Chapter 5

Determinants of productivity growth and competitiveness

A number of studies on agricultural productivity and competitiveness have tried to identify their main determinants. This chapter discusses the results they found regarding the impact of farm size, factor intensity, farm specialisation, human capital, consumer demand, the natural environment, investments in general infrastructures, regulations, and agricultural policies. The impact of R&D on productivity growth is discussed on the basis of the analysis contained in OECD Agricultural Working Paper No. 31 on the impact of R&D investments on productivity growth in agriculture. Estimation issues are first discussed and the importance of a good specification of the lags between investments and their observed benefits is outlined. According to the meta-analysis of over 1 000 estimates of returns to agricultural R&D reported in the Working Paper, the rate of return appears to be quite large, ranging between 20% and 80% per annum in most cases

Review of the impact of possible determinants

To further understand cross-country disparity in productivity and competitiveness and their change over time, many empirical studies have been carried out. Some studies reported in Latruffe (2010) attempt to identify the determinants of productivity and competitiveness, regressing scores over a set of explanatory variable, looking at correlations or using cluster analysis to extract farmers' performance by groups. The comparison of productivity and competitiveness can also be made directly across groups with different characteristics. Other studies specifically investigate the impact of one specific element, for example expenditures in research R&D, on productivity growth. The first section of this chapter considers this specific issue on the basis of results reported in Alston (2010).

Latruffe (2010) distinguishes determinants that are under the managers' control from those that are beyond the managers' control. The first category includes the size of the business, its legal status, factor intensity, product specialisation, production and marketing practices, structure of the land, labour and capital (rented/own), and the characteristics of farm labour. The second category includes factor endowment such as climatic and geographical conditions, general resources in land, labour and capital, consumer demand, government intervention in the agricultural sector (e.g. agricultural policies, regulations, taxation), expenditures in research, extension and infrastructure and location of activities.

The relationship between **farm size** and competitiveness is a widely debated issue, particularly in relation to structural change. A wide range of results is found, depending on the circumstances, the farm type, the type of indicators of size and competitiveness chosen, and the criteria used to define small(er) or large(r) farms. A general finding from these studies is that larger farms are better performers as they can achieve economies of scale and benefit from access to output and input markets (Annex Table A.9). In particular, they suffer less from hidden unemployment. However, there are also some other studies showing that smaller farms are better performers. The main argument to explain this inverse relationship is that very large farms using hired labour may be affected by labour supervision and organisational problems, while family labour is highly motivated as it benefits directly from farm profits. In addition, smaller family farms are also considered to be more resilient because family labour is more adaptable and because family farms are less dependent on external capital than larger farms. Finally, some studies also find that the relationship between farm size and performance is U-shaped, or depend on the farm size variable. It is also obvious that the "optimal" farm size usually depends on the type of production. In the food processing sector, size is less of an issue although smaller firms may be constrained in adopting labour-intensive technologies and face higher input prices.

There is no clear picture in the literature on efficiency superiority of either family farms or corporate farms in OECD and transition countries. Similarly, there is no clear relationship between technical efficiency and **factor intensity** indicators such as capital-labour ratio, or land- labour ratio. Conflicting results are also found regarding the relationship between technical efficiency and the share of hired labour and rented land in, respectively, total labour and total land use. Hired labour may imply better educated workers or workers with specific skills, but may result in supervision problems. Renting land may give farmers an incentive to be productive in order to pay rent, but may prevent them from applying long-term improvements. Regarding the level of indebtedness, some researchers report that this has a positive impact on technical efficiency, suggesting that farmers who are indebted need to meet their repayment obligations and, therefore, are motivated to improve their efficiency. However, highly indebted farmers might incur high credit costs and thus less technically efficiency. In terms of productivity change, borrowing may help farmers to invest in new technology, as found by Zhengfei and Oude Lansink (2006) for Dutch farms for the period 1990-99.

Farm specialisation might be beneficial to technical efficiency since it enables farmers to concentrate their attention on a few tasks and their capital on specific technology, and thereby improve management practices. On the other hand, diversification may improve efficiency by reducing the risk related to the loss of all crops to disease (Latruffe, 2010). Diversification can also result in economies of scope leading to higher efficiency, when several outputs are jointly produced at a lower cost.

The impact of **human capital** on farm technical efficiency and productivity change is often investigated using indicators such as farmers' age or number of years of experience, education level or type, gender, and time spent on the farm. The impact of a farmer's age on technical efficiency can be positive or negative as found in various studies reported by Latruffe (2010). While older farmers may be reluctant or unable to adopt technological innovations, they are more experienced and can use their knowledge to use inputs more efficiently. As expected, most studies found that education has a positive effect on technical efficiency since better educated farm managers are expected to have more skills to run their farm efficiently. Gender is usually not found to affect technical efficiency, although in some developing countries, women might have lower access to inputs. The effect of time spent on off-farm work on performance is ambiguous. While farm managers working off the farm may have less time for managerial activities that would improve farm efficiency work, they might be better able to acquire information and knowledge. Some studies find that part-time farming decreases technical efficiency, others find the opposite (part-time farmers are more efficient) or insignificant results.

When explaining changes in competitiveness or productivity in a sector or a country, some authors mention **consumer demand** (Venturini and Boccaletti, 1998); Viaene and Gellynck, 1998 or Banterle and Carraresi, 2007). As Porter (1990) underlines, the presence of sophisticated and demanding buyers is important in creating and sustaining competitive advantage.

Differences in competitiveness across farms may be explained by the characteristics of the **natural environment** in which they operate (e.g. climate, soil quality, altitude or slope). These are often represented using location dummy variables for regions. They are usually found to have a significant impact on technical efficiency. For example, high quality soils are associated with high technical efficiency. Climate and climatic events are also important. Alston *et al.* (2010) mention catastrophic climatic events to explain bad performance in some years, and increase in population to explain the decrease of labour productivity in some countries.

Higher **density** of a farm type in a region is found to have a positive impact on the technical efficiency in that sector, suggesting knowledge spillovers. Better access to infrastructure and upstream and downstream **facilities** are associated with higher farm technical efficiency. **Public investments in infrastructures** are found to have a positive impact on productivity growth in agriculture, in particular when investment is in public transportation (Ahearn *et al.*, 1998; Yee *et al*., 2004; Rao *et al*., 2004), as well as in the food processing industry by acting as a substitute for technological change (Bernstein and Mamuneas, 2008).

Public policies and regulations influence producers' decisions on resource allocation. They may also distort firms' competition (OECD, 2001) and have an effect on competitiveness. Several studies have included a policy indicator in the list of variables used to explain farm competitiveness (Annex Table A.10). They generally find there is a negative correlation between protection and support and competitiveness. The relationship between support and technical efficiency is almost consistently negative across the literature. However, there are diverse results regarding the link between support, and productivity and technological change. Some find a negative correlation, other no significant correlation, while others estimate a positive correlation. For example, support may have a positive effect on technological change as extra income might help farmers overcome their credit constraints and invest in new technology, but the effect on the component efficiency change is not straightforward (Serra *et al*., 2008). Sauer and Park (2009) report the positive influence of organic subsidies on technical efficiency change and technological change for organic dairy farms in Denmark in the period 2002-04.

The link between government programmes and regulations other than income support, and farm technical efficiency has also been explored. For example, Makki *et al*. (1999) finds that government programme encouraging the diversion of acres from production and conservation reserve programmes had both a negative effect on US agricultural TFP during the period 1930-1990. For German dairy farms during 1987-94 and Greek farms during 1993-97 respectively, Brümmer and Loy (2000) and Rezitis *et al*. (2003) conclude that the European farm credit programme decreased participants' technical efficiency. Larue and Latruffe (2009) find that environmental regulations encourage pig farmers to be more efficient, but that this effect may be counteracted when legal dispositions are too stringent (i.e. when farmers are forced to spread their manure outside their sub-county).

Regarding the **agri-food industry**, regional capital subsidies seem to have had a negative impact on the technical efficiency of food and beverage manufacturing firms in Greece in the period 1989-94 (Skuras *et al*., 2006). Analysing the effect of trade liberalisation on TFP of five food processing industries in 34 countries (developed and developing) with annual data during 1993-2000, Ruan and Gopinath (2008) conclude that a greater exposure to trade increases productivity, a process that is faster in low productivity countries than in high productivity countries. According to Alpay *et al*. (2002), environmental regulations during 1962-94 were found to have a negative impact on the productivity growth of the Mexican agri-food sector during 1971-94, but not on that in the United States. Based on an opinion survey of 63 stakeholders in the food industry, Wijnands *et al.* (2008) conclude that EU regulation in the sector (which they claim is the third most regulative after the automotive and the chemical sectors) is not a strong obstacle to the competitiveness of the EU15 food sector.

Over the past half century, hundreds of studies have attempted to estimate the impact of agricultural **research and development** on agricultural productivity growth. Main findings are discussed in the following chapter on the basis of a report prepared to that specific end by Julian Alston for the OECD Secretariat (Alston, 2010). The impact of research and development on productivity growth and its economic benefit

The impact of research and development on productivity growth and its economic benefits

Research involves an expenditure of effort to increase the stock of knowledge. Ideas are likely to be generated from the larger stock of knowledge and can be converted (through commercialisation and adoption) into production technologies, good and services, and other forms of innovation. The use of public resources to support agricultural research and development (R&D) begs a critical question of how expenditures on R&D affect the long run competitiveness of the sector.

Estimation issues of R&D impacts on productivity

While there is a good deal of evidence that links R&D expenditure to agricultural productivity growth, quantifying the relationships is challenging and is subject to the availability of suitable methodology and data (Alston, 2010).[1] Some of these data and measurement issues are related to the measurement of R&D expenditure and TFP, while some are related to the often complex problem of relating productivity growth to R&D expenditure. Moreover, measures of agricultural inputs (especially capital, but also farm labour) and outputs are sometimes found problematic. Unpaid owner and family labour, is often an approximation of labour at best. Changes in soil quality or changes in the use of ground water, or influences of changing climate can have important impact but are seldom measured carefully. Limitations on the types and quantities of data that are available, combined with some misunderstanding or misuses of the measures, are likely to have contributed to weaknesses in some studies linking agricultural R&D to productivity.

There are also many data issues in measuring R&D effort. Data on private research expenditures is particularly difficult to obtain as firms often protect this strategic information.[2] Even finding data on public research expenditures in a useful form is often an arduous task because of how agricultural research expenditures are recorded over time. In addition, the data issues with respect to TFP and agricultural R&D expenditures are also confounded by the need to find a series of data which are long enough to reliably estimate the long lags involved in agricultural research particularly in countries which have conducted basic research for extended time periods.

Besides the data issues, attribution problems have bedevilled studies of the effects of research on agricultural productivity (Alston and Pardey, 2001). The principle areas of difficulty are: 1) in determining how much productivity growth is attributable to organised R&D; 2) in attributing responsibility among alternative public and private providers of R&D, and 3) in identifying the research lag structure. Many studies assume implicitly or explicitly that all measured agricultural productivity growth is attributable to R&D. This implicitly assumes that other important drivers of productivity such as education, or infrastructure development, scale economies, clustering effects[3] and changing weather patterns would not have increased productivity growth in the absence of the R&D expenditure. There is also an implicit assumption that productivity would not have decreased due to disease and pest pressure, weather changes or resource depletion in the presence of R&D.

Research usually takes a long time to affect production, and then it affects production for a long time. One element of the attribution problem, then, is to identify the specific dynamic structure linking research spending, knowledge stocks accumulation, and productivity growth. A large number of previous studies have regressed a measure of agricultural output or productivity and variables representing agricultural research and extension, often with a view to estimating the rate of return to research.[4] The specification of the determinants of the lag relationship between research investments and production, which involves the dynamics of knowledge creation, depreciation, and utilisation, is crucial. Only a few studies have presented much in the way of formal theoretical justification for the particular lag models they have employed in modelling returns to agricultural research.

Table 5.1 summarises some key features of research lag distribution models applied in studies of agricultural productivity in OECD countries. Until quite recently, it was common to restrict the lag length to be less than 20 years. In the earliest studies, available time series were short and lag lengths were very short, but the more recent studies have tended to use longer lags. Since the time span of the data set is usually not much longer than the assumed maximum lag length, and the individual lag parameter estimates are unstable and imprecise, most studies have restricted the lag distribution to be represented by a small number of parameters.[5]

Table 5.1. Research lag structures in studies of agricultural productivity

		Estimation period				
Characteristic	**Number of estimates**	**1958-69**	**1970-79**	**1980-89**	**1990-98**	**1958-98**
	Count	*Percentage*				
Research lag length (benefits)						
0 to 10 years	253	9.7	6.2	17.9	12.7	13.4
11 to 20 years	537	41.9	22	38.8	22.8	28.5
21 to 30 years	376	0	20.7	12	25.9	19.9
31 to 40 years	178	0	4.3	5.6	14.3	9.4
40 up to ∞ years	141	0	9.5	6.6	7.6	7.5
∞ years	102	35.5	7.5	2.9	5.4	5.4
Unspecified[1]	109	12.9	13.1	3.2	4.9	5.8
Unclear[2]	190	0	16.7	12.7	6.3	10.1
Total	1 886	100	100	100	100	100

Note: This table is based on the full sample of 292 publications reporting 1 886 observations.
1. Unspecified estimates are those for which the research lag length is not made explicit.
2. Lag length is unclear.
Source: Alston *et al.* (2009b), as adapted from Alston *et al.* (2000).

In their application using long-run, state-level data on US agriculture, Alston *et al.* (2009a) found evidence in favour of a gamma lag distribution model with a much longer research lag than most previous studies had found — for both theoretical and empirical reasons.[6] Their empirical work supported a research lag of at least 35 years and up to 50 years for US agricultural research, with a highest correlation in year 24.[7] This comparatively long lag has implications both for econometric estimates of the effects of public R&D on productivity and the implied rate of return to research. It should be noted, however, that lags are likely to depend on the type of research (general or applied, scientific or organisational, by sector, etc.) and the starting point. For example, basic research most likely takes more time to affect productivity gains than applied or adaptive research. Research lags are likely to be longer in OECD countries, which spent significant resource on basic research, than in developing countries, which adopt or adapt existing technologies from international research centres or other countries.

More recently, agricultural economists have been paying increasing attention to the fact that knowledge created within a particular geopolitical entity can have impacts on technology elsewhere, with implications that may matter to both the creators of the spillouts and the recipients of the spillins. For example, Huffman and Evenson (1993) and Alston *et al*. (2010) found that a sizable share of the benefits from research conducted in US State Agricultural Experiment Stations was earned as interstate spillovers. Given the size of these spillovers studies that did not allow for spillovers probably have overestimated the local benefits of research, while underestimating the regional benefits.

Studies that have examined research spillovers have found that knowledge created in neighbouring jurisdictions, or in similar agro-climatic regions can have large impacts on productivity (e.g. Huffman and Evenson, 1993; Pardey *et al.*, 1996 and Alston *et al.*, 2010). Similarly, the varieties and germplasm created in the international research institutions find their way into varieties around the world. Upstream basic research or downstream expenditures on extension can also impose the spillover impacts. Finally private and public research can create spillovers across organisational boundaries and can not only affect research outcome but can also affect research investment decisions by "crowding out" or "crowding in" other research activities. Being able to estimate the spillover effects requires that expenditure data be collected from each potential source of spillover, which further compounds the difficulty of data collection.

Economic benefit of agricultural R&D

Policy makers are fundamentally interested in how investment in R&D affects productivity growth, and whether these investments have a high rate of return relative to the cost capital. Over the past half century or so, hundreds of studies have been published reporting measures of agricultural productivity, the effects of agricultural R&D on agricultural innovation and productivity patterns, and the resulting social payoffs to investments in agricultural R&D. In the standard model of research benefits, research causes the commodity supply curve to shift down and out against a stationary demand curve, giving rise to an increase in quantity produced and consumed, and a lower price (Alston, Norton, and Pardey, 1995). The benefits are assessed using Marshallian measures of research-induced changes in consumer surplus for consumer benefits and of research-induced changes in producer surplus for producer benefits. The total gross annual research benefits depend primarily on the size of the research-induced supply shift and the scale of the industry to which it applies.[8] Other aspects of the analysis typically have second-order effects on the measures of total benefits but may have important implications for the distribution of the benefits between producers and consumers and others.[9]

Measures of the size and distribution of research benefits will be affected by various complications that can be introduced to extend the basic model. Models of research benefits have been extended to incorporate various types of market distortions, including 1) those resulting from the introduction of distortions associated with government policies such as farm commodity programmes or trade barriers (e.g. Alston, Edwards, and Freebairn, 1988); 2) those resulting from the exercise of market power by middlemen (e.g. Huang and Sexton 1996); and 3) those resulting from environmental externalities (e.g. Antle and Pingali 1994). A general finding is that the main effect of a market distortion in this context is to change the distribution of research benefits, with comparatively small effects on the total benefits.

There are mainly two alternatives to assess the economic benefit of agricultural R&D. First, the net present value (NPV) of a stream of research benefits is a widely accepted measurement. This index can be calculated as the difference between the present value of research benefit and cost. In some case, the benefit cost ratio is calculated as a ratio between the present value of research benefits and costs. Second, calculating the internal rate of return (IRR) of the research benefit is also a common way of estimating the benefit of agricultural R&D. IRR is defined as a discount rate that yields NPV equal to zero.

Alston *et al.* (2010) showed that, although the specific estimates were somewhat sensitive to the modelling choice, the annual value of agricultural productivity gains is worth many times more than the annual value of expenditures on research. Consequently the benefits from productivity growth attributed to agricultural R&D exceed the costs by an order of magnitude (i.e. a factor of 10 or more), regardless of methods of measurement or assumptions about attribution (e.g. the shape and length of the R&D lag distribution, inter-regional or inter-institutional spillovers, or the roles of private R&D or extension).

Alston *et al.* (2000a) conducted a comprehensive meta-analysis of studies that had reported estimates of returns to agricultural R&D. The study sample includes 292 studies that reported a total of 1 852 estimates of rates of return to agricultural R&D, from which Alston *et al.* (2000a) reported an overall mean internal rate of return of 81.3%, with a mode of 40%, and a median of 44.3% (Table 5.2). After dropping some outliers and incomplete observations, they conducted regression analysis using a sample of 1 128 estimates with a mean of 64.6%, a mode of 28%, and a median of 42.0%. They found results that were generally consistent with expectations but in many cases they could not distinguish statistically significant effects on the estimated rates of return associated with the nature of the research being evaluated, the industry to which it applied, or the evaluation methodology, because the signal-to-noise ratio was too low. Nevertheless, a predominant and persistent finding across the studies was that the rate of return was quite large. The main mass of the distribution of internal rates of return reported in the literature is between 20% and 80% per annum. Other reviews of the literature may not have covered the same studies or in the same ways, but nevertheless reached similar general conclusions – for example, Evenson (2002), and Fuglie and Heisey (2007). However, Alston *et al.* (2000a) raised a number of concerns about the methods used in the studies that were likely to have led to upwards biases in the estimates. In particular, they suggested that many of the studies may have suffered from estimation bias associated with 1) using research lag distributions that were too short (the results showed that increasing the research lag length resulted in smaller rates of return, as theory would predict), 2) "cherry picking" bias in which only the most successful research investments were evaluated, 3) attribution biases associated with failing to account for the spillover roles of other private and public research agencies, both at home and in other states or other countries, in contributing to the measured benefits, or 4) other aspects of the methods used.

Table 5.2. Lag structures and rates of return to agricultural R&D

Characteristic	Estimates		Rate of return				
	Number	Share of total	Mean	Mode	Median	Minimum	Maximum
	Count		*Percentage*				
Research lag length							
0 to 10	370	20.9	90.7	58	56	-56.6	1 219.0
11 to 20	490	27.7	58.5	49	43.7	-100	677
21 to 30	358	20.2	152.4	57	53.9	0	5 645.0
31 to 40	152	8.6	64	40	41.1	0	384.4
40 to ∞ years	113	6.4	29.3	20	19	0.3	301
∞ Years	57	3.2	49.9	20	35	-14.9	260
Unspecified	205	11.6	48.7	25	34.5	1.1	337
Unclear	27	1.5	43.1	27 and 60	38	9	125
Research gestation lag							
Included	468	59.2	65.5	46	47.1	-14.9	526
Omitted	314	39.7	96.7	95	58.8	0	1 219.0
Unspecified or unclea	8	1	25.1		24.1	6.9	55
Total	790	100	77.5	46 and 58	50.2	-14.9	1 219.0
Spillovers							
Spillins	291	16.7	94.5	95	68	0	729.7
Spillouts	70	4	73.7	95	46.4	8.9	384.4
No spillovers	1 428	81.7	78.8	49 and 57	40	-100	5 645.0

This table is based on a full sample of 292 publications reporting 1 886 observations. For all characteristics, the sample excludes two extreme outliers and includes returns to research only and combines research and extension so that the maximum sample size is 1 772. For the research gestation lag, the sample includes only observations with an explicit lag shape, resulting in a sample size of 790 observations. For spillovers, 25 observations were lost owing to incomplete information, resulting in a sample size of 1 747 observations. Some estimates have spillover effects in both directions.

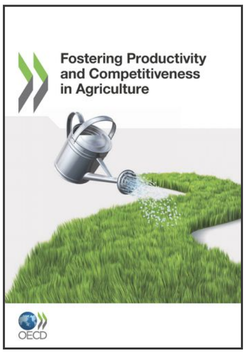
Source: As reported by Alston *et al.* (2009b), based on data reported in Alston *et al.* (2000a).

Notes

1. This chapter is almost entirely drawn from Alston (2010).
2. As shown in Table 4.2, only six OECD countries provide data on private expenditure on agricultural R&D to the OECD. They are based on national surveys of R&D expenditure.
3. A farmer is more inclined to adopt innovations if its neighbours do so.
4. A comprehensive reporting and evaluation of this literature is provided by Alston *et al.* (2000); see also Schuh and Tollini (1979), Norton and Davis (1981), Evenson (2002) and Alston, Andersen, James and Pardey (2009a).
5. As documented by Alston *et al.* (2000a), common types of lag structures used to construct a research stock include the de Leeuw or inverted-V (e.g. Evenson 1967), polynomial (e.g. Davis 1980; Leiby and Adams 2002; Thirtle and Bottomley 1988), and trapezoidal (e.g. Huffman and Evenson, 1989, 1992, 1993, 2006; Evenson 1996). A small number of studies have used free-form lags (e.g. Ravenscraft and Scherer 1982; Pardey and Craig 1989; Chavas and Cox 1992).
6. The detailed arguments are laid out in Alston, Norton, and Pardey (1995) and some earlier evidence is presented by Pardey and Craig (1988) and Alston, Craig, and Pardey (1998). See also Huffman and Evenson (1989). Alston, Craig, and Pardey (1998) discussed the issue of knowledge depreciation drawing on the previous literature and these arguments are restated and refined by Alston, Pardey, and Ruttan (2008), and Alston, Andersen, James and Pardey (2009a).
7. Alston, Pardey, and Ruttan (2008) documented the adoption lags for particular agricultural technologies and their results are consistent with relatively long overall lags.
8. As noted by Alston, Norton, and Pardey (1995, pp. 60-61), and more recently elaborated by Oehmke and Crawford (2002), the elasticity of supply can have important implications for

measures of research benefits if it is used to translate an assumed horizontal shift into a vertical shift, or vice versa.

9. The distribution of the benefits between producers and consumers depends on the relative elasticities of supply and demand, the nature of the research-induced supply shift and, less importantly, on the functional forms of supply and demand (Alston, Norton, and Pardey, 1995). The nature of the research-induced supply shift has been controversial because it matters, especially for findings concerning the distribution of benefits, and is not easy to observe. Another issue is the distribution of producer benefits among producers. Even if we can be assured that producers as a whole would benefit, those who do not adopt the new technology will not gain and may even be made worse off if the adoption by others leads to price reductions.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