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

Yu Sheng, Tom Jackson and Alistair Davidson

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Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES)

Postal address GPO Box 1563 Canberra ACT 2601
Switchboard +61 2 6272 2010
Facsimile +61 2 6272 2001
Email info.abares@daff.gov.au
Web daff.gov.au/abares

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This report draws heavily on data collected in ABARES surveys of broadacre industries. The success of these surveys depends on the voluntary cooperation of farmers, their accountants and marketing organisations in providing data. The dedication of ABARES survey staff in collecting these data is also gratefully acknowledged. Without this assistance, the analysis presented in this report would not have been possible.

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This report uses farm survey data to measure the contribution of cross-farm resource reallocation to industry-level productivity growth within Australian broadacre agriculture. Resource reallocation between farms accounted for around half of the industry-level productivity growth that occurred between 1978 and 2010, and its contribution appears to have increased over time.

Our findings show that resource reallocation was more likely to occur between incumbent farms (rather than through farms entering and exiting) and between farms with different productivity growth (rather than different productivity levels). The results also indicate that resource reallocation effects vary across different inputs (in particular, capital and labour), 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 the relationship between technological progress and aggregate productivity growth. For policy makers, the findings also suggest that initiatives directed at lowering the cost of resource transfers between farms may have two benefits: the amelioration of short-term production inefficiencies and the promotion of long-term productivity growth at the industry level.

1 Introduction

A well-functioning market economy is usually characterised by ongoing reallocation of resources between production units (Andrews and Cingano 2012). As such, policy makers have directed considerable effort at identifying policy reforms to channel resources more efficiently, with a view to promoting productivity. This is because it is known that shifting resources from less productive to more productive firms tends to raise aggregate productivity, even though various adjustment costs may be incurred. However, 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. 2010), there is increasing interest in better understanding the role that resource reallocation may play.

Australian broadacre agriculture—extensive, non-irrigated cropping and grazing—has experienced significant productivity growth over the past three decades. Between 1978 and 2010, aggregate total factor productivity growth in this industry averaged 1.3 per cent a year. For much of this time, productivity growth in Australia's agriculture industry as a whole was broadly comparable with that of other developed countries (Fuglie et al. 2012). Further, when compared with other market sectors of the Australian economy, agricultural productivity growth has been relatively strong (ABARES 2011).

Concurrently, considerable structural change has also occurred, with industry production becoming increasingly concentrated. From 1978 to 2010 the number of Australian broadacre agriculture farms decreased by one quarter, while average farm size (measured by the gross 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 shifted towards fewer, larger farms (Sheng et al. 2014).

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 continuous invention of new technologies and management practices has led to wide-spread 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 (for example, Alston et al. 2010; Hayami and Ruttan 1985; Mundlak 2005), 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 a 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?

Theoretically, structural change can affect industry-level productivity growth as resources move between farms with different productivity levels. Industry-level productivity increases when more efficient producers obtain more inputs, either through resources moving between incumbent farms, or through firms entering and exiting (Foster et al. 2008; Petrin et al. 2011). In this way, theory suggests resource reallocation may be a mechanism (independent of within-farm productivity growth) for sustaining industry-level productivity growth, given farms with lower productivity are less likely to survive than their more efficient counterparts. However, understanding the importance of resource reallocation for industry-level productivity growth and the nature of this process are largely empirical questions.

This technical report investigates the link between cross-farm resource reallocation and industry-level productivity growth using farm survey data from Australia's broadacre agriculture industries between the financial years 1977–78 (1978) and 2009–10 (2010). For robustness, it uses three approaches: Baily et al. (1992); Olley and Pakes (1996); and Petrin et al. (2011). Each approach is used to decompose industry-level total factor productivity (TFP) growth into within-farm productivity growth and other components that represent the effects of resource reallocation between farms. In addition, the pattern of resource reallocation and its potential determinants are analysed by comparing the results of each approach.

The results indicate that resource reallocation has contributed significantly to productivity growth in Australian broadacre agriculture. Between 1978 and 2010, it accounted for around half of industry-level TFP growth, and its contribution appears to have increased over time. Furthermore, resource reallocation was more likely to occur between incumbent farms (rather than through farms entering and exiting) and between farms with different productivity growth (rather than different productivity levels), implying that incumbent farms with greater potential to adopt new technologies have increasingly dominated adjustment in industry structure. The results also indicate that resource reallocation varies across different inputs (in particular, capital and labour), partly due to their different mobility.

To our knowledge, this study is the first to examine cross-farm resource reallocation effects in Australian agriculture. It contributes to the literature by using different approaches for decomposing industry-level productivity to measure and analyse the patterns and determinants of resource reallocation. This analysis improves our understanding of how reforms targeting structural adjustment and the ensuing resource reallocation can influence the relationship between technological progress and aggregate productivity growth. For policy makers, the findings also suggest that initiatives directed at lowering the cost of resource transfers between farms may have twin benefits: the amelioration of short-term production inefficiencies and the promotion of long-term productivity growth at the industry level. In addition, the approach used in this study can be extended to allow international comparison of industry-level agricultural productivity and its determinants.

The remainder of the report is arranged as follows. Section 2 describes structural adjustment in Australian broadacre agriculture over the past three decades and reviews the literature on analysing resource reallocation. 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 and Section 7 contains the conclusions.

2 Structural adjustment in broadacre agriculture and resource reallocation

Broadacre agriculture comprises the majority of Australian agriculture. In 2013, the gross value of broadacre output was around A$48 billion, equivalent to 70 per cent of total agricultural output (ABARES 2013). In addition, broadacre industries occupy around 90 per cent of agricultural land in Australia and employ 244 000 workers, around 2.1 per cent of the total labour force. The major commodities produced are grains (mainly wheat, barley and oilseeds), beef, sheep meat and wool. More than two-thirds of production is exported.

Until the early 1980s, Australian agriculture received significant government assistance aimed at promoting agricultural production, generating foreign exchange through exports and stabilising farm incomes. Broadacre farms in particular 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 and the wool reserve price scheme), input assistance (such as fertilizer subsidies, concessional credit and an agricultural tractor bounty) and various income tax concessions for agricultural businesses (Gray et al. 2014; Industry Commission 1998 & 1995).

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. Consequently, they impeded efficient resource allocation between farms in the face of ongoing technology progress and industry adjustment. In the first instance, the benefits obtained from government assistance were often capitalised into land values, thereby providing additional gains to landowners. In addition, home consumption price schemes transferred income from domestic consumers to farmers by raising domestic prices. In turn, these blunted incentives for farmers to innovate and protected less efficient farms from releasing economic resources or exit the industry (Gray et al. 2014).

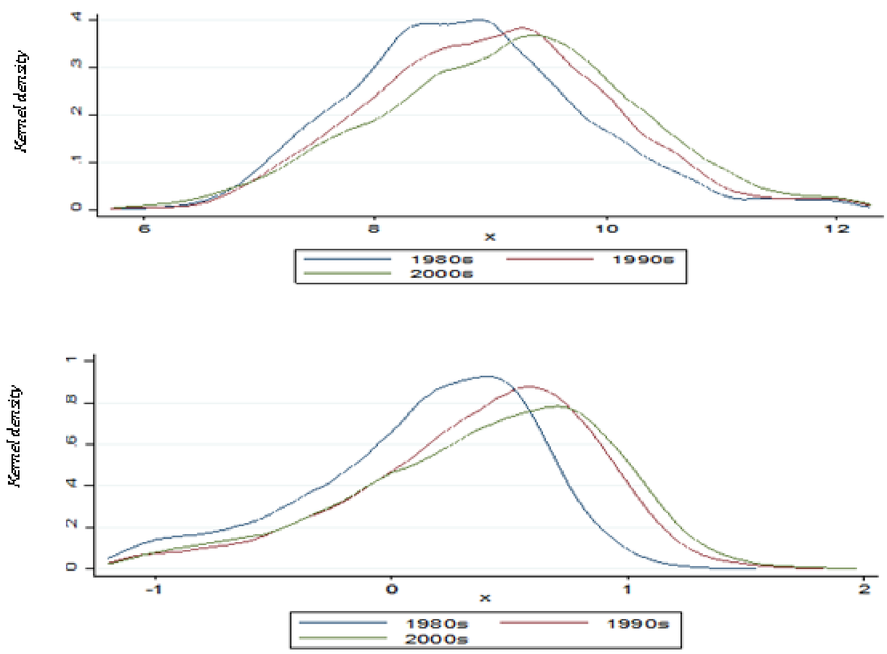
Recognising these problems, government began reforming agricultural policies in the mid-1980s. Early reforms started by replacing ‘guaranteed’ prices with ‘stabilised’ prices in wheat and wool, while providing adjustment assistance to these industries (Industry Commission 1998). Subsequent reforms focused on restoring market mechanisms to reallocate resources within agriculture, progressively reducing the level of assistance provided, and harmonizing differences in assistance across sectors. Accompanying these reforms was a phased reduction in tariffs and other border protection measures for major export products, the removal of the fertilizer consumption subsidy 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 reforms saw the dismantling of statutory marketing authorities (SMAs) and their monopoly powers. Under the purview of National Competition Policy (NCP), all Commonwealth and the majority of state SMAs were dismantled by 2010, except for the New South Wales Rice Marketing Board and the Potato Marketing Corporation of Western Australia.

As a consequence of these reforms, government assistance to Australian agriculture significantly declined over time. Between 1986 and 2012, the level of producer support (PSE) in Australian agriculture decreased from 10 per cent to 3 per cent (OECD 2013). Price subsidies, which previously accounted for 87 per cent of PSE, had declined to only 6 per cent by 2012 (Gray et al.

2014). In addition, Australia no longer provides any market price support to agricultural products (OECD 2013), although some items (for example, cheese, certain vegetables, certain oils and fats) continue to receive tariff protection and tariff-rate quotas protect certain cheeses.

Over the past three decades, these reforms haved contributed to considerable structural change by exposing broadacre agriculture to greater international and domestic competition and by ensuring prices reflected actual production costs. Consequently, average broadacre farm size (measured by 'dry sheep equivalent' or DSE—an indicator for total output or farms' carrying capacity) and productivity (measured by total factor productivity or TFP) have both increased, and so too their dispersion (ABARES 2013). The distributions of farm size (Figure 1) and productivity (Figure 2) have shifted, becoming flatter and more skewed to the right—toward farms that are larger and have higher productivity. Significant technological progress, in particular, its asymmetric diffusion across farms, has also served to reinforce these changes (Sheng et al. 2014; Sheng et al. 2010).

Figure 1 Changing distribution of farm size (DSE) and productivity (TFP) in broadacre agriculture



Source: ABARES estimates.

These structural changes have significantly increased concentration within the sector. Between 1978 and 2010, the share of gross output (measured using total farm cash receipts) accounted for by the largest 30 per cent of farms relative to the smallest 30 per cent of farms increased more than ten times—from 2.4 to 24.4. In part, this reflects the exit of around a quarter of farms (42 526 out of 178 218), which released land, capital and labour to incumbent farms and new entrants (Sheng et al. 2014).

The growing productivity gap between farms and the trend towards increasing output concentration suggest 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.

Following a theoretical finding on the relationship between technological progress and heterogeneity across firms (Aghion and Howitt 1992; Cooper et al. 1999; Melitz 2003), a large number of empirical studies have investigated cross-firm resource reallocation and its implications for industry-level productivity growth (Baily et al. 1992; Bartelsman et al. 2009; Foster et al. 2001; Olley and Pakes 1996). These studies found that the reallocation of resource inputs to more efficient producers (either through market share shifts among incumbents, or through entry and exit) acts as a mechanism for promoting aggregate productivity growth, provided there are differences in productivity levels or growth rates between individuals (Foster et al. 2008).

Three broad approaches have been developed to estimate the contribution of resource reallocation to aggregate productivity growth using firm-level data, namely: Baily, Hulten and Campbell (1992) (hereafter the BHC approach); Olley and Pakes (1996) (OP approach); and Petrin, White and Reiter (2011) (PWR approach). (Appendix A contains a detailed discussion of the literature related to these approaches.) Although different in their assumptions and data requirements, each approach offers useful insights and provides a cross-check of the other approaches. For example, the BHC approach splits resource reallocation effects into contributions made between continuing firms and those caused by firms' entry and exit, while the PWR approach splits out the contributions made by different inputs. This report applies all three approaches to analyse resource reallocation and its contribution to industry-level productivity growth in Australian broadacre agriculture.

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

To measure resource reallocation and its effects, we begin by discussing how industry-level productivity is constructed. Specifically, an index of industry-level productivity (either partial or total factor productivity) is defined as a weighted sum of firm-level productivity, where individual firms' shares of total industry output (or input) are used as the weights:

$$\Pi_t = \sum_{i \in I} s_{it} \pi_{it} \qquad (1)$$

where Π_t is the index of industry-level productivity, s_{it} is the share of firm i in the industry (market/output share or input share) and π_{it} is an index of firm-level productivity. For our purpose, it is assumed there are disparities in firm productivity (unlike the representative firm assumption of neoclassical theory) 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).

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 to decompose industry-level productivity growth into changes in firm productivity and share, Baily et al. (1992) proposed an approach to measure resource reallocation and its contribution to industry-level productivity growth in a detailed and transparent way. Specifically, the BHC approach derives a standard decomposition function by differencing Equation (1) by one period (Foster et al. 2001), such that:

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

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:

i) **within-firm effects**: within-firm productivity growth weighted by initial output shares

ii) **between-firm effects**: the change in output shares weighted by the deviation of initial firm TFP growth from the industry average

iii) **covariance effects**: the sum of farm TFP growth multiplied by firm share change

iv) **entry effects**: a year-end share-weighted sum of the difference between TFP of entering firms and initial industry TFP

v) **exit effects**: 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. The BHC's detailed specification of cross-firm resource reallocation effects allows the drivers of aggregate reallocation effects to be analysed more transparently than 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 the industry as the comparison group, implying that 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 industry average. 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. Thus measurement errors specific to the initial period may contaminate measures of resource reallocation effects, as these are derived as the difference between industry-level productivity and the within-firm effects. If such errors did exist, the measured contribution of resource reallocation to industry-level productivity growth would be too 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:

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

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:

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

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

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 importance, 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. In particular, they have used variation in this indicator over time and across countries to identify institutional obstacles and market distortions, after accounting for changes in demand and its potential impacts through prices (Hsieh and Klenow 2009). Other examples include: Asker et al. (2012); Bartelsman et al. (2011); and Restuccia and Rogerson (2008).

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)). The key difference lies in their reference groups, which require different interpretations. 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.

With respect to the stability of estimation results, the OP approach generates more consistent estimates of resource reallocation effects than the BHC approach. This is because it uses cross-sectional data to measure between-firm effects, which are more resistant to measurement errors caused by transitory shocks.

A criticism of the OP approach is that it cannot distinguish effects caused by firms' entry and exit from those caused by the reallocation of resources between incumbent firms. Meltz and Polanec (2008) 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 (equation 7) and exit (equation 6) can be written as:

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

$$\prod_{t} = s_{C,t}\,\hat{\pi}_{C,t} + s_{N,t}\,\hat{\pi}_{N,t} \tag{7}$$

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

The change in industry-level productivity is written as:

$$\Delta \prod_{t} = (\pi_{C,t} - \pi_{C,t-1}) + s_{N,t}(\pi_{N,t} - \pi_{C,t}) + s_{E,t-1}(\pi_{C,t-1} - \pi_{E,t-1})$$

$$= \left(\bar{\pi}_{C,t} - \bar{\pi}_{C,t-1}\right) + (cov_{C,t} - cov_{C,t-1}) +$$

$$s_{N,t}\left(\bar{\pi}_{N,t} - \bar{\pi}_{C,t}\right) + s_{N,t}(cov_{N,t} - cov_{C,t}) +$$

$$s_{E,t-1}\left(\bar{\pi}_{C,t-1} - \bar{\pi}_{E,t}\right) + s_{E,t-1}(cov_{C,t-1} - cov_{E,t-1}) \qquad (8)$$

The PWR approach

A potential shortcoming of the BHC and OP approaches 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 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) devised such weights by combining firms' output and input shares to decompose 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:

$$\prod_{t} \equiv \textstyle\sum_{i} P_i dY_i - \sum_{i}\sum_{k} W_{ik} dX_{ik} \qquad (9)$$

where W_{ik} equals the unit cost of the kth input and dX_{ik} is the change in the use of that input in firm i. Converting the industry productivity levels into growth rates gives:

$$d\prod_{t} \equiv \textstyle\sum_{i} D_i d\ln Y_i - \sum_{i}\sum_{k} c_{ik} d\ln X_{ik} \qquad (10)$$

where $D_i = \frac{P_i Y_i}{\sum_i P_i Y_i}$ is the Domar weight, $d\ln Y_i = \frac{dY_i}{Y_i}$ is the growth rate of firm i's output, and $c_{ik} = W_{ik} dX_{ik} / \sum_i P_i Y_i$ is the input share. Domar weights are used to combine firm-level, gross output-based multi-factor productivity estimates to higher-level aggregates (OECD 2008). 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:

$$\sum_i \sum_k (P_i \frac{\partial Y_i}{\partial X_k} - W_{ik}) dX_{ik} + \sum_i \sum_j \left(P_i \frac{\partial Y_i}{\partial M_k} - P_j \right) dM_{ij} - \sum_i P_i d\, \pi_i \tag{11}$$

which can be rearranged as:

$$\prod_t \; = \sum_i \overline{D_{it}^{V}} \sum_k (\varepsilon_{ik} - \overline{s_{ik}}) \text{dln} X_{ik} + \sum_i D_i \sum_j (\varepsilon_{ij} - s_{ij}) \text{dln} M_{ij} + \sum_i D_i \text{dln}\, \pi_i \tag{12}$$

where D_i is the Domar weight, 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 $\text{dln}\, \pi_i$ 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. This suggests that, in addition to technological progress and efficiency gains, the relative abundance of particular resources can also play a role in affecting the contribution of resource reallocation to industry-level productivity.

4 Data sources and variable definitions

Data used for the decomposition analysis performed in this study are mainly drawn from two databases maintained by the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES): the Australian Agricultural and Grazing Industry Survey (AAGIS) and ABARES Commodity Database. ABARES has surveyed individual broadacre (predominantly non-irrigated crop and livestock) farms annually since the late 1970s on a financial year basis (year ending 30 June), including detailed information on revenue, physical output, land, labour, capital and various intermediate inputs.

The number of sample farms varied between 770 and 2294 over the study period of 1978 to 2010. Sample farms are chosen using a stratification strategy over 22 survey regions by five sectors (crop specialists, mixed crop-livestock, beef specialists, sheep specialist and mixed beef-sheep). Sample weights are assigned to survey farms to reflect population totals. Information obtained from the Australian Agricultural Census (carried out by the Australian Bureau of Statistics every five years) is used to maintain sample representativeness.

The second data source, the ABARES Commodity database, contains commodity prices received and paid by broadacre farms. These prices (or price indexes) are usually collected at the state level, to capture regional differences in transportation costs and markets.

This study used a total sample of 41 708 observations, which included farms in each of the five broadacre agricultural sectors covered by the AAGIS survey. 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 impact of outliers. Nevertheless, for the purpose of measuring resource reallocation, it is necessary to resolve three remaining issues with the data: identification of farms' entering and exiting; measurement of farm productivity; and selection of appropriate farm weights.

Identification of the entering and exiting farms

To capture the turnover of farms and its impact on industry structure, we use data obtained from ABARES' AAGIS farm survey. Although the survey does not track every farm's movements (as an annual census would), the data can still be used to approximate farms' entry and exit under certain assumptions, as explained next.

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 participated in the survey in the previous year (and would like to participate in the current year) and then re-sample 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 total 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 (Table 1). 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’ in and out of the sample will tend to have the same average productivity as the incumbent population, while farms interchanged ‘naturally’ will not. As such, when incumbent farms form the comparison group, the estimated covariance effect related to farms' entry and exit using ‘unmatched farms’ is more likely to represent the real effect.

Notwithstanding, this method will tend to overstate the actual effects of entry and exit by farms to the extent that the number of unnaturally interchanged farms is large relative to the matched population. A greater number of unnaturally interchanged farms will increase the likelihood of the measured farm productivity 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, to the extent that it increases the representativeness of matched farms to incumbent farms.

Table 1 Continuing, entering and exiting farms in the AAGIS Survey, 1978–2010

	Sample size	Share of sample (%)		
year		Entering	Exiting	Continuing
1978	1375	-	44.8	55.2
1979	917	15.3	62.2	22.5
1980	892	42.1	41.5	16.5
1981	923	55.6	33.1	11.3
1982	921	42.3	17.1	40.6
1983	924	18.6	28.9	52.5
1984	778	20.8	25.0	54.2
1985	770	27.3	20.3	52.3
1986	794	24.7	14.5	60.8
1987	1047	37.6	19.1	43.3
1988	1043	17.5	21.7	60.8
1989	1114	19.1	22.7	58.2
1990	1041	14.7	17.7	67.7
1991	1654	41.2	19.6	39.2
1992	1611	12.1	26.8	61.2

year	Sample size	Share of sample (%)		
		Entering	Exiting	Continuing
1993	1525	15.6	24.0	60.4
1994	1641	19.9	25.9	54.1
1995	1435	18.8	36.7	44.6
1996	1303	28.4	35.6	36.0
1997	1387	33.9	42.8	23.3
1998	1322	33.9	37.5	28.6
1999	1224	31.8	41.5	26.7
2000	1186	43.5	22.4	34.0
2001	1221	23.2	28.0	48.8
2002	1091	19.0	25.0	55.9
2003	1342	32.8	24.6	42.5
2004	1226	16.2	41.9	41.8
2005	1508	40.3	28.0	31.8
2006	1458	24.3	34.2	41.4
2007	1482	38.5	43.9	17.6
2008	2294	50.5	36.8	12.7
2009	1638	23.0	27.1	49.9
2010	1621	25.0	-	75.0

Note: '-' means no value.
Source: ABARES AAGIS.

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. Revenue-based total factor productivity (calculated using the regression-based method) is usually used as an approximation, since 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 report 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 (that is, to satisfy the transitivity condition). The Fisher index was used because it satisfies more axioms for the quantity aggregation than other index methods and, relative to the Tornqvist index, is easier to adjust for transitivity. Also, the index uses a flexible aggregation function which provides a second-order approximation to any form of production function (Diewert 1992). This allows our firm-level TFP estimates to account for heterogeneous production techniques across farms.

To derive the firm-level TFP index, let the subscripts *s* and *t* represent two farms (or the same farm in two different years). The non-transitive Fisher quantity index between the two farms (or of the same farm in different years) can be expressed as the geometric mean of the Laspeyres and Paasche indexes:

$$Q_{st}^{F} = \sqrt{Q_{st}^{L} Q_{st}^{P}}. \tag{13}$$

where the Laspeyres and Paasche quantity indexes are defined as

$$Q_{st}^{L} = \frac{\sum_{i=1}^{N} p_{is} q_{it}}{\sum_{i=1}^{N} p_{is} q_{is}} \quad \text{and} \quad Q_{st}^{P} = \frac{\sum_{i=1}^{N} p_{it} q_{it}}{\sum_{i=1}^{N} p_{it} q_{is}}, \tag{14}$$

respectively, and $1 \leq i \leq N$, represents the input (or output) used (or produced) by farms *s* and *t*. *N* is the total number of inputs (outputs), p_{is} is the price for input (output) *i* for farm *s* and q_{is} is the quantity of input *i* used (output produced) by farm *s*. Input and output quantities are aggregated using corresponding farm-level prices. Appendix B contains detailed definitions of each outputs and input.

To ensure that the estimated farm-level TFP index is comparable across farms and over time, the Fisher quantity indexes are adjusted using the EKS formula, such that:

$$Q_{st}^{T} = \left(\prod_{r=1}^{n} Q_{sr}^{F} Q_{rt}^{F} \right)^{1/n} \tag{15}$$

where *n* is the number of sample points such that $1 \leq r \leq n$, including repeated observations of the same farm at different points in time.

Before applying equations (8), (9) and (10), a farm in a given year is chosen as the numeraire and given the value 1. The index values of all other farms at all other points in time are then normalised relative to this base farm. Each farm index represents the change in their total inputs or gross outputs relative to the base farm in the base year. Individual input and output quantities are aggregated using corresponding farm-level prices. Thereafter, equation (15) is used to impose transitivity. By doing this, any pair of farms at any two points in time can be compared by dividing their respective index numbers. As such, farm-level input, output and TFP estimates are comparable with each other and over time irrespective of which farm is chosen as the base.

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 2.

Table 2 Descriptive statistics of the sample of broadacre farms, 1978–2010

Variable	Mean	Std. Dev.	Min	Max
Year	-	-	1978	2010
Weight	60	79	1	1565
State	-	-	1	7
Industry	-	-	1	5
crop_value	3.81	8.96	0	371
livestock_value	4.58	15.00	0	2590
wool_value	2.33	3.90	0	90
tot_output_value	10.70	18.4	0	2590
land_value	1.95	2.88	0	127
capital_value	3.73	11.00	0	1860
labour_value	2.33	2.48	0	75
material&service_value	4.86	6.85	0	450
tot_input_value	12.90	18.20	0	2370
log_input_index	1.99	4.99	0	189
log_output_index	2.37	7.10	0	446
farm-level tfp	1.51	0.76	0	12

Note: n=41 708 in all instances. Values are logarithms of million Australian dollars, except for the number of observations.
Source: ABARES AAGIS.

It is important to note that the estimates of industry-level productivity growth presented in this paper differ from ABARES' regularly-published productivity estimates and vary depending on the decomposition method used. Differences in estimated TFP growth do not indicate a failing of the methods used in this paper, but reveal the impact of differences in the assumptions and mathematics that underlie them. A detailed explanation of these differences is provided in Appendix C.

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

This chapter discusses the contribution of resource reallocation to TFP growth in Australian broadacre agriculture based on the three methods. The methods offer complementary measures of resource reallocation and provide different insights on two issues—key drivers and linkages to input mobility. To enable comparison across methods, the results are expressed in terms of their contribution to industry-level TFP growth, thereby providing a useful cross-check of resource reallocation's importance.

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 Australian broadacre agriculture. 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 3). This implies that resources have shifted from broadacre farms with lower productivity to those with higher productivity, which has contributed significantly 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 resources in the industry flow to 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—is not entirely due to increasing returns to scale (Sheng et al. 2014).

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 resource reallocation effects across three sub-periods: 1978–1990, 1990–2000 and 2000–2010 (Table 3). The analysis focused on the results obtained from the BHC and OP approaches, as the PWR approach is sensitive to output and input prices (as discussed above).

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). These changes are reflected in the 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 (1990-2000) to -6.08 per cent a year and -0.90 per cent a year (2000-2010). 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 (1990-2000) to 5.92 per cent a year and 0.94 per cent a year (2000-2010).

Table 3 Effect of resource reallocation and within-firm 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-firm 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-firm 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-firm 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-firm TFP growth	-6.08	-0.90	-3.45
Resource Reallocation	5.92	0.94	-6.64

Note: 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' estimation.

The observed negative relationship between within-farm technological progress and resource reallocation occurred in almost all sub-periods—all three sub-periods when using the BHC approach and two out of three sub-periods when using the OP approach. These results suggest that when technological progress slowed in the past decade, resource reallocation increased, and thereby helped to maintain industry-level TFP growth.

To some extent, this can be explained by the rational behaviour of farmers. When faced with rapid technological progress and amenable climate conditions, farmers have many opportunities to adopt new production technologies and increase productivity. For example, within-farm TFP growth was strong in Australian broadacre industries during the 1990s. Because most farms were able to increase productivity and thus make profits during this period, there was little pressure for less efficient farms to release resources relative to their more efficient counterparts

(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.

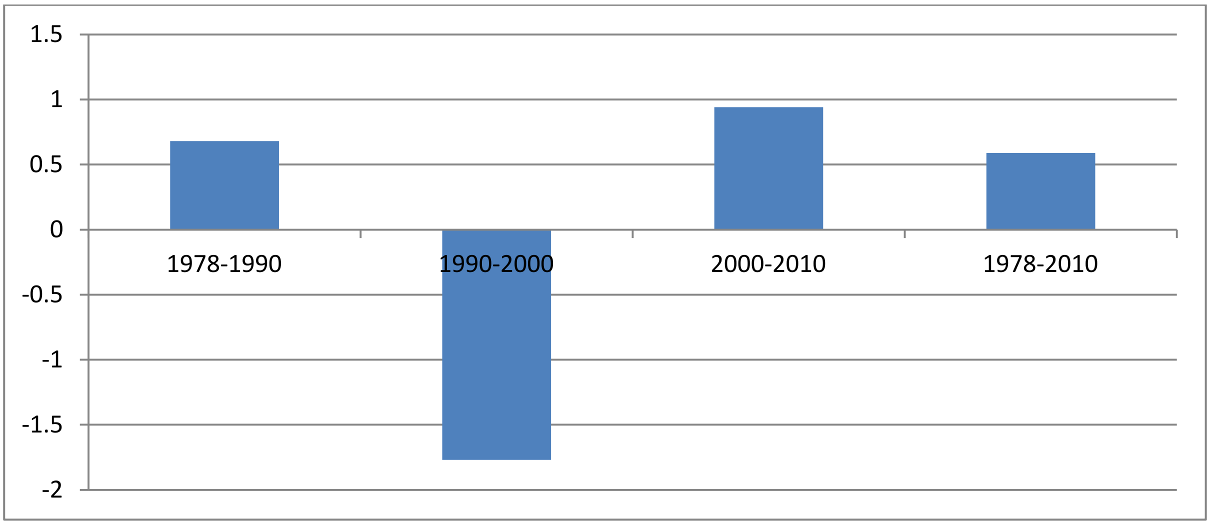
Technological progress, farm entry and exit and reallocation effects

Although it is clear that resource reallocation has made a significant contribution to productivity growth in Australian broadacre agriculture, the drivers of this process remain unclear. Previous studies (Foster et al. 2008; Meltz 2003) identified at least two possible drivers. 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. The empirical results indicate how these two factors drive resource reallocation in the Australian broadacre industry.

Asymmetric technology diffusion across farms

Differences in farm productivity levels and growth are important drivers of between-farm resource reallocation, particularly in the long run. Between 1978 and 2010, the average covariance terms between farm productivity and output share obtained using the BHC and OP approaches were both positive (Figures 2 and 3). Because the covariance terms capture co-movement between firm size and productivity, the positive sign 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.

Figure 2 Average annual contribution of OP covariance effects to industry-level TFP (%), 1978–2010



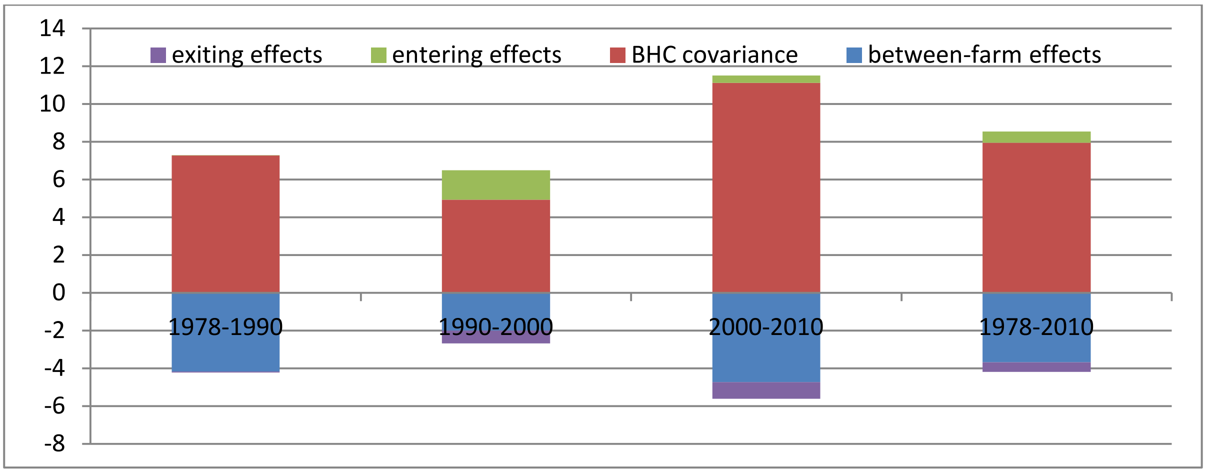
Source: Authors' estimation.

However, between-farm resource reallocation is also sensitive to farm profit. Since farm profit is also influenced by market prices, between-farm resource reallocation can sometimes deviate from farm productivity growth, which is driven by technological progress and technology diffusion. In particular, when factors such as demand shocks and market distortions dominate farm profitability and break the positive link between productivity and 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 sub-periods (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 4).

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 relatively high productivity level). Between 1978 and 2010 (and in all sub-periods), 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 sub-period 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. A possible interpretation is that farms adopting new technologies are more likely to expand their operating scales and thus reshape industry structure. In contrast, farms with relatively high productivity levels are more stable in size and resource use.

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' estimation.

Farm self-selection in entering and exiting the industry

Resource reallocation between incumbent farms contributes more to industry-level TFP growth than farms that enter and exit. 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 farm 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.

Table 4 Comparison of covariance effects and other resource reallocation components for the OP and BHC methods (%)

	OP decomposition		BHC decomposition		
	Covariance term	between-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' estimation.

Asymmetric effect of resource reallocation across inputs

Finally, we used the PWR approach to investigate how the movement of different inputs across farms contributes to resource reallocation. This is because the different mobility of various inputs determines their relative contributions 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, capital, and materials and services), as shown in Table 5. Since 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, farm 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 since the observed technology progress in this period was still strong (Jackson 2010). Instead, it reflects a short-term inconsistency between profitability and productivity.

Table 5 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' estiamtion

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 0.77 per cent a year (Table 5), 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 and policy implications

There is increasing interest in exploring all avenues to raise agricultural productivity growth, which has slowed in recent years. In this regard, it has long been believed that technological progress and structural adjustment have played important roles in promoting productivity growth in Australia. However, the extent to which these drivers interact and drive industry-level productivity growth is largely unknown. In this regard, the Productivity Commission has outlined wide-ranging reforms that have been undertaken in Australia and how these have served to benefit various sectors of the economy, including agriculture (Banks 2005, Productivity Commission 2005). In addition, ABARES has reviewed past reforms that have shaped Australian broadacre agriculture (Gray et al. 2014). However, these studies have not attempted to explain how such reforms have served to promote industry-level productivity growth.

This report 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 resource reallocation between farms has contributed substantially to industry-level productivity growth in Australian broadacre agriculture over the past three decades. More specifically, 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. This has largely been underpinned by the asymmetric diffusion of new technologies, climate changes and market structure reforms. Furthermore, its importance has tended to increase with cyclical downturns in within-farm innovation. In recent years, this has helped to offset the impacts caused by poor seasonal conditions and sluggish technological progress.

The analysis provides some useful insights for governments and industry bodies in considering policies to promote industry-level productivity. In particular, it suggests that efforts to enhance between-farm resource reallocation could be a significant mechanism for increasing agricultural productivity. However, the effects of resource reallocation depend considerably on industry structure, institutional arrangements and the level of marketisation in the economy, all of which affect farm profit independently of productivity (Foster et al. 2008). As such, facilitating the free movement of resources between farms remains a key consideration for policy makers in Australia.

Finally, it should be noted that the estimates of industry-level productivity growth produced for this analysis are specific to this paper, and should be considered as complements, not substitutes to ABARES' regularly-published productivity estimates. In particular, the methods used in this paper are designed to reveal drivers of productivity growth, while those used to construct our annual statistics are designed to consistently measure the long-term trend in productivity growth.

Appendix A: A brief review of the literature on resource reallocation

This appendix summarises the literature on resource reallocation between firms, and its measurement. Three widely-used approaches are discussed and compared.

The study by Baily et al. (1992) (hereafter, the BHC approach) represents an early attempt to measure the effects of resource reallocation. Recognising that industry-level productivity growth equals the weighted average of firm-level productivity growth, they proposed an approach to decompose industry-level productivity growth into within-firm productivity growth and various between-firm effects. The BHC approach defines between-firm effects as deviations of firm-level productivity from the initial industry-level index, taking account of effects caused by resource reallocation among continuing firms and those caused by firms' entry and exit. This approach treats heterogeneity in firm-level productivity as the driver of between-firm effects. Heterogeneity itself is assumed to be caused by idiosyncratic shocks relating to, for example, uncertainty, capital vintage and diffusion of knowledge.

Applying the BHC approach to US manufacturing, Baily et al. (1992) found substantial reallocation of outputs and inputs between firms with different productivity. Specifically, they found that between-firm effects had dominated within-firm effects over the period 1972 to 1987. Further, the entry and exit of firms had played a dominant role in driving the reallocation process. Although widely used, the BHC approach has been criticised for being too sensitive to measurement errors. Specifically, year-to-year fluctuations in productivity growth and revenue/cost share changes are likely to contaminate between-firm effects because the approach uses an industry-level productivity index in the base year as the reference group. Although the methodology has been adjusted (by defining the reference group as the average of base and end years), this has not fully resolved the issue (Foster et al. 2001).

An alternative decomposition approach was proposed by Olley and Pakes (1996) (hereafter, the OP approach), which is simpler to apply. Using firm-level productivity and output share (rather than growth rates), the OP approach decomposes industry-level productivity into two parts: an unweighted average of firm-level productivity (within-firm effects) and the covariance between farm productivity and size (between-firm effects). In contrast to the BHC approach, the OP approach was designed to analyse cross-sectional data and thus cannot distinguish the effects caused by resource reallocation among incumbent firms from those caused by firms' entry and exit. Nonetheless, the covariance term provides useful insights into how resource reallocation occurs. In particular, a positive covariance term means that firms with relatively high productivity levels are likely to expand, suggesting that resource reallocation moves in the same direction as firm productivity growth (Foster et al. 2008).

Although BHC and OP approaches have different strengths and weakness, they have underpinned many recent studies analysing the contribution of resource reallocation to aggregate productivity levels and growth. For example, Foster et al. (2008) analysed the relationship between profit maximisation, firms' self-selection behaviour (in choosing operating scale, or to enter or exit) and resource reallocation between firms. They found that because self-selection is made on the basis of profitability rather than productivity, resource reallocation may not always align with firm productivity growth, particularly in the short run. When demand shocks deviate from technological progress, there can be resource misallocation within an industry (the resource base of less productive firms grows more rapidly than that of more productive firms) and, in turn, a reversal of industry-level productivity growth. However, the enduring positive link between productivity and profitability means that such misallocation is likely to be a short-run effect.

Hsieh and Klenow (2009) extended the idea of resource misallocation by linking it to inefficient institutional arrangements. Comparing the marginal products of labour and capital in the manufacturing industries of China and India with those of the United States, they concluded that the significant disparities in aggregate productivity levels can be partly explained by differences in institutional arrangements that influence resource allocation between firms. From a policy perspective, this finding underscores the productivity imperative to improve the efficiency of institutional arrangements. Other studies that have investigated the role of resource misallocation in explaining differences in cross-country/cross-industry productivity include: Restuccia and Rogerson (2008), Bartelsman et al. (2011) and Asker et al. (2012).

More recently, researchers have investigated the effects of input mix and technological progress on resource reallocation between firms. Most importantly, Petrin et al. (2011) and Petrin and Levinsohn (2012) developed a decomposition approach (hereafter, the PWR approach) to measure the resource reallocation effects for different production factors, and to distinguish resource reallocation between farms from allocative efficiency gains within farms. Similarly, using firm-level data from the US steel industry, Collard-Wexler and De Locker (2012) highlighted the importance of input mix and technological progress in explaining differences in resource reallocation between firms that used different production techniques.

In sum, three distinct approaches for measuring cross-firm resource reallocation effects have been reviewed. Although they differ in assumptions and data requirements, each offers useful insights and provides a cross-check for the other approaches. In some cases, resource reallocation effects are split into the contributions made by movements between continuing firms and those caused by firms' entry and exit, while in other cases, they are split into the contributions made by different inputs.

Appendix B: Definition of outputs and inputs

The outputs and inputs of Australian broadacre farms are defined in categories to reflect the diverse farm production systems that exist across different sectors of this industry. Consistent with ABARES' TFP estimation system for the broadacre sector as a whole, quantity and price variables are distinguished for each product/commodity and, when physical observations are not available, implicit quantities/prices derived from the corresponding revenues/costs are used as substitutes (Zhao et al. 2012). The specification of output/input quantities and prices are described in detail below.

Outputs consist of 12 items which are divided into 4 major groups: crops, livestock sales, wool and other farm income.

Crops are split into wheat, barley, oats, grain sorghum, oilseeds and other crops. For wheat sold during the single desk arrangements (up to 2008), the value variable for wheat is estimated by multiplying the quantity harvested by the Australian Wheat Board's average net return for that year's pool. For other grains and other crops, the value variable is net receipts in that year. The quantity variable for each of the grains is the quantity harvested. For other crops, it is receipts deflated by the index of prices received for crops.

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

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

For other farm income the value variable is receipts and the quantity variable is receipts deflated by the corresponding prices received index.

Inputs consist of 28 items that are categorised into three major groups: capital (comprising land, physical capital and livestock purchases), labour, and material and services.

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

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

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

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

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

Appendix C: Explanation of differences in industry-level TFP estimates

Industry-level TFP can be estimated as either the weighted-average of individual farm productivity, or as the ratio of aggregate industry output to input. In theory, these approaches are equivalent. Similarly, estimates of industry-level TFP growth obtained when using different methods to average individual farm productivity should theoretically be identical when using the same set of farm productivity values. However, as the results in tables 3–5 show, this is not the case in practice. Differences in estimated TFP between the approaches used in this paper do not indicate a failing of the methods, but reveal the impact of differences in the assumptions and mathematics that underlie them. This appendix provides three explanations for differences in estimates of industry-level productivity growth between the three methods used in this paper.

First, the differences in industry-level TFP growth reflect differences in the weights used to aggregate individual farm productivity estimates. Because industry-level productivity is defined by the ratio of aggregate output to input, the weights used in aggregation should reflect both the input and output shares of each farm. In practice, this is rarely done. Instead, either input or output-based weights are typically used. However, industry-level productivity growth in Australian broadacre agriculture has been driven by changes in both inputs and outputs. Thus the choice of input or output-based weights will affect measured TFP growth. For example, the estimates obtained when using the PWR method differ from the BHC and OP estimates at least partly because the PWR method uses input elasticities to construct weights, whereas the other two methods use output weights (Petrin and Levinsohn 2012).

Second, the differences in estimates of industry-level TFP growth obtained from the three methods also reflect the effects of measurement errors specific to each method. Specifically, to increase our understanding of the fundamental drivers of productivity growth, we estimate industry-level productivity growth as the sum of the contributions made by the individual components (that is, the within- and between-farm effects) that are distinguished in each decomposition. The definition of each component varies between the decomposition methods, and differences in the contribution made by each component are not necessarily offset by differences in other components because of measurement errors. As such, the sum of these components (that is, the industry-level productivity estimates) can vary. This explains some of the difference between the estimates obtained from the BHC and OP approaches.

Third, the industry-level productivity growth rate for agriculture is best estimated using an exponential trend fitted to annual productivity levels, as there is significant yearly volatility (largely caused by fluctuating seasonal conditions). However, when using each of the methods applied in this paper to decompose productivity growth, it is necessary to estimate productivity growth using differences from year to year (Forster et al. 2001), as well as to reflect the entry and exit effects of farms. This creates significant additional volatility in estimated industry-level productivity growth rates, in particular for the BHC method, and increases the average annual productivity growth rate relative to estimates obtained when using an exponential trend.

Finally, the estimates of industry-level productivity growth produced in this paper are specific to this paper, and should be considered as complements, not substitutes to ABARES' regularly-published productivity estimates. In particular, the methods used in this paper are designed to reveal drivers of productivity growth, while those used to construct our annual statistics are designed to consistently measure the long-term trend in productivity growth.

Glossary

ABARES	Australian Bureau of Agricultural and Resource Economics and Sciences
ABS	Australian Bureau of Statistics
OECD	Organisation of Economic and Cooperation Development
PC	Productivity Commission
TFP	Total Factor Productivity
R&D	research and development

References

ABARES 2000, *Farm productivity in Australian grain industry*, GRDC Research Report.

—— 2011, ‘Agricultural productivity: trends and policies for growth’, *Australian Commodities*, March Quarter.

—— 2013, *Australian Commodity Statistics*, ABARES Annual Release, December.

Aghion, P and Howitt, P 1992, ‘A model of growth through creative destruction’, *Econometrica*, vol. 60, no. 2, pp. 323–351.

Alston, JM, Andersen, MA, James, JS and Pardey, PG 2010, *Persistence Pays: U.S. Agricultural Productivity Growth and the Benefits from Public R&D Spending*, Springer, New York.

Andrews, D and Cingano, F 2012, *Public policy and resource allocation: evidence from firms in OECD countries*, OECD Economics Department Working Paper no. 996.

Asker, J, Collard-Wexler, A and De Loecker, J 2012, *Productivity volatility and the misallocation of resources in developing economies*, NBER Working Paper.

Baily, MN, Bartelsman, EJ and Haltiwanger, J 1996, ‘Downsizing and productivity growth: myth or reality?’ *Small Business Economics*, vol. 8, pp. 259–278.

Baily, MN, Hulten, NC and Campbell, D 1992, ‘Productivity dynamics in manufacturing plants’, *Brookings Papers on Economic Activity, Microeconomics*, pp. 187–249.

Banks, G 2005, *Structural Reform Australian-style: Lessons for others?*, Productivity Commission, Melbourne.

—— 2012, *Productivity Policies: the ‘to-do list, speech to the Economic and Social Outlook Conference*, ‘Securing the Future’, November 2012, Productivity Commission, Canberra.

Bartelsman, E, Haltiwanger, J and Scarpetta, S 2009, *Cross-country differences in productivity: the role of allocation and selection*, NBER Working Paper, no. 15490.

Bartelsman, E, Haltiwanger, J and Scarpetta, S 2011, *Cross-country differences in productivity: the role of allocation and selection*, NBER Working Paper.

Collard-Wexler, A and De Loecker, J 2012, *Reallocation and technology: evidence from the U.S. steel industry*, Griswold Center for Economic Policy Studies, Working Paper, no. 230.

Cooper, R, Haltiwanger, J and Power, L 1999, ‘Machine replacement and the business cycle: lumps and bumps’, *American Econmic Review*, vol. 89, no. 4, pp. 921–46.

Diewert, WE 1992, ‘Fisher ideal output, input and productivity indexes revisited’, *The Journal of Productivity Analysis*, vol. 3, pp. 211–248.

Dunlop, M, Turner, GM and Howden, SM 2004, *Future Sustainability of the Australian Grains Industry*, CSIRO Sustainable Ecosystems, Canberra.

Elteto, O and Koves, P 1964, 'On a problem of index number of computation relating to international comparison', *Statsztikai Szemle*, vol. 42, pp. 507–518.

Foster, L, Haltiwanger, JC and Krizan, CJ 2001, ‘Agregate productivity growth: lessons from microeconomic evidence’, in *New Developments in Productivity Analysis*, (eds.) Hulten, CR, Dean, ER and Harper, MJ, University of Chicago Press.

Foster, L, Haltiwanger, JC and Syverson, C 2008, ‘Reallocation, firm turnover, and efficiency: selection on productivity or profitability?’, *The American Economic Review*, vol. 98, no. 1, pp. 394–425.

Fuglie, K., S.L. Wang and V.E. Ball (2012) Productivity Growth in Agriculture: An International Perspective, Oxfordshire, UK: CAB International.

Gray, EM, Oss-Emer, M and Sheng, Y 2014, *Australian agricultural productivity growth: past reforms and future opportunities*, ABARES Research Report, no. 14.2, Canberra.

Hayami, Y and Ruttan, VW 1985, ‘Factor prices and technical change in agricultural development: the United States and Japan, 1880-1960’, *Journal of Political Economy*, vol. 78, no. 5, pp. 1115–1141.

Hsieh, CT and Klenow, PJ 2009, ‘Misallocation and manufacturing TFP in China and India’, *Quarterly Journal of Economics*, vol. CXXIV, no. 4, pp. 1403–1447.

Industry Commission 1995, Assistance to agricultural and manufacturing industries, Australian Government Publishing Service, Canberra.

—— 1998, Microeconomic reforms in Australia: a compendium from the 1970s to 1997, research paper, Australian Government Publishing Service, Canberra, January.

Jackson, T, 2010, *Harvesting Productivity: ABARE-GRDC workshops on grains productivity growth*, ABARE research report 10.6 to the Grains Research and Development Corporation, Canberra, May.

Melitz, M J 2003, ‘The impact of trade on intra-industry reallocations and aggregate industry productivity’, *Econometrica*, vol. 71, no. 6, pp. 1695–1725.

Melitz, M J and Polanec, S 2008, *Dynamic Olley-Pakes decomposition with entry and exit*, Working Paper.

Mundlak, Y 2005, ‘Economic growth: lessons from two centuries of American agriculture’, *Journal of Economic Literature*, vol. XLIII, pp. 989–1024.

Nossal, K , Sheng, Y, and Zhao, S 2008, *Productivity in the beef cattle and slaughter lamb industries*, ABARE research report 08.13 for Meat and Livestock Australia, Canberra, December.

OECD 2008, *OECD Glossary of Statistical Terms*, Paris.

—— 2013, Agricultural Policy Monitoring and Evaluation 2013: OECD Countries and Emerging Economies, OECD Publishing.

Olley, G S and Pakes, A 1996, ‘The dynamics of productivity in the telecommunications equipment industry’, *Econometrica*, vol. 64, no. 6, pp. 1263–1297.

Petrin, A and Levinsohn, J 2012, ‘Measuring aggregate productivity growth using plant-level data’, *Rand Journal of Economics*, vol. 43, no. 4, pp. 705–725.

Petrin, A, White, TK and Reiter, JP 2011, *The impact of plant-level resource reallocations and technical progress on U.S. macroeconomic growth*, NBER Working Paper, no. 16700.

Productivity Commission 2005, *Trends in Australian Agriculture*, Research Paper, Canberra.

Restuccia, D and Rogerson, R 2008 'Policy distortions and aggregate productivity with heterogeneous establishments', *Review of Economic Dynamics*, vol. 11, no. 4, pp. 707–720.

Sheng, Y, Mullen, JD and Zhao, S 2010, 'Has growth in productivity in Australian broadacre agriculture slowed?', paper presented to 2010 Conference (54th), February 10–12, 2010, Adelaide, Australia 59266, Australian Agricultural and Resource Economics Society.

Sheng, Y, Zhao, S, Nossal, K and Zhang, D 2014, 'Productivity and farm size in Australian agriculture: reinvestigating the returns to scale', *Australian Journal of Agriculture and Resource Economics*, vol. 58, pp. 1–23.

Szulc, BJ 1964, 'Indices for multiregional comparisons', *Statistical Review*, vol. 3, pp. 239–254.

Tybout, JR 1996, 'Heterogeneity and productivity growth: assessing the evidence' in *Industrial Evolution in Developing Countries: Micro Patterns of Turnover, Productivity, and Market Structure*, (eds.) Roberts, MJ and Tybout, JR, pp. 43–72.

Zhao, SJ, Sheng, Y and Gray, E 2012, 'Productivity of the Australian Broadacre and Dairy Industries: Concept, Methodology and Data', in Fuglie, K., E. Ball and S.L. Wang (eds.) *Productivity Growth in Agriculature: An International Perspective*, CABI Press.