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Exploring the relationship between farm size and productivity: Evidence from the Australian grains industry

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ABSTRACT

The effect of farm size on productivity remains to be one of the longest standing debates in the agricultural development literature. In this paper, we use farm level data for the Australian grains industry from 1989 to 2004 to investigate the relationship between farm size and total factor productivity and its potential determinants. We show that a positive farm-size productivity relationship could be linked to farmer capital choice. In particular, the productivity advantage of larger farms is likely to diminish as farms use contract services to replace self–owned capital, suggesting that the hire of capital services (hereafter ‘capital outsourcing’) may lift the productivity level of small farms compared to their larger counterparts.

1. Introduction

Over the last three decades, structural adjustment has been responsible for much of the productivity improvement in the Australian grain industry. This structural adjustment has seen resources shift from smaller and less productive farms to the larger and more productive. Between 1989 and 2004, the average farm size increased by nearly 50% while the total number of farms declined from 24,989 to 18,748 (ABARES, 2016). By 2004, the largest 16% of farms accounted for around 75% of total industry output (Sheng et al., 2016). Given the apparent productivity disadvantage of the small relative to their larger counterparts, survival of the remaining ‘small farms’ has become an important public concern. Because of various political, social and economic complexities, this issue cannot be simply resolved by encouraging small farms to exit the industry. Rather, it requires closer examination to see whether there are economically efficient means to reduce the productivity disadvantage of small farms.

An important means through which farms improve productivity is by acquiring new technologies embodied in the purchase of new plant and equipment. Yet, large farms have traditionally been the main recipients of these technology related productivity gains—due to their size related budgetary capacity and ability to purchase and own the most advanced equipment. These large farms are better able to capture the benefits of technological progress and increasing returns to size (Kokic et al., 2006; Sheng et al., 2015, 2016). By contrast, small farms often lack the willingness and financial ability to invest in similarly advanced and expensive capital equipment—limiting potential benefits from increasing returns to size. This in turn narrows the ability of small farms to gain the productivity benefits of adopting newly invented technology. We therefore expect that a majority of small Australian grain farms are equipped with outdated capital equipment and unable to expand. To some extent, we also expect that the productivity disparity between small and large farms can be partially explained by limited access to technological progress embodied in capital equipment.

Building on the work of Sheng et al. (2010, 2011), we consider whether capital outsourcing could provide a complementary strategy for productivity improvement if a slowing down of land consolidation decelerates resource reallocation from small to large farms. Central to this is our hypothesis that small farms may be able to access the same technological progress (embodied in capital) as their larger counterparts if they are able to replace self-owned capital (which may incur excessive sunk costs and redundant capital capacity for smaller farms) with capital outsourcing. To test this hypothesis, we use data from a panel of Australian grain producers to examine the impact of capital outsourcing as well as its interaction with farm size on farm productivity.

To our best knowledge, this paper makes at least two contributions to the literature. First, it re-visits the farm size-productivity relationship in an Australian context and links it to farmer capital choice. Many previous studies have found a positive productivity to size relationship

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in Australian agriculture (Knopke et al., 2000; Alexander and Kokic, 2005; Kokic et al., 2006; Sheng et al., 2015; Sheng et al., 2016). However, none of these studies highlighted the role of capital investment in determining the productivity gap between farms of different sizes. Second, we show that capital outsourcing is an effective way to improve productivity of small farms relative to their larger counterparts. Findings from our study will assist in informing farmers and policy makers about a potential avenue for small farm productivity improvement and could prompt further research to better understand this potential driver of productivity improvement.

The remainder of this paper is organised as follows. Section 2 outlines the econometric model and the estimation strategy used to examine the effect of capital outsourcing on farm productivity of different sizes. In Section 3, the data sources and descriptive statistics are provided. Section 4 discusses the empirical results, followed by robustness checks. Conclusion are made in Section 5.

2. Econometric model and estimation strategy

To examine the farm size-productivity relationship and its determinants, we first regress a farm-level total factor productivity (TFP) measure on the variables representing farm size while controlling for various farmer characteristics and region and time specific factors. Following the farm size-productivity literature such as Sen (1962), Barrett (1996), Lamb (2003) among others, our basic empirical model incorporates the influence on TFP of both observed and unobserved farm characteristics:

$$\ln TFP_{irt} = \alpha + \beta lnFarmSize_{irt} + \sum_k \gamma^k X_{irt}^k + \sum_t \varphi^t DT_t + \varepsilon_{irt} \tag{1}$$

where TFP_{irt} is the logarithm of TFP level of the i^{th} farm operating in r^{th} region at year t, $FarmSize_{irt}$ is the variable representing farm size. The variable X_{irt}^k represents different farm characteristics, and specifically, k is the dimension of farm characteristics. These factors include land quality, water availability, farmer age and education, off-farm income, ownership and management practices (i.e., choice of crop variety) among others. We use a group of dummy variables: DT_t to capture the time specific effects; and ε_{irt} for random errors.

The dependent variable, farm TFP, is measured using the growth accounting approach developed for these data by Zhao et al. (2012). Specifically, price and quantity data for each input and output at the farm level are used to derive farm-specific TFP as a Fisher output index divided by a Fisher input index. In order to ensure transitivity, we applied the Èltetö-Köves-Szulc (EKS) method as in Eltetö and Köves (1964) and Szulc (1964). TFP is expressed as an index relative to a specific 'base' farm and year. For any farm-year observation, this measure gives the relative difference in TFP between that and the base observation. A detailed methodological description which includes the construction of inputs and outputs is available in Zhao et al. (2012).

To define farm size, we apply the dry sheep equivalent (DSE) measure as used in Sheng et al. (2015). This variable is essentially a measure of farmland carrying capacity and is frequently used as a unit of quality-adjusted land size in Australian cropping and grazing analysis. For our purposes, one hectare of high-quality cropping land for grain production is the equivalent to 12 units of DSE (Millear et al. 2003). Given that DSE adjusts for land quality, we consider that it provides a better measure of farm size than land area operated.

Using Eq. (1), we measure the impact of farm size on productivity when other farm characteristics such as natural land conditions and management practices are controlled for. Our hypothesis is that the relationship between farm size and productivity is positive, such that the coefficient (β) in front of the farm size variable ($FarmSize_{irt}$) is positive and significant. Since farm TFP is estimated using the index method, the effects of farm size captured by the coefficients may contain both the effects of increasing returns to size as well as the effects of other factors such as disembodied technological progress or changes in input substitution.

To examine the role of capital outsourcing and the effect this has on the farm size-productivity relationship, we introduce a dummy variable to define whether a farm is employing hired plant and machinery services in production (as a substitute for self-owned capital). Both this dummy variable and its interaction with farm size are incorporated into the regression, such that:

$$\ln TFP_{irt} = \alpha' + \beta' lnFarmSize_{irt} + \lambda PH_{irt} + \theta lnFarmSize_{irt} * PH_{irt} + \sum_k \gamma'^k X_{irt}^k + \sum_t \varphi'^t DT_t + u_{irt} \tag{2}$$

where the dummy variable for plant and machinery hire (PH_{irt}) takes a value of '1' if a farm uses capital outsourcing and '0' if it does not. As we include the capital-labor ratio in X_{irt}^k to control for total capital usage when labor is fixed, the dummy variable for capital outsourcing (PH_{irt}) only reflects the way through which farms obtain capital service. Finally, u_{irt} accounts for random errors.

Two hypotheses behind Eq. (2) are defined. First, a positive and significant effect of the plant hire variable (PH_{irt}) implies that capital outsourcing improves the average farm productivity level. Second, a negative and significant effect of the interaction term ($FarmSize_{irt} * PH_{irt}$) indicates that the productivity gap between the small and larger farms diminishes when capital outsourcing is used.

Although we have attempted to control for all relevant farm characteristics (including region and year dummies), the use of ordinary least squares (OLS) for the estimation of Eqs. (1) and (2) may be susceptible to omitted variable bias. Potentially, the omitted variables not included in the regression analysis could correlate to farm size, productivity and capital outsourcing activities, such that $cov(\varepsilon_{irt}, lnFarmSize_{irt}) \neq 0$ and $cov(u_{irt}, PH_{irt}) \neq 0$. As a remedy, we use the instrumental variable (IV) regression to deal with the time-invariant and time-variant omitted variable problem, such that:

$$\ln TFP_{irt} = \alpha + \beta lnFarmSize_{irt} + \sum_k \gamma^k X_{irt}^k + \sum_t \varphi^t DT_t + \sum_t \phi^t DR_r + \varepsilon_{irt} \tag{3}$$

$$\ln TFP_{irt} = \alpha' + \beta' lnFarmSize_{irt} + \lambda PH_{irt} + \theta lnFarmSize_{irt} * PH_{irt} + \sum_k \gamma'^k X_{irt}^k + + \sum_t \varphi'^t DT_t + \sum_t \phi'^t DR_r + u_{irt} \tag{4}$$

where a group of dummy variables DR_r are used to capture the region specific effects and farm size is identified by a series of selected instruments plus other control variables.

Three instrumental variables have been used in this paper to identify farm size, capital outsourcing and their interaction terms respectively. Following the study of Foster and Rosenzweig (2017) we first use the land area originally operated by a given farmer as an instrument to its current farm size. Essentially, land area may change over time and there is usually a positive relationship between land area initially owned and the current operational scale. However, only the current farm size is relevant to current production, which makes the instrument valid. Next, we use farms accessing to external advisory services as an instrument for the farm level capital outsourcing variable. This is based on the logic that farmers who use external advisory services are also likely to outsource their physical capital, noting that the use of external advisory services in this sample of farms did not necessarily result in higher productivity gains: the average TFP index of farms using external advisory services is 0.70, compared with 0.69 for farms not using external advisory services. Next, we use the interaction between the two aforementioned instrumental variables as a third instrument for the interaction term between farm size and capital outsourcing activity. All three instrumental variables have passed through the first-stage F test of excluded instruments.

To further improve the estimation efficiency, we adjust cluster effects for farms within each of the three grain production regions, as well as control for heteroscedasticity using the White's error correction procedure.

3. Data sources and independent variables

Data used in our study were obtained from three sources: the Australian Agricultural and Grazing Industries Surveys (AAGIS) and the Natural Resource Management (NRM) surveys conducted by ABARES and the drought index database maintained by the Queensland government and the University of Queensland. This section provides a brief description on data sources and key variables, followed by the summary statistics.

3.1. Data source

The AAGIS and NRM are two regular farm surveys conducted by ABARES on an on-going basis that collect a broad range of information on the current and historical economic performance of farm business units in Australian broad-acre agriculture. They cover industries including specialised cropping, mixed crop-livestock, beef and sheep. The sample for these two surveys are randomly selected from the stratified population of all broad-acre farms by region and farm size in Australia. Between consecutive years this sample maintains a high proportion of resurveyed farms (70–80%), while also introducing new farms so as to account for change in the target population. Given this rotating sampling strategy, we therefore obtain an unbalanced panel with the sample for each year varying between 1200 and 1500 farms.

As the surveys provide detailed financial, physical and socio-economic information at the farm level, they offer a number of advantages for the purpose of the current analysis. First, the AAGIS survey provides detailed input and output information in terms of both quantities and prices, allowing farm-level TFP to be estimated. Second, the NRM survey collects micro-data at the farm level, offering a remarkably rich source of information on farm specific characteristics and management practices. These data make it possible to control for some time-variant variables. For this study, we restrict the sample to farms that specialize in grain crops and are observed in at least two consecutive years during 1989–2004 with each farm being observed in at least for two consecutive years and cover crop specialist farms spread across 16 years from 1989 and 2004. This yields a total of 5969 observations that vary annually from 525 (for 1991) to 258 (for 2002).

3.2. Definition of control variables

Our analysis controls for a large number of farm characteristics — which we group into three categories.[2] The first is *farmer characteristics* and includes variables such as farmer age, formal education and off-farm income. The second category is *management and farming practice* and includes farm size, land use intensity, crop specialization and others. The third is *natural and market conditions* and includes land slope and market risk. Overall, these variables are expected to affect farm productivity independently. In addition, we include region and year dummies to account for region- and year-specific effects.

Controlling for climate is an important feature of our study, as farm TFP performance is likely to vary according to weather conditions — in turn influencing farm size and geographical distribution. We incorporate the 'moisture availability index',[3] developed by the Agricultural Production Systems Research Unit (sponsored by the Queensland government and the University of Queensland) as a proxy to measure variability in climate conditions (Potgieter et al., 2002). This index is based on a soil water balance model, taking into account a wide range of environment related factors such as rainfall, soil type, sunlight and temperature. It measures the amount of moisture available for wheat production during the winter growing seasons at the shire level.[4] This index has been tested and validated for a large number of sites across Australia and has been used in past studies of farm productivity (Alexander and Kokic, 2005; Kokic et al., 2006).

Table 1
Sample summary statistics from the Australian agricultural and grazing industries survey.
Source: AAGIS 1989–2004.

	Small farms	Medium farms	Large farms
Number of farms	3442	1879	647
Average farm TFP index	1.97	2.10	2.26
	[0.82]	[0.76]	[0.75]
Average farm DSE	534.5	1551.1	3864.3
	[255.7]	[402.0]	[1440.8]
Average land areas operated (ha)	1131.2	3316.7	8880.7
	[1441.3]	[2922.1]	[10615.3]
Average labor (weeks worked)	109.3	157.3	259.7
	[49.6]	[62.7]	[222.6]
Average capital stock excluding land (million A$)	1.1	2.2	4.6
	[0.8]	[1.6]	[3.5]
Average farm cash income (thousand A$)	81.4	177.6	340.1
	[98.2]	[197.8]	[400.1]
Average total debt (million A$)	0.16	0.36	0.90
	[0.23]	[0.45]	[1.08]
Share of Farms	57.7%	31.5%	10.8%

Note: numbers in the brackets are standard deviations.

3.3. Descriptive statistics by farm size

To portray the difference in productivity and characteristics among farms of different size, we split the sample into three size categories[5]: large (DSE = > 2500), medium (DSE = 1000–2500) and small (DSE = < 1000) farms. Descriptive statistics on these three categories of farms are presented in Tables 1 and 2.

From Table 1, small farms make up the vast majority in terms of farm numbers, accounting for approximately 57.7% of total farms between 1989 and 2004. Yet, in terms of output, these small farms account for only 29.6% leaving the remaining 70.4% of total output to be produced by the medium and large farms, which is similar to the United States case in McDonald et al. (2017). We note that the uneven distribution of farm output by farm size is underlined by differences in the distribution of production inputs such as land, labor and capital in the Australian grains industry. For example, the average capital-labor ratio for a small farm is A$10,100 per worker, whereas for medium and large farms these ratios are 39.0% and 76.1% higher respectively. This suggest that small farms tend to be more labor intensive and larger farms more capital intensive on average.

Given that the average capital-labor ratio and capita-land area ratio usually reflects embodied technology in use (Ball et al., 2010), it may imply that small farms have less access to technological progress compared to their larger counterparts. Consistent with capital and land equipment ratios, there are significant differences in productivity between farms of different sizes. For example, the average TFP level of medium farms in our sample was 13.6% higher than their small counterparts. Similarly, large farms achieved an average TFP level 28.8% higher than small farms.

Finally, when comparing descriptive statistics by farm size (Table 2), we also note that larger farms are more likely to have relatively higher human capital (i.e., higher TAFE education) and lower

[2] Table A.1 in Appendix A provides details about the variables derived from the AAGIS survey.

[3] This index is otherwise known as 'wheat water stress index' in Potgieter et al. (2002).

[4] 'Shire level' is the equivalent of a 'Local Government Area (LGA)' small area statistical boundaries and aligns to the Australian Statistical Geography Standard (ASGS).

[5] 1 hectare of high quality wheat farm land is the equivalent of 12 DSE units

Table 2
Characteristics of sample farms.
Source: AAGIS 1989 to 2004.

	Small farms	Medium farms	Large farms	All farms
Farmer characteristics				
Age	50.48	49.83	50.49	50.49
	[11.61]	[11.17]	[11.41]	[11.45]
Missing (%)	4.59	8.62	11.75	6.64
Not reported (%)	0.20	0.15	0.15	0.18
No schooling (%)	7.76	6.87	2.78	6.94
1–4 year high school (%)	49.59	39.17	40.49	45.33
5–6 year high school (%)	22.69	29.06	30.45	25.54
TAFE[a] (%)	7.58	5.96	8.66	7.19
Tertiary (%)	7.58	10.16	5.72	8.19
Off farm income (%)	9.55	2.51	1.23	6.43
	[33.7]	[5.05]	[2.68]	[26.03]
Family farms (%)	95.09	97.13	94.13	95.63
	[21.61]	[16.71]	[23.53]	[20.45]
Management and farming practices				
Land use intensity (%)	61.35	58.69	58.29	60.18
	[26.36]	[22.86]	[24.27]	[25.11]
Crop specialist[b] (%)	60.51	66.60	71.62	63.63
	[25.13]	[22.47]	[21.20]	[24.23]
Partners (number)	3.55	4.49	5.50	4.06
	[1.37]	[1.66]	[1.98]	[1.67]
Product diversity (%)	1.73	1.92	2.14	1.83
	[0.89]	[0.80]	[0.78]	[0.86]
Management Cost (%)	4.16	3.35	3.20	3.80
	[4.78]	[2.58]	[2.92]	[4.04]
Natural and market condition				
Moisture availability	4.31	4.28	4.27	4.30
	[0.24]	[0.25]	[0.24]	[0.25]
Land gradient[c]	0.35	0.40	0.36	0.37
	[0.60]	[0.48]	[0.41]	[0.54]
Market risk index[d]	8.98	10.26	11.25	9.63
	[0.82]	[0.54]	[0.51]	[1.08]
Other characteristics				
Number of farms	3442	1879	647	5968
Farms hiring capital (%)	32.8	38.1	40.3	35.2

Note: numbers in [brackets] are standard deviations.
[a] Technical and Further Education, a type of post-secondary vocational training.
[b] Farms are classified as crop specialists if they engaged mainly in growing cereal grains, coarse grains, oilseed and/or pulses and at least 50% of their income is generated from these farming activities.
[c] This variable is defined as average slope of land per farm measured in natural log.
[d] It is defined as variance of market prices of output, measured in natural log.

share of income from off-farm sources than their medium and small counterparts. Furthermore, in terms of farming practice, small farms generally use land more intensively, but large farms have relatively lower management costs and are more specialised in their crop production. Given these size related characteristics, it is hard to tell whether the size related productivity differences observed in the descriptive statistics are driven by farm size or some other farm characteristic.

4. Empirical results

In this section, we first discuss structural transformation and its impact on farm TFP in the Australian grains industry, and then examine the farm size to productivity relationship using OLS, OLS with regional fixed effects and IV with regional fixed effects regressions. The productivity variation between differently sized farms are further linked to the use of capital outsourcing in replacement of self-owned plant and machinery, followed by two robustness checks: one uses the panel data regression and the other use farm land area operated as an alternative measure of farm size.

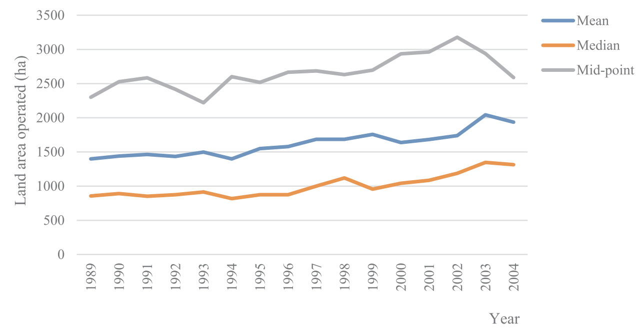

Fig. 1. The evolution of farm size (measured using farmland operating area) over time in Australia: 1989–2004.
Source: Authors own estimates.

4.1. Structural transformation and between-farm productivity differences

The broad-acre grains industry is an important sector in Australian agriculture. In 2016, the industry produced a gross output value of A$10.1 billion which accounted for around 20% of total agricultural output. Between 1978 and 2015, the annual TFP growth for the industry was on average 1.3% a year contributing to more than half of the output growth (ABARES, 2016). As a consequence, the average farm-level TFP of the industry is higher than that of the beef industry, the sheep industry and the horticultural industry (ABARES, 2016).

Underlying the aggregate industry-level productivity improvement over time, significant structural transformation has been widely observed in the Australian grains industry since the early 1990s. For decades, land and other agricultural resources have gradually moved from small to large farms as the Australian broad-acre grains industry became more consolidated. Moreover, the gap between the median, mean and mid-point of average farmland operating area increased over time (Fig. 1), suggesting that the distribution of farm size has shifted towards the large.

By analysing the structural transformation in the Australian broad-acre grains industry, many studies have found that farm productivity differs according to farm size (Knopke et al., 2000; Kokic et al., 2006). In particular, Sheng et al. (2015) demonstrated that large farms were more productive than their small counterparts, partly because they were better able to access advanced production technologies. More recently, Sheng et al. (2016) examined the role of input substitution (in particular, capital and intermediate inputs for labor) in determining the farm size-productivity relationship, pointing out that differently sized broad-acre farms could adopt different production technology due to their operational scale. Yet, none of these studies attempted to split the effects of farm size on productivity from farmer characteristics and their choice of capital outsourcing.

As in Fig. 2a, large farms had on average 20% higher levels of TFP than medium farms and 40% higher TFP levels than small farms. In addition, the productivity gap between these two groups of farms did not diminish over time. While farm productivity increased with size, there is a wide dispersion in the data with some small farms achieving TFP levels comparable to the largest farms as in shown in Fig. 2b.

4.2. The productivity to farm size relationship

Although the descriptive statistics provide supportive evidence for a positive correlation between farm size and productivity, the endogeneity problem arising from potential omitted variables means that this relationship cannot be claimed as causal. To examine this relationship further, we apply the IV regression with the control of regional fixed effects in addition to OLS. The results from these three methods are presented according to our farm-level variable groupings (*Farmer Characteristics, Management and Farming Practices and Natural*

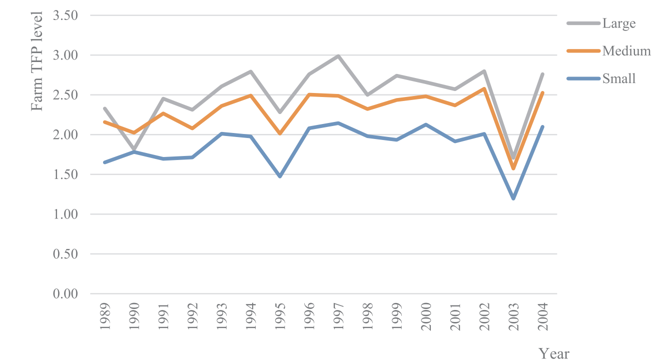

Fig. 2a. Average farm TFP level by size category: 1989–2004.
Source: Authors own estimates.

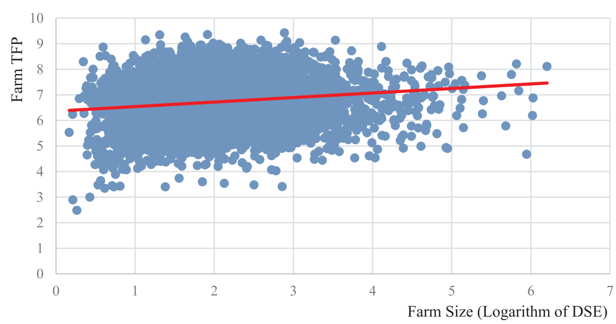

Fig. 2b. Farm size-productivity level relationship: 1989–2004. Note: the TFP index for farm 23,283 at 1989 is normalised to be one.
Source: Authors own estimates.

and Market Conditions). See Appendix A for detailed definitions of each variable.

After controlling for various farm characteristics, region and year specific effects and the potential omitted variable problem, we find a positive relationship between farm size and farm production (as is shown in OLS with regional fixed effects and IV with regional fixed effects in Table 3). The estimated coefficient of farm size in IV regression is statistically significant and equal to 0.093, which is smaller than that obtained from the OLS regression (e.g. 0.129), suggesting the OLS regression tends to over-estimate the impact of farm size of productivity. The positive relationship between farm size and TFP in the Australian grains industry suggests larger farms are more competitive and is consistent with the rising market share of these farms.

Several reasons may explain the positive farm size-productivity relationship. For example, large farms may benefit from increasing returns to size as the relative sunk cost associated with using the expensive yet more efficient plant and machinery declines with farm size (Diewert and Fox, 2010; O'Donnell, 2010). In addition, there are benefits from accessing technological progress embodied in the capital equipment (Sheng et al., 2015). We consider that due to size-related budgetary capacity, large farms are better equipped to benefit from technological progress through regular investment in the most advanced and efficient capital equipment. Meanwhile, many small farms may face greater budgetary constraints, meaning that they are unable to access the same technological progress as their larger counterparts or use acquired capital to its optimum capacity.

In addition to farm size, other farm characteristics influence TFP as well. The sign and magnitude of these variable coefficients are generally consistent with our expectations. For example, formal education positively contributes to farm productivity. Conversely, off-farm income has a negative and significant impact on productivity, suggesting that the more income farmers obtain from off-farm activities, the less likely they are to concentrate on farming. Our estimation also shows that moisture availability has a large impact on TFP, indicating the

Table 3
The impact of farm size on TFP level.

	OLS [1]	OLS with region fixed effects [2]	IV with region fixed effects [3]
Dependent variable: Ln of farm TFP			
Ln of farm size (measured by DSE)	0.097***	0.129***	0.093***
	[0.001]	[0.002]	[0.004]
Moisture availability (mean)	0.500***	0.459***	0.474***
	[0.003]	[0.003]	[0.005]
Moisture availability (std.)	−0.043***	−0.078***	−0.052***
	[0.002]	[0.003]	[0.004]
Land gradient	−0.022***	−0.011***	−0.006***
	[0.001]	[0.001]	[0.001]
Farm owner age	0.011***	0.010***	0.015***
	[0.000]	[0.000]	[0.000]
Farm owner age (squared)	−0.001***	−0.001***	−0.001***
	[0.000]	[0.000]	[0.000]
Off-farm income (%)	0.143***	0.115***	0.125***
	[0.005]	[0.005]	[0.005]
Education: not reported (%)	0.314***	0.308***	0.472***
	[0.008]	[0.008]	[0.014]
Education: no schooling (%)	−0.077***	−0.069***	−0.079***
	[0.002]	[0.002]	[0.003]
Education: 1–4 year high school (%)	0.115***	0.101***	0.122***
	[0.002]	[0.002]	[0.003]
Education: 5–6 year high school (%)	0.137***	0.121***	0.136***
	[0.003]	[0.003]	[0.004]
Education: TAFE (%)	0.201***	0.175***	0.179***
	[0.003]	[0.003]	[0.004]
Education: Tertiary (%)	0.089***	0.0916***	0.124***
	[0.002]	[0.002]	[0.002]
Land use intensity index	0.224***	0.203***	0.226***
	[0.00123]	[0.001]	[0.002]
Crop specialization	0.004***	0.004***	0.005***
	[0.000]	[0.000]	[0.000]
Crop diversity	−0.003	0.007***	0.027***
	[0.002]	[0.002]	[0.003]
Crop diversity (squared)	0.008***	0.003***	−0.002***
	[0.001]	[0.001]	[0.001]
Dummy for family farm	−0.190***	−0.195***	−0.157***
	[0.002]	[0.002]	[0.003]
Number of partners	−0.007***	−0.010***	−0.001
	[0.001]	[0.001]	[0.002]
Number of partners (squared)	0.001***	0.001***	0.001***
	[0.000]	[0.000]	[0.000]
Management costs	−0.029***	−0.029***	−0.030***
	[0.001]	[0.001]	[0.001]
Market price variability	−0.018***	−0.026***	−0.027***
	[0.001]	[0.001]	[0.002]
Capital-labor ratio	−0.029***	−0.031***	−0.017***
	[0.001]	[0.001]	[0.001]
Region dummies	No	Yes	Yes
Year dummies	Yes	Yes	Yes
Constant	−2.139***	−2.158***	−2.153***
	[0.021]	[0.023]	[0.031]
Number of observations	5968	5968	5968
R-squared	0.597	0.613	0.618
F-statistics for IV			97.9

Note: Robust standard errors in parentheses, base education group is primary school $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Numbers in brackets are standard deviations. The first-stage for IV regression with the control of regional fixed effects is provided in Appendix C.

importance of rainfall in the performance of dryland grain production in Australia.

4.3. Capital outsourcing and the farm size-productivity relationship

If a size-related budgetary constraint and associated capacity to invest in capital provides a partial explanation for the farm size-

Table 4
Impact of capital outsourcing on the farm size-productivity relationship.

	OLS [1]	OLS with region fixed effects [2]	IV with region fixed effects [3]
Dependent variable: Ln of farm TFP			
Ln of farm size (measured by DSE)	0.107***	0.139***	0.085***
	[0.002]	[0.002]	[0.009]
Interaction between farm size and capital outsourcing	−0.028***	−0.027***	−0.018***
	[0.001]	[0.001]	[0.023]
Dummy for capital outsourcing	0.173***	0.168***	0.113***
	[0.008]	[0.008]	[0.015]
Moisture availability (mean)	0.500***	0.459***	0.463***
	[0.003]	[0.003]	[0.005]
Moisture availability (std.)	−0.045***	−0.080***	−0.077***
	[0.002]	[0.003]	[0.005]
Land gradient	−0.0211***	−0.011***	−0.005***
	[0.001]	[0.001]	[0.001]
Farm owner age	0.011***	0.010***	0.014***
	[0.000]	[0.000]	[0.000]
Farm owner age (squared)	−0.0001***	−0.0001***	−0.0001***
	[0.000]	[0.000]	[0.000]
Off-farm income (%)	0.144***	0.115***	0.127***
	[0.005]	[0.005]	[0.006]
Education: not reported (%)	0.319***	0.313***	0.516***
	[0.008]	[0.008]	[0.016]
Education: No schooling (%)	0.076***	0.069***	0.071***
	[0.002]	[0.002]	[0.003]
Education: 1–4 year high school (%)	0.115***	0.102***	0.122***
	[0.002]	[0.002]	[0.003]
Education: 5–6 year high school (%)	0.138***	0.123***	0.150***
	[0.003]	[0.003]	[0.004]
Education: TAFE (%)	0.201***	0.176***	0.183***
	[0.003]	[0.003]	[0.004]
Education: Tertiary (%)	−0.087***	−0.090***	−0.119***
	[0.002]	[0.002]	[0.002]
Land use intensity index	0.223***	0.201***	0.226***
	[0.001]	[0.001]	[0.002]
Crop specialization	0.004***	0.004***	0.005***
	[0.000]	[0.000]	[0.000]
Crop diversity	−0.005**	0.005**	0.009***
	[0.002]	[0.002]	[0.003]
Crop diversity (squared)	0.008***	0.003***	0.002**
	[0.001]	[0.001]	[0.001]
Dummy for family farm	−0.189***	−0.195***	−0.157***
	[0.002]	[0.002]	[0.003]
Number of partners	−0.009***	−0.012***	−0.019***
	[0.001]	[0.001]	[0.003]
Number of partners (squared)	0.001***	0.001***	0.003***
	[0.000]	[0.000]	[0.000]
Management costs	−0.029***	−0.028***	−0.030***
	[0.001]	[0.001]	[0.001]
Market price variability	−0.019***	−0.027***	0.025***
	[0.001]	[0.001]	[0.002]
Capital-labor ratio	−0.029***	−0.031***	−0.014***
	[0.001]	[0.001]	[0.001]
Region dummies	No	Yes	Yes
Year dummies	Yes	Yes	Yes
Constant	−2.184***	−2.205***	−2.397***
	[0.021]	[0.024]	[0.049]
Number of observations	5968	5968	5968
R-squared	0.535	0.612	0.592
F-statistics for IV			74.8

Note: Robust standard errors in parentheses, base education group is primary school ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Numbers in brackets are standard deviations. The first-stage for IV regression with the control of regional fixed effects is presented in Appendix C.

productivity relationship, small farms are expected to increase their productivity provided they are able to access the same efficient capital services as their larger counterparts. We propose that this may be possible through capital outsourcing—such that small farms can access the latest embodied technological progress without incurring the associated financial commitment and high sunk costs. This does, however, raise several challenges in an Australian context.

Anecdotal information suggests certain segments of the capital outsourcing market are not well developed, such as for land preparation and sowing processes—particularly for the small farm market. As such, the cost of capital outsourcing may be high and the availability and suitability of equipment may be limited. Furthermore, due to the expansive size of Australia and its volatile climate, many farming activities are time sensitive and may need capital equipment that is not immediately available through capital outsourcing. Many small farms have therefore insisted on self-owned capital and the use of potentially less efficient equipment, while large farms have been able to update their equipment on a more frequent basis.

However, if the barriers to capital outsourcing are reduced, we hypothesise that small farms may be able to access the same advanced technological progress embodied in capital as is available to larger farms. To test this, we incorporate the dummy variable for plant hire and its interaction terms with the continuous variable for farm size into the regression (Table 4).

Based on the IV regression with regional fixed effects, the farm size-productivity elasticity is positive and significant with a value of 0.085. This implies that each 1% increasing in farm size increases average TFP by 0.085%. In addition, the capital outsourcing variable appears to have a positive effect on farm TFP. Farms that outsourced at least some of their capital experienced 11.3% higher TFP, on average, than farms that did not. Moreover, the interaction terms between farm size and the dummy for capital outsourcing is negative and significant at 1% level. This suggests that outsourcing helped close the productivity gap between small and large farms. With outsourcing, the farm size elasticity falls by 0.018, i.e., from 0.085 to 0.067. However, capital outsourcing does not completely close the productivity gap—suggesting that access to advanced technology through using custom services to substitute self-owned capital addresses part of the small farm issue only. Therefore, while increased use of capital hire is likely to offer benefits for small farms, our results suggest that a productivity deficit will remain between large and small farms.

4.4. Robustness check

To test whether our regression results are sensitive to the way that we measure farm size and the estimation methodology, we conduct two robustness checks. First, we replace our DSE farm size definition with farmland operating area and re-do the exercise. This test confirms whether the use of a different farm size measure has different effects on the role of capital outsourcing in the farm size-productivity relationship. Generally, the estimation results (see Table B.1 in Appendix B) are consistent with what we have obtained when using farm DSE as a size measure.

Second, it could be argued that the panel data regression with fixed effects might have better properties to control unobserved farm specific effects in examining the farm size-productivity relationship and the impact of capital outsourcing, though the fixed effect model may remove many farm characteristics and constrain the representativeness of our sample. We therefore re-do the panel data regression exercise with the instrumental variable by using the unbalanced panel data. The results indicate that the farm TFP level increases with farm size and that capital outsourcing tends to reduce the productivity gap between small farms and their larger counterparts. This is generally consistent with findings in the previous section (see Table B.2 in Appendix B).

5. Conclusion

This paper sets out a simple empirical strategy to examine the relationship between farm size and productivity in the Australian grains industry, linking to the way that farms obtain capital services. We show that there is a positive relationship between farm size and TFP in an Australian farm level context, helping to strengthen our understanding of why farms become larger, a widely observed phenomenon in the structural adjustment process of agriculture in developed countries. Moreover, our analysis demonstrates that capital outsourcing is likely to assist farms to increase their TFP and help close (but not eliminate) the productivity gap between small and large farms in the grains sector. This implies that identifying and addressing market and institutional barriers to capital outsourcing would assist small farms in moving towards the productivity levels achieved by their larger counterparts, and reduce economic incentives for land consolidation.

These results suggest several avenues for further analysis, including the importance of capital outsourcing in other commodity sectors, and the extent to which policy settings (such as taxation) or market arrangements block or discourage efficient capital outsourcing. Importantly, these contributions provide an insight for policy makers endeavouring to lift the productivity (and profitability) of small farms, and hence, productivity of the overall agricultural industry. Based on our findings, capital outsourcing appears to provide a successful avenue to lift the productivity of small farms in the Australian grains sector unlocking additional productivity gains by allowing them to access more advanced technologies.

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Appendix A. List of control variables

See Table A.1.

Table A.1
Control variables defined.

Variables	Descriptions
Logarithm of farm size	Continuous variables, measured using dry sheep equivalent (DSE)
Farmer characteristics	
Farm owner age	Continuous variable (year); age of the farm operator.
Farm owner age (squared)	Continuous variable (year2); a square term of age.
Farm owner education	Dummy variables (1, 0); including ▪ 'Not reported' (# = 1); ▪ 'No schooling' (# = 2); ▪ 1–4 year high school (# = 3) ▪ 5–6 year high school (# = 4) ▪ TAFE[a] (# = 5) ▪ Tertiary (# = 6)
Off-farm income (%)	Continuous variable (%); off-farm wage in total income
Dummy for family farm	Dummy variable (1, 0); '1' if it is a family farm and '0' if a corporate farm
Management and farming practice	
Land use intensity index	Continuous variable (S.E./hectare); total output per farm divided by area operated, measured in natural log
Crop specialization	Continuous variable (%); proportion of land area used for producing crops
Number of partners	Continuous variable; number of partners in the farm management team, measured in persons
Number of partners (squared)	Continuous variable; a square term of 'partners'
Crop diversity	Continuous variable; number of crop varieties
Crop diversity (squared)	Numerical variable; a square term of 'diversity'
Management costs	Continuous variable (%); proportion of management costs in total farm income
Capital to labor ratio	Defined as the logarithm of self-owned capital stock dividing by labor usage
Natural and market conditions	
Moisture availability (index)	Continuous variable (index); moisture availability index measured in natural log
Moisture availability (log)	Continuous variable; natural log of the standard deviation of moisture availability index
Land gradient	Continuous variable (degree); average slope of land per farm measured in natural log
Market price variability	Continuous variable ($/ton); variance of market prices of output, measured in natural log
Other controlled variables	
Year dummies	Dummy variable (1, 0); for individual years between 1989–1990 to 2003–2004
Dummy for capital outsourcing	Dummy variable (1, 0), assigned to farms according to plant hire

[a] Technical and further education.

Appendix B. Robustness check

See Tables B.1 and B.2.

Table B.1
Impact of capital outsourcing on farm TFP level by farm size category.

	OLS [1]	OLS with region fixed effects [2]	IV with region fixed effects [3]
Dependent variable: Farm TFP (ln)			
Logarithm of farm size (land areas)	0.109***	0.142***	0.103***
	[0.002]	[0.002]	[0.012]
Interaction between farm size and capital outsourcing	−0.033***	−0.033***	−0.022***
	[0.001]	[0.001]	[0.029]
Dummy for capital outsourcing	0.224***	0.225***	0.154***
	[0.008]	[0.008]	[0.204]
R-squared	0.589	0.614	0.573
Number of observations	5968	5968	5968
F-statistics for IV			835.8

Note: all other controlled variables have been included in the regressions but their coefficients are not reported for simplicity. Robust standard errors in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Numbers in brackets are standard deviations.

Table B.2
Panel data fixed effects for robustness.

	Panel FE [1]	Panel IV [2]
Logarithm of farm size (land areas)	0.143***	0.192***
	[0.0253]	[0.0270]
Interaction between farm size and capital outsourcing	−0.011***	−0.382***
	[0.001]	[0.0417]
Dummy for capital outsourcing	0.0413**	0.487***
	[0.017]	[0.027]
R-squared	0.586	0.473
Number of observations	5968	5968
F-statistics for IV		92.2

Note: all other controlled variables have been included in the regressions though many of them, such as land gradient, moisture availability (std.) etc., are dropped. Robust standard errors in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Numbers in [brackets] are standard deviations.

Appendix C. First-stage IV regression

See Table C.1.

Table C.1
First-stage regression results for Tables 3 and 4.

	First-stage for Table 3	First-stage test for Table 4		
	Farm size (DSE)	Farm size (DSE)	Interaction term	Capital outsourcing
Initial farm land area (IV)	0.401***	0.399***	0.133 ***	−0.001
	[0.002]	[0.002]	[0.012]	[0.002]
Farm consultancy (IV)	–	−0.002***	0.5193479***	−0.079***
	–	[0.000]	[0.000]	[0.000]
Interaction term (IV)	–	0.026***	0.234***	0.023***
	–	[0.002]	[0.015]	[0.002]
Moisture availability (mean)	0.136***	0.132***	−0.428***	−0.0151***
	[0.005]	[0.005]	[0.036]	[0.0010]
Moisture availability (std.)	−0.025***	−0.008***	−0.057***	−0.015***
	(0.002)	(0.001)	(0.005)	(0.002)
Land gradient	0.012***	0.012***	−0.064***	−0.010***
	[0.001]	[0.001]	[0.012]	[0.002]
Farm owner age	0.001	0.001***	0.001	−0.0020***
	[0.000]	[0.000]	[0.004]	[0.0003]
Farm owner age (squared)	−0.000	−0.000***	0.000	0.0000***

(*continued on next page*)

Table C.1 (*continued*)

	First-stage for Table 3	First-stage test for Table 4		
	Farm size (DSE)	Farm size (DSE)	Interaction term	Capital outsourcing
	[0.000]	[0.000]	[0.000]	[0.0000]
Off-farm income (%)	0.016***	0.016***	−0.062***	−0.0110***
	[0.002]	[0.002]	[0.010]	[0.0005]
Education: not reported (%)	−0.220	−0.214***	0.432***	−0.0532***
	[0.006]	[0.006]	[0.041]	[0.0032]
Education: No schooling (%)	−0.098***	−0.098***	−0.2060***	−0.0215***
	[0.006]	[0.006]	[0.0037]	[0.0015]
Education: 1–4 year high school (%)	0.086	−0.086***	0.0862***	−0.0405***
	[0.003]	[0.003]	[0.0056]	[0.0028]
Education: 5–6 year high school (%)	0.132***	−0.132***	0.0978***	−0.0689***
	[0.003]	[0.003]	[0.0057]	[0.0030]
Education: TAFE (%)	0.099***	0.096***	0.0659***	−0.0439***
	[0.004]	[0.004]	[0.0068]	[0.0031]
Education: Tertiary (%)	0.117***	0.112***	−0.0527***	−0.0311***
	[0.004]	[0.004]	[0.0069]	[0.0035]
Land use intensity index	0.168***	0.167***	0.2496***	−0.0007***
	[0.003]	[0.003]	[0.0037]	[0.0007]
Crop specialization	−0.001***	−0.001***	0.0008***	0.0000
	[0.000]	[0.000]	[0.0000]	[0.0000]
Crop diversity	0.017***	0.018***	0.0465***	0.0046***
	[0.004]	[0.004]	[0.0027]	[0.0011]
Crop diversity (squared)	−0.004***	−0.004***	−0.0087***	−0.0008***
	[0.001]	[0.001]	[0.0006]	[0.0002]
Dummy for family farm	0.150***	0.149***	0.0456***	−0.0063***
	[0.003]	[0.003]	[0.0030]	[0.0013]
Number of partners	0.079***	0.079***	−0.0199***	0.0085***
	[0.002]	[0.002]	[0.0022]	[0.0008]
Number of partners (squared)	−0.003***	−0.003***	0.0029***	−0.0010***
	[0.000]	[0.000]	[0.0002]	[0.0001]
Management costs	−0.005***	−0.005***	0.0005***	0.0002***
	[0.000]	[0.000]	[0.0002]	[0.0001]
Market price variability	−0.393***	−0.392***	0143***	0.003*
	[0.002]	[0.002]	[0.010]	[0.001]
Capital-labor ratio	0.019***	0.019***	−0.0187***	0.0034***
	[0.001]	[0.001]	[0.0015]	[0.0004]
Regional dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Constant	−0.357***	0.1247***	0.0705***	0.0395***
	[0.029]	[0.0039]	[0.0071]	[0.0026]
F-test of excluded instruments	97.85	77.04	52.17	83.46
Sanderson-Windmeijer multivariate F-test of excluded instruments		240.97	226.73	226.78

Note: Robust standard errors in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Numbers in [brackets] are standard deviations.

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