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Towards the measurement of the impacts of improving research capacity: an economic evaluation of training in wheat disease resistance*

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It is notoriously difficult to assess the economic value of research aimed at improving research capacity, particularly for the human capital component of research capacity. In this paper, a framework is developed and an analysis is undertaken of the value of training for scientists in wheat rust resistance. The value of improving human capital is assessed through a framework based on marginal analysis of the improvement in productivity outcomes flowing from the increased capacity. On that basis, the value of programs to build human capacity through training or further education can be estimated. Although such estimates are necessarily qualified, they provide a basis for quantifying the value of building research and development capacity.

Key words: capacity building, economic, rust, training, wheat.

1. Research and development capacity building

Economic assessment of research and development (R&D) in agriculture generally focuses on valuing the enhanced productivity of some or all elements of the farming system, although maintenance research can also be important (Smale *et al*. 1998). The outcomes of R&D, whether it enhances or maintains productivity, will depend on the capacity of researchers to undertake that research. Following the Danish Agency for Development Assistance (DANIDA 2000), the capacity to undertake high-quality and effective research involves

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four components: (i) tangible capital; (ii) human capital; (iii) organisational capital; and (iv) social capital.

Tangible capital refers to the physical facilities, infrastructure, and capital that underlie and contribute to maintaining or enhancing research, and includes, for example, laboratories, microscopes, and molecular marker testing equipment. Human capital refers to the people and their skills, motivation, knowledge, training, and experience. Organisational capital refers to mandate, management procedures, policy-making procedures, funding arrangements, and so forth. Social capital refers to the political and economic support for the R&D.

Investment aimed at building research capacity is an important component of R&D investment (e.g., Ryan 1999), as it enhances the productivity of R&D resources. R&D capacity building can alter the mix of R&D resources available. However, despite the large number of studies that have assessed the extent of R&D capacity building, few have quantified the economic value of the increased R&D capacity that has resulted. If informed decisions are to be made about the extent of resources allocated to R&D capacity building relative to direct R&D technologies, estimates of those values are needed. Therefore, the development of a method for measuring the level of returns from investment in R&D capacity building is one of the most important gaps in R&D impact assessment. There is a need to develop a framework for evaluating the benefits of improved R&D capacity.

Although there is no universally accepted definition of capacity building in published works, it can take a number of forms, including: laboratories, buildings, and glasshouse facilities; scientific training; 'hands-on' experience for key personnel; and visiting scholars. Such investment can have an effect through increased productivity, or through increased maintenance research, or both. Given the presence of research spill-overs from one environment to another (Alston 2002), some productivity enhancement or productivity maintenance may occur in a particular environment without any R&D capacity in that environment, although generally both environments require some R&D capacity (Maredia and Byerlee 2000). The larger the capacity, the larger will be the potential productivity enhancement and maintenance, and hence, the larger the potential economic outcomes.

As capacity within a particular region is increased, research outputs can also increase, and the final outcomes can be expected to have higher economic value. There can be minimum threshold levels of R&D capacity below which progress will be very slow, so that there can be a critical mass of capacity before strong progress can be expected (e.g., see Brennan 1993; Maredia and Byerlee 2000). There are also likely to be diminishing returns to increasing investment in R&D capacity within a single production environment.

At the basic R&D level, scientists need to develop the capacity to understand, identify, and classify the relevant biological aspects of their research before other stages of the process of productivity enhancement can be implemented. When that capacity exists, it needs to be implemented and used to produce improved outcomes before measurable benefits can occur. Therefore, research capacity is a necessary but not sufficient condition for the development of improved productivity and/or maintenance outcomes.

Where the enhanced capacity is utilised in the R&D program, benefits will flow in the future from the improved outcomes. The economic analysis needs to identify and measure those improved outcomes compared with what would have occurred otherwise.

It is possible that R&D capacity can be improved without any change in the productivity outcomes, as improved R&D capacity is not a sufficient condition for the development of improved productivity. However, there may still be benefits in having built the capacity, even if it is not implemented immediately in the R&D program, as such capacity can: (i) set the environment for future implementation; (ii) enhance benefits once implementation has occurred; (iii) stimulate training and education for possible future changes (through sparking an interest in others); and (iv) encourage implementation of improvements in R&D, by identification of gaps in the process.

In this paper, an analytical framework for evaluating the benefits of improving the R&D capacity is proposed. The application of that framework is then illustrated by an evaluation of the training in Australia of wheat pathologists for the management of rust resistance in wheat in India.

2. An analytical framework for valuing capacity building

2.1 Analytical framework

Research and development impacts can generally be measured by an assessment of productivity outcomes with and without the R&D. The measures of productivity outcomes depend on the nature of the R&D investment being assessed and the data available, and can range from total factor productivity to partial factor productivity measures such as yield per hectare. Similarly, productivity outcomes will be related to R&D capacity. The precise form and nature of those productivity outcomes will depend on the analysis being undertaken.

Now consider the nature of R&D capacity and its relationship with productivity outcomes. Each of the four components of R&D capacity (tangible, human, organisational, and social capital) can range from 'zero' to 'full' capacity. The overall R&D capacity itself is a combination of the components, and the R&D outcomes are a function of the level of each component.

The relationship between the outcomes and the levels of the components is hypothesised to have the following features:

- The greater the human capital, the greater the productivity outcome, for a given level of the other three components
- The greater the tangible capital, the greater the productivity outcome, for a given level of the other three components
- The greater the organisational capital, the greater the productivity outcome, for a given level of the other three components

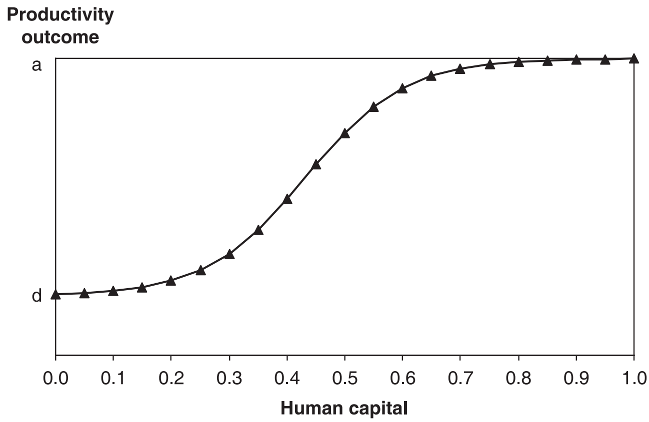

Figure 1 Relationship between human capital and productivity outcomes, with technology spill-ins.

- The greater the social capital, the greater the productivity outcome, for a given level of the other three components
- If any of the components is zero, productivity outcomes are determined by the level of technology spill-ins that would occur without domestic research capacity
- If all components are at full capacity, productivity outcomes are maximised for a given level of investment in R&D projects

Using these principles, an analytical framework was developed to enable the changes in R&D capacity to be quantified. Within region *i*, the general model for assessing the impact of R&D capacity can be defined as:

$$y_i = f(x_{1i}, x_{2i}, x_{3i}, x_{4i}, z), \tag{1}$$

where y_i is the productivity of R&D in region i, x_{1i} is the human capital in region i, x_{2i} is the tangible capital in region i, x_{3i} is the organisational capital in region i, x_{4i} is the social capital in region i, and z is a vector of other factors.

The relationship between each of the components and the productivity outcomes is hypothesised as in Figure 1. In the case of human capital, for example, for a given level of the other components of capacity, increases in human capital may follow a logistic curve rather than a linear response. At low levels of human capital in a given region, productivity outcomes will be positive because of technology spill-ins from other regions and/or farmer experimentation within the region. As human capital is further developed, the rate of increase of productivity outcomes will increase, but as human capital is increased even further, productivity outcomes will reach diminishing marginal returns so that ultimately additional human capital will not increase productivity outcomes.

For simplicity, this relationship ignores lags that are likely to occur between a change in research capacity and the resulting increase in productivity outcomes. However, it is feasible to build in a set of distributed lags where the productivity outcome this year depends on research capacity for a number of

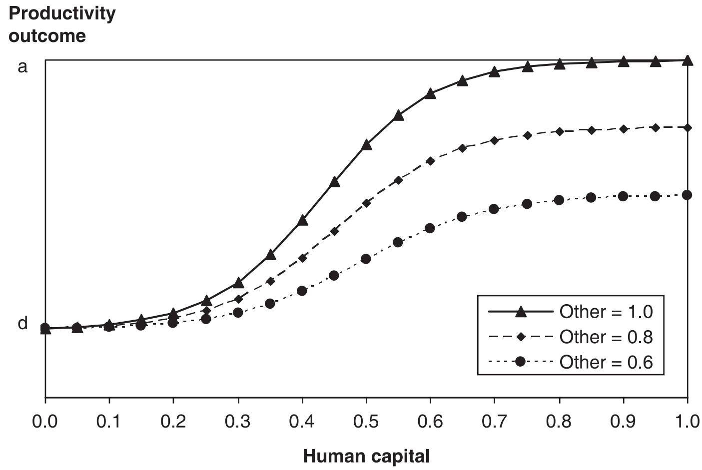

Figure 2 Relationship between human capital and productivity outcomes with different levels of other capacity components.

past years. The shape and distribution of the weights in any distributed lag system would depend on the nature of the research being analysed.

With different levels of the other components of R&D capacity assumed, different response curves can be identified for increases in human capital. For example, in Figure 2, the productivity outcomes respond to increasing human capital with three different levels of the other components. Where the other components are at 60 per cent capacity, then the response to human capital is lower than where they are at 80 per cent or 100 per cent capacity. It is likely that each of the four components of R&D capacity would behave in this manner.

2.2 Estimating the relationship between human capital and productivity outcomes

The relationship between human capital and productivity outcomes can be specified as a logistic curve:

$$y = a/[1 + e^{-(b+cx)}], \tag{2}$$

where y is the (observed or estimated) productivity outcome in a target region; x is the level of the component of R&D capacity; and a, b, and c are parameters to be determined. The parameter a represents the value of y that can be achieved at full human capacity, and b and c are parameters that define the path of the response that asymptotically approaches the maximum.

With spill-ins of d where $x = 0$, $y = d$. The maximum level (ceiling) is then $(a - d)$. Thus, Equation (2) becomes:

$$y' = A/[1 + e^{-(b+cx)}], \tag{3}$$

where

$$A = a - d, \tag{4}$$

and

$$y = y' + d, \tag{5}$$

where d is the level productivity that results from the technology spill-ins from other regions when there is no R&D capacity in the target region; y' is the productivity outcome from R&D capacity within the region; and A is the parameter of the logistic curve.

The question then is how to elicit values that will define the parameters of the logistic curve. Considering the case of human capital improvement (through training, for example), with all other components fixed, x can represent the years of scientific experience in a region, and y can represent the rate of crop yield improvement per year. The maximum level of yield improvement, a, can be determined from experimental or expert information. If the level of human capital in an area of scientific expertise within a particular region were zero, then productivity outcomes would rely on technology 'spill-ins' from other regions or farmer experimentation.

As the curve is asymptotic to the floor set by the spill-ins, we can set $y = y_0$ when $x = 0$, where y_0 is an arbitrarily small positive number. Thus, from Equation (3):

$$y_0 = A/(1 + e^{-b}), \tag{6}$$

so that

$$A = y_0/(1 + e^{-b}), \tag{7}$$

This can be rearranged to give:

$$b = -\log_e(a/y_0 - 1) \tag{8}$$

Substituting Equation (8) into Equation (2) and rearranging, we get:

$$c = (1/x)[\log_e(A/y_0 - 1) - \log_e(A/y - 1)] \tag{9}$$

Thus, given a and d (that is, A) and y_0, we can calculate b. If we define one other point on the curve for which both x and y are known, we can then calculate c, and hence define the entire logistic curve.

Once the curve has been defined, changes in x represent a movement along the response curve. Thus, we can then calculate the expected change in y for a given change in x, and then place an economic value on changes in R&D capacity. A change in one of the other components being held fixed in this analysis would lead to a shift from one curve to another as in Figure 2.

2.3 Units of measurement of parameters

For any relationships to be useful in assessing the value of specific R&D capacity-building activities, the units of measurement of R&D capacity and the productivity outcomes need to be defined carefully. If the aim of the analysis is to evaluate the impact of a training program, the units for the human capital component may be expressed in a range of possible measures, such as cumulative years of professional experience, years of experience post-training, years of post-graduation work, the number of workers with a particular qualification, or other measures of research worker intensity.

In some cases, those inputs may need to be scaled or normalised in some way. Where the analysis relates to a single region or system, there will be no need to normalise the data inputs. However, where comparisons are being made across regions, or where data from different regions are being combined, the human capital inputs need to be scaled to the crop area or production that is being targeted by the R&D. For example, two qualified workers in a small region may well be able to allow productivity to be maximised, whereas that would be inadequate for a large diverse region with 100 times as much production. In that case, the human capital measure can be a measure of research intensity (e.g., see Scobie *et al*. 1991), and may be expressed in terms such as 'years of experience per hectare of crop (or per tonne of production) in the target region'.

Similarly, tangible capital inputs need to be defined in such a way as to capture the productivity of the capital involved, and it may be appropriate for them to be scaled to the crop area or production being targeted by the R&D. Possible measures of research capital intensity include the number of laboratories in a particular region or the money invested in R&D tangible capital facilities, per tonne or per hectare of crop in the region.

The other components of R&D capacity, namely organisational capital and social capital, are difficult to quantify for any given region. However, conceptually, it is possible to develop a measure of these components. Again, those measures may need to be scaled to the production in the target region, and would also need to be consistent with the scales used in the measures of the other components and the productivity outcomes.

The productivity outcomes need to be related to a measurable outcome such as total factor productivity, wheat yields per hectare, or the value of disease resistance in each region. The productivity measure needs to be something that will reflect the differences in outcomes from a change in the components of R&D capacity.

3. Evaluation of rust resistance capacity building for wheat in India

3.1 Training for rust resistance

To test empirically the framework developed above, we analysed a project that brought Indian wheat pathologists to Australia for training in wheat rust resistance in the late 1980s and early 1990s. Over that period, four scientists were brought from India for extensive training at the National Cereal Rust Control Program at the University of Sydney (Brennan and Quade 2004). In undertaking an economic evaluation of that training, data were gathered on the value of wheat rust resistance in India (the productivity outcome), and the impact that the training had on that value was estimated using the framework outlined above. Although there are likely to be many qualifications to any such estimates, the analysis illustrates the method for quantifying the value of building R&D capacity.

3.2 Productivity outcomes for rust resistance

Following Brennan and Murray (1998), we can estimate the potential losses from diseases that could have been controlled by genetic resistance, as well as estimates of the current losses that occur in the presence of the existing levels of resistance. These two figures can be combined to determine the extent to which the current use of resistance is successful in controlling the diseases. When expressed as a percentage of potential losses, the current level of control represents a measure of the success of the R&D capacity in relation to wheat disease resistance. Where other forms of control can be used as well as genetic resistance (see Brennan and Murray 1998), only that proportion relating to resistance is to be included. Thus, the measure of productivity outcomes from disease-resistance capacity can be defined as:

$$y_i = \Sigma[r_j(P_{ij} - A_{ij})/P_{ij}], \tag{10}$$

where y_i is the productivity outcome in region i; r_j is the relative contribution of disease resistance to the control of disease j; P_{ij} is the potential economic losses in region i from disease j (in dollars); and A_{ij} is the actual current economic losses in region i from disease j (in dollars) given current controls.

3.3 Data

For the purposes of data collection on rust diseases in India, six key wheat production regions were defined. Northern Plains was the dominant wheat production region, although the Central and North-eastern regions were also significant producers (Table 1).

Data on the productivity outcomes for rust resistance in wheat were obtained from a survey of wheat pathologists in India (R.G. Saini, pers. comm. 2003). Scientists were first asked to estimate the incidence and severity of each of the three main rust diseases (stem, leaf, and stripe rust) for each of the six main wheat production regions in India. The results are shown in Table 2. For each of the rusts, there are regions where the potential (uncontrolled) level of severity in the event of a disease outbreak is given a score of 4.0 ('severe') or 4.5 ('severe'/'very severe') out of a possible 5.0 (see Brennan and Quade 2004 for a discussion of the scoring system used). However, given

Table 1 Regional wheat data for India (average of 5 years to 2001–2002)

	Area (000 ha)	Yield (t/ha)	Production (000 t)
Southern Hills	256	0.74	190
Peninsular India	0	1.00	0
Central	6 025	1.76	10 590
North-eastern India	2 601	2.05	5 323
Northern Plains	15 682	3.01	47 259
Northern Hills	1 558	2.06	3 212
Total India	**26 122**	**2.55**	**66 574**

current controls, the present severity of the diseases is 2.5 ('light'/'moderate') or lower. The incidence scores indicate that environmental conditions for the rusts are such that the rusts are generally 'localised' (scores 2–3) although in some regions the scores are 1.0 ('rare') or 4.0 ('widespread in some seasons').

In consultation with experienced plant pathologists, these qualitative scores can be converted to quantitative estimates of yield loss associated with each level of disease severity and incidence (see Brennan and Murray 1998), although there is inevitably an element of subjectivity in that process. The yield losses associated with each combination of severity and incidence is shown in Table 3.

The value of the potential and present yield losses can then be estimated by using representative yields (Table 1) and prices ($A150/t). On this basis, estimates were obtained of the total value of resistance to each of the three diseases (Table 4). The calculations show that the highest level of disease losses per hectare occur in Southern India where wheat production is low, whereas in the main production regions (Northern Plains, Central, and North-eastern) the diseases are generally more under control. Overall, with current controls, stem rust causes average annual losses in India of $A0.51 million, leaf rust $A4.06 million, and stripe rust $A4.86 million. Without controls, the losses would be $A47 million, $A45 million, and $A258 million, respectively. The losses vary markedly between regions (Table 4).

Because of the difficulty in undertaking separate analyses for the different rust diseases, all three rusts were combined for this analysis. Aggregating across the three rusts for India as a whole, resistance to the three rusts has the potential to provide benefits of $A344.3 million per year (Table 5). At present, benefits of $A335.3 million are being provided, so that the productivity outcome in terms of rust resistance is 97.4 per cent (= 335.3/344.3) of potential. Thus, the productivity outcome for rusts in India is that resistance is providing 97.4 per cent of the potential benefits.

3.4 Human capital for rust resistance in wheat

Craig *et al*. (1991) and Pardey *et al*. (1991) used the number of full-time equivalents in research, defined by educational status, as their measure of the

Table 2 Scores for disease severity and incidence for rust diseases in India

	Stem rust			Leaf rust			Stripe rust		
	Severity			Severity			Severity		
	Potential	Present	Incidence	Potential	Present	Incidence	Potential	Present	Incidence
Southern Hills	4.5	2.5	4.0	4.0	2.5	3.5	3.5	2.5	3.0
Peninsular India	4.5	1.0	2.5	3.5	1.5	2.0	0.0	0.0	0.5
Central	4.5	1.0	2.5	3.5	1.5	2.0	0.0	0.0	0.5
North-eastern India	1.5	0.0	0.5	3.5	2.0	2.5	1.0	1.0	0.5
Northern Plains	0.5	0.0	0.0	2.5	1.5	2.0	4.5	1.5	3.0
Northern Hills	1.5	0.0	0.0	4.0	1.5	3.0	4.5	1.0	2.0

Source: Based on a survey of Indian wheat pathologists (Brennan and Quade 2004).

Table 3 Yield loss associated with disease incidence and severity scores

	Incidence score										
	0.0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0	4.5	5.0
Severity score					*(% yield loss)*						
0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.5	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.02	0.03	0.03
1.0	0.00	0.00	0.01	0.01	0.01	0.01	0.02	0.03	0.04	0.06	0.07
1.5	0.00	0.00	0.01	0.02	0.03	0.03	0.04	0.06	0.10	0.14	0.17
2.0	0.00	0.00	0.03	0.04	0.05	0.07	0.08	0.13	0.20	0.28	0.33
2.5	0.00	0.00	0.08	0.12	0.15	0.20	0.25	0.38	0.60	0.83	1.00
3.0	0.00	0.00	0.15	0.23	0.30	0.40	0.50	0.75	1.20	1.67	2.00
3.5	0.00	0.01	0.30	0.46	0.60	0.80	1.00	1.50	2.40	3.33	4.00
4.0	0.00	0.01	0.60	0.92	1.20	1.60	2.00	3.00	4.80	6.67	8.00
4.5	0.00	0.02	0.80	1.23	1.60	2.13	2.67	4.00	6.40	8.89	10.67
5.0	0.00	0.03	1.25	1.92	2.50	3.33	4.17	6.25	10.00	13.89	16.67

Source: Derived from Brennan and Murray (1998).

Table 4 Estimation of value of resistance to wheat rusts in India

	Yield loss (%)		Economic loss ($A/ha)		Loss total ($A′000)		Value controls		% resistance	Value of resistance		
	Potential	Present	Potential	Present	Potential	Present	$A/ha	$A′000		Potential	Actual	Resistance % Potential
Stem rust												
Southern Hills	6.40	0.60	9.54	0.89	2 445	229	8.65	2 216	100%	2 445	2 216	91%
Peninsular India	2.13	0.01	4.27	0.03	0	0	4.24	0	100%	0	0	99%
Central	2.13	0.01	7.50	0.05	45 190	282	7.45	44 908	100%	45 190	44 908	99%
N-eastern India	0.00	0.00	0.00	0.00	3	0	0.00	3	100%	3	3	100%
Northern Plains	0.00	0.00	0.00	0.00	0	0	0.00	0	100%	0	0	100%
Northern Hills	0.00	0.00	0.00	0.00	0	0	0.00	0	100%	0	0	100%
– India Total	***0.36***	***0.00***	***1.82***	***0.02***	***47 638***	***512***	***1.80***	***47 126***	***100%***	***47 638***	***47 126***	***99%***
Leaf rust												
Southern Hills	3.00	0.38	4.46	0.56	1 143	143	3.90	1 001	95%	1 086	950	88%
Peninsular India	0.60	0.03	1.20	0.05	0	0	1.15	0	95%	0	0	96%
Central	0.60	0.03	2.11	0.09	12 711	530	2.02	12 182	95%	12 076	11 572	96%
N-eastern India	0.80	0.07	3.28	0.27	8 523	710	3.00	7 813	95%	8 097	7 422	92%
Northern Plains	0.15	0.03	0.90	0.15	14 181	2384	0.75	11 797	95%	13 472	11 207	83%
Northern Hills	2.00	0.04	8.25	0.19	12 855	292	8.06	12 564	95%	12 213	11 935	98%
– India Total	***0.37***	***0.03***	***1.89***	***0.16***	***49 414***	***4059***	***1.74***	***45 355***	***95%***	***46 944***	***43 087***	***92%***
Stripe rust												
Southern Hills	1.00	0.25	1.49	0.37	381	95	1.11	286	95%	362	271	75%
Peninsular India	0.00	0.00	0.00	0.00	0	0	0.00	0	95%	0	0	100%
Central	0.00	0.00	0.00	0.00	0	0	0.00	0	95%	0	0	100%
N-eastern India	0.00	0.00	0.00	0.00	1	1	0.00	0	95%	1	0	0%
Northern Plains	2.67	0.04	16.08	0.30	252 151	4693	15.78	247 458	95%	239 543	235 085	98%
Northern Hills	1.60	0.01	6.60	0.04	10 281	69	6.55	10 212	95%	9 767	9 702	99%
– India Total	***1.97***	***0.04***	***10.06***	***0.19***	***262 814***	***4858***	***9.87***	***257 956***	***95%***	***249 673***	***245 058***	***98%***

Source: Derived from data supplied by Indian wheat pathologists (Brennan and Quade 2004).

Table 5 Value of wheat rust resistance in India and productivity outcomes

	Stem rust	Leaf rust	Stripe rust	All rusts
Potential costs ($A′000)	47 638	49 414	262 814	359 866
Present costs ($A′000)	512	4 059	4 858	9 429
Value of controls ($A′000)	47 126	45 355	257 956	350 437
% resistance	100.0	95.0	95.0	95.7
Potential ($A′000)	47 638	46 944	249 673	344 254
Actual ($A′000)	47 126	43 087	245 058	335 272
Resistance % potential	98.9	91.8	98.2	97.4

Source: Derived from Table 3.

Table 6 Scientist numbers in wheat rust resistance in India, 2004

Educational status	Scientists (FTE)	Number of scientists with experience of:			
		0–5 yrs	6–10 yrs	11–20 yrs	21–30 yrs
Master's degree	3.5	2	2	0	0
PhD	16.7	7	7	8	6
– Total	*20.2*	*9*	*9*	*8*	*6*

Source: R.G. Saini (pers. comm. 2003).

human capital input into agricultural research. Pardey *et al*. (1991) acknowledged the practical difficulties associated with qualification levels, expatriate researchers, and research managers in constructing a measure of human capital in developing countries. Such inherent difficulties remain in this study as well.

The information on personnel working on wheat pathology was obtained from personal contact with wheat pathologist Dr R.G. Saini (Punjab Agricultural University, Ludhiana, India; pers. comm. 2003). For India, detailed data were available on the individuals involved in rust resistance work at present. The human capital involves 32 scientists, contributing a total of 20.2 full-time equivalents (FTE) on wheat-rust resistance. The data on the qualifications and experience of those staff are summarised in Table 6.

In measuring the level of human capital in the area of disease resistance in a region, the most appropriate measure appears to be a combination of the level of educational status and the total cumulative years of post-graduate experience among the plant pathologists in wheat diseases resistance. Three alternative methods for estimating the total human capital for wheat rust resistance as a single parameter are explored in this paper:

(i) Total years of experience ('Sum of years')
(ii) Total years in study and years of experience ('Years plus qualifications')
(iii) Weighted years of experience, with MSc experience as less valuable than PhD experience ('PhD equivalents')

It is arguable whether it is appropriate to include years of experience for each individual in a linear fashion, as it is possible that diminishing marginal returns from further experience prevail. However, for simplicity in this analysis, these are treated in a linear fashion. In assessing the years in study, a basic degree is taken as 3 years, a Master's degree as 2 additional years, and a PhD a further 3 years. In assessing PhD equivalents, an assumption was made that 1 year of experience with MSc as the highest qualification was equivalent to 75 per cent of 1 year's experience with PhD qualification. The impacts of these assumptions are tested in the sensitivity analysis in the subsequent section.

In each case in this study, the measures are scaled to the wheat area, and are expressed as 'years of experience per million hectares of wheat sown'. Allowing for the proportion of the time each individual allocates to rust resistance, the three alternative measures of the current human capital for wheat rust resistance per million hectares of wheat sown in India are: (i) sum of years: 9.0 years/million ha; (ii) years plus qualifications: 12.5 years/million ha; and (iii) PhD equivalents: 8.8 years/million ha.

In addition, spill-ins are likely to be high for a characteristic such as rust resistance in India (R.A. McIntosh, University of Sydney, pers. comm. 2003), because of the similarity of production environments and technologies to those in other countries. As the precise level of spill-ins is difficult to assess, two different levels of technology spill-ins are allowed in the analysis: (i) 50 per cent spill-in, so that resistance would be 50 per cent of potential if there were no local human capital; and (ii) 80 per cent spill-in, so that resistance would be 80 per cent of potential if there were no local human capital.

From Equation (2), the relationship between human capital for rust resistance and outcomes for wheat rust resistance in India is estimated. Each specification provides a separate estimate of the relationship. From each relationship, an estimate of the value of a change in human capital can be estimated (ignoring any lags inherent in the system). Using each of these specifications of human capital and spill-ins, the relationship illustrated in Figure 1 is estimated, using Equations (8) and (9) to estimate the required parameters. The parameter estimates for Equation (2) are shown in Table 7.

The relationships determined from these data are illustrated in Figure 3. The two curves shown represent the relationships with 50 per cent and with 80 per cent R&D spill-ins.

3.5 Analysis of training in rust resistance

In determining the effect of bringing the Indian wheat pathologists to Australia for training at the National Cereal Rust Control Program, some further assumptions are required: (i) each round of training lifts the human capacity of that individual for a number of years; (ii) the additional value for each year is equivalent to one-half of an FTE of additional experience; and (iii) the training has a 'life' of 10 years in terms of improving human capacity of that individual.

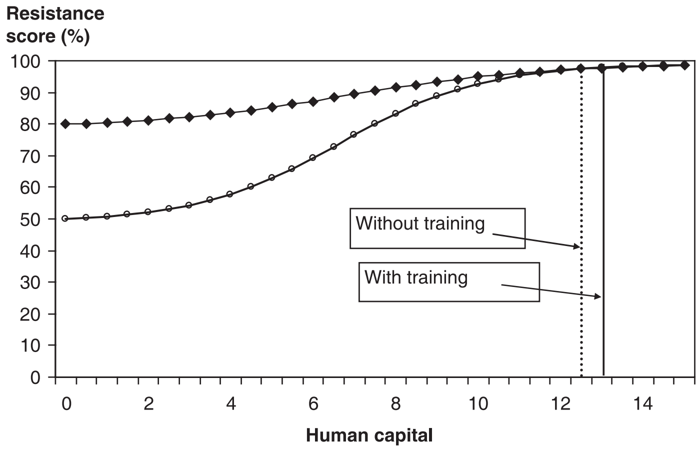

Figure 3 Effect of human capital on rust resistance in India.

Table 7 Parameters for alternative specifications of human capacity curves

Specification of human capital	Spill-ins	Productivity outcome (y)	Human capital (x)	Maximum outcome (a)	Value at axis (y_0)	Param. b	Param. c
Sum of years	50%	97.39%	9.02	100%	50%	−3.892	0.809
Sum of years	80%	97.39%	9.02	100%	80%	−2.944	0.596
year + qualifications	50%	97.39%	12.48	100%	50%	−3.892	0.585
year + qualifications	80%	97.39%	12.48	100%	80%	−2.944	0.431
PhD equivalent	50%	97.39%	8.83	100%	50%	−3.892	0.826
PhD equivalent	80%	97.39%	8.83	100%	80%	−2.944	0.609

Thus, for each plant pathologist trained, the human capacity in India increases by a total of 5 years. With four Indian scientists trained under the project, the aggregate human capacity at present is 20 years (or 0.8 years per million ha.) higher than it would have been without that training, under each alternative measure.

Inserting that shift in the equation for each set of parameter estimates, the productivity outcome without that additional human capacity is estimated (Table 8). The annual gain in productivity outcome varies from 0.43 per cent to 0.74 per cent. These gains are valued at between \$A1.47 million and \$A2.55 million per year.

It is apparent that allowing for 80 per cent spill-ins rather than 50 per cent reduces the gain from the training, by approximately 20 per cent in each case. It is also apparent that the different specification of human capital can lead to significant differences in the value of the training. This finding points to the importance of determining the most appropriate measure of human capital. Further work on exploring the best options is needed.

For a benefit–cost analysis of the training itself, the lags and time-frame need to be estimated, as well as the costs involved in the training. While such

Table 8 Value of training plant pathologists in rust resistance

	With training	Without training	Benefit from training
50% spill-ins			
Rust resistance research capacity (%)			
– Sum of years	98.1%	97.4%	0.73%
– Sum of years plus qualification	98.0%	97.4%	0.57%
– PhD equivalents	98.1%	97.4%	0.74%
Value of current rust resistance ($Am)			
– Sum of years	$A337.78	$A335.27	$A2.51
– Sum of years plus qualification	$A337.23	$A335.27	$A1.96
– PhD equivalents	$A337.82	$A335.27	$A2.55
80% spill-ins			
Rust resistance research capacity (%)			
– Sum of years	97.9%	97.4%	0.56%
– Sum of years plus qualification	97.8%	97.4%	0.43%
– PhD equivalents	98.0%	97.4%	0.57%
Value of current rust resistance ($Am)			
– Sum of years	$A337.20	$A335.27	$A1.92
– Sum of years plus qualification	$A336.74	$A335.27	$A1.47
– PhD equivalents	$A337.23	$A335.27	$A1.96

an analysis is beyond the scope of this paper, Brennan and Quade (2004) found that a project that brought plant pathologists from both India and Pakistan for training in Australia had a net present value of $A54 million, a benefit–cost ratio of 17 and an internal rate of return of 51 per cent (see Brennan and Quade 2004 for more details).

3.6 Sensitivity analysis

The results are likely to be sensitive to changes in a number of the parameter values assumed in the analysis. A sensitivity analysis is presented in Table 9, where the value of the productivity gains from the training is shown for alternative assumptions about the level of spill-ins, the impact of training on individuals, length of benefits, and parameters used in defining the human capital measures. The results are found to be sensitive to the extent to which training influences the capacity of the individual and the length of time that the trainee continues working in the system, as increasing either of these parameters markedly increases the overall benefits of the training. The results are also sensitive to the level of spill-ins, with higher spill-ins implying a lower level of return from a given increase in research capacity within the target region. The results with 80 per cent spill-ins are approximately 70–80 per cent of the results with 50 per cent spill-ins. On the other hand, the figures shown in Table 9 indicate that the results for the 'PhD equivalents' or the 'Years plus qualifications' measures are not sensitive to the precise way the individual measures of human capital have been constructed.

Table 9 Sensitivity analysis of the value of rust resistance training ($A million)

	With 50% spill-in			With 80% spill-in		
	Sum of years	Years plus qualifications	PhD equivalent	Sum of years	Years plus qualifications	PhD equivalent
Training increases capacity for individuals by:						
0.2 years	1.2	0.9	1.2	0.9	0.6	0.9
0.5 years	2.5	2.0	2.6	1.9	1.5	2.0
1.0 years	3.9	3.2	3.9	3.2	2.6	3.2
Trainee continues working for:						
5 years	1.4	1.1	1.5	1.1	0.8	1.1
10 years	2.5	2.0	2.6	1.9	1.5	2.0
15 years	3.3	2.7	3.4	2.6	2.1	2.7
MSc experience equivalence to PhD experience:						
50%			2.6			2.0
75%			2.6			2.0
100%			2.5			1.9
PhD qualification over BSc qualification:						
4 years		2.0			1.5	
5 years		2.0			1.5	
6 years		1.9			1.4	

4. Discussion

The analysis reported in this paper provides a basis for determining the value of a project aimed at improving R&D capacity. The approach provides a framework for assessing other similar projects in the future and provides a platform for an improved understanding of the economic value of investments aimed at improving research capacity.

However, the analysis involves a number of simplifying assumptions that require further investigation before the framework can be applied more broadly. In particular, areas where further investigation and improved data are likely to lead to improved outputs from the analysis include further consideration of: (i) the nature of the relationship between human capital and productivity outcomes; (ii) the most appropriate measure of human capital; (iii) the role of spill-overs and the level of spill-ins likely in each case; (iv) the development of improved measures of the impact of training on the level of R&D capacity; and (v) the lags inherent in the relationships between human capital and productivity outcomes. In addition, more extensive and more disaggregated data are likely to be valuable in enabling further understanding of the role of human capital and consequent productivity improvements.

Among the three measures of human capital used, there are no empirical grounds for preferring one measure over the other. In this analysis, the 'Years plus qualifications' gives a lower level of benefit than the other two measures. However, for other similar studies, data are likely to be more easily obtained for the simpler 'Sum of years' measure, and the results from this analysis provide some support for the suggestion that the results obtained from that measure are not likely to differ significantly from the other, more data-intensive, measures.

5. Conclusion

In this paper a framework is presented for assessing improvements in R&D capacity through training. Although many avenues for improvement and further development remain, the framework provides a much-needed and flexible method for determining the value of improvements in R&D capacity. In applying it to the project on training in Australia for Indian wheat pathologists in rust resistance, a number of elements of the empirical application of that framework are highlighted. The results provide a useful analysis of the impact of training in wheat rust resistance, and provide a basis for determining whether such training is a worthwhile use of agricultural R&D funds.

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