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Traditional farm expansion versus joint venture remote partnerships

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Traditionally, farms expand by buying out a neighbour. But might remote partnerships be a better way of expanding a farm business given projected climate change and price volatility? This question is addressed using farm business financial modelling. Representative farms at 27 locations in Western Australia are constructed to enable comparison of the value of buying out a neighbour versus expansion using geographically distant joint venture (JV) partners. The farm models consider economies of size, bulk purchase price discounts, the variability and correlation of returns associated with farm expansion, and impacts of climate change. Random selection of a remote partner generates little improvement in wealth; on average only 2.3 and 1.6 per cent, respectively, under current and projected future climate across all locations. However, there is large variation in wealth appreciation opportunities for each location and between locations. Preferred partnerships are a function of each farm's characteristics. Locations highly preferred as JV partners under current climate are similarly preferred partners under projected future climate. The main sources of additional wealth come from economies of size advantages, risk-spreading benefits of combining geographically separated farms and bulk discounts. Farmers seeking business expansion will often benefit greatly from careful selection of a remote partner.

Key words: farming, business expansion, risk, climate change, asset pricing.

1. Introduction

One of the major investment decisions a farm family faces is the expansion of their farm. There can be several motivations for this expansion, such as facilitating business succession within the family, seeking further wealth through purchasing more land assets, a desire to lift profits via scale economies or a need to diversify the farm business through owning an additional farm with different soils or enterprises.

Traditionally, farm businesses have expanded by buying out neighbours using bank loans as the principal source of finance. However, purchasing a neighbour typically exposes the expanded business to the same climatic and enterprise risk as experienced on the original home property. In Australia, where climate, soil and commodity price variation underpin the risky

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environment of farming, sometimes a question asked is: Will expanding the farm business less locally be a better option, especially given the greater ease of communication and travel nowadays?

In this article, we explore this issue of farm expansion. First, we outline a traditional conceptual framework but then highlight its deficiencies and argue for the preferred use of farm financial modelling. Its utility is illustrated by examining farm expansion in the broadacre study region of Western Australia. This region supplies 40 per cent of Australia's annual grain exports, most of Australia's live sheep exports and substantial proportions of Australia's canola, oat and barley exports, yet the region is known to be vulnerable to projected adverse climate change (Reisinger *et al.* 2014; Thamo 2016).

The main question addressed in this study is where and when might a less local expansion of a farm business be a better option in this study region? To address that question issues affecting farm expansion are explored. Those issues include economies of size, price discounts on bulk purchases of inputs, the method of structuring the expansion, the variability of returns associated with the expansion, the role of climate change and the degree of correlation of returns between locations that comprise the expansion.

This article is structured as follows. First, a traditional conceptual model of asset investment is described, highlighting its limitations when applied to farm expansion. Then, financial simulation models of farm businesses at 27 locations are described under current and future climatic conditions. These models, along with a farm asset pricing model, are used to assess the value of farm expansion which could occur locally or in combination with a more distant farm. Results and discussion of different sorts of farm expansions involving 27 locations are provided before conclusions are drawn.

2. A conceptual framework

Farm expansion at its simplest is a portfolio problem (Markowitz 1952) involving the combination of two assets, the home farm plus another purchased farm. Merton (1972) derives the efficient capital allocation among asset choices, showing the efficient frontier to be:

$$E(R_c) = R_f + \sigma_c \frac{E(R_p) - R_f}{\sigma_p}$$

where applied to a portfolio of risky assets and access to a risk-free asset (e.g. Treasury bonds), 'c' is a combination of portfolios 'p' (risky assets) and 'f' (a risk-free asset), and $E(R_c)$ is the expected returns to the capital investment. At some point on this frontier, the investment portfolio solely comprises risky assets. Such a point for the asset mix of two farms would be where:

$$E(R_p) = w_a E(R_a) + w_b E(R_b) = w_a E(R_a) + (1 - w_a) E(R_b); \quad (1)$$

and

$$\sqrt{\sigma_p^2} = \sqrt{w_a^2 \sigma_a^2 + w_b^2 \sigma_b^2 + 2w_a w_b \sigma_a \sigma_b \tau}. \quad (2)$$

where $E(R_a)$ and $E(R_b)$ are the expected returns from investments in farm A and B, respectively, σ_a^2 and σ_b^2 are the variance of respective returns, τ is the correlation of returns from farm A and B, and w_1 and w_2 are the respective shares of the total investment in farm A and B. Farm A could be the home farm whilst farm B would be the newly purchased farm.

In practice, *ceteris paribus*, if a farm was to increase in size at its current location, then it is highly likely that subsequent expected returns to capital and standard deviation of those returns would be similar to those on the home farm before the expansion. This would be due to the farmer likely maintaining on the expanded farm a similar mix of enterprises to that on the original farm, the climate experienced by the expanded farm being similar to that on the original farm, the soils on the expanded farm perhaps being similar to those on the original farm and the per hectare price of land on the neighbouring farms also being similar. In short, returns on the original farm and returns on the expanded farm could be similar and be highly positively correlated. Hence, using Equation (2), where in this case $\tau = 1$, $\sigma_a^2 = \sigma_b^2$ and assuming equal shares of w_1 and w_2 , then:

$$\sqrt{\sigma_p^2} = \sqrt{0.25(\sigma_a^2 + \sigma_b^2) + 0.5\sigma_a \sigma_b} = \sqrt{\sigma_a^2}.$$

In other words, the variance of returns for the locally expanded farm would in this specific case be the same as the variance of returns for a sole investment in the home farm.

This portfolio theory developed by Markowitz (1959) and Sharpe (1964) earned them a Nobel prize in economics in 1990. However, the theory has attracted a range of theoretical and practical criticisms, including that correlations between assets may not be fixed, asset returns may not be jointly normally distributed, information asymmetry may exist, some assets are not easily divisible, and investor actions may directly influence the price of an asset.

In the case of investment in farm expansion, there are some important characteristics of the investment problem that the traditional portfolio theory ignores. Firstly, a farmer who acquires an additional farm is able to subsequently influence returns on both the home farm and the acquired farm. Principally, this is due to the capture of economies of size that allow a lowering of unit costs of production, thereby increasing profitability and increasing returns to capital. In practice, economies of size are achieved in various ways including: (i) economising on some overhead or fixed costs then

spreading those costs across a larger volume of production; (ii) investing in higher work-rate machinery and equipment that improves the timeliness and reliability of field operations resulting in higher crop yields that underpin a further lowering of unit costs of production; and (iii) achieving price discounts on some inputs via bulk purchasing or more easily accessing early purchase deals with commensurate price discounts.

Another important consideration overlooked by the simple portfolio model applied to farm expansion is that the nature of climate that underpins farm production, at least in many parts of Australia, is changing both spatially and temporally (BOM & CSIRO 2015; Stephens 2016), complicating the decision choice of location for expansion.

Hence, rather than apply a model of farm expansion based on simple portfolio theory, we adopt a numerical analysis that draws on farm financial simulation modelling to show the relative importance of issues such as spatial diversification, economies of size, bulk discounts and climate change in affecting farm expansion decisions. The broadacre farming region of Western Australia is used as a study region to show how representative farms in different locations have expansion opportunities that may deliver greater wealth than traditional farm expansion involving acquiring a neighbouring farm.

3. Financial simulation modelling of farm expansion

Financial simulation models of farm businesses at 27 locations (see Figure 1 and Tables 2, 3) within the broadacre study region of Western Australia were created in order to assess their farm expansion opportunities. These locations were where the APSIM wheat model (Farré *et al.* 2007) has been applied and validated. The farm models considered economies of size in farm operations, bulk purchase price discounts, the variability and correlation of crop and pasture yields and commodity prices, the impacts of climate change and spatial correlations. The key steps and data sources used in constructing the models are described in the following subsections.

3.1 Farm sizes and enterprise mixes

Farm survey data (Planfarm-Bankwest 2014, 2015) for the study region revealed that the asset value of the average farm in most shires containing APSIM validation sites was close to \$6 million. This valuation was associated with farms of different sizes across the 27 locations. In low rainfall locations, farms were larger in area and dominated by wheat production, whereas in high rainfall southern areas, farms were far smaller in area, and canola, barley and sheep production were often important enterprises.

The Planfarm-Bankwest farm survey data were used to characterise the farm size and enterprise mix of a representative farm at each location (see Appendix S1). Soil type maps for the study region (Schoknecht and Pathan 2013) were used to identify the proportions of three main soil types (sands, sandy



Figure 1 The study region in south-western Western Australia. The marked sites are Bureau of Meteorology weather stations. Data from all these sites were used in validating applications of the APSIM model at nearby sites.

duplex, loams and clays) surrounding the 27 locations. Those soil type proportions at each location were included in each particular representative farm.

Drawing on expert opinion, typical land use sequences for each soil type at each location were created. A check on their veracity was that, when aggregated across soil types, enterprise areas as proportions of farm area should approximate those reported in regional farm survey data (e.g. Planfarm-Bankwest 2014, 2015). Fortunately, this was mostly the case, although some minor changes in land use sequences were needed in some situations to ensure regional representation was accurate. Land use sequences were implemented by proportionally allocating each area of crop or pasture to their respective soil area(s). For example, if a wheat–barley–canola sequence applied to sandy soils over an area of 1200 ha, then in any year each crop type would be assigned an area of 400 ha on the sandy soil. This allocation assumption may have lessened income fluctuation as in any 1 year farmers may allocate enterprises to soil types in a more disproportionate manner to better capture a perceived market or agronomic opportunity or to abide by paddock size constraints.

3.2 Farm crop yields

The APSIM wheat model (Asseng *et al.* 2004) was used to generate estimates of wheat yields on the three main soil types (sands, sandy duplex and loamy clays) at each location under current and projected climate scenarios. Using

ten sets of 30-year periods, under each climate scenario (current versus future), the APSIM wheat model was repeatedly run. The climate data represented firstly the period 1976–2005 with concentrations of CO₂ of 350 ppm, and secondly, the period 2035–2064 when a higher concentration of CO₂ at 440 ppm is expected.

To generate the daily weather data used in the 30-year simulation periods, the Cubic Conformic Model (CCAM), which is a higher-resolution nested model of the CSIRO GCM MK3, was downscaled to provide samples of daily climate data for the period 1976–2005 and, drawing on the IPCC's RCP2.6 emission trajectory, for a future period 2035–2064 at the 27 sites. The 300 ($10 \times 30 = 300$) simulations at each site for each soil under each climate scenario ensured wheat yield distributions were adequately described.

Wheat production is by far the main enterprise for most mixed enterprise farms in the study region (Planfarm-Bankwest 2015), so it was important to ensure that wheat yields were accurately estimated. However, the APSIM yields assume a sowing date triggered by rainfall events, yet in practice, many farmers plant their wheat crops both dry and over a 2-week period after rainfall events known as the break of the season. As outlined by Kingwell and Farré (2009), wheat crops planted after the break of season tend to be lower yielding and so APSIM yields based on sowing at the break of season overstate the wheat yield achieved on average over the farm's entire sowing program. To account for this overstatement of yield, the APSIM yields were adjusted downwards such that average yields reflected those recorded in farm surveys over several years (e.g. Planfarm-Bankwest annual farm surveys). A further reason for the revision of yields was that APSIM does not account for frost, water-logging, weed competition and disease or pest damage (Fletcher *et al.* 2016).

Wheat yields on each soil type were weighted according to the proportion of each soil in the vicinity of each location, enabling weighted representative farm wheat yields to be calculated. Then, a supplementary decadal data set of crop yields of 245 farms in the study region (Kingwell *et al.* 2013) was used to generate yield comparisons and a yield correlation matrix for the main crop types (wheat, barley, canola and lupins). This correlation matrix was used to form yield distributions for all crop types, with barley, canola and lupin yields being on average across the decadal data set 102 per cent, 62 per cent and 54 per cent of wheat yield, respectively. These yield correlations and yield relativities among crops were spatially consistent. However, an important assumption was made that these yield relativities would continue to apply in the same way under future climate. There is some evidence, for example, that in the study region canola may be more adversely affected than wheat under future climate (Anwar *et al.* 2015).

3.3 Farm sheep production

Due to time and resource constraints, and difficulties in providing spatial validations at each location, pasture and animal modelling (e.g. GrassGro) were not used to generate sheep production estimates. Instead, an analysis of

the decadal performance of 245 broadacre mixed enterprise farms in the study region (Kingwell *et al.* 2013) was used to reveal that sheep production is mostly a function of two factors; growing season rainfall (GSR) and the area of pasture measured as winter-grazed hectares (WGha). GSR is the growing season rainfall (mm) from May 1 to October 31, and DSE is the dry stock equivalent. The number of sheep in a grazing enterprise on average is 2.2 DSE/WGha/100 mm of GSR. Using the downscaled data sets of daily climate data for the period 1976–2005 and a future period 2035–2064 at the 27 sites, combined with information about farm size and enterprise mix, the sheep population on each of the 27 representative farms was estimated for each year of simulation, principally by drawing on GSR data sets.

Additional parameters used to estimate wool production were the survey-based finding that on average 4.2 kg of greasy wool is produced per DSE. Also, market report data indicated that typical carcass weights for lambs, ewes and wethers were 20 kg, 22 kg and 24 kg, respectively. Drawing on expert opinion, we assumed for each location that if the GSR in a particular simulation year was in the top 20 per cent of GSRs, then all carcass weights would increase by 2 kg, primarily due to the greater availability of feed caused by the additional rainfall. Also, if the GSR was in the next top 20 per cent of GSR, then all carcass weights would increase by 1 kg for the same reason. By contrast, if the GSR was in the lowest 20 per cent of rainfall years, then all carcass weights would decrease by 2 kg due to poor feed availability. Lastly, if the GSR was in the next 20 per cent lowest GSR, then all carcass weights would decrease by 1 kg.

From the previously mentioned supplementary decadal data set of broadacre farm businesses in the study region (Kingwell *et al.* 2013) and from other farm survey data (Planform-Bankwest 2014, 2015), the variable costs of sheep production in 2013 dollar terms were estimated to be \$15/DSE. If the GSR was in the lowest 20 per cent of rainfall years, then variable costs of sheep production increased to \$25/DSE, mostly due to higher costs of supplementary feeding. Also, if the GSR was in the next lowest 20 per cent of rainfall years, then variable costs of sheep production increased to \$20/DSE for the same reasons.

Drawing on expert opinion and the supplementary decadal data set, lamb sales each year (i.e. the number of lambs sold) were estimated for each representative farm to be 12 per cent of total DSE. Similarly, ewe sales and wether sales each year were 17 per cent and 10 per cent, respectively, of total DSE.

3.4 Farm crop and sheep prices

Nominal prices from 1995 to 2013 of wheat, barley, canola, lupins, greasy wool and carcasses of lambs, ewes and wethers were adjusted to be farm-gate prices in 2013 dollar terms and a price correlation matrix was calculated (see Table 1). BestFit[®]:Palisade Corporation, New York, USA, an Excel[®] add-in, distributions were determined for each commodity's prices. The best-fit distributions were mostly lognormal and normal distributions. Using these distributions in

Table 1 Correlation matrix of farm-gate commodity prices in the study region

	Wheat \$/t	Barley \$/t	Lupins \$/t	Canola \$/t	Wool \$/kg greasy	Lamb c/kg cwt	Ewe c/kg cwt	Wether c/kg cwt
Wheat	1							
Barley	0.84	1						
Lupins	0.73	0.82	1					
Canola	0.73	0.77	0.65	1				
Wool	0.41	0.23	0.28	0.26	1			
Lamb	-0.08	-0.05	0.08	0.19	0.44	1		
Ewe	0.11	0.07	0.11	0.15	0.66	0.72	1	
Wether	0.29	0.24	0.16	0.16	0.66	0.61	0.90	1

conjunction with the price correlation matrix, 1000 price simulations of commodity prices were generated.

3.5 Farm fixed and overhead costs

The decadal data set of 245 broadacre mixed enterprise farms in the study region (Kingwell *et al.* 2013) was used to derive estimates firstly of machinery replacement costs (Figure 2) and secondly for other fixed cost components (Figure 3). Machinery replacement costs were based on 10 per cent of the value of plant and machinery on the farm each year. The regression equations in Figures 2 and 3 were based on data re-expressed in 2013 dollar terms and the equations were applied to each representative farm business. Fixed costs, other than machinery replacement, included rates, licences, water, administration, electricity, gas, insurance, professional and sundry fees, and permanent labour. Where permanent labour was a family member, their imputed cost was based on median average weekly earnings.

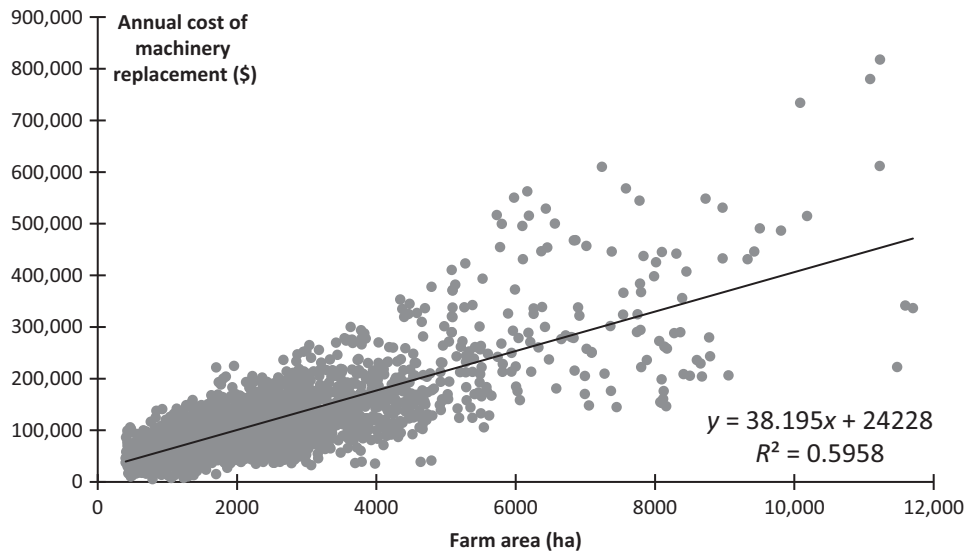


Figure 2 Machinery replacement costs, in constant 2013 dollars, on farms in the study region.

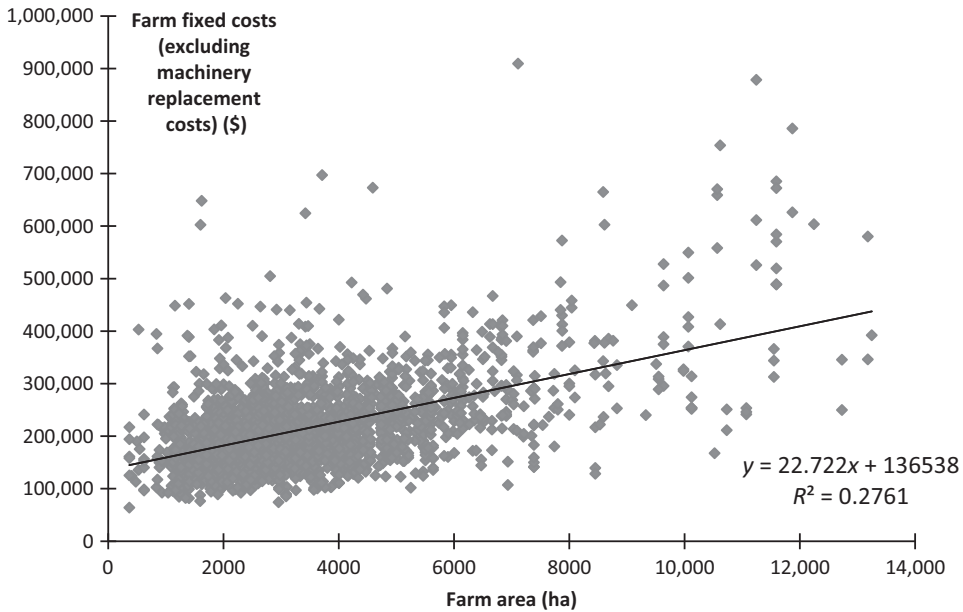


Figure 3 Other fixed costs, in constant 2013 dollars, on farms in the study region.

Given the focus of this article, the farm financial modelling specified the variance and expected values of returns. Figures 2 and 3 reveal increasing variation in farm fixed costs and the annual cost of machinery replacement as farm size increases. We incorporated those characteristics into the farm financial modelling along with interest payments that were identical across all farm comparisons, as each expanded farm involved acquisition of an additional \$6 million of farm assets.

3.6 Farm crop production variable costs

Planfarm-Bankwest (2013, 2014) and more detailed farm survey data (Kingwell *et al.* 2013) provided estimates of variable costs of crop production and interest costs on working capital at each location. Those costs were related to the average wheat yield (see Figure 4) at each location, as generated across all years in APSIM simulations based on current climate with some downwards revisions of those yields for reasons specified earlier. A significant linear relationship ($R^2 = 0.83$) was found between average wheat yield and variable costs of crop production across the 27 sites. A similarly significant relationship applied when future climate was separately considered.

Rather than make operating costs constant at each location, we introduced production year variability by adopting the regression line in Figure 4 and its equivalent under future climate. This ensured a more accurate representation of farmer behaviour whereby in poorer years, farmers would reduce their expenditure on crop inputs such as fertiliser and lime, and conversely, in more favourable years, farmers would increase fertiliser, fungicide and pesticide applications.

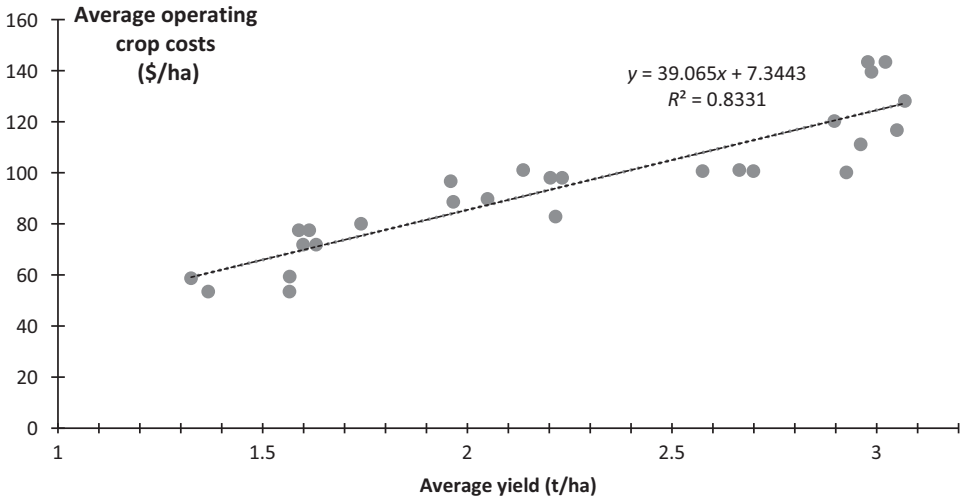


Figure 4 Average operating costs versus average yield for 27 locations under a current climate scenario.

3.7 Bulk discounts

In addition to seasonal changes in operating costs, there are additional changes in some operating costs attributable to price discounts on bulk purchases of inputs such as fertilisers and chemicals. For some inputs, such as chemicals, seller margins are already constrained so the magnitude of discounts for their bulk purchase may not be large. However, large farms often have greater ability to capture early-bird prices and use backloading to lower transport costs for some inputs, thereby lowering unit prices of those inputs. Industry experts were not unanimous in indicating the magnitude of these discounts and so we adopted a mid-range of views whereby bulk discounts were assumed commence at a farm size of 5000 ha and were a maximum of 4 per cent at 15,000 ha. Between these farm sizes, the following equation for bulk discounts applies:

$$D = 4A/10,000 - 2$$

where A is farm size (ha), and D is the percentage reduction in relevant input prices (i.e. fertilisers and chemicals). We conducted sensitivity analyses on the magnitude of bulk discounts.

These assumptions mean that some farms in lower rainfall areas are already large enough to receive these price discounts, so their further expansion generates no additional price discounts. Conversely, smaller farms can receive price discounts from expansions, particularly for expansions into lower rainfall locations where lower land prices provide an opportunity to increase farm size and crop areas.

3.8 Types of expansion

After constructing representative farms, each worth \$6 million, at each location, the following farm expansion options were considered:

- (1) a doubling in the size of an existing farm at each location; and
- (2) a 50:50 joint venture (JV) with another farm at one of the 26 other possible locations.

The first option is the traditional method of farm expansion whereby farms at two separate locations individually expand at their current locations by doubling their farm size. Each property which was worth \$6 million before the expansion would purchase an equivalent nearby farm worth \$6 million.

The second option was for the two farms to form a JV whereby each farm would expand but would bear half the cost of expansion at the farm remote from them, but would also receive half the annual profits from that remote farm. The JV arrangement would also mean each farm would give up half the profits from the farm expansion at their current location. In practice, this would entail each farmer managing their own home farm and the farm expansion at their current location, thereby avoiding travel to and management of the remote farm in which they had equity.

The options for farm expansion were examined under current climate as well as future projected climate. Implementing the JV arrangements was assumed to require some additional management, legal and accounting costs that were assumed to be \$20,000 annually.

3.9 Summary of farm financial modelling

The financial performance of each farm at each location was assessed, both before and after the two expansion options, through application of Equations (3) and (4).

$$E[R_{ij,s}] = E[I_{ij,s} - C_{ij,s} - F_{ij,s}] \quad (3)$$

$$Var[R_{ij,s}] = E[I_{ij,s} - C_{ij,s} - F_{ij,s}]^2 - (E[I_{ij,s} - C_{ij,s} - F_{ij,s}])^2 \quad (4)$$

where $E[R_{ij,s}]$ is expected annual net return in constant 2013 dollar term for farm i that has farm income I , farm variable costs of production C and farm fixed or overhead costs F . Note that the nature of farm i depends on the location(s) of the farm and which expansion option is being considered.

For each representative farm, its revenues and costs were generated for a 15-year sequence under each either current or projected climate using 20 random draws ($j = 20$) from yield distributions each year and $s = 50$ random draws of

commodity prices). Hence, each farm’s net return distribution over the 15-year sequences was based on 15,000 observations ($15 \times 20 \times 50 = 15,000$). From these distributions of net return, for each farm under each expansion option and climate scenario, their mean and variance of annual net returns were calculated and then were converted in asset values as described in the next subsection.

A limitation to the modelling approach based on Equations (3) and (4) is that interyear cumulative financial consequences, and their impacts on the viability of farm expansion are not explicitly considered, yet these impacts can be important (Kingwell and Xayavong 2016). Under future, more likely adverse climate change, interyear effects overlooked in this study could more deleteriously affect farm asset values.

3.10 Farm asset pricing

The capital asset pricing models of Sharpe (1964) and Lintner (1965) based on Markowitz (1959), and their later refinement by Black (1972), traditionally have been used to price assets and identify mean-variance-efficient investment portfolios. However, as indicated earlier, in spite of their didactic popularity, these models have received several serious criticisms. An example of the many criticisms is the blunt comment of Fama and French (2004): ‘The version of the CAPM developed by Sharpe (1964) and Lintner (1965) has never been an empirical success’ (p. 43).

Accordingly, we applied a capital asset pricing model based on observed farm capital prices, mean returns and their variability. The data in Figure 5 are derived from a decadal study of farms in the study region (Kingwell *et al.* 2013).

An empirically based pricing model that conforms to these data is as follows:

$$E(r) = \sqrt{a.\sigma_r + f^2} \tag{5}$$

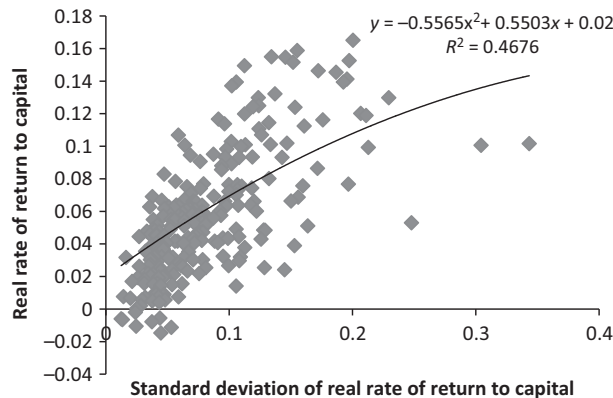


Figure 5 A pricing model applied to the upper tercile of farms, ranked by real rate of return to capital, in the study region.

where $E(r)$ is the expected rate of return to capital, f is the real risk-free rate (2 per cent), a is a parameterisation constant ($a = 0.042$ in Figure 5), and σ_r is the standard deviation of the rate of return to capital. This pricing model is not the frontier of all observed mean-variance efficient points. Rather, it implicitly assumes that some farm businesses are either overvalued or undervalued and that, in general, the pricing of farm assets is a function of upper tercile farms' expected returns and the variability of those returns. The upper tercile of farms, ranked by their real rate of return to capital, tend to be those farms which by the strength of their commercial performance are more likely to be expanding their farms and therefore determining farm asset prices in the market place. In a decadal study of farm businesses in the study region, Kingwell *et al.* (2013) found that almost 70 per cent of the farms in the upper tercile of rate of return to capital expanded their farm's area during the decade, whereas only about half the farms in the two lower terciles expanded their farms.

Note in Equation (5) R/C can replace r where R is the annual net return from the farm and C is the capital value of the farm. The equation can then be rearranged as follows to find C as a function of f , $E(R)$ and σ_R .

$$E(R/C) = \sqrt{a \cdot \sigma_{R/C} + f^2}$$

$$\frac{E(R)}{C} = \sqrt{a \cdot \frac{\sigma_R}{C} + f^2}$$

$$\left(\frac{E(R)}{C}\right)^2 = a \cdot \frac{\sigma_R}{C} + f^2$$

$$E(R)^2 = a \cdot C \cdot \sigma_R + C^2 \cdot f^2$$

Solving for C and eliminating the negative solution gives:

$$C = \frac{-a \cdot \sigma_R + \sqrt{a^2 \cdot \sigma_R^2 + 4 \cdot E(R)^2 \cdot f^2}}{2 \cdot f^2}$$

This empirically derived pricing model can be used to show how different types of farm expansion, by affecting $E(R)$ and σ_R , generate new capital values of the expanded farm business. It is possible then to estimate if the capital value of the expanded farm is greater than the sum of the original capital values of each separate farm. As outlined in Appendix S2, drawing on

Euler's homogeneous function theorem, this pricing model has the useful feature that:

$$C = \frac{\partial C}{\partial E(R)} \cdot E(R) + \frac{\partial C}{\partial \sigma_R} \cdot \sigma_R. \quad (6)$$

Equation (6) shows that the capital value, C , can be decomposed into point $(E(R), \sigma_R)$ and slope $(\partial C/\partial E(R), \partial C/\partial \sigma_R)$ components that affect $E(R)$ or σ_R . Hence, given the focus of this article on the value and riskiness of farm expansion, it is possible to see what components of farm expansion (size economies, bulk price discounts, imperfectly correlated enterprise returns) influence $E(R)$ and σ_R and therefore farm asset value. We stress that the farm models were not constructed to pre-ordain the importance of any particular component as we were agnostic about their relative importance.

3.11 Validation and debugging of farm models

As pointed out by McCarl (1997), two validation approaches exist: validation by construct and validation by results. The former asserts the model was built properly; therefore, it is valid, while the latter refers to exercises where model outputs are systematically compared against real-world observations. McCarl also notes that validation by construct will always precede validation by results. In this study, validation by construct was achieved by careful design of the farm models to ensure they accurately represented key features of farm businesses at each location.

Various tests were applied to the representative farms to ensure that formulae associated with farm expansion were error-free. For example, when a farm was expanded, an initial test was to check if that farm when expanded at its current location and receiving no economies of size or bulk discount savings, the enlarged farm had an asset value of \$12 million. Pannell *et al.* (1996) outline some other useful practical steps and principles for debugging models, some of which we applied.

3.12 Caveats

Use of representative farms and a capital asset pricing model to appraise farm expansions is an abstraction from reality. In practice, farm expansion decisions are complex financial and social decisions, and there can be different motivations and methods for expanding the farm business not captured in this analysis. Often the success or failure of expansion is attributed to social factors such as; are the partners competent and trustworthy in serving both partners' interests? Also the costs and effectiveness of dispute resolution and dissolution procedures in the partnership are important considerations overlooked in this study.

The future climate scenario considered in this article is a best case scenario for limiting anthropogenic climate change. Hence, in the absence of innovation and adaptation to fully offset adverse climate impacts, some JV partnerships under future climate may be less lucrative than portrayed in this article.

4. Results and discussion

Figure 6 displays the additional farm wealth generated by a JV farm expansion with remote versus local locations, under current climate. Results are based on 702 observations (i.e. 27 locations each with 26 expansion opportunities). The mean increase in wealth is \$413,316, or only an additional 2.3 per cent increase in wealth from the JV farm expansion with a remote locational partner. Under future climate a similar a 1.6 per cent mean increase in wealth occurs from the JV farm expansion with a remote locational partner. Hence, random geographical remote partnerships offer little expected commercial gain, in spite of the best-fit distributions under either climate scenario being logistic with a slight skewness to the left whereby the median exceeds the mean. The large variability in changes to wealth (Figure 6) indicates many expansion combinations either increase or erode

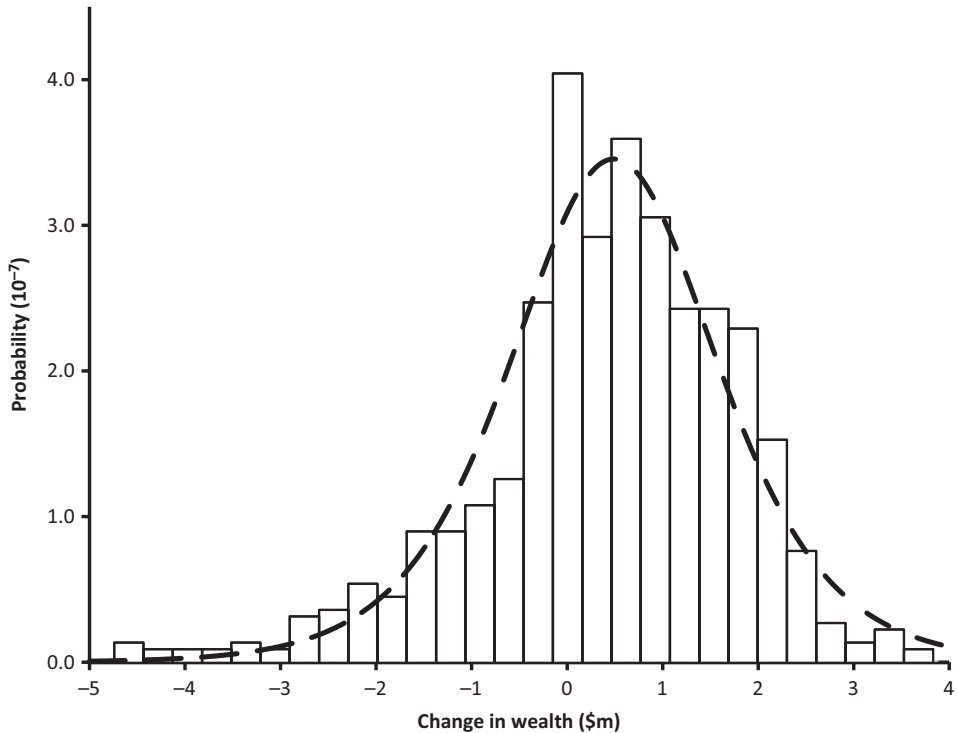


Figure 6 The distribution of the change in wealth generated by a joint venture farm expansion with a remote location versus a local expansion, for all 27 locations, under current climate.

wealth. Fitting a cumulative density function to the data in Figure 6 reveals a 9.2 per cent chance of a remote JV partnership generating over \$2 million in additional wealth, and conversely only a 5.5 per cent chance of at least a \$2 million erosion of wealth. Given this spread of wealth impacts, it is important to understand the characteristics of investment options that constitute worthwhile investments.

Accordingly Table 2 displays quantile regression results for the difference in asset valuations of JV remote expansions versus local expansions, under current and future climate. Charts in the Appendix S3 also show the pattern across quantiles in coefficients of the various factors affecting the difference in asset valuations. Results in Table 2 and *t*-test comparisons in Table A1 in Appendix S4 reveal what factors or characteristics of JV farm expansions with remote locations are significant sources of additional value. Under current climate the significant factors include the distance between farms, the rainfall index, the combined area of the farms, the difference in farm areas between the locations and the enterprise diversity of the combined farms. Most value is generated by the JV remote expansions when farms are not geographically close, where their farm size is not similar but neither is there a very large difference in farm size, the combination of farm areas is over 15,000 ha, and the locations' GSR is poorly correlated. The same findings apply under future climate except that geographical distance between farms and the rainfall index are less important factors.

The data underpinning both Figure 6 and the analysis in Table 2 are expressed as Figure 7 showing the change in wealth associated with remote partnerships for each location. The average wealth change associated firstly with the best 10, and then, the worst 10 remote partnerships for each location are shown (i.e. 20 out of the 26 possible partners). Several locations (e.g. Esperance, Badgingarra, Katanning, Southern Cross, Pingelly, Merredin) strongly benefit from forming remote partnerships. By contrast, several other locations face much smaller benefits from remote partnerships (e.g. Wandering, Moora, Geraldton, Wongan Hills) and these locations also face serious erosion of their wealth if they select an inferior remote partner. Although over all locations on average there is little gain in wealth via remote partnerships, as shown in Figure 6, the results in Figure 7 show there can be large differences between locations in the prospective increases or decreases in wealth associated with forming a remote JV partnership.

Inspection of the data summarised in Table 2 and Table A4 in the Appendix S4 and Figure 7 (and equivalent data under future climate) reveals that under either climate, a suite of locations are either highly preferred partners or are often worth avoiding, for different reasons. Under current climate, desirable partner locations (e.g. in the top 10 per cent of additional wealth increase), include Esperance, Salmon Gums, Ravensthorpe, Carnamah, Morawa, Mullewa and Geraldton. Esperance and Geraldton offer partnership advantages to some locations with less correlated GSR, yet high, often dependable rainfall and farm sizes (see Table A1 in Appendix S1)

Table 2 Factors affecting the value of JV remote expansions under current and future climate: quantile regression results†

Factor	Q10	Q25	Q50	Q75	Q90
Current climate					
Distance between farms (km)	-1,200* (628)	-365 (510)	258 (498)	658 (483)	-552 (456)
Rainfall index‡	639 (791)	399 (651)	294 (435)	1,546*** (514)	2,001*** (465)
Rainfall correlation coefficient	-2,092,016*** (586,498)	-1,234,295*** (282,654)	-1,274,451*** (329,053)	-869,665** (340,491)	-1,559,965*** (327,459)
Combined farm areas (ha)	96*** (24)	68*** (20)	117*** (23)	172*** (30)	173*** (25)
Difference in farm areas (ha)	-452*** (60)	-273*** (26)	-224*** (32)	-221*** (30)	-118** (47)
Farm diversity	858,587 (841,479)	-153,465 (519,951)	-384,323 (479,419)	-1,182,141** (551,754)	-802,610* (479,605)
_const	-1,032,916 (1,144,767)	433,655 (905,796)	623,528 (678,496)	885,973 (824,058)	1,023,753 (641,387)
Future climate					
Distance between farms (km)	-606 (788)	-662 (526)	310 (608)	841* (442)	665 (700)
Rainfall index‡	-1,575* (803)	-254 (649)	560 (732)	1,234** (581)	2,474*** (498)
Rainfall correlation coefficient	-1,288,690** (602,898)	-1,430,497*** (272,525)	-1,440,414*** (371,704)	-1,113,376*** (344,718)	-1,223,342*** (501,766)
Combined farm areas (ha)	59*** (27)	60*** (19)	120*** (43)	153*** (26)	223*** (24)
Difference in farm areas (ha)	-276*** (35)	-263*** (25)	-260*** (44)	-228*** (27)	-298*** (30)
Farm diversity	517,591 (969,303)	274,591 (464,245)	369,649 (734,957)	-1,364,383*** (457,219)	-1,752,873*** (494,556)
_const	61,542 (1,416,868)	422,230 (788,030)	123,741 (1,120,674)	1,750,399** (752,998)	1,821,278** (730,825)

Note: *** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$. †The differences in farm asset valuations of remote JV farm expansions versus local expansions were categorized into five quantiles and regressed against six explanatory factors under current and then future climate. ‡The rainfall index (mm) is calculated as the maximum of the growing season rainfall (GSR) at location a versus location b plus the absolute value of the difference in average GSR of locations a and b .

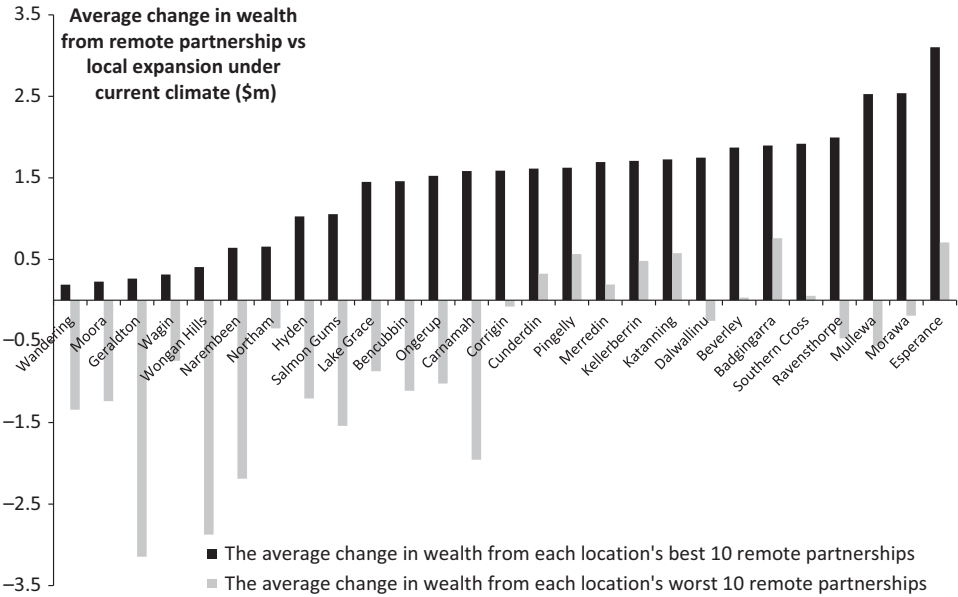


Figure 7 The average wealth change associated with the best 10 and worst 10 remote joint venture partnerships for each location under current climate.

which when expanded deliver economies of size benefits. Salmon Gums and Ravensthorpe are southern locations whilst Carnamah, Morawa and Mullewa are northern locations. These locations have less average GSR compared to Esperance and Geraldton, yet offer the same advantage of less correlated GSR as well as economies of size advantages. Lastly, Narembeen, Wongan Hills and Bencubbin are mostly central eastern grainbelt, low GSR locations that offer economies of size advantages when paired with locations which offer less correlated GSR but moderate farm size.

By contrast, locations that generate poor returns when selected as a remote JV partner often include high rainfall, relatively small farms situated largely on the central western edge of the grainbelt such as Northam, Moora, Wandering and Wagin, as well as Geraldton, Wongan Hills and Narembeen. Farm land in the higher rainfall locations is often expensive so economies of size, and bulk price discounts are restricted. Further, their locations, often near the centre of the grainbelt, mean they offer little advantages from their GSR correlations, unlike southerly locations such as Salmon Gums or northerly locations like Carnamah. Geraldton, Wongan Hills and Narembeen are wealth-eroding remote partners when teamed with locations that have more GSR and small farm sizes. Such combinations offer little economies of size or bulk discounts and often there are no enterprise diversity or rainfall correlation benefits.

Under future climate, Morawa and Mullewa feature as undesirable partners, as the projected climate change is adverse at these low rainfall locations. Conversely, as under current climate, Esperance, Wongan Hills,

Table 3 Components of additional value in the JV farm expansion for each location under current climate (%)†

Location	Bulk discounts (%)	Economies of size (Machinery) (%)	Economies of scale (Overheads) (%)	Joint venture costs (%)	Imperfect correlation of returns (%)	Adjustment effects (%)
Badgingarra	8.1	6.0	33.6	-4.9	17.4	-14.3
Bencubbin	26.2	5.4	30.2	-4.4	22.1	-20.2
Beverley	13.6	5.8	32.6	-4.8	15.3	-13.2
Carnamah	28.3	4.4	25.1	-3.7	16.5	-19.9
Corrigin	13.6	5.8	32.8	-4.8	14.6	-12.5
Cunderdin	9.8	5.9	33.2	-4.9	13.5	-11.1
Dalwallinu	14.7	5.7	32.3	-4.7	18.2	-13.9
Esperance	12.9	5.8	32.5	-4.8	26.5	-20.5
Geraldton	30.2	5.1	28.8	-4.2	17.5	-16.8
Hyden	20.6	5.7	32.2	-4.7	17.7	-14.4
Katanning	8.3	5.9	33.0	-4.8	13.6	-10.6
Kellerberrin	9.7	5.9	33.5	-4.9	17.3	-14.3
Lake Grace	20.2	5.7	32.1	-4.7	19.1	-16.6
Merredin	11.9	5.9	33.3	-4.9	17.4	-13.9
Moora	2.7	6.2	35.0	-5.1	12.6	-12.9
Morawa	22.7	4.1	23.4	-3.4	17.2	-20.6
Mullewa	26.0	4.4	24.9	-3.6	19.8	-21.5
Narembeen	26.1	5.5	31.2	-4.6	19.1	-16.3

Table 3 (Continued)

Location	Bulk discounts (%)	Economies of size (Machinery) (%)	Economies of scale (Overheads) (%)	Joint venture costs (%)	Imperfect correlation of returns (%)	Adjustment effects (%)
Northam	5.0	6.1	34.3	-5.0	11.6	-11.5
Ongerup	21.2	5.6	31.5	-4.6	19.4	-16.9
Pingelly	7.6	5.9	33.3	-4.9	13.5	-11.8
Ravensthorpe	16.9	5.5	31.1	-4.6	17.4	-14.7
Salmon Gums	22.5	5.6	31.6	-4.6	20.7	-16.4
Southern Cross	14.8	5.8	32.8	-4.8	22.1	-17.2
Wagin	3.9	6.1	34.6	-5.1	12.3	-11.4
Wandering	2.7	6.3	35.5	-5.2	15.1	-14.8
Wongan Hills	31.7	5.0	28.1	-4.1	21.7	-22.2
Average	16.0	5.6	31.6	-4.6	17.4	-15.6
Coefficient of Variation	54.7	9.9	9.7	9.9	20.1	21.9

†Percentages for each location are the means of combinations with all other 26 partner locations. Each component item is expressed as a percentage of the additional asset value generated by the JV partnership.

Bencubbin and Narembeen feature as desirable partners for some locations for reasons previously mentioned.

Although these findings point to certain locations being preferred, or not preferred, it is worth pointing out that for any location, it is possible to form a JV farm expansion with a remote location that delivers additional value. However, the converse is also true for all locations other than Pingelly and Badgingarra, whereby loss of wealth can occur through poor selection of a partner location. Hence, it is important to elucidate where and why a JV farm expansion with a remote location delivers large gains or losses in wealth.

Insights about the desirability of particular locations can be gleaned by decomposing the additional value in JV farm expansions for each location (Table 3). Results in Table 3 complement the quantile regression results in Table 2 by drawing on Equation (6) to decompose the components of the capital value of farm expansions. For all locations listed in Table 3, the average percentage of the additional value attributable to the JV remote partnerships comes mostly from economies of scale via the spreading of overheads across more hectares (32 per cent), price discounts for bulk purchases (16 per cent) and the risk-spreading benefits that stem from the imperfect correlation of farm returns (17 per cent) which in turn are linked to imperfect correlation of GSR. These advantages, alongside machinery size economies (6 per cent), are offset somewhat by the JV administration and set-up costs (−5 per cent), and various technical adjustment costs (−16 per cent). However, on balance, the key advantages of the JV remote partnerships are the size economies associated with farm inputs and risk-spreading benefits from spatial diversification.

The traditional buying out a neighbour involves highly correlated returns, whereas the JV partnerships with geographically separated farms entails imperfect correlations as the different locations have different soil mixes, different enterprise mixes and different weather-years that in concert cause farm revenues to be imperfectly correlated. Hence, the imperfect correlation value in percentage terms is often greater for farms at the latitudinal or low rainfall extremes of the WA grainbelt (e.g. Esperance, Southern Cross, Mullewa) and is far less for farms in more reliable, higher rainfall, central environments such as Northam, Moora, Wandering, Wagin, Pingelly, Katanning and Badgingarra. Often locations associated with small farm sizes (Wagin, Wandering, Moora, Northam; see Table A1 in Appendix S1) offer little opportunity for bulk discounts and some currently very large farms (Mullewa, Carnamah) offer less additional advantages of economies of size from expansion compared to many other locations. The large coefficient of variation in the value of bulk discounts (see Table 3) arises from the assumptions about how and when those discounts apply. For example, at some locations, farm sizes are so small that few bulk discounts apply, whereas some other JV partnerships provide sizeable bulk discount benefits. As and side, although farm acquisition may unveil an opportunity for bulk discounts, these discounts could also arise via other means, such as farm businesses forming a buyer cooperative.

The technical adjustment costs (see Table 3) arise through the interplay between the various components (bulk discounts, machinery size economies, overhead cost size economies and JV administration costs) that affect the overall risk and return of the JV. Through the capital pricing model, these various components alter the variances and expected values of returns and thereby affect the JV's capital valuation. Equation (6) shows how the components of farm expansion influence $E(R)$ or σ_R and therefore the JV asset value. The interplay of all the components within the capital asset pricing model is summarised as technical adjustment costs that often lessen the magnitude of the wealth increases.

Not reported here for brevity's sake is the consistency of the selections of preferred partner locations under either climate scenario for each of the 27 locations. Pearson's rank order correlation coefficients reveal that the lists of preferred (and nonpreferred) partners for each location are often similar under current and future climate. The practical inference is that if a location is currently identified as a highly preferred (or not preferred) JV partner for a particular location then that same location, even under projected climate change, will often remain preferred (or not preferred).

5. Conclusions

Greater climatic adversity is projected for some farming regions of Australia. Hence, in those regions, rather than buying out a neighbour, a less risky expansion path might be to purchase additional farmland elsewhere. This study used farm business financial modelling to compare the value of buying out a neighbour against a joint venture (JV) involving a geographically distant partner. Both forms of expansion involved identically expensive initial investments.

The modelling considered representative farms at 27 locations in the Western Australian grainbelt under current and projected climate. These farms either expanded locally or expanded with a JV remote partner. Over all locations, and considering all possible partner locations, the JV remote partnerships on average offered only small gains in wealth relative to local expansions under either climate scenario. However, there was large variation between locations in the relative attractiveness of JV remote partnerships. JV remote partnerships were much less worthwhile for several locations on the wetter western edge of the agricultural region. These locations exhibited low variability of returns, expensive land and small farm size, relative to most other locations. For almost all other locations, JV remote partnerships were more strongly preferred. Although there were additional costs to establish and maintain the JV, those costs were offset by scale and size economies associated with farm input use and risk-spreading benefits from spatial diversification.

Under current or future climatic conditions, to profit from a JV arrangement required careful selection of a geographical partner. Hence,

the simple adage that farms should spatially diversify is unwise general advice in the study region. Sound advice is to undertake due diligence, as the best commercial partner is shown to be a function of each farm's characteristics. As revealed by this study, key questions to ask are: Does the remote partnership offer (i) sufficient economies of size, (ii) price discounts on bulk purchases and (iii) weakly correlated returns?

Locations highly preferred (or not preferred) as JV partners under current climate were also highly likely to be preferred (or not preferred) under future climate. An implication is that the projected change in climate need not greatly alter farmers' choice of commercially attractive partners. However, as mentioned in the caveats section, the findings for the future climate scenario are for a best case scenario that limits anthropogenic climate change.

If a JV model of expansion is adopted, its commercial success importantly is additionally conditional on finding a competent, trustworthy partner similarly keen to expand their farm business and embrace a JV partnership.

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Supporting Information

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

- Appendix S1.** Key characteristics of representative farms.
- Appendix S2.** The asset pricing model.
- Appendix S3.** Additional quantile regression results.
- Appendix S4.** t-test results.