity of modern farm management places great demands on the skill, knowledge and capability of farm managers and their families. Keeping abreast of emerging technologies and innovations that can affect each key farm enterprise, and knowing how best to marshal the resources required for profitable farm production, are key tasks of farm management. This study draws on a longitudinal data set of 240 broadacre farmers to compare and analyse their farm performance over a decade. Using structural equation modelling, we examine relationships between the farm family's involvement in training, their human capital, their use of various innovations and ultimately the linkages of these factors to farm financial and productivity performance. Several statistically significant inter-relationships are found, and some factors are shown to have significant positive links to farm performance. We find that training undertaken by the farm family, the farm family's human capital and their use of innovations, particularly key cropping innovations, have significant beneficial impacts on farm performance. The farmer's skills in time and organisational management, their engagement in business planning and the unique environmental characteristics of the farm also significantly and positively influence farm performance.

Key words: farm management, farm profit, human capital, innovations, training.

1. Introduction

Training is often viewed as an investment in human capital (Chapman and Pope 1992; Maglen 1995). In agriculture, various studies have examined the linkages between training, education and farmers' adoption of productivity-enhancing innovations (Nelson and Phelps 1966; Welch 1970; Wozniak 1987; Reimers and Klasen 2013). For example, in Australia, Kilpatrick (1997) surveyed 2500 farms and found 80 per cent had participated in training, with field days being the most popular form of training. Using gross operating surplus as the measure of farm profit, Kilpatrick reported that managers who had more often participated in education and training had more profitable farm businesses than other farm managers, although the statistical significance of findings was not assessed. In a subsequent much smaller study of 65

[†] Vilaphonh Xayavong (email: vila.xayavong@agric.wa.gov.au) is a researcher at the Department of Agriculture & Food, Western Australia, 3 Baron-Hay Crt, South Perth, Western Australia, 6151, Australia. Ross Kingwell is a Professor at the School of Agricultural & Resource Economics, University of Western Australia, Nedlands, Western Australia, Australia. Nazrul Islam is a private economic consultant, 39 Sholto Crescent, Canning Vale, Western Australia, 6155, Australia.

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Tasmanian farm businesses, Kilpatrick (2000) applied simple statistical tests and found that farmers who attended training, other than field days and made changes in farm practice, had higher average gross operating surpluses than other farmers who neither engaged in training nor had made any changes to farm practice.

Nossal and Gooday (2009) note the importance of training in their examination of opportunities to raise the productivity of Australian agriculture. One of five priority areas they identified was the need to facilitate innovation through improving access to research findings, training and education, communication services and public infrastructure. However, agricultural training is not always perceived by farmers as being relevant or easily accessible (Murray-Prior *et al.* 2000; Industries Development Committee Workforce Training and Skills Working Group 2009).

In spite of training and education not always being accessed or well-tailored to farmers' needs, various studies (Nelson and Phelps 1966; Welch 1970; Reimers and Klasen 2013) have indicated that training and education might generally be regarded as a means of facilitating farmers to adopt innovations that lift farm productivity and increase farm profitability. In theory, training and education should allow farmers to improve their management by enhancing their decision-making skills (Asadullah and Rahman 2009). Appropriate training and education should help farmers to more readily and more accurately assess and adopt superior technologies and change farm practices from which they can potentially derive commercial advantage (Feder *et al.* 1985; Asadullah and Rahman 2009).

In describing the link between farmer training and farm profitability, Kilpatrick (1997) noted:

> Isolating the impact of education and training on profit is not a simple matter. There are many internal and external factors which affect the profitability of a business. In agriculture, examples of internal factors are as follows: farm business management skills; length of experience in farming; ability to earn off-farm income and amount of time spent earning off-farm income; and the quality of the physical resources of the business including the extent of land degradation and water management. External factors are climate, prices obtained for produce and costs including the cost of financing borrowing. Every farm business is different; in common with most social science research there cannot be groups which receive a 'treatment' of education and identical control groups which do not.(p. 14)

The few Australian studies like Kilpatrick (1997, 2000) that describe the relationship between farmer training and farm profitability unfortunately have relied on data sets and methods of analysis that reveal little of the mechanisms whereby farm profitability is improved. For example, the studies of Kilpatrick and many other studies of the role of training (Baldwin and Johnson 1995) use cross-sectional data from a single year and examine only current training activity and do not collect information on farm practices, technologies and innovations adopted. Longitudinal data sets are not compiled, farm profitability measures (e.g. gross operating surplus) are simple and inadequate, and the nature and impacts of previous years' training are overlooked. The data sets often do not specify who in the farm business undertakes training, nor is the duration and nature of the training described. In addition, how long certain innovations or new practices have been in use is not recorded.

By contrast, this study accesses a unique panel data set of farm physical, financial and socio-managerial characteristics that enables a richer analysis of the relationships between training, human capital (HC), innovation use and farm profitability. Using the advanced technique of structural equation (SE) modelling, this study adds to the literature on the links between farmer training, the farm family's HC and the financial and productivity performance of their farm businesses by identifying in greater detail the significant causal aspects of the pathway from training to farm financial performance.

The next section of this study describes the data and methods used to explore the relationship between training, innovation use and farm profitability for rainfed mixed-enterprise broadacre Australian farms. The method of SE modelling is briefly outlined, and then results of its application are presented and discussed. The paper concludes after a brief discussion of the implications of the study's key findings.

2. Data and methods

Data describing farm businesses in the study region (Figure 1) were supplied by three agricultural consulting firms with farm business clients in the region. Annual records of 240 farms were obtained for the period 2002 to 2011. Because each consultancy firm reported slightly different sets of physical and financial variables, and some variables were measured differently by each firm, care was taken to form a consistent unified data set.

As the data come from farms sufficiently viable to afford an agricultural consultant, they may not be truly representative of the wider farming community. The data may be upwardly biased if only above average farmers use consulting firms. In Western Australia, over 40 per cent of broadacre grain farmers use various commercial advisory services including consultant and fee for service advisers (Llewellyn and D'Emden 2009; IPSOS-Eureka 2010). Although comparisons of the sample against Australian Bureau of Statistics (2002), agricultural census data for all farms in the study region revealed no significant differences in farm characteristics, such as farm size or enterprise mix, nonetheless comparisons of financial characteristics were not possible; as such, farm financial census data are not available in Australia. Hence, some caution must surround extrapolating this study's findings to any wider population of broadacre farms in the study region or to other parts of Australia.

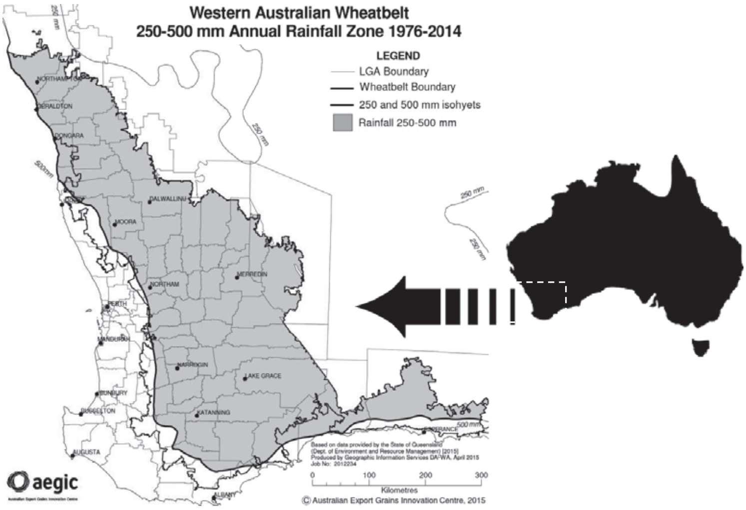

Figure 1 The study region of south-western Australia. Sample farms are located in the grey shaded region between the 250 and 500 mm isohyets of average annual rainfall.

Drawing on each farm's financial and physical records, farm performance (FP) financial measures were derived (Kingwell *et al.* 2013) including a fitted growth rate of farm equity. Change in farm equity is one measure of FP used in previous studies of FP (Lawes and Kingwell 2012). Farm productivity measures were also generated using the methodology outlined in Islam *et al.* (2014) that in turn drew on O'Donnell (2012).

The unique longitudinal data sets of physical and financial records were complemented by socio-economic and managerial data derived from client questionnaire assessments provided by the consultants. Because the farmers have been clients of each consultancy firm for at least the period 2002 to 2011, and because the farmers tend to retain the same consultant, often a close relationship forms between the consultant and their client. Accordingly, the consultant is often well informed about the socio-managerial environment of their client's farm business, and consequently, they are well placed to provide reliable and independent assessments of that environment. The socio-managerial questionnaire was pilot-tested, revised and then sent to the consultants who dealt with each particular farm business. The eight-page questionnaire is available as appendix 2 in Kingwell *et al.* (2013).

The questionnaire yielded data on the type of training, who provided the training, who participated in the training and when the training was undertaken. For example, questions on training provided by the private sector included questions on who in the farm family participated in the training and what was the nature of the training: crop specific, livestock specific, commodity marketing, finance and business management, landcare and natural resource management, or for other industry purposes.

Besides questions on training, the survey also included several questions about the farmer's use of a range of innovations. Broadly, the innovation categories included those related to land management, cropping enterprises, livestock enterprises, business management and associated technologies. Questions were also asked about the farmer's organisational and time management abilities.

The panel datasets on training, innovation use, farmer characteristics and farm profitability were used to examine the nature of linkages between training and FP. The formal examination and testing of the nature and strength of relationships between training, HC, use of innovations and FP was based on SE modelling, briefly described in the next subsection. Regression tree analyses and principal component analyses were also applied to the data set, but SE modelling provided the richest set of findings.

2.1. Structural equation modelling

Structural equation modelling is a second-generation data analysis technique that allows complicated variable and causal relationships to be expressed through hierarchical or nonhierarchical, recursive or nonrecursive SEs (Blalock 1971; Bullock *et al.* 1994). Annotated bibliographies and reviews of SE modelling are provided by Wolfle (2003), Hair *et al.* (2006) and Mulaik (2009).

Structural equation models can include a number of statistical methodologies allowing the estimation of a causal theoretical network of relationships linking latent (unobserved) variables, each measured by means of a number of observed indicators. Latent variables that only predict other latent variables are called exogenous variables, whilst latent variables that are dependent variables in at least one causal relationship are called endogenous variables.

There are three approaches to SE modelling (Hwang *et al.* 2010; Henseler 2011): covariance structure analysis, partial least squares (PLS) analysis and generalised structured component analysis, each with their particular software programs. SE modelling based on PLS, known as the PLS-SEM approach, is increasingly popular (Vinzi *et al.* 2010). Hair *et al.* (2012) note that PLS-SEM provides more flexibility when formative measures are involved and is more robust in situations in which data are extremely non-normal (Cassel *et al.* 1999; Reinartz *et al.* 2009). Hair *et al.* (2012) note that PLS-SEM generally works with nominal, ordinal, interval, and ratio scaled variables (Fornell and Bookstein 1982; Reinartz *et al.* 2009), so PLS-SEM was applied in this study. Specifically, we used SmartPLS 2.0 software developed by Ringle *et al.* (2005). Drawing on our raw data or its standardised transformations generated similar PLS-SEM results so the raw data form was retained.

PLS-SEM is used to test complex relationships between observed (measured) and unobserved (latent) variables and also relationships between two or more latent variables. Latent variables are not measured directly but are assumed to bring about the observed responses. Hair *et al*. (2012) report on 311 PLS-SE published models and find that the average number of latent variables in these models is 7.9. In the current study, nine latent variables form the PLS-SE model.

This study's key endogenous variable is FP, indicated by growth in farm equity over the decade and also by change in farm total factor productivity over the same decade. FP is hypothesised to be causally linked to a range of exogenous variables that include the extent of participation in training by the farm family, the farmer's preparedness to use a range of innovations, their commitment to farm business planning and their abilities regarding organisation and time management (OTM). Relationships between variables are hypothesised in accordance with theoretical and logical reasoning, informed by existing literature, and the PLS-SE model is designed as a causal chain with there being no loops in the causal paths.

Latent (unobserved) variables can have reflective or formative indicators. This study's PLS-SE model contains mostly reflective indicators and a few formative indicators. The decision about whether a latent variable is reflective or formative is based on logic, prior knowledge and relevant published findings. Vinzi *et al*. (2010) note that formative relationships are increasingly common in PLS-SEM applications, although they can pose a few problems for statistical estimation. Coltman *et al*. (2008) observe that reflective indicator models dominate the psychological and management sciences, whilst the formative view is more common in economics and sociology. The distinction between formative and reflective measures is important for proper model specification (Anderson and Gerbing 1988).

The broad logic underlying this study's PLS-SE model is that training increases the HC of the farm family and this facilitates the assessment and adoption of relevant innovations which boost the profitability and productivity of the farm business. Examples of formative and reflective latent variables in this study's PLS-SE model are illustrated in Figure 2, using the standard SE graphical symbols.

> 'extent of training' is a formative latent variable because the farm family's extent of training is formed or influenced by their engagement in a range of training activities that are the formative indicators of the 'extent of training'. These indicators include crop-specific training, commodity marketing training, finance and business management training and landcare and NRM training. Put simply, the more training and education courses attended by members of the farm family the greater is their 'extent of training'.

By contrast, 'preparedness and ability to use relevant cropping innovations' (CI) is a reflective latent variable because the farm family's preparedness to adopt relevant CI is reflected in their early adoption and use of a range of CI likely to support farm profitability such as minimum tillage techniques,

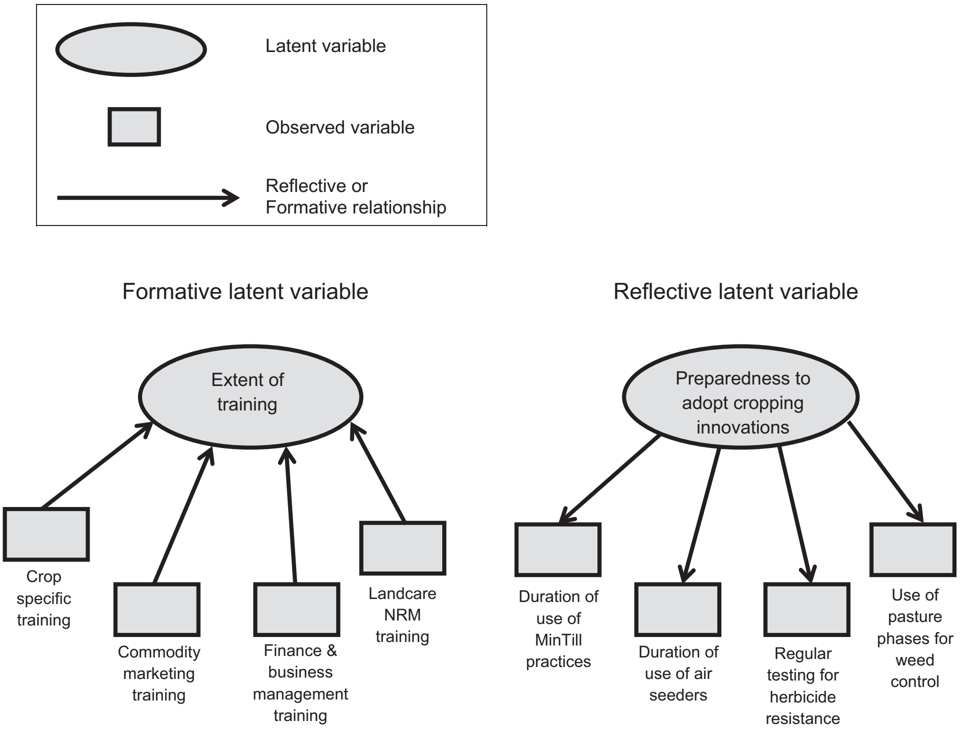

Figure 2 Examples of formative and reflective latent variables.

use of air seeders and chaff carts. In other words, if the farm family is highly prepared and able to adopt relevant CI, then we observe them being early users rather than laggards of those CI known to be effective and profitable.

Figure 3 shows the full PLS-SE model designed to test the cascade of relationships between training, farm family HC, adoption of innovations, organisational skills and FP. The model consists of a range of reflective latent variables (shaded circles) that mostly describe the farm family's preparedness to use different types of innovations and two formative latent variables (shaded circles), one describing the extent of training undertaken by the farm family and the other specifying their HC that has formative indicators such as the aggregate level of formal qualifications of all members of the farm family, the cumulative days per week of work on the farm by the farm family and the aggregate years spent on the farm by the farm family. Each latent variable has its associated set of reflective or formative indicators (shaded boxes).

The latent variables are as follows:

- Extent of training by the farm family (TR),
- The farm family's human capital (HC),
- The farm manager's preparedness and ability to use (i) relevant CI, (ii) livestock system innovations (LSI), and (iii) land management innovations and NRM practices (LMI),

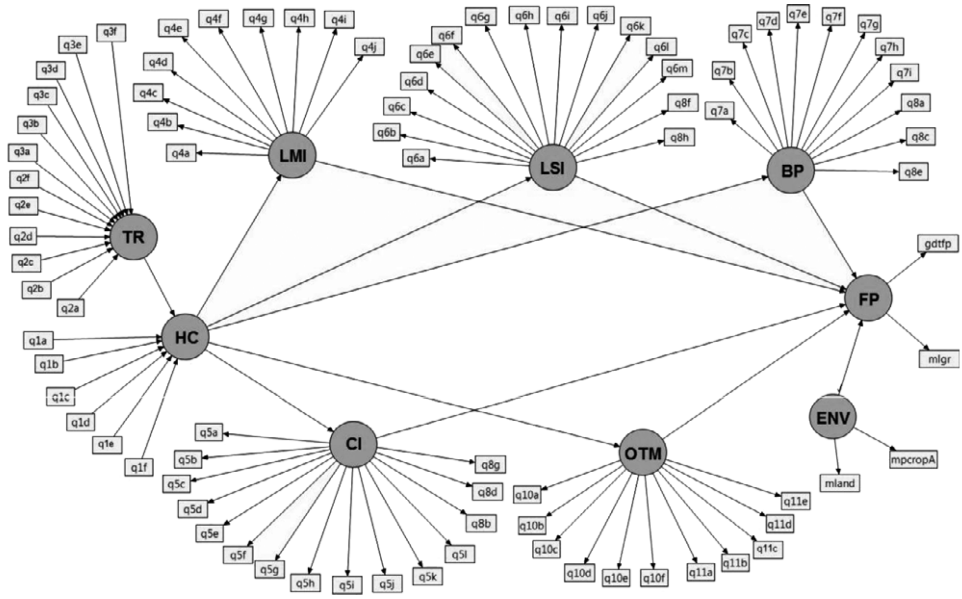

Figure 3 The full structural equation (SE) model showing latent variables, their indicators and linkages.

- The farm manager's skill in organisation and time management (OTM) and commitment to business planning (BP),
- Farm business environment (ENV) and
- Farm performance (FP).

Farm performance has two reflective indicators: the rate of change in total factor productivity and the average annual growth in farm equity over the decade of observations. See the Appendix S1 for the list of latent variables and their corresponding reflective or formative indicators with measurements.

To form some of the reflective and formative indicators, Likert scales were used to quantify responses to some questions in the questionnaire (Appendix S1), especially where a question was actually a series of subquestions. Also, to improve the reliability of some latent variables, some indicators were regrouped. The full SE model depicted in Figure 3 was constructed based on logic and previously identified significant causal relationships (e.g. training improves HC).

2.2 Model estimation and assessment

As mentioned above, PLS estimation was used in this study because PLS has advantages over covariance-based estimation when dealing with non-normally distributed data, large numbers of reflective indicators (Vinzi *et al.* 2010) and inclusion of formative indicators. Model estimation occurred in two steps: (i) a goodness-of-fit assessment for the hypothesised model and (ii) hypothesis testing of the structural model and its path coefficients.

The measurement adequacy of the latent variables was assessed using various tests of reliability and validity (Bollen 2005). Reliability is the degree to which what is measured is free from random error, whilst validity refers to whether what is measured is truly what is intended to be measured.

Refining the model involved the following steps:

- Reflective-innovation indicators with loadings <0.3 were dropped, as they are deemed to be unreliable (Igbaria *et al.* 1997),
- The internal consistency reliability of a latent variable was accepted if the composite reliability was >0.7 and the average variance extracted was >0.5 (Fornell and Larcker 1981; Mooi and Sarstedt 2011),
- The potential problem of having overlapping variables and associated indicators was avoided firstly by inspecting the list of indicators associated with each latent variable to ensure no logically undesirable overlap was present. Secondly, we checked that the square root of the average variance extracted was greater than the latent variable correlations (Fornell and Larcker 1981) to ensure adequate discriminant validity.

The path coefficients of the SE model were tested for their statistical significance. The path coefficients between latent variables are standardised beta coefficients that result from estimation procedures, with the goodness-of-fit of the combination of path coefficients being tested via asymptotic *t*-statistics, obtained by resampling methods (Venaik *et al.* 2001).

3. Results and discussion

After applying goodness-of-fit tests to the model depicted in Figure 3, only reflective-innovation indicators with a loading value >0.3 were retained and many were statistically significantly different from zero. To err on the side of parsimony, some indicators were regrouped, mostly due to not many farmers using those particular innovations or practices described by those indicators. For example, enterprise training with the government sector attracted few participants among this sample of 240 farmers during the decadal study period. Zero entries were recorded with high frequency in responses to questions q3a, q3b and q3c (Appendix S1), so these indicators were regrouped as q3c1 = q3a + q3b + q3c.

Some formative indicators were not significant and often these variables were highly correlated as they were constructed using a common variable. For example, q1a (number of family members on the farm) was part of q1b where q1b = q1a * Likert scale of family member's education level; so q1a was dropped to reduce the multicollinearity problem.

The PLS-SE model that was preferred on the basis of goodness-of-fit is shown in Figure 4 in which the signs, magnitudes and statistical significance of path coefficients being greater than zero are displayed.

Figure 4 shows the statistical significance of the path coefficients of the direct relationships between the latent variables. Table 1 lists the total effects (direct and indirect) that arise from the extent of training by the farm family (TR) and the family's HC.

The extent of training by the farm family (TR) has a significant positive impact on the farm family's HC. Training also has significant indirect positive effects (see Table 1) on the farm manager's skill in OTM, their use of CI, LSI, and their use of LMI.

The farm family's HC that is significantly influenced by training in turn has significant positive impacts on some other latent variables: the farm manager's skill in OTM, the farmer's preparedness and ability to use CI, LSI and LMI. The farm family's HC also has positive, but not statistically significant, impacts on BP. The farm family's HC also has significant indirect positive effects on FP.

Of all the modelled latent variables affecting FP, the farm manager's preparedness and ability to use CI, the farm manager's skill in OTM, BP and the ENV, all have significant positive impacts on FP. Other latent variables (LSI and LMI) have positive but not significant impacts on FP.

Considering in concert only the statistically significant path coefficients, the key paths of influence upon FP are as follows. When farm families have involved themselves in training, especially crop-specific training and finance and business management training, then such training helps increase these

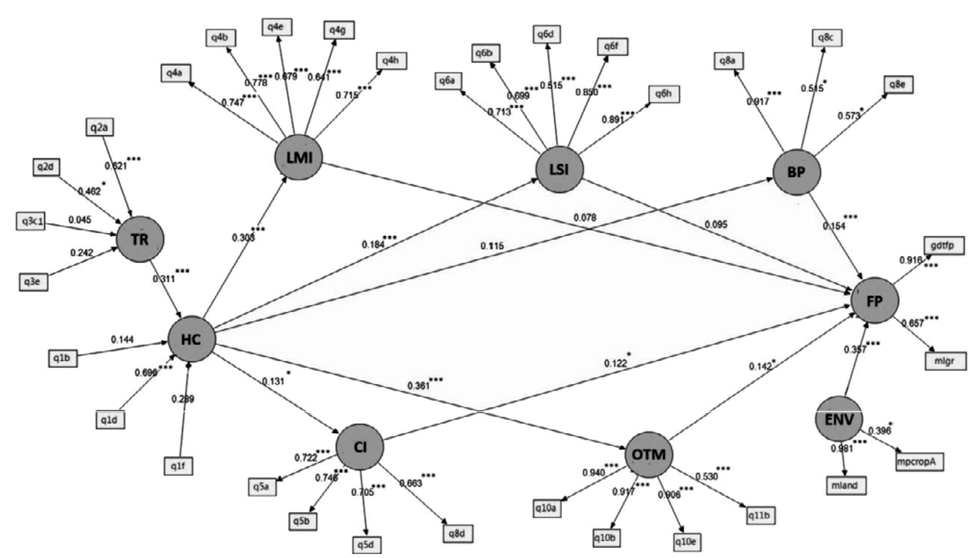

Figure 4 The best-fit structural equation (SE) model of the latent variables, their indicators, linkages and estimated path coefficients. Asterisks show the significance of the *t*-statistics associated with each path coefficient.

Table 1 The total effects (direct and indirect) associated with the training and human capital latent variables

Causal path†	Path coefficient	*t* statistic	Significance level
TR → BP	0.036	1.2	
TR → CI	0.041	1.5	
TR → FP	0.037	2.4	*
TR → LMI	0.095	2.7	**
TR → LSI	0.056	1.7	
TR → OTM	0.113	3.5	***
HC → FP	0.119	3.2	***

†The calculation of the total effect draws on direct and indirect effects. For example, the path coefficient 0.036 (TR → BP) is calculated as 0.312 * 0.115. That is, TR → HC (0.312) * HC → BP (0.115) (Figure 4).

farm families' HC. This capital is also significantly boosted by the cumulative days per week that members of the farm family reside on the farm (Appendix S1). Hence, the farm family's human capacity (HC) is influenced not only by training that improves the quality of the family's human resources but also by the quantity of family labour available each week. The farm family's HC in turn positively affects some other characteristics and abilities of the farm family, as outlined in a previous paragraph. In concert, these factors significantly and positively affect FP.

The significant positive influence on FP attributable to the farm manager's preparedness and ability to use CI is no surprise. The farm region from which the farm sample was drawn is a region in which cropping is increasingly important, both as a share of farmland and as a major source of farm revenue (Planfarm-Bankwest 2012). Farmers with a preparedness and ability to use CI would have been more likely to adopt the several crop innovations available over the last decade or so (Carberry *et al.* 2010). Using these innovations would have fuelled the profitability and productivity of those farm businesses. Somewhat similar findings about the relative importance of cropping and its associated innovations were reported by Lawes and Kingwell (2012). They found that wheat yield was the main explanator of FP in their study of 123 farms in northern–eastern part of the study region over the years 2004 to 2009. The prime importance of wheat yield, often favourably supported by CI, translated into higher wheat revenues and higher returns to farm capital for these crop-dominant farm businesses.

A perhaps unexpected finding in this study is that whilst the farm manager's preparedness and ability to use CI has a significant positive effect on FP, by contrast, the farm manager's preparedness and ability to use LSI does not. However, farm survey findings for the study region (Planfarm-Bankwest 2012) indicate that livestock income (sheep and cattle sales and wool) often form <30 per cent of total farm income in contrast to the dominance of crop income. Hence, the farmer's ability to generate crop revenues (and more importantly crop profits) is often more crucial to FP than the farmer's ability to generate livestock profits. This may partly explain why in this current study the farm manager's preparedness and ability to use CI has a significant positive effect on FP, whereas the farm manager's preparedness and ability to use LSI has a positive but not significant impact on FP.

The significant effect on FP of the farmer's skill in OTM is also a finding consistent with other recent studies that identify OTM as an increasingly important aspect of Australian farm management (Rabobank 2007; Kingwell 2011). Kingwell reported that broadacre farm management in Australia was no longer simple with farms often being often large, multi-enterprise businesses underpinned by expensive capital investments, changing production technologies, volatile markets and social challenges. The significant influence of BP on FP is also worth noting. This is perhaps another indicator of farmers being organised in that they allow time for BP that ultimately beneficially affects FP.

There are many significant reflective indicators of the farmer's skill in OTM, suggesting that a farmer's organisational skill is expressed in many ways. Because broadacre mixed-enterprise farming involves many labour-saving and capital-intensive technologies, it follows that labour resources are scarce, so the farmer's ability to marshal, prioritise and monitor farm activity, particularly during crucial periods like crop sowing and harvesting, is likely to play a positive role in supporting business success. Crops sown late, for example, can attract large yield penalties so timeliness of sowing is essential if maximum crop revenues are to be generated. Hence, the farmer's organisational skills are almost certainly likely to positively influence the commercial reward from farm operations.

The ENV is another significant positive influence on FP. A farm's physical environment, reflected in the farm's enterprise mix and magnitude of arable area, affects FP. Such a finding is consistent with results from Lawes and Kingwell (2012) and Kingwell *et al*. (2013). Kingwell *et al*. (2013) studied the same set of farms and Lawes and Kingwell (2012) examined a similar subset of farms in part of the study region. Both studies used linear mixed models and found that the 'farm' effect was the main influence on measures of FP. In other words, often the financial performance of a farm had much to do with the unique characteristics of that particular farm business, including the physical environment in which the farm operated. These findings add weight to observations made 45 years ago by Mauldon and Schapper (1970) about the limitations of benchmarking for inter-farm comparisons; observations reiterated more latterly by Ferris and Malcolm (1999).

Because FP is often influenced by the unique characteristics of a farm business, drawing generalisations from farm surveys or parsimonious models and applying them to particular farm businesses is fraught with danger. These findings about the importance of the ENV do lend support for the idea that the peculiar characteristics of a farm business might first need to be properly understood before discerning ways to improve the financial performance of that business. It suggests that there is a legitimate role for personalised advice and support for individual farm businesses to further improve their performance. However, nonetheless, this present study does also suggest that provision of training (e.g. farm management and business training) is likely to raise the HC of the farm family. Such training could spawn a range of behavioural changes tailored to the specific characteristics and needs of that farm business, eventually leading to improved farm productivity and profitability (George *et al*. 2007; Keogh *et al*. 2011).

Another finding is that the farmer's preparedness and ability to use LMI has a positive, but not significant, impact on FP. Its lack of significance possibly is attributable to the dominant effect of the profitability of cropping enterprises in effecting FP. Activities such as support for NRM practices, although positively supporting FP, may not sufficiently affect FP over the 10-year time frame of this study to be significant.

An important caveat to the findings in this paper that considers 240 farm businesses over a decade is that the best-fit PLS-SE model only has an $R^2 = 0.42$. So there is variability in FP not captured by this model's small set of latent variables. There are likely to be other influences on FP, not captured by this model such as each farm's unique soil mixes, soil fertility, topography and seasonal conditions over the decade. Also strategic shifts in the farm's enterprise mix and the farm's financial position at the start of the decade are liable to affect FP. These factors are either not captured or are inadequately described in the current data set. These unique features of each farm add to the 'farm' effect that is only partially captured in the current data set. Due to these unique characteristics of each farm, generalisations of findings, especially from parsimonious models such as described in this study, require some caution. There are likely to be feedback effects not captured in this analysis. For example, a profitable farm may be more able to invest in training and adoption of innovations that in turn delivers greater profitability.

4. Conclusions

This study finds that farm performance (FP) is significantly influenced by the farmer's preparedness and ability to use a suite of cropping innovations (CI), their organisational and time management skill, their engagement in business planning (BP) and their good fortune to manage a farm with characteristics and environment conditions that aid FP. These findings suggest that so long as these farmers who mostly run mixed-enterprise farming systems have ongoing access to worthwhile innovations, particularly CI, whilst also becoming skilled in time and organisational management and BP, then their ongoing viability is likely. An implication is that an essential ingredient of future FP will be ongoing investment in agricultural R,D&E to ensure these farmers have access to profitable innovations. Such a role for R,D&E has previously been identified (Mullen and Crean 2007; Salim and Islam 2010). Additionally, training in time and organisational management and BP may encourage greater farm business performance.

This study also finds that the farm family's human capital (HC) positively and significantly affects firstly the farmer's preparedness and ability to use a suite of innovations and secondly, the farmer's skill in organisational and time management. In turn, these farmer characteristics positively influence FP. Of importance to note is that the farm family's HC is positively and significantly affected by the family's engagement in training. In short, training enhances HC. One implication is that provision of farm management and business training and education is likely to generate beneficial productivity and profitability outcomes through the beneficial effect of training on the farm family's HC and the subsequent positive changes in farmers' abilities and behaviour.

Although training is identified as an important precursor to FP, this study does not consider who should pay for this training nor who should provide it. Overall, this study finds that training, the farm family's HC, their use of innovations, the farm manager's organisational and time management skills and engagement in BP, as well as the farm's environment, in combination have beneficial and significant impacts on FP. Increasing our understanding of the pathways to FP helps identify those parts of the pathway that most importantly influence FP. Such information can assist the resource allocation and activity choices of stakeholders and participants in these pathways.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1. Latent variables and their corresponding reflective or formative indicators.