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Resource reallocation and its contribution to productivity growth in Australian broadacre agriculture

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This article uses farm survey data to measure the contribution of cross-farm resource reallocation to industry-level productivity growth in Australian broadacre agriculture. We show that resource reallocation between farms mainly occurred between incumbent farms and between farms with different productivity growth. Resource reallocation is estimated to account for around half of the industry-level productivity growth that occurred between 1978 and 2010, and its contribution appears to have increased over time. Moreover, we also show that resource reallocation effects vary across different inputs, partly due to their different mobility. This analysis improves our understanding of how reforms targeting structural adjustment – and the resource reallocation this generates – can influence aggregate productivity growth.

Key words: total factor productivity, resource reallocation, Australian agriculture.

1. Introduction

A well-functioning market economy is usually characterised by ongoing reallocation of resources between production units (Andrews and Cingano 2012). As such, policymakers have directed considerable effort at identifying barriers to efficient allocation of resources and pursuing associated reforms, with a view to promoting productivity. This is because it is known that shifting resources from less productive to more productive farms tends to raise aggregate productivity, even though various adjustment costs may be incurred. What is less clearly understood is the mechanism by which resource reallocation occurs. Against a backdrop of slowing agricultural productivity growth in Australia (Sheng *et al*. 2011), there is increasing interest in better understanding the role that resource reallocation may play.

Australian broadacre agriculture has experienced significant productivity growth over the past three decades. Between 1978 and 2010, aggregate total factor productivity (TFP) growth in Australian broadacre agriculture averaged 1.3 per cent a year. Concurrently, considerable structural change has also occurred, with industry production becoming increasingly concentrated. Since 1978, the number of Australian broadacre agriculture farms decreased by one quarter, while average farm size (measured by the gross

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value of output per farm in real terms) nearly doubled. Moreover, the top 20 per cent of farms now account for more than half of total output as market share and input use shift towards fewer, larger farms (Sheng *et al.* 2015).

Both of these changes reflect technological progress that has occurred since the 'green revolution' of the 1960s, but in different ways. With respect to productivity growth, the continued innovation of new technologies and management practices has led to widespread within-farm innovation. For example, the adoption of minimum-till practices, combined with the use of new crop varieties, increased yields on Australian cropping farms throughout the 1990s (Dunlop *et al.* 2004). With respect to industry structure, the uneven pace of technology adoption across farms has created differences in farm size and productivity. Indeed, differences in the size and productivity performance of the best and worst-performing Australian farms have been growing (Nossal *et al.* 2008).

Although there has been extensive research on the impacts on productivity growth within farms (Hayami and Ruttan 1985; Mundlak 2005; Alston *et al.* 2010), little is known about the impact of technological progress on industry structure and its implications for aggregate productivity growth. In particular, three questions persist. First, is there any relationship between structural change and productivity growth at an industry level? Second, what are the relative contributions of structural change and within-farm productivity growth to industry-level productivity growth? Third, how does the mechanism work?

This article investigates the link between cross-farm resource reallocation and industry-level productivity growth using farm survey data from Australia's broadacre agriculture industry between 1978 and 2010. For robustness, it uses three approaches: Baily *et al.* (1992); Olley and Pakes (1996); and Petrin *et al.* (2011; or, BHC, OP and PWR). Each approach is used to decompose industry-level TFP growth into within-farm productivity growth and other components that represent the effects of resource reallocation between farms. The three approaches produce somewhat different interpretations of the pattern of resource reallocation and its potential determinants.

To our knowledge, we are the first to examine cross-farm resource reallocation effects in Australian agriculture by decomposing industry-level productivity into within-farm technology progress and between-farm resource reallocation. This analysis improves our understanding of how reforms targeting structural adjustment and the resource reallocation this generates can influence the relationship between technological progress and aggregate productivity growth. For policymakers, the findings also suggest that initiatives directed at lowering the cost of resource transfers between farms may have twin benefits: not only the amelioration of short-term production inefficiencies, but also the promotion of long-term productivity growth at the industry level.

The remainder of the article is arranged as follows. Section 2 describes structural adjustment in Australian broadacre agriculture over the past three decades. Section 3 discusses the three decomposition methodologies used in this analysis. Section 4 defines the variables used in this study and discusses the data sources. Section 5 presents the empirical results. Policy implications are drawn in Section 6 contains the conclusions.

2. Structural adjustment in broadacre agriculture and resource reallocation

Broadacre agriculture comprises the majority share of Australia's agriculture industry: in 2013, the gross value of broadacre output was around A$48 billion, equivalent to 70 per cent of total agricultural output (ABARES 2013). Until the early 1980s, the industry had received assistance through a wide range of measures, including market and price support for selected commodities (such as home consumption price schemes, export price underwriting for wheat, the wool reserve price scheme), input assistance (such as a fertiliser subsidies, concessional credit and an agricultural tractor bounty) and various income tax concessions for agricultural businesses (Productivity Commission 2005, Gray *et al*. 2014).

Although levels of assistance were not comparable to those received by other sectors (in particular, manufacturing) and by agriculture in North America and Europe, these interventions nevertheless distorted price signals and thereby impeded efficient resource allocation between farms in the face of ongoing technology progress and industry adjustment. On one hand, the expected benefits obtained from government assistance were often capitalised into land values, thereby providing additional gains to landowners. On the other hand, home consumption price schemes transferred income from domestic consumers to farmers by raising domestic prices. In turn, this blunted incentives for farmers to adopt new technologies that would lower their marginal costs of production (Gray *et al*. 2014).

Recognising these problems, government began reforming agricultural policies in the mid 1980s. Early reforms started with replacing 'guaranteed' prices with 'stabilised' prices in wheat and wool, while providing adjustment assistance to these industries (Productivity Commission 2005). Subsequent reforms focused on installing market mechanisms to reallocate resources within the industry, progressively reducing the level of assistance provided, and harmonising differences in assistance across sectors. Accompanying these reforms was a phased reduction in tariff and other border protection for major export products, removal of the fertiliser consumption subsidy (Productivity Commission 2005) and a reduction in assistance for major crop and livestock products (including barley, cotton, grain legumes, maize, oilseeds, sorghum, wheat and wool). During the 1990s and 2000s, further deregulation reforms were carried out to dismantle statutory marketing authorities and their monopoly powers. Under the purview of National Competition Policy, all Commonwealth and the majority of state statutory marketing authorities were dismantled by 2010, except for the New South Wales Rice Marketing Board and the Potato Marketing Corporation of Western Australia.

The above reforms contributed to considerable structural change by exposing the broadacre industry to greater international and domestic competition, and by ensuring prices reflected actual production costs. Consequently, the distributions of farm size and productivity (Figure 1) have shifted, becoming flatter and more skewed to the right – towards farms that are larger and have higher productivity.

These structural changes have occurred along with significantly enlarged disparity in productivity between farms and increased concentration within the sector. Between 1978 and 2010, the ratio of gross output share accounted for by the largest 30 per cent of farms relative to the smallest 30 per cent of farms more than doubled – from 1.1 to 2.3. In part, this reflects the exit of around a quarter of farms (42,526 of 178,218), which released land, capital and labour to incumbent farms and new entrants (Sheng *et al.* 2015).

The growing productivity gap between farms and the trend towards increasing output concentration suggests that resource reallocation between farms is likely to be a continuing driver of industry-level productivity growth. In particular, as more productive farms use a greater proportion of total resources in the industry, the efficiency of resource use at the industry level will increase. Although conceptually straightforward, the extent to which ongoing structural change and its attendant resource reallocation have influenced industry-level productivity growth has not been determined empirically for Australian agriculture. Remedying this deficiency is assisted by recent advances in the literature which provide several approaches for analysing the contribution of resource reallocation to industry productivity growth.

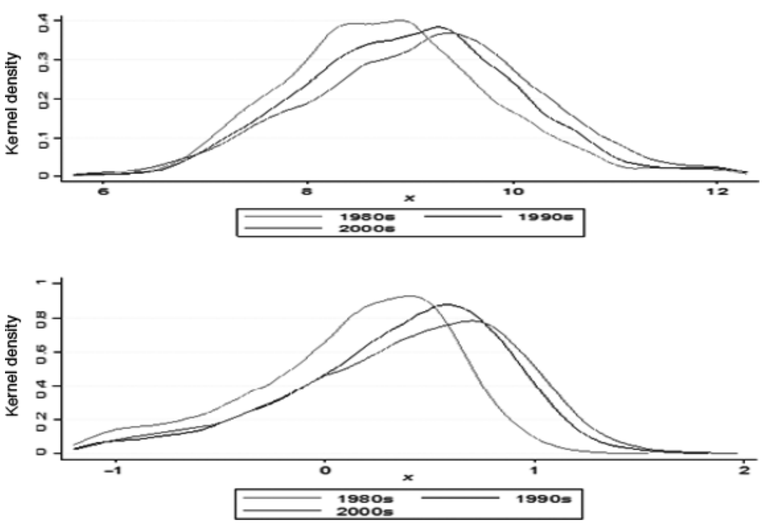

Figure 1 Changing distribution of farm size (DSE) and productivity (TFP) in broadacre agriculture. Source: ABARES AAGIS Survey.

3. Measuring resource reallocation: the BHC, OP and PWR approaches

An index of industry-level productivity (either partial or TFP) is usually defined as a weighted sum of firm-level productivity, where individual firms' shares of gross industry output (or input) are used as the weights:

$$\Pi_t = \sum_{i \in I} s_{it} \pi_{it} \tag{1}$$

where Π_t is the index numbers of industry-level productivity, s_{it} is the share of firm i in the industry, and π_{it} is an index of firm-level productivity. For our purpose, it is assumed there are disparities in firm productivity, and thus, the choice of weights will affect industry-level productivity. Using Equation (1), three approaches (BHC, OP and PWR) have been developed to measure the effect on industry-level productivity growth of changes in weights (cross-firm resource reallocation) and changes in firm-level productivity (within-firm effects).[1]

The BHC approach

If a firm's productivity level or input/output share deviates from its initial level, the industry productivity level (defined as the weighted average of firm-level productivity levels) will change. Applying this principle, Baily *et al.* (1992) proposed an approach to measure resource reallocation and its contribution to industry-level productivity growth according to firms' dynamic behaviour. Specifically, the BHC approach derives a standard decomposition function by differencing Equation (1) by one period (Foster *et al.* 2001), such that:

$$\begin{aligned}\Delta\Pi_t = & \sum_{i \in C} s_{it-1} \Delta\pi_{it} + \sum_{i \in C} (\pi_{it-1} - \Pi_{t-1}) \Delta s_{it} + \sum_{i \in C} \Delta\pi_{it} \Delta s_{it} \\ & + \sum_{i \in N} s_{it} (\pi_{it} - \Pi_{t-1}) - \sum_{i \in E} s_{it-1} (\pi_{it-1} - \Pi_{t-1})\end{aligned} \tag{2}$$

where C denotes continuing firms, N denotes entering firms, and E denotes exiting firms. According to Equation (2), industry-level productivity growth contains five components, in position order:

1. A within-firm effect: within-firm productivity growth weighted by initial (i.e. period $t - 1$) output shares.
2. A between-firm effect: the change in output shares weighted by the deviation of initial firm TFP growth from the industry average.

[1] In literature, there are many other decomposition approaches which can be used to analyse firm dynamics (Balk 2003; Breunig and Wong 2007; Hyytinen and Maliranta 2011). However, since these studies are not targeting resource reallocation between firms, we did not elaborate the discussion here.

3. A covariance term: the sum of farm TFP growth multiplied by change in firm share change.
4. An entry effect: a share-weighted sum of the difference between TFP of entering firms and initial industry TFP.
5. An exit effect: an initial share-weighted sum of the difference between initial TFP of exiting firms and initial industry TFP.

Four of these five components (the second to the fifth) are related to cross-firm resource reallocation. Specifically, the second and third components distinguish the between-firm effects from the covariance effects for continuing firms, while the fourth and fifth components identify firms' entry and exit effects. This detailed specification of cross-firm resource reallocation effects allows the BHC approach to analyse the drivers of aggregate reallocation effects in a more transparent way than is possible when using the other approaches.

Although the BHC approach for measuring cross-firm resource reallocation is simple to apply, two problems may be encountered. First, the approach uses the average productivity of firms as the comparison group, and thus, resource reallocation effects (for both continuing and entering/exiting firms) can be detected only when the productivity of those firms gaining/losing resources is significantly different from the average productivity of the industry. As most firms' productivity is distributed around the industry average, the BHC approach is likely to underestimate resource reallocation effects. Second, the approach uses firms' output or input shares in the initial period to estimate the within-firm effects, and thus, measurement errors specific to the initial period may contaminate measures of resource reallocation effects. If such errors did exist, the measured contribution of resource reallocation to industry-level productivity growth would be very volatile.

To deal with these two problems, Foster *et al.* (2001) proposed using the average of industry-level productivity and firm share over time as the comparison group, and combining the between-firm effects with the covariance term for continuing firms. With these changes, the decomposition function in the BHC approach can be written as:

$$\begin{aligned}\Delta\Pi_t = &\sum_{i\in C}\bar{s}_{it-1}\Delta\pi_{it} + \sum_{i\in C}(\pi_{it-1}-\bar{\Pi}_t)\Delta s_{it} \\ &+ \sum_{i\in N}s_{it}(\pi_{it}-\bar{\Pi}_t) - \sum_{i\in E}s_{it-1}(\pi_{it-1}-\bar{\Pi}_t)\end{aligned} \tag{3}$$

where a bar over a variable indicates an average of the base and end years. Comparing Equations (2) and (3) indicates that the adjustment to the BHC approach proposed by Foster *et al.* (2001) is likely to mitigate the adverse effects of measurement errors over time and to reduce the year-to-year fluctuation in measured resource reallocation effects.

The OP approach

Although useful, the BHC approach is not applied widely in practice as it requires tracking farms over time to identify their entry and exit. To overcome this data constraint, Olley and Pakes (1996) proposed an alternative way to measure the contribution of resource reallocation to industry-level productivity growth. This involved using cross-sectional data to decompose the industry productivity level into within-firm effects and resource reallocation effects. The OP approach defines within-firm effects as the unweighted average of firm-level productivity and the resource reallocation as the difference between the industry productivity level and the within-firm effects. A standard decomposition function and its change over time can thus be derived directly by rearranging Equation (1), such that:

$$\Pi_t = \bar{\pi}_t + \sum_{i \in A} (s_{it} - \bar{s})(\pi_{it} - \bar{\pi}_t), \tag{4}$$

$$\Delta\Pi_t = \Delta\bar{\pi}_t + \Delta \sum_{i \in A} (s_{it} - \bar{s})(\pi_{it} - \bar{\pi}_t) \tag{5}$$

where a bar over a variable represents the unweighted mean for all firms in an industry. An implied assumption behind Equation (4) is that, in the steady state, firms with the same productivity level should have the same output/input share, which is the neoclassical assumption necessary to ensure the market clearing condition holds.

Compared with the BHC approach, the OP approach is a simpler way to quantify resource reallocation and its contribution to industry-level productivity growth. It combines all the effects related to resource reallocation and attributes them to the covariance between each firm's productivity and its share in the industry (the second term in Equation (4)). However, the simplicity of this method does not reduce its usefulness, because the covariance term reflects an important dynamic mechanism through which resource reallocation can affect industry-level productivity. Specifically, the covariance term will be positive if firms with above-average productivity levels also have above-average market/input share. This implies that industry-level productivity can be improved independent of within-firm productivity growth. Based on this principle, many studies have used the OP covariance term as an indicator of the efficiency of markets in allocating resources between firms. Examples include Restuccia and Rogerson (2008), Hsieh and Klenow (2009), Bartelsman *et al.* (2011) and Asker *et al.* (2012).

It is important to recognise that the covariance term in the OP approach is quite different to the covariance term in the BHC approach (as defined in Equation (2)). Specifically, the OP covariance term is defined relative to the industry average and can be interpreted as resource reallocation between firms with different productivity levels. In contrast, the BHC covariance term is defined relative to each firm in the initial period and can be interpreted as resource reallocation between firms with different productivity growth.

A criticism of the OP approach is that it cannot distinguish the effects caused by firms' entry and exit from those caused by the reallocation of resources between incumbent firms. Melitz and Polanec (2012) remedied this by decomposing the covariance term into components related to incumbent firms' restructuring, and the entry and exit of firms. Specifically, this dynamic OP decomposition with firm entry and exit can be written as:

$$\Pi_{t-1} = s_{C,t-1}\widehat{\pi}_{C,t-1} + s_{E,t-1}\widehat{\pi}_{E,t-1} \tag{6}$$

$$\Pi_{t} = s_{C,t}\widehat{\pi}_{C,t} + s_{N,t}\widehat{\pi}_{N,t} \tag{7}$$

where $\Pi_t = \sum_{g\in G} s_{g,t}\widehat{\pi}_{g,t}$ and $\sum_{g\in G} s_{g,t} = 1$ ($G = C, E, N$ denotes the sets of incumbent, exit and entry firms) and $\widehat{\pi}_{g,t} = \bar{\pi}_{g,t} + \sum cov_{g,t}$.

The change in industry-level productivity is written as:

$$\Delta\Pi_t = (\pi_{C,t} - \pi_{C,t-1}) + s_{N,t}(\pi_{N,t} - \pi_{C,t}) + s_{E,t-1}(\pi_{C,t-1} - \pi_{E,t-1}). \tag{8}$$

The PWR approach

A potential shortcoming of both the BHC and the OP approaches for measuring resource reallocation effects is that the weighted sum of firm-level productivity is not always equal to industry-level productivity. This occurs when firm-specific weights are calculated as the firms' share of industry gross output, or of a specific input (typically labour). While this practice simplifies the calculation process, it distorts the estimation of industry-level productivity. To obtain accurate industry-level productivity estimates (defined as the ratio of industry-level output to input), it is necessary to construct firm-specific weights by combining firms' output and input shares.

Petrin *et al*. (2011) designed such weights by combining firms' output and input shares for aggregating the Tornquist–Divisia productivity index. In addition, they recognised that resource reallocation effects can vary across particular outputs/inputs due to differences in their mobility. To investigate this, Petrin and Levinsohn (2012) designed a decomposition approach (the PWR approach) to quantify input-specific resource reallocation and its effect on industry-level productivity growth, as distinct from changes in efficiency within firms.

The PWR approach is derived by first assuming that firms with different productivity levels can choose different output and input mixes. Given this condition, the relationship between industry-level productivity and firm-level output and input (or firm-level productivity in Equation (1)) can be re-arranged as:

$$\Pi_t \equiv \sum_i P_i Y_i - \sum_i \sum_k W_{ik} X_{ik} \tag{9}$$

where Π_t is the productivity level (as in Equation (1)) and Y_i is the gross output. W_{ik} equals the unit cost of the k th input, and $\mathrm{d}X_{ik}$ is the change in the use of that input in firm i. Converting the industry productivity levels into growth rates gives:

$$\mathrm{d}\Pi_t \equiv \sum_i D_i \mathrm{d}\ln Y_i - \sum_i \sum_k c_{ik} \mathrm{d}\ln X_{ik} \tag{10}$$

where $D_i = P_i Y_i / \sum_i P_i Y_i$ is the Domar weight, $\mathrm{d}\ln Y_i = \mathrm{d}Y_i / Y_i$ is the growth rate of firm i's output, and $c_{ik} = W_{ik} \mathrm{d}X_{ik} / \sum_i P_i Y_i$ is the input share. The growth accounting identity is imposed at the firm level when the assumptions of competitive markets and free entry hold.

Taking the first-order condition of Equation (9) yields the expression:

$$\mathrm{d}\Pi_t = \sum_i \sum_k (P_i \frac{\partial Y_i}{\partial X_k} - W_{ik}) \mathrm{d}X_{ik} + \sum_i \sum_j \left(P_i \frac{\partial Y_i}{\partial M_k} - P_j \right) \mathrm{d}M_{ij} - \sum_i P_i \mathrm{d}\pi_i \tag{11}$$

which can be rearranged as:

$$\Pi_t = \sum_i \overline{D_{it}^v} \sum_k (\varepsilon_{ik} - \overline{s_{ik}}) \mathrm{d}\ln X_{ik} + \sum_i D_i \sum_j (\varepsilon_{ij} - s_{ij}) \mathrm{d}\ln M_{ij} + \sum_i D_i \mathrm{d}\ln \pi_i \tag{12}$$

where D_i is the Domar weight, and M_{ij} is the intermediate inputs used by firm i produced by firm j. ε_{ik} and ε_{ij} are the elasticities of output with respect to primary and intermediate inputs, $s_{ik} = (W_{ik} * X_{ik})/(P_i * Y_i)$ and $s_{ij} = (P_j * M_{ij})/(P_i * Y_i)$ are the corresponding firm-specific revenue shares for both primary and intermediate inputs, and $\mathrm{d}\ln\pi_i$ denotes the growth rate of within-firm productivity.

The PWR approach overcomes the aggregation inconsistency problem of the BHC and OP approaches. As such, using it to aggregate firm-level productivity estimates yields the same estimate of industry-level productivity that would be obtained if industry-level output and input data were used. In addition, the approach provides new insights about the interaction between technological progress and resource reallocation. In particular, resource reallocation effects can differ across inputs when their use is driven by their relative marginal products.

4. Data sources and variable definitions

Data used for the decomposition analysis performed in this study are mainly drawn from two databases: the Australian Agricultural and Grazing Industry Survey (AAGIS); and Australian Commodity Database (ABARES 2013). A total sample of 41,708 observations have been used, which included farms in each of the five broadacre agricultural sectors covered by the AAGIS survey between 1978 and 2010. In constructing the sample, we dropped observations with incomplete information and the top/bottom 1 per cent of observations by gross output and total inputs to reduce the impacts of outliers. Three issues with the data were resolved as below.

Identification of farms' entering and exiting

Although the survey does not track every farm's movements (as an annual census would), the data can still be used to identify farms' entry and exit approximately under certain assumptions, as explained below.

Each year, ABARES determines the target number and types of farms to include in the AAGIS survey. To obtain the desired sample, survey collectors first keep those farms that have participated in the survey in the previous year (and would like to participate in the current year) and then resample the remaining population to reach the target number and composition of farms. Appropriate survey weights are assigned to sample farms to maintain representativeness of the state population.

Accordingly, between consecutive years, continuing 'matched' farms serve to represent the incumbent population, while other 'unmatched farms' approximate the entry and exit of farms.[2] Underpinning this approach are the survey weights, which serve to adjust entering, exiting and incumbent subsamples to represent their respective subpopulations over time. In the case of incumbent farms, pseudo resource allocation effects that are not caused by farms actually entering and exiting the industry will generally be negligible from a statistical perspective. This is because farms interchanged 'unnaturally' (i.e. due to sample rotation) in and out of the sample will tend to have the same average productivity as the incumbent population, while farms interchanged 'naturally' (i.e. caused by farms' entry and exit) will not. As such, the effects of farms' entering and exiting naturally will dominate the estimates using 'unmatched farms' when the average productivity of incumbent farms is used as a benchmark.

Notwithstanding, this method tends to overstate the actual effects of entry and exit by farms to the extent that the number of unnaturally interchanged

[2] Based on this method, farms' entry and exit (when taking into account of sample weights used in the farm survey) have on average accounted for one-third of total population in terms of number, gross output and input for the whole period. This estimate is much higher than the effect from farms' natural entering and exiting rate from year to year. Furthermore, the proportion of entering farms is similar as that of exiting farms, reflecting the sample rotation strategy used by the farm survey in practice. The corresponding estimates are available upon request from authors.

farms is large relative to the matched population. A greater number of unnaturally interchanged farms will increase the likelihood of the measured productivity of these farms deviating from the average productivity of the matched population, which is assumed to represent the true incumbent population. For example, the risk of overestimation is magnified in drought years when farmers' willingness to participate in the survey can wane. However, ABARES efforts to maintain samples that closely match between consecutive years should render such effects relatively small.

Measurement of farm productivity and weights for aggregation

Measuring resource reallocation effects requires estimates of farm-level productivity that are comparable across farms and over time. TFP (calculated using the regression-based method) is usually used as an approximation, as firm-level price information is not always available (Petrin and Levinsohn 2012). In cases when other inputs (for example, capital and intermediate inputs) are difficult to measure, labour productivity has also been used as a substitute (Foster *et al*. 2008; Hsieh and Klenow 2009). However, neither of these methods closely matches the theoretical concept of firm-level productivity.

This article uses the index method to estimate farm-level TFP. Using this method, farm-level TFP is defined as the ratio of an output quantity index to an input quantity index. Both indexes were estimated using the Fisher index adjusted by the EKS (Elteto and Koves 1964; Szulc 1964) formula to ensure trans-temporal and cross-farm comparability (i.e. to satisfy the transitivity condition). The Fisher index was used because it uses a quadratic transformation function for output and input aggregation which provides a second-order approximation to any form of the production function (Diewert 1992). When combined with the EKS formula for transitivity adjustment, it allows our farm-level TFP estimates to be compared consistently across farms and over time.

Finally, we use Domar weights to aggregate farm-level TFP. In doing so, farm shares in the industry are calculated as each farm's value of output divided by the total value of output of the industry. A similar estimation procedure is also applied to particular inputs, in which case the input value share is used. Some descriptive statistics for the major variables used in this study are presented in Table 1.

5. Resource reallocation and its contribution to industry-level TFP growth

The estimates of industry-level productivity growth presented in this article vary depending on which decomposition method is used and are also different from ABARES' regularly published productivity estimates. Differences in estimated TFP growth do not indicate a failing of the methods used in this article, but reveal the impact of differences in the assumptions and mathematics that underlie them.

Table 1 Descriptive statistics of the sample of broadacre farms, 1978–2010

Variable	Mean	SD	Min	Max
Year	—	—	1978	2010
Weight	60	79	1	1565
State	—	—	1	7
Industry	—	—	1	5
Crop_value	0.13	0.36	0.00	12.90
Livestock_value	0.24	0.14	0.00	77.00
Wool_value	0.05	0.13	0.00	6.71
Tot_output_value	0.51	1.84	0.01	174.00
Land_area (1000 ha)	37.88	1558.38	0.09	3219.24
Capital_value	0.03	0.06	0.00	1.51
Labour_value	0.04	0.02	0.00	0.24
Material&service_value	0.04	0.33	0.00	120.58
Tot_input_value	0.41	1.63	0.01	163.87
Input_index	0.81	4.99	0.11	23.73
Output_index	1.17	7.10	0.09	19.41
Farm-level TFP index	1.44	0.76	0.18	3.66

Notes: n = 41,708 in all instances. Values are measured as million Australian dollars, except for the number of observations. The minimum values for particular input and output still can take zeros because of rounding-up issues.Source: ABARES AAGIS Survey.

Between-farm resource reallocation vs. within-farm productivity growth

The results from all three approaches indicated that resource reallocation between farms has made a substantial contribution to industry-level TFP growth in the Australian broadacre agriculture industry. Between 1978 and 2010, it accounted for more than half of industry-level TFP growth when using the BHC and the PWR approaches and 44.4 per cent of industry-level TFP growth when using the OP approach (Table 2). This implies that resources have shifted from broadacre farms with lower productivity to those with higher productivity, which has significantly contributed to the overall efficiency improvement of the industry.

In the long run, Australian broadacre farms with higher productivity tend to earn higher profits and are thus better placed to expand production relative to farms with lower productivity. As more resources in the industry flow to the more efficient farms, the overall efficiency of the industry increases. This finding also helps to explain why the positive relationship between farm size and productivity – a widely observed phenomenon in Australian broadacre agriculture – is not entirely due to increasing returns to scale (Sheng *et al.* 2015).

However, resource reallocation effects have not occurred evenly over time. In general, we would expect resource reallocation effects to be relatively small when technological progress is strong and relatively large when technological progress is weak. To test this hypothesis, we compared within-farm and resource reallocation effects across three subperiods: 1978–1990, 1990–2000 and 2000–2010 (Table 2). As the PWR approach is sensitive to output and input prices (as discussed above), our analysis focuses on the results obtained from the BHC and OP approaches.

Table 2 Effect of resource reallocation and within-farm total factor productivity (TFP) growth on average annual industry-level TFP growth (%), 1978–2010

	BHC Approach	OP Approach	PWR Approach*
Whole period (1978–2010)			
Industry-level TFP growth	1.25	1.33	0.88
Within-farm TFP growth	−3.11	0.74	0.11
Resource reallocation	4.36	0.59	0.77
First period (1978–1990)			
Industry-level TFP growth	1.89	1.88	5.86
Within-farm TFP growth	−1.15	1.20	2.28
Resource reallocation	3.04	0.68	3.59
Second period (1990–2000)			
Industry-level TFP growth	2.26	2.24	7.37
Within-farm TFP growth	−1.53	4.02	1.72
Resource reallocation	3.79	−1.77	5.65
Third period (2000–2010)			
Industry-level TFP growth	−0.16	0.04	−10.09
Within-farm TFP growth	−6.08	−0.90	−3.45
Resource reallocation	5.92	0.94	−6.64

Notes: *The time periods for the PWR estimates are between 1978 and 2007 due to data constraints. In addition, the industry-level annual TFP growth is aggregated from their components, which could slightly differ from each other when using different decomposition approach (due to measurement errors). Source: Authors' own estimation.

It is widely believed that in the most recent decade (2000–2010), Australian broadacre farms experienced a slowdown in technological progress and faced more frequent droughts compared to the previous decade (1990–2000; Jackson 2010; Sheng *et al.* 2011). These changes are reflected in our estimates of within-farm effects for these periods, which show that the contribution of within-farm innovation to industry-level TFP growth has declined over time. Specifically, the average within-farm effects obtained when using the BHC and the OP approaches declined from −1.53 per cent a year and 4.02 per cent a year to −6.08 per cent a year and −0.90 per cent a year. In contrast, the average resource reallocation effects obtained when using these two approaches increased from 3.79 per cent a year and −1.77 per cent a year to 5.92 per cent a year and 0.94 per cent a year.

This finding is consistent with the observation that resource reallocation moves in the opposite direction to technological progress in almost all subperiods (all three subperiods when using the BHC approach and two of three subperiods when using the OP approach). This supports the argument that there is a negative relationship between within-farm productivity growth and resource reallocation effects. In particular, these results show that when technological progress slowed in the past decade, resource reallocation increased, and thereby helped to maintain industry-level TFP growth.

The negative relationship between within-farm effects and resource reallocation effects can be explained to some extent by the rational behaviour of farmers. Specifically, when faced with rapid technological progress and amenable climate conditions, farmers have many opportunities to adopt new production technologies and increase productivity. For example, as reflected in our statistics, within-farm TFP growth was strong in Australian broadacre industry in the 1990s. Because most farms were able to increase productivity and thus make profits during this period, there was little pressure for farms to release (or obtain) resources (Jackson 2010). However, when technology progress slowed in the 2000s, a relatively small proportion of farms were able to increase productivity, which enlarged the differences in productivity between farms. In these circumstances, resources are likely to move from farms with low productivity to those with high productivity at relatively low cost. Accordingly, as reflected in our statistics, resource reallocation effects become much more significant after 2000.

Technological progress, farms' entry and exit and reallocation effects

Although resource reallocation has made a significant contribution to productivity growth of the broadacre industry, the drivers remain unclear. Previous studies (Melitz 2003; Foster *et al.* 2008) identified at least two possible drivers when analysing cross-firm resource reallocation effects in the United States, which can be used to explain the phenomenon in Australian broadacre agriculture. One is asymmetric technology diffusion across farms – farms with different adoption capacities achieve different productivity despite facing the same technological progress. The other is farmers' self-selection when entering and exiting the industry. Usually the two factors work interactively.

Asymmetric technology diffusion across farms

Differences in farm productivity levels and growth are important drivers of between-farm resource reallocation in the Australian broadacre industry, particularly in the long run. Between 1978 and 2010, the average covariance terms between farm productivity and output share obtained when using the BHC and OP approaches were both positive (Figures 1,2). Because the covariance terms capture co-movement between farm size and productivity, this implies that resource reallocation moves in the same direction as technological progress. This phenomenon reflects the fact that asymmetric technology diffusion creates differences in farm productivity, which in turn stimulates the movement of resources between farms. Farms with higher productivity levels or growth are more likely to earn profits and expand than farms with lower productivity levels or growth, which are more likely to make losses and shrink.

As farm profit is also influenced by market prices, between-farm resource reallocation can sometimes deviate from farm productivity, which is driven by technological progress and technology diffusion. As such, between-farm resource reallocation is also sensitive to farm profit. In particular, when factors such as demand shocks and market distortions dominate farms' profitability and break the positive link between farms' productivity and

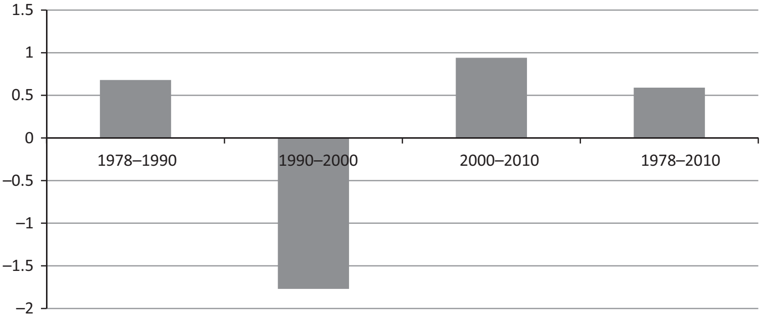

Figure 2 Average annual contribution of OP covariance effects to industry-level TFP (%), 1978–2010. Source: Authors' own estimation.

profitability, the contribution of resource reallocation to industry-level productivity can be negative. This situation is reflected in our results, where the covariance term obtained from the OP approach for the period 1990–2000 is negative, in contrast to the other subperiods (1978–1990 and 2000–2010). This result suggests that during the 1990s, resources moved to farms with relatively low productivity (a so-called resource misallocation).

Moreover, differences in farm productivity growth matter more for resource reallocation than differences in levels. As discussed in Section 3, the measured covariance effects obtained from the OP and BHC approaches reflect these two drivers of resource reallocation. Comparing the OP and BHC covariance estimates shows that resources have tended to flow to farms with relatively high productivity growth, rather than those with relatively high productivity levels (Table 3).

In particular, the covariance terms obtained from the BHC approach reflect the possibility of farms obtaining additional resources by improving productivity relative to their performance in earlier periods (that is, the effects of productivity growth), while the covariance terms obtained from the OP approach reflect the possibility of farms obtaining additional resources by improving productivity relative to the industry average (that is, the effects of a

Table 3 Comparison of covariance effects and its components: the OP vs. BHC approaches (%)

	OP Decomposition		BHC Decomposition		
	Covariance term	Within-farm effects	Covariance term	Entering effects	Exiting effects
1978–2010	0.59	−3.68	7.95	0.60	−0.52
1978–1990	0.68	−4.18	7.27	0.01	−0.05
1990–2000	−1.77	−2.00	4.94	1.55	−0.69
2000–2010	0.94	−4.73	11.13	0.39	−0.88

Source: Authors' own estimation.

relatively high productivity level). Between 1978 and 2010 (and in all subperiods), the BHC covariance term is positive and dominates the resource reallocation effects. In contrast, the OP covariance term is positive but not as strong as the BHC covariance term when compared to other effects. In particular, in the subperiod 1990 to 2000, the covariance term obtained from the OP approach is negative, while the estimate obtained from the BHC approach is still positive and strong. This suggests that resource reallocation is most likely driven by productivity growth and its difference between farms (Figure 3).

Farms' self-selection in entering and exiting the industry

Resource reallocation between incumbent farms contributes more to industry-level TFP growth than farms' entering and exiting. In contrast to the widely held belief that farmers' self-selection behaviour when entering and exiting the industry is a major determinant of resource reallocation, our empirical results show that while the effects are positive, they are not large. In particular, the results from the BHC approach suggest that the share of total resource reallocation effects accounted for by farms' entry and exit is relatively minor – around 20 per cent – between 1978 and 2010. In some cases, exiting farms have relatively few productive assets to sell (relative to incumbent farms) immediately prior to leaving the industry, while entering farms may need some time to enlarge their operation to the minimum efficient size. Yet, it is to be noted that this finding could result from the method used for approximating actual rates of entry and exit has potential to bias the estimates.

Resource reallocation and its asymmetric effects across inputs

Finally, we used the PWR approach to investigate how the movement of different inputs across farms contributes to resource reallocation. Specifically, industry-level TFP growth was decomposed into within-farm TFP growth and the contributions made by the reallocation of particular inputs (labour,

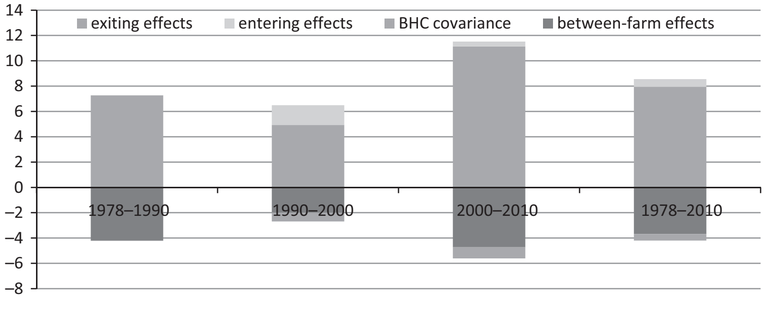

Figure 3 Average annual contribution of the BHC covariance effects and other between-farm components to industry-level TFP (%), 1978–2010. Note: Measures are based on industry-level TFP growth. Source: Authors' own estimation.

capital, and materials and services), as shown in Table 4. As there are differences in methodology and data, the estimates of industry-level TFP growth and its components obtained from the PWR approach are not directly comparable with those obtained from the BHC and OP approaches.

These results indicate that different inputs have played different roles in affecting the resource reallocation process and its consequences. Two key findings are discussed below.

First, the contribution of materials and services to the resource reallocation effects is much greater than that of labour and capital. Between 1978 and 2007, the effect on industry-level TFP generated by farms' intake and release of materials and services was around twice as large as that of labour, and around 40 times greater than that of capital. These results are similar among incumbent farms and between entering and exiting farms. One possible explanation for this (related to the process of resource allocation) is that, compared to labour and capital, farmers can vary their use of materials and services relatively easily from year to year, as they are relatively mobile.

Second, there was evidence of resource misallocation of some inputs in some time periods. For example, between 1998 and 2007, farms' entry and exit negatively affected the intake and release of materials and services between farms, and reduced industry-level TFP growth by more than 13 per cent a year. As discussed above, this does not necessary imply technological regress as the observed technology progress in this period was still strong (Jackson 2010). Instead, it reflects a short-term inconsistency between profitability and productivity.

Table 4 Contribution of various inputs to resource reallocation using the PWR approach (%), 1978–2007

	Labour contribution	Capital contribution	Material/ Service contribution	Within-farm TFP growth	Industry TFP growth
Incumbent farms					
1978–1987	1.34	−1.53	2.90	2.22	4.93
1988–1997	−0.47	1.54	3.18	1.22	5.47
1998–2007	3.02	0.16	6.73	−1.68	8.24
1978–2007	1.30	0.11	4.32	0.53	6.26
Entering and exiting farms					
1978–1987	−0.40	−0.02	1.30	0.05	0.93
1988–1997	1.09	−1.63	1.94	0.50	1.90
1998–2007	−4.89	1.14	−12.81	−1.76	−18.33
1978–2007	−1.44	−0.18	−3.34	−0.42	−5.38
All farms					
1978–1987	0.93	−1.54	4.20	2.28	5.86
1988–1997	0.62	−0.09	5.12	1.72	7.37
1998–2007	−1.87	1.30	−6.08	−3.45	−10.09
1978–2007	−0.14	−0.06	0.97	0.11	0.88

Note: Due to data constraints, the PWR approach can provide estimates for the period 1978–2007. Source: Authors' own estimation.

Consistent with the results from the BHC and OP approaches, overall resource reallocation effects obtained from the PWR approach are found to be strong, and make a significant contribution to industry-level productivity growth. Over the period 1978 to 2007, the PWR results suggest that the average annual industry-level TFP growth caused by resource reallocation was 0.9 per cent a year (Table 4), which represents 87 per cent of the total annual industry-level TFP growth. Further, when comparing the relative importance of different drivers of this resource reallocation, the contribution made by the entry and exit of farms is much smaller than that made by resource reallocation among incumbent farms. Both of these findings are consistent with those obtained from using the BHC and the OP approaches, supporting our previous findings.

6. Conclusions

Although it has long been believed that technological progress and industry structural adjustment have played important roles in promoting productivity growth in Australian broadacre agriculture, it has not been known how these two factors interact. To explore these drivers of industry-level productivity growth and the potential policy implications, this article investigates between-farm resource reallocation and its effects on industry-level TFP growth in Australian broadacre agriculture using three recently developed methods to analyse differences in farm-level productivity. The results suggest that structural adjustment and the resulting resource reallocation between farms has accounted for around half of industry-level agricultural productivity growth between 1978 and 2010.

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Supporting Information

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

Appendix S1. A brief literature review on resource reallocation
Appendix S2. Definition of outputs and inputs
Appendix S3. Explanation of differences in industry-level TFP estimates