The value of environmental health in agricultural production across nonparametric efficiency quantiles

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Paper presented at the 2014 NZARES Conference
Tahuna Conference Centre, Nelson, New Zealand. August 28-29, 2014

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Abstract

The valuation of environmental assets is a key current issue in the analysis of environmental assets from an economic viewpoint. Economic assessment often involves the assessment of community values for environmental protection (public benefits) and any complementary or offsetting changes to production (net private benefits). Whilst the majority of studies focus on final demand aspects of environmental values (e.g. recreational use, existence and amenity values from better environmental protection) there is a need to consider any associated impacts on production of economic commodities. The shadow prices and elasticity of production with respect to environmental inputs is of interest in determining efficient public procurement mechanisms for environmental improvements. In particular, distributional aspects of the use of environmental assets by agricultural enterprises may have implications for the efficiency of different approaches to environmental benefit procurement. We use production data from rangelands beef enterprises in Australia and nonparametric conditional quantiles to show that the efficiency of enterprises may be associated with the efficiency of utilisation of environmental inputs and thus may indicate that environmental procurement mechanisms may be benefiting relatively inefficient producers.

Introduction

Social values for environmental assets arise from a range of considerations including their existence and amenity values, the ability to utilise environmental assets for recreational purposes and the indirect and direct contributions environmental assets provide to economic activities via so-called ecosystem services. The valuation of environmental assets is approached from two main perspectives. The most common approach in the literature is that of assessing values for the existence and direct usage of environmental assets in consumption via the use of revealed preference and stated preference survey methods. A less common approach, but one that was popular in the 1980's and 1990's are methods considering the value of environmental assets in terms of their capacity to increase the efficiency, with respect to human inputs, of production or in terms of their capacity to induce costs on enterprises when their level is diminished (Costanza et al. 1997). The recent increase in interest over ecosystem services indicates that the latter approach is undergoing something of a renaissance.

The valuation of environmental assets is being increasingly considered from the perspective of its utility as a productive input in the generation of commodities and services valuable to humans (Bateman et al. 2013). In particular, environmental inputs have increasingly been viewed as 'environmental services' which provide valuable contributions to a range of primary and intermediate production systems providing utility to humans (e.g. Power 2010; Gomez-Baggethun *et al.* 2010). Agricultural production in particular almost invariably relies, either directly or indirectly, on some input from environmental factors and interest has focused on agriculture as the primary land use across the globe to provide environmental services (e.g. Power 2010). The environmental input in extensive (broad-acre) systems is generally explicit being derived from rainfall, soil health, temperature, landscape function, etc. In extensive agricultural production the environment serves as the main medium and input into production with environmental conditions determining the economic viability of different commodity alternatives (Bastin *et al*. 2002).

In agricultural systems reductions in environmental health can also have detrimental effects on social values as shown by the substantial interest in recent years over consideration of public values for environmental health using stated preference methods. Australian examples include the choice modelling technique used by van Bueren and Bennett (2004) to assess community values for additional areas of farmland repaired and bush protected across Australia, and the same approach used by Rolfe and Windle (2008) to assess public values for healthy soils, vegetation and waterways in different areas of Queensland. As a result of the substantial social concern over environmental health on agricultural lands there has been an increasing interest in procuring improvements in environmental health in these areas and in the economic literature in particular in finding the most efficient methods for such procurement (Latacz-Lohmann and van der Hamsvoort 1998; Windle and Rolfe 2007; Hanley et al. 2012; Schilizzi and Latacz-Lohmann 2013). One key limiting factor in efficient procurement of environmental health on agricultural lands is the information asymmetry implicit in such processes – farmers tend to have usually been thought to have a far better understanding of their opportunity costs than society does. As a result substantial effort has been made into developing procurement methods which alleviate these informational asymmetries (e.g. Rolfe et al. 2007, 2008; Hajkowicz 2009).

The proliferation of alternative procurement methods has however been slow to be adopted by policy makers and key assumptions implicit in them have recently been challenged, including the assumption that agricultural producers have strong knowledge of the opportunity costs of improving environmental health on their properties. For example bidders in conservation auctions or resource by-back schemes may experience, or be concerned, over the potential for 'winners curse' indicating that they are unsure over the opportunity costs involved in participating in these schemes (Rolfe *et al* 2006; Squires *et al.* 2009). Additionally, the use of 'payments for ecosystem services' methods of procurement are based on the presumption that purchased improvements in environmental health involve an opportunity cost in terms of foregone agricultural production. Whilst this is likely to be the case in many situations such as in programs which require land to be set aside from production for a certain time period, other programs involve purchases for which it is far less clear that a production trade-off exists. For example Pannell (2008) show that land use change can involve different combinations of public and private benefits and costs, while Coggan et al. (2010) show that transaction costs can be significant in limiting takeup even when private benefits exist. As Pannell (2008) argues, prior information over the costs of providing environmental health is an essential first step to selecting the appropriate policy instrument, and is typically needed for the implementation of mechanisms such as extension with land managers or conservation tenders.

The valuation of environmental factors from a production perspective is a well-established, if relatively neglected, field of research (e.g. Freeman 1993; Point 1994). Early studies of environmental values associated with production, damage functions, or dose-response analyses (e.g. Barbier 2000), were estimated using assumptions over the form of cost which environmental degradation imposed on firms (Freeman 1993). In more recent times focus has shifted to consideration of the direct effect on production itself where environmental assets are inputs to production, and removal or deterioration leads to production losses. Many of these studies have utilised a ‘household production function’ approach (e.g. Barbier 2000; Alberini *et al*. 1997) within a statistical framework considering the mean response. However, many public programs aiming to facilitate improved environmental practices on agricultural lands focus on retiring marginal land (e.g. the Conservation Reserve Program in the United States (Hanley et al. 2012)) or acquiring environmental benefits most ‘cheaply’ using market-based instrument procurement mechanisms (e.g. the BushTender program in Australia (Stoneham et al. 2003)). Such programs obviously do not specifically target the average or frontier producers but, for example, agricultural areas which are relatively inefficient with respect to land inputs in the former case and least-cost providers of environmental inputs in the latter case.

Clearly then, models of the average or most efficient value of environmental inputs to producers provide only a partial description and one which is potentially not highly relevant to evaluation of public investments in environmental protection on agricultural lands. The use of more discriminating measures of production tradeoffs, such as quantile regression analysis, provides a more complete view of aspects of input usage across the conditional distribution of output allowing insights into expected marginal productivity, elasticities and values of environmental inputs of the production process for different groups of producers or production inputs. Dimelis and Louri (2002) and Landajo *et al*. (2008) show that conditional quantiles may be interpreted as efficiency quantiles when used in a production framework whilst O’Donnell (2010) shows how productive efficiency is a key component of enterprise profitability, providing a linkage between the value of environment at each conditional quantile and opportunity costs for producers. In principle this allows consideration of ‘least cost’ providers of environmental inputs and some characterisation of the usage of environmental inputs by inefficient versus efficient enterprises.

In this paper we present a case-study analysis of the value of environmental inputs to agricultural production utilising a nonparametric conditional quantile analysis so as to capture the range of production tradeoff costs. Our case-study is based on extensive beef production in the northern Australian rangelands. The quantile analysis employs regression splines with data-driven selection of polynomial degree, knot selection and bandwidths of Generalised Product Kernel functions for discrete data. Our approach is based on recent developments in the use of conditional quantile analysis, and in particular non-parametric conditional quantiles, for measurement of productivity and applied in the novel setting of consideration of the value of environmental inputs. In the following we outline briefly the theory of measurement of the value of environmental factors in production (next section) and then outline the non-parametric conditional quantile method (Section 3). A description of our data is provided in Section 4 with Section 5 presenting summaries of statistical results from our estimated B-spline models. A discussion on results of relevance and their interpretation is provided in Section 6 and is followed by conclusions in Section 7.

The measurement of the value of the environment in production

Evaluation of both the net benefits of environmental protection as well as the design of mechanisms to achieve this typically requires detailed information about the costs of production tradeoffs involve. The data available to the analyst is the primary determinant of the analytical approach able to be undertaken with respect to valuing the environment as an input to production (Vincent 2008). In the best case, data on input and output prices and input and output levels are available to the analyst allowing the estimation of either a system of production and input demand equations or a system of the profit function along with input cost share equations (Vincent 2008). However, in the case that, for example, individual input prices are unavailable an estimate of environmental values is still available utilising the production function directly and either considering only marginal changes or by integrating the production function from the initial environmental endowment to the final (hypothetical or predicted) environmental endowment (Freeman 1993) whilst assuming fixed input prices. Specifically, consider a production function:

$$
\begin{aligned}
&y = f(x, E, K) \\
&Where: \\
&y = output \\
&x = variable\ inputs \\
&K = fixed\ productive\ factors \\
&E = environmental\ input
\end{aligned}
$$

The first order conditions to choosing x_i to maximise private returns (assuming profit maximisation) is:

$$
\begin{aligned}
&\frac{dy}{dx_i} p(y) - w_i = 0 \\
&Where: \\
&p(y) = price\ for\ output \\
&w_i = Price\ for\ input\ i
\end{aligned}
$$

Denoting the output-maximising input choices at the starting point for environmental condition (E^0) as x^* and assuming that output prices are exogenous, the marginal value product of an increase in environmental condition (input) is calculated as:

$$MVP_E = p(y) \cdot \frac{\partial f(x^*, E^0, K)}{\partial E^0}$$

The net gain is thus the value of the marginal product of environmental condition in the production function – i.e. the Marginal Value Product (MVP) of environmental condition (Freeman 1993).

In addition to this measure requiring information on the prices of input and output it is possible to obtain a partial measure of the value of environmental condition by simply taking the derivative of output with respect to the environmental input at the sample input levels (Vincent 2008) – note that this statistic is assessed at sample input levels, not the optimal input levels:

$$MVP_{E,partial} = p(y) \cdot \frac{\partial f(x, E^0, K)}{\partial E^0}$$

This partial measure will tend to underestimate the value of (exogenous) environmental improvements as it will not account for decreases in costly input usage due to substitution effects associated with environmental quality, however this will depend on the elasticity of input demands (Vincent 2008; Freeman 1993).

If interest is focused on the shadow price or value of environmental health in production we may obtain such an estimate by using the result that profit maximising producers will utilise an input up to the point that it's marginal value product (MVP) is equal to it's marginal cost (MC). Because estimation of the production function provides us with an estimate of the marginal product and information on output prices is usually readily available we may formulate an estimate of the MVP and from this make some inference on the MC, or shadow price, of the environmental input.

Conditional output quantiles and the measurement of environmental value with respect to technical efficiency

Production theory typically assumes that the output observed for a given level of inputs will be the lower boundary of the input requirement set in order to ensure that producers are rational and not employing excess inputs. However, a large literature has developed on the measurement of technical inefficiency in production with evidence from empirical studies indicating that the conditions for efficient production are often not met by a substantial proportion of a given sample of producers (Coelli *et al*. 2005; Kumbhakar and Lovell 2000). The literature on technical efficiency allows analysis of matters of production with relaxation of the assumption involving production on the lower boundary of the input requirement set.

Several approaches to the measurement of technical efficiency are available to the analyst interested in such matters. The two most common approaches involve the measurement of a technical relation between outputs and inputs which is located at the lower boundary of the input requirement set, or the upper boundary of the production possibilities set, one of which allows a stochastic measure of the technical relation and the other which employs a deterministic measure of the technical relation. Respectively these approaches are referred to as Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). Measurement of economic aspects of interest for the production function using these approaches is then generally based on this boundary measure of technically efficient production. Whilst the SFA and DEA approaches relax the assumption involving ubiquitously efficient production they model inefficiency as a latent factor and limit examination of economic measures of production to the frontier technical relation – even though many studies indicate that producers at different efficiency levels with respect to a global frontier may in fact be utilising different technologies which are not adequately represented by the frontier technology (e.g. O'Donnell *et al*. 2007). In many cases it is of interest to consider the technical production relation which exists at non-frontier locations – i.e. it may be considered that some producers are unaware, or are rationally aware, of their inefficiency and base production decisions on their own (inefficient) technical production relation rather than that of the efficient relation.

One approach to developing an understanding of non-frontier technologies used in production is conditional quantile analysis. This approach can be thought of as an analogue to conditional mean analysis, encompassed within Ordinary Least Squares (OLS) and Maximum Likelihood analyses, but allowing for interest to be centred on arbitrary quantiles of the conditional distribution (Koenker 2006). Conditional output quantiles are related to the efficiency of production as they conceptually describe arbitrary levels of efficient productions from the frontier (efficient) output level for a given input level at the 100th percentile to the least efficient output level for a given input level at the 1st percentile. From a statistical perspective, conditional quantiles are differentiated from conditional means (e.g. as measured by Ordinary Least Squares and SFA) in that they allow measurement of an arbitrary conditional quantile. The most common quantile of interest is the median which has long been associated with the Least Absolute Deviations (LAD) regression model (Koenker 2006). However, as noted above, it is possible to specify a function which identifies a statistical relation between a dependent and independent variables for any quantile including the median.

Measurement of economic quantities of interest arising from conditional quantiles allows examination of these quantities across the spectrum of efficiency from very low levels of efficiency (e.g. as characterised by a model for the 10th percentile) to very high levels of efficiency (e.g. as characterised by a model for the 90th percentile). Such measurements provide detailed information over how values for environmental, and other, inputs changes with respect to the relative efficiency of production and thus may indicate how the usage of environmental inputs is related to productive efficiency.

Efficiency measure is relevant to cost effective provision of environmental assets because (technically) inefficient producers are able to contract their usage of or all inputs whilst maintaining output by adoption of improved technology or management. As such, identification of marginal productivities and output elasticities of human and environmental inputs at the range of inefficient and efficient production technologies may carry substantial potential information over the ability of enterprises to increase provision of environmental inputs at least cost.

Nonparametric conditional quantiles using regression splines

The statistical analysis of economic phenomena is increasingly making use of nonparametric methods in place of parametric methods because they are more robust than parametric methods in many common economic analysis problems (Landajo *et al*. 2008) and because they allow the analyst to focus on the economic measures of interest rather than on effectively arbitrary and potentially misleading parametric forms which are generally unknown a priori. Whilst parametric analyses using, for example, OLS on the correctly specified functional form provide for efficient and unbiased inference under mild conditions, it is only in exceptional cases that the correct functional form is actually known a priori (Landajo *et al*. 2008). This result also holds for the Quantile Regression (Koenker 2006) approach which, whilst allowing for arbitrary distributions of errors, requires the analyst to first specify a correct functional form for the conditional response. It is fortunate that in production economics, focus is centred on simple functions of the conditional response rather than on a particular parametric form for the conditional response – although this latter consideration has been a major component of research in production economics due to its centrality to analysis prior to the advent of empirically useful nonparametric methods. In particular, the main measures we were interested in this research – the MVP, output elasticities and Returns To Scale (RTS) – are simply functions of the conditional response of output to input:

$$MVP = P \times MP = P\frac{dy}{dx} = P\frac{d(y|x)}{dx}$$

$$Elasticity = \eta = MP\frac{x}{y} = \frac{d(y|x)}{dx} \cdot \frac{x}{y}$$

$$RTS = \sum_i \eta_i$$

The quantities outlined above are clearly conceptually independent of the functional form chosen for the conditional response. Thus, if parametric forms for the conditional response influence the measurement of the conditional response they may be considered as ‘nuisance’ factors in the measurement of our quantities of interest. In particular if the use of parametric forms for conditional response is associated with bias due to the infinite possible range of functions which may be specified then we should be concerned that they also influence the measurement of our quantities of interest. In such cases nonparametric methods provide a statistical framework in which to obtain measures of quantities of interest whilst allowing the analyst to bypass issues of the choice of functional form to represent the conditional response (Landajo *et al*. 2008).

Two main approaches to nonparametric econometrics are in common usage: (1) the kernel density framework, and; (2) the regression spline framework. The former approach involves a local measure of conditional response based on smooth functions of the dependent variable in a region around its immediate location. The latter approach involves a global approximation involving the joining of a number of linear or polynomial segments together into a smooth global regression curve representing the conditional response for a given sample of data. We chose to use the regression spline framework as it is more closely linked to the standard regression framework and involves a conditional quantile formulation that is more developed than the analogous approach in the kernel framework. Recent research (Landajo *et al*. 2008) has emphasised the linkages and advantages of the regression spline framework for conditional quantiles in a range of different types of economic analysis.

In this analysis we chose to use the common B-spline approach due to its flexibility and well-known characteristics. Three main factors characterise a B-spline regression analysis: (1) The number of segments to be joined; (2) The polynomial degree of each segment, and; (3) Whether the splines basis is additive or multiplicative. Historically, B-splines have been considered semi-parametric when an additive basis was utilised as they typically involved analytical choice over the number of segments or the degree of the polynomial to be considered – a more general restriction than fully parametric functional forms but one which was still potentially an important restriction affecting analytical results. In more recent times improved algorithms have led to the development of data-driven models which use cross-validation to jointly select the number of segments, the degree of each segment for each variable and the form of the basis for the B-splines (i.e. additive or multiplicative). This has allowed B-splines utilised in the regression framework to become truly non-parametric in an a-priori sense with functional form restrictions driven by data information rather than the choices of the analyst (Racine and Li 2004).

The methods we utilise are fully outlined in Racine and Zhenghua (2014) for the non-parametric regression functions and in Hsiao *et al*. (2007) for the consistent functional form test. The routines we used were implemented using the 'crs' package (Racine and Zhenghua 2014) and the 'np' package (Hayfield and Racine 2008) in the free R program (R Core Team 2013) in addition to the authors own code for generating data for regressions and data summaries/plotting. The latter is available as an R-script (including data used) from the author on request.

Data

The data for our case study application were obtained from a private consulting service which provides comparative data to extensive beef producers in northern Australia on a range of measures including: Return On Assets, Labour Productivity, Overhead-Value ratio, etc. As a result this service has collected a range of data useful to examination using economic production analysis methods. In particular we obtained a range of data series which enabled estimation of the production technology using the primal (production function) formulation.

We transformed data to a per-hectare basis due to the diversity of enterprise sizes in our dataset and in order to depict production in a form more relevant to the key limiting variable (land area) which itself is generally priced on a per-hectare basis in northern Australian beef property markets. On this basis the output variable was obtained as the production of beef per hectare per year whilst inputs were characterised as input usage per hectare of land.

Four input variables were initially available for use in our model being: An inflation-adjusted Land quality value index, inflation-adjusted Animal Health expenditures, Inflation-adjusted Supplement and Fodder expenditures and Labour (full-time equivalent person-weeks per hectare multiplied by 100). The variables 'Supplements and Fodder' and 'Animal Health' were obtained as total annual expenditure. We applied a Producer Price Index transformation to these to transform the variables to indices of real expenditures per hectare. Labour was included as Full-Time-Equivalent Labour days per Hectare on the basis of reported labour usage by sample enterprises. A rainfall variable was included to account for exogenous variation in the productive potential of these enterprises across years. The rainfall variable was calculated using information on the average and actual rainfalls recorded for each enterprise as the percentage deviation of actual from average rainfalls.

Four land-type classifications were provided in the dataset utilised in this research. Enterprises were classified into these on the basis of whether part of their property was located in the relevant land-type region. As a result we classified enterprise land condition as a pseudo dummy variable taking the value 0.5 for two land-types respectively for those it was located in and 1 (for the respective land type) if it was located only in one of them.

Finally, the variable defining environmental condition was derived as a 3 year moving average of satellite observations on end-of-dry season ground cover. Satellite observations of end-of-dry season ground cover have been utilised as measures of land condition in several research programmes (Bastin *et al*. 2002; Ward and Kutt 2009). The raw satellite data provides a measure of bare ground predicted for 25m x 25m pixels in the months between August-November for areas where the satellite is expected to provide substantial accuracy in actual versus expected ground cover. This time period represents a measure of the extent to which grasslands are intact immediately prior to the start of the growing season and are considered to represent a measure of environmental health (Bastin *et al*. 2002). However, it is likely that annual variation in this measure also provides an indication of the available pasture for consumption by cattle herds at the start of the growing season. As we wished to capture a measure of environmental health rather than pasture availability (the year on year variation of which was hoped to be incorporated via the rainfall deviations variable) we generated the environmental input variable as a 3 year moving average of this series averaged across all measured pixels for each enterprise. The use of a moving average was expected to remove the effect of annual variation in pasture availability and provide a measure more reflective of medium-term environmental health on these properties.

Table 1 below provides a summary of the data used for the production functions estimated in this research.

Table 1: Summary of data for models

	Beef produced (Kg/Ha)	Land Value index	Health ($/Ha)	Supplements and Fodder ($/Ha)	Labour (FTEs)	Rainfall (Proportion of average)	Environmental health*
Min.	1.90	0.04	0.01	0.00	0.07	0.12	52.04
25th Perc.	12.17	0.35	0.35	0.81	0.51	0.75	70.40
Median	19.74	0.98	0.83	1.92	1.00	0.91	77.42
75th Perc.	31.62	4.61	1.63	3.92	1.92	1.11	82.84
Max.	69.10	10.08	7.17	21.08	6.57	2.34	92.32
Mean	23.51	2.52	1.23	3.12	1.39	0.95	76.20
Std. Dev.	14.92	2.86	1.24	3.60	1.15	0.32	8.40
				Landtype = Ironbark (n=90)			
Mean	22.39	0.40	1.58	3.92	1.58	0.91	82.46
Std. Dev.	10.02	0.32	1.46	3.63	1.22	0.28	5.17
				Landtype = Desert Uplands (n=98)			
Mean	12.03	0.44	0.42	2.08	0.49	1.08	75.02
Std. Dev.	6.01	0.24	0.52	1.72	0.23	0.37	9.69
				Landtype = Mitchell (n=52)			
Mean	12.53	0.33	0.47	1.81	0.71	0.99	67.79
Std. Dev.	6.64	0.19	0.38	2.23	0.60	0.40	7.54
				Landtype = Brigalow (n=224)			
Mean	31.54	4.78	1.63	3.54	1.87	0.91	76.16
Std. Dev.	15.65	2.64	1.24	4.22	1.16	0.27	6.99

* measured as a 3 year historical moving average of remotely sensed mean groundcover for each enterprise

Estimation and comparison against parametric models

As outlined in the previous section the use of non-parametric regression methods allows the analyst to obtain information over quantities of interest (e.g. *d*y/*d*x) without making restrictive assumptions over the exact form of conditional response within the analytical model. In contrast, standard econometric methods employed in the economic analysis of matters of production typically assume that the conditional response is derived from a subset of families of production functions which are then subject to testing in order to obtain the most 'correct' form which is then subject to analyse. The use of conditional quantile analysis is also possible in the parametric framework using the quantile regression framework of Koenker (2006). Whilst our interest was not in whether the data used in this analysis was representable with a particular parametric form, this rather being a nuisance factor in our analysis, the preference for parametric forms in empirical work suggests we test whether nonparametric approaches offer a less restrictive analysis in our case. Statistical tests of correct specification are available in the nonparametric framework with rejection of parametric functional forms implying that the regression results from retaining such forms may be biased (Racine REF).

In order to test whether a parametric representation of the data is suitable we considered second order flexible function forms for the natural logs of input variables (the Trans-Log functional form) and for the levels of the input variables (the Quadratic functional form) which allow representation of output elasticities and marginal products in the nonparametric framework respectively.

The translog functional form is defined as:

$$lnQ = \ln\alpha + \sum_i \gamma_i lnz_i + \sum_i \beta_i lnx_i + \frac{1}{2}\sum_i\sum_j \delta_i\,(\ln x_i)(\ln x_j) + \lambda \ln E_i$$

$Where:$

$Q = output$

$x_i = Variable\ inputs$

$z_i = Fixed\ factors\ of\ production$

$E_i = Environmental\ inputs$

$\alpha, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\delta}, \lambda = parameters\ to\ be\ estimated$

Whilst the Quadratic function form is defined as:

$$Q = \alpha + \sum_i \gamma_i z_i + \sum_i \beta_i x_i + \frac{1}{2}\sum_i\sum_j \delta_i\, x_i x_j + \lambda E_i$$

We used the 'npcmstest' test for functional form which is available in the NP package (Hayfield and Racine 2008) in the free R statistical program (R Core Team 2013). Rejection of the null hypothesis of correct specification indicates that the functional form tested is incorrect and use of these functional forms may induce bias in results.

Results

Nonparametric functional form tests for the 2nd order approximation forms outlined in the previous section, namely the common Trans-Log and Quadratic functional forms, indicated these forms were strongly rejected by the data with p-values for the Hsiao *et al.* (2007) consistent model specification test using the 'Jn' statistic. A summary of these results is shown in Table 2.

Table 2: Results for functional form testing based on OLS estimation of restrictions of the Trans-Log form

H0: Parametric functional form is correct	# of parametric regressor variables	Bootstrap replications	Jn Statistic	P-value
Log-Log model	28	399	7.3099	0.0000
Levels model			1.5712	0.0000

The strong rejection of the two tested flexible function forms for the conditional mean model indicates that there is substantial non-linearity in the conditional mean response of output for this data which is unlikely to be captured by 2nd order flexible functional forms such as the Translog and Quadratic production functions. The strength of rejection of these flexible function forms indicates that it is unlikely that similar functional forms (e.g. Generalised Constant Elasticity of Substitution) will hold at a substantial number of quantiles and that standard additive models of the conditional mean and conditional quantiles are unsuitable for our analysis. On this basis we employed the B-spline regression framework, described in Section 4 earlier, to estimate conditional quantile models in a nonparametric framework. Summary results for the estimated models at a subset of quantiles spanning the range of quantile models estimated are presented below.

Tables 3 and 4 present the results from leave-one-out Cross Validation utilised on the B-spline conditional quantile models to select the number of segments, polynomial degree of segments, basis (additive or tensor-product) for continuous predictors and the bandwidth for the discrete predictor LAND. All regressions for both the log-log and levels formulations involved CV-selection of an additive basis rather than the fully locally flexible tensor-product basis. Historically additive bases for B-spline regression models have been considered semi-parametric however, given that the CV algorithm we use tests for performance of the tensor-product basis, we can consider the estimated models to be fully non-parametric with data-driven restrictions on functional form.

Table 3: Model summary results for log-log regression spline model

		Quantile								
		10th	20th	30th	40th	50th	60th	70th	80th	90th
Land Quality ('LQ')	Spline segments	10	1	6	9	1	9	1	8	4
	Degree of spline segments	2	15	15	14	6	1	1	1	2
Health Exp. ('H')	Spline segments	1	1	2	1	1	1	1	1	2
	Degree of spline segments	4	2	1	2	1	1	1	1	1
Supp. And Fodd. Exp ('S')	Spline segments	1	2	1	1	1	1	1	1	1
	Degree of spline segments	1	1	1	7	1	1	2	2	1
Labour FTEs/100 ('L')	Spline segments	2	1	1	1	1	6	1	1	1
	Degree of spline segments	1	2	1	1	9	5	9	1	1
Rainfall % of average ('R')	Spline segments	3	1	1	1	1	1	1	1	1
	Degree of spline segments	1	1	1	1	1	1	1	1	1
Environmental Health ('E')	Spline segments	1	1	4	1	1	1	1	1	1
	Degree of spline segments	1	1	1	2	1	1	1	2	1
Land Type	Bandwidth	0.4237	0.9394	0.3783	0.1859	1.0000	0.8633	1.0000	0.2851	0.3670
Basis type (chosen using Cross-Validation)		Add.	Add.	Add.	Add.	Add.	Add.	Add.	Add.	Add.
R squared		0.33	0.43	0.60	0.67	0.60	0.58	0.48	0.40	0.26

The log-log and levels formulations were in general agreement over complexity of conditional output representations from the respective input variables with *Land Quality* (LQ) and *Labour* (L) generally involving more complexity (number of segments and polynomial degree) than the other input variables. Complexity of the conditional response appeared to be higher for *Land Quality* at lower quantiles and at the lower and middle quantiles for *Labour* whilst *Environmental Health* appeared to involve a relatively stable and more simple functional form across the quantiles. The relatively higher complexity of conditional response at lower quantiles for human inputs may be reflective of the inefficiency of these observations and lack of consistency in selection of input quantities for managers of these enterprises. Alternatively it may be a result of poor recording of some input data for very low quantile data points (i.e. below the 30th percentile). Overall, these results on the interpretation of complexity of the conditional response function indicate that there is substantial variation in the usage of human inputs for relatively inefficient producers suggesting that they are likely not adequately represented by a frontier production function alone (as employed in SFA and DEA type analyses).

Table 4: Model summary results for levels regression spline model

		Quantile								
		10th	**20th**	**30th**	**40th**	**50th**	**60th**	**70th**	**80th**	**90th**
Land Quality ('LQ')	Spline segments	10	1	6	9	1	9	1	8	4
	Degree of spline segments	2	15	15	14	6	1	1	1	2
Health Exp. ('H')	Spline segments	1	1	2	1	1	1	1	1	2
	Degree of spline segments	4	2	1	2	1	1	1	1	1
Supp. And Fodd. Exp ('S')	Spline segments	1	2	1	1	1	1	1	1	1
	Degree of spline segments	1	1	1	7	1	1	2	2	1
Labour FTEs/100 ('L')	Spline segments	2	1	1	1	1	6	1	1	1
	Degree of spline segments	1	2	1	1	9	5	9	1	1
Rainfall % of average ('R')	Spline segments	3	1	1	1	1	1	1	1	1
	Degree of spline segments	1	1	1	1	1	1	1	1	1
Environmental Health ('E')	Spline segments	1	1	4	1	1	1	1	1	1
	Degree of spline segments	1	1	1	2	1	1	1	2	1
Land Type	Bandwidth	0.4237	0.9394	0.3783	0.1859	1.0000	0.8633	1.0000	0.2851	0.3670
Basis type (chosen using Cross-Validation)		Add.	Add.	Add.	Add.	Add.	Add.	Add.	Add.	Add.
R squared		0.09	0.27	0.46	0.51	0.55	0.55	0.48	0.42	0.37

Discussion

The matters of interest in this study pertained primarily to the output elasticities and marginal products for human inputs (*x*) and environmental inputs (rainfall – *R* and environmental health – *E*) as measures of the value of an environmental input to output obtained from an estimated production function. For non-parametric spline regression models these can be obtained as the first derivatives of the function at each data point for the log-log and levels models respectively. Thus, in estimating 81 models for each percentile between the 10th and 90th quantiles we obtained a matrix of first derivatives for each data point and each human and environmental input. To summarise these we calculated the mean and lower 25th and upper 75th percentiles as error bounds for each vector of derivatives. Graphical plotting of these series (across estimated quantile models) and tables of summaries (for every 10th percentile between the 10th and 90th conditional quantile models) provide detail over the pattern of usage of these inputs over the range of technical efficiency in our sample.

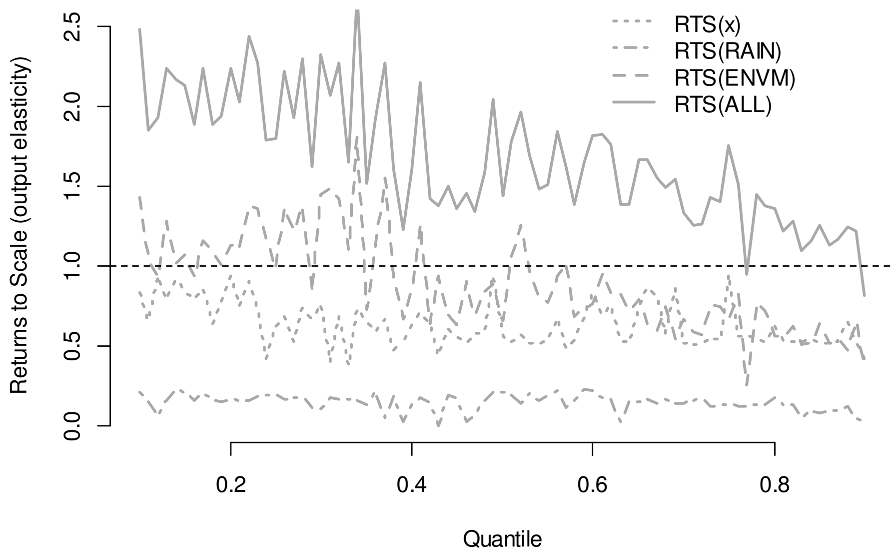
Table 5 below provides a summary of the Returns to Scale (RTS) for all human inputs together, the elasticity of output with respect to *Rainfall*, with respect to *Environmental Health* and with respect to all human inputs, *Rainfall*, and *Environmental Health* together. Sums of output elasticities arising from inputs can be considered RTS for the included inputs and allow consideration of the relative efficiency of scale of production as they measure the percentage change in output for a percentage change in the input(s). Typically an RTS score below 1 indicates that the manager should decrease usage of included inputs and a score above 1 indicates that the manager should increase usage of the combined inputs included. Total RTS for all inputs is shown to be well above 1 for the lower quantiles and approximately equal to 1 for the highest estimated quantile. Human inputs contribute approximately 0.5 of the total RTS score whilst *Rainfall* and *Environmental Health* inputs contribute the remainder with the latter accounting for the vast majority of environmental contributions. The relatively high contribution of *Environmental Health* in particular is interesting as this variable may be considered as coming under management influence in the medium to long run as a result of stocking rate decisions in addition to exogenous (e.g. rainfall) realisations. Indeed, our construction of the *Environmental Health* input involved simply the use of a 3 year moving average of remotely sensed average ground cover values for each property with annual ground cover being substantially an indicator of pasture availability within the early summer months of that year.

Table 5: Returns To Scale for human and environmental inputs

	Quantile regression estimates								
Returns to Scale for:	**10th**	**20th**	**30th**	**40th**	**50th**	**60th**	**70th**	**80th**	**90th**
Variable inputs only	0.84	0.93	0.76	0.63	0.56	0.83	0.52	0.62	0.42
Envm Health	1.43	1.13	1.45	0.84	0.66	0.76	0.67	0.56	0.37
Rainfall	0.22	0.17	0.11	0.13	0.21	0.22	0.14	0.18	0.03
TOTAL	2.48	2.23	2.32	1.61	1.43	1.81	1.33	1.36	0.82

Table 5 and Figure 1 together show that the RTS for the *Environmental Health* input alone is above 1 for the lower quantiles and below one for the higher quantiles. Additionally, it is interesting to note that the total RTS for all inputs is approximately equal to 1 for the most efficient production quantiles (see Figure 1) indicating that efficient productions involve selection of human inputs which, combined with environmental inputs, achieve an approximately optimal scale of production. In contrast, inefficient productions involve the usage of *Environmental Health* at such a level that for every percentage increase in provision of this input alone output would increase by more than 1%. Thus, inefficient producers may have a strong incentive to increase the provision of *Environmental Health* on their properties if the marginal cost of such provision is low enough. Fortunately, if we assume producers are rational and knowledgeable over their (inefficient) production function we can approximate the marginal cost (MC) of an input by its MVP. We consider this in the following.

Figure 1: Output Elasticity of Environmental health for quantile (grey lines) and OLS models



The MVP of an input is calculated as the partial derivative of the regression function with respect to that input and multiplied by the price of a unit of output. In the non-parametric approach we are not required to define a functional form beforehand and so can represent this as simply a function of the conditional distribution:

$$MVP = P \times MP = P\frac{dy}{dx} = P\frac{d(y|x)}{dx}$$

Assuming that our sample were price takers (we do), the price of output can be considered fixed across the sample meaning the MVP is simply proportional to MP as shown above. As a result we can consider the MP as being reflective of the MVP across efficiency quantile. To save making further assumptions on the price level being received by these growers and because we were more interested in the trend in MVP across quantiles then its level we focus in the remainder on the MP.

In an earlier section we indicated that the MVP of Environmental Health was reflective of its shadow price if we assumed that producers were rational profit maximisers and, under the presence of inefficiency, also rationally aware of their own level of inefficiency. This essentially implies that, in order to consider the calculated MVP of Environmental Health as a shadow price, we must assume that inefficient enterprises know their technology (e.g. the respective quantile model they are located within). Under these, restrictive, assumptions we have the result that:

$$MC = MVP = P \times MP = P\frac{d(y|x)}{dx}$$

These assumptions allow us to approximate the implied cost of supplying marginal additions to *Environmental Health* for producers located in different efficiency quantiles as some constant (a fixed and exogenous output price) multiplied by the derivative of output with respect to *Environmental Health* across estimated conditional quantile regressions. Given the high RTS for *Environmental Health* shown from the analysis of the log-log formulation for inefficient producers, in order for inefficient producers to not be least cost suppliers of *Environmental Health* we would need to observe a relatively higher MP for this variable amongst the lower quantile models relative to the higher quantile models. In contrast, no such pattern (i.e. either a similar MP or a decreasing MP across quantiles) would provide evidence that low efficiency producers should not require incentives to increase provision of *Environmental Health* but rather can obtain increases in profits in the long run via an increase in the level of the *Environmental Health* variable – i.e. an extension rather than direct incentive approach would likely be most socially efficient and is based on a presumption of bounded rationality in these producers optimisation of their production systems if we assume that they are profit maximisers. Table 6 and Figure 2 together provide a numerical and graphical summary, respectively, of the patterns of the MP for the *Environmental Health* input across estimated conditional quantile models.

Table 6: MP of Environmental Health for sample observations across estimated quantile regression models

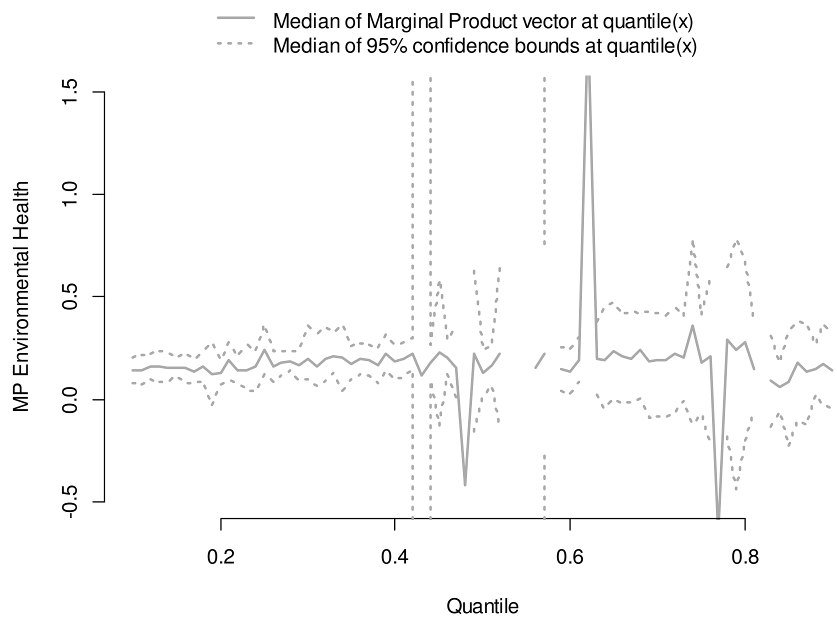
	Quantile regression estimates								
	10th	20th	30th	40th	50th (Med.)	60th	70th	80th	90th
Minimum	0.14	0.12	0.03	0.18	0.12	0.11	-0.08	-1.22	0.13
25th Percentile	0.14	0.12	0.10	0.18	0.12	0.11	0.00	-0.20	0.14
Median	0.14	0.13	0.20	0.18	0.13	0.14	0.19	0.28	0.14
Mean	0.14	0.14	0.29	0.18	0.13	0.13	0.30	0.25	0.16
75th Percentile	0.14	0.15	0.49	0.18	0.14	0.15	0.52	0.71	0.17
Maximum	0.14	0.21	0.62	0.19	0.16	0.15	1.68	1.06	0.21

The patterns shown in Table 6 and Figure 7[1] are strongly supportive of a stable MP, and thus MVP and MC, for the *Environmental Health* input indicating that there is no pattern of increase or decrease in the MP for this variable across efficiency quantiles. Thus, whilst the elasticity of output for *Environmental Health* is very high (above 1) for low efficiency producers, their MC of supply appears to be the same as that for high efficiency producers. These results indicate that low efficiency producers are indeed least-cost suppliers of *Environmental Health* but that they are likely least cost to the extent that they actually have a pure private incentive to increase provision of *Environmental Health* on their properties. Such an outcome would appear to be irrational. However it is widely thought that the management of rangelands beef enterprises involves a complex integration of a range of marginal effects of different human inputs and management approaches in addition to a great deal of uncertainty over the contributions of environmental factors to production. In addition, the marginal contributions of stock to declines in environmental health on the rangelands is a highly uncertain depending on a range of other factors such as rainfall and temperature. Thus, this outcome

[1] The series was calculated as the median of the vector of observation-specific partial derivatives for output (levels model) with respect to *Environmental Health* for each quantile model estimated. Spaces are for models which failed to achieve convergence. Lower and Upper bounds are the medians of 95% confidence bounds for the observation-specific derivative value obtained from the crs algorithm (Racine and Zhenghua 2014).

could be explained as a result of relatively higher bounds on the rationality and ability of producers to optimise their systems for lower efficiency observations relative to higher efficiency observations. In this case an optimal social response may be to increase access to education on better management and the medium term implications of alternative stocking rates with respect to the profitability of grazing enterprises.

Figure 7: Marginal product of Environmental health for estimated conditional quantile models



Conclusions

Economic evaluation and mechanism design for improved environmental protection requires some assessment of the impacts of changed environmental conditions on production outputs. Although the importance of environmental factors to ecosystem services and other inputs to agriculture are widely recognised, most value estimates of the benefits provided tend to be too coarse to be useful. In this paper we have presented a well-known method of the valuation of environmental assets from the production perspective (i.e. an input demand perspective) but using the relatively new statistical method of non-parametric conditional quantile regression. Our approach allowed a detailed examination of the patterns of value across the distribution of the efficiency of production for our case study – beef production in the north eastern rangelands of Australia.

Our results indicated that the environmental input we considered was treated as a management input by the most efficient enterprises with returns to scale inclusive of this input being close to 1 for efficient observations. In contrast, less efficient enterprises had strongly increasing returns to scale when these were considered inclusive of the environmental input. This indicated that lower efficiency enterprises were possibly lacking knowledge over the contributions of environmental inputs and, in combination with results indicating no difference in the marginal product of environmental contributions, indicated that they probably have a pure private incentive to increase provision of environmental health on their properties.

It was shown that environmental inputs generally, composed of our environmental health variable and a rainfall variable, comprised the vast majority of productivity in our sample (between 76% to 66% of total returns to scale) showing that this form of production is heavily reliant on contributions of healthy environmental factors to maintain productivity. These results suggest that substantial increases in rangelands productivity in northern Australia, and other regions, may be achieved by a focus on the efficient spatial and temporal use of environmental assets rather than a focus on improving the efficiency of human input.

It was shown that, considering environmental health as an input alone, the most inefficient producers could achieve increases in output of greater than 1% in output by increasing the provision of environmental health by only 1% - i.e. the least efficient producers were expected to have increasing returns to scale for environmental health alone. Given the high returns to improvements in this variable for inefficient producers and efficient producers alike then, we may say that producers are in general better off from improvements in environmental health on their enterprises and may be limited in obtaining these improvements from a range of factors including, but not limited to: equity constraints, bounded rationality (the joint effects of complexity in optimisation and cognitive limitations) and a lack of information. The possibility that producers have high discount rates which may manifest as low equilibrium levels for renewable assets such as environmental health and pastures is generally ruled out as returns on asset in the industry are extremely low – in the order of 1-4% for the best (most efficient) producers.

The results presented in this paper indicate that the use of the quantile regression methodology potentially extends the utility of economic analysis into distributional aspects – a matter of significant concern in policy formulation that is relatively poorly considered using the standard tools of econometric analysis which focus on the analysis of the conditional mean (average) response. The results also indicate that valuation of environmental assets can usefully be undertaken from a production perspective and indeed should be considered from this viewpoint in order to obtain information over the costs of supply of environmental improvements.

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