Journals, Preferences, and Publishing in Agricultural and Environmental Economics

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Research quality is an increasingly important metric for determining funding allocations, promotion and tenure, and professional prestige. A key metric often used as a proxy for research quality is the ranking of the journal in which a manuscript appears. While citation-based measures of journal quality are commonly used, less is known about other dimensions of journal quality and prestige. We report results from an international study using Best-Worst Scaling to investigate researchers' journal preferences. Respondents used two criteria to assess journals: the impact a paper in the journal would have on career progression, and the impact beyond academia of papers in the journal. Among the sample of journals studied, the *American Journal of Agricultural Economics* is ranked at the top for career progression for the aggregate sample, while *Science* was rated at the top for broader impact. We find no significant correlation between the journal scores based on the two criteria, nor between them and the journals' impact factors. These results suggest that impact beyond academia is poorly aligned with career incentives and that citation measures reflect poorly, if at all, peers' esteem of journals. Heteroscedastic scale-adjusted latent class models reveal marked heterogeneity in journal preferences related to researchers' institutional affiliation and geographic region. We find significant differences in error variance over people and choices: people were less consistent when choosing their least, as opposed to their most, preferred journal. This finding has broader implications given the burgeoning use of best-worst surveys.

Key words: Journal rankings, best worst scaling, citations, impact factor.

JEL codes: A11, I21, I23, Q10, Q20, Q50.

Academic research is increasingly scrutinized and assessed. This process has become more systematic as the flow of public and private funds into higher education is increasingly determined by assessments of research output, particularly of journal papers. The external assessments of research have been internalized and replicated by institutions—in their internal processes of appointment, promotion, and payment. A recurring issue in these research assessment processes is the extent to which the evaluation of a research paper should be influenced, or indeed determined, by an assessment of the journal in which it is published, rather than the intrinsic quality of the work itself.

While one expects the quality of a paper and the standing of the publishing journal to be correlated, there is ample evidence of imperfections in this relationship. There are numerous examples of what would become classic papers that were first rejected from leading journals (Gans and Shepherd 1994), of highly-cited papers appearing in second-tier journals, and a substantial overlap in the distributions of citations among low-, mid-, and high-ranked journals (Oswald 2007; Louviere et al. 2013). Laband (2013) finds

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that the 409 most highly-cited economics articles from 2001–2005 were published in 58 different journals. While assessing individual papers in research evaluations would be most accurate, a system based on reading every paper is likely to have excessive transaction costs. Instead, journals are taken as proxy indicators of a paper's quality. Given this, we expect research assessment processes, both formal and informal, and the resulting conceptions of journal hierarchies, to generate incentives that affect researcher behavior.

This study investigates researchers' understanding of the career impacts of publishing in different journals in agricultural, resource, and environmental (ARE) Economics. This is achieved by directly eliciting preferences between journals in a stated-preference survey with a sample of over 900 researchers in the field. Analysis of choice data from this Best-Worst Scaling study yields a hierarchy of journals in terms of perceived career impact. The consistency of journal quality assessment by respondents from different countries and institutions is investigated. The degree of correlation between researchers' subjective assessment of journals and "objective" citation-based journal metrics is determined. The degree of (in)consistency between researchers' journal rankings based on the criterion of career impact and those using the criterion of impact beyond academia is assessed. The Heteroscedastic Scale Adjusted Latent Class models reveal considerable scale (error variance) heterogeneity, as well as preference heterogeneity. In addition, we find significant increases in error variance when respondents make their worst as opposed to their best choices: people are less consistent when choosing their least-preferred options.

Research Assessment, Journals, and Rankings

While academics are prone to spending inordinate amounts of time discussing experiences with journals, and their frustrations and aspirations regarding them, the issue of journal rankings and peer assessment is more significant than simple self-contemplation. Rather, it is an economic issue because the assessment of research output influences the allocations of large amounts of public and private money, and is a major determinant of the career trajectories and salaries of researchers, who are often paid from the public purse.

Research rankings play a role in resource allocation among universities, either directly (e.g., through state funding) or indirectly (through the reputational effects). In the UK, state funding for higher education includes a block grant of £1.6 billion quality-related research (QR) funding. The allocation of QR funding across universities and departments is linked to periodic national research assessment exercises (e.g., RAE 2008; REF 2014) in which the primary assessment is of published research output. It seems inconceivable that in this assessment the ranking of journals in which papers appear does not play a major role in determining the quality scores ascribed to those papers. In Australia, the role of journal classifications in the national research assessments has been clearer, with journals explicitly assigned to 1 of 4 tiers. In the United States, listing journal impact factors (rather than a paper's own citations) beside publications is commonplace in promotion and tenure documents.

At the level of the individual researcher there is a long history of research suggesting a link between career trajectories, salaries, and where an individual publishes (see O'Keefe and Wang 2013; Sauer 1988; Tuckman and Leahey, 1975). In agricultural economics, Hilmer and Hilmer (2005) and Hilmer, Hilmer, and Musk (2012) have estimated the returns to publishing journal articles in the United States using 3 explicit tiers of journal quality for both agricultural economics and economics based on the classifications of Perry[1] and Scott and Mitias (1996), respectively. Gibson, Anderson, and Tressler (2014) make use of California's public disclosure of state employees' salaries to explain the salaries of California's university-employed economists in terms of their publishing profiles, using 9 alternative measures of journal quality. At least one Australian university defines staff as "research active" (a factor used for tenure and promotion decisions) according to publication rates in specified journals.

The lists of journal "quality" that inform or determine assessments of research come in various forms (see Harvey et al. 2010). Some are generated by institutions or departments

[1] Ranking M.S. and Ph.D. Graduate Programs in Agricultural Economics, Oregon State University. Available at: http://appliedecon.oregonstate.edu/sites/default/files/faculty/perry/Ranking2004.pdf (accessed on June 12, 2014).

within them (Cranfield 2012), while others are inferred from external research assessments such as the Research Assessment Exercise (RAE) in the UK (Mingers, Watson, and Scaparra 2012). Alternatively, the journal rankings may be based on citation metrics or peer surveys.

Proponents of citation-based approaches argue that they have the advantages of being relatively robust, "objective," and are based on publicly available data. Within economics, this approach was given impetus with the "Diamond list" of journals (Diamond 1989), which was influential in early UK research output assessment exercises. Contributions to this citation-based literature have appeared regularly (see Burton and Phimister 1995, 1996; Laband and Piette 1994; Liner 2002; Kodrzycki and Yu 2006; Engemann and Wall 2009; Rousseau, Verbeke, and Rousseau 2009; Chang and McAleer 2014; and Chang, McAleer, and Oxley 2011).

Stern (2013) investigated the degree of uncertainty around economics journals' impact factors, and hence the rankings derived from them. Even if metric-based ranking approaches are used, a choice has to be made between the number of alternative metrics based on citations now available, such as the Eigenfactor and Article Influence score (see Perry 2012). Further, it is argued that the number of citations per article is skewed, such that a significant proportion of articles in high-impact journals may be cited at lower frequency than the highest-cited paper in lower-impact journals (see Oswald 2007; Editorial 2005). The biasing effect of review articles (Garfield 2005) and the potential effects of "coercive citation" (Wilhite and Fong 2012; Arnold and Fowler 2011) are also cited as a weakness with citation-based metrics. Concerns with citation-based measures have led to the San Francisco Declaration on Research Integrity (see Alberts 2013), which opposes the use of impact factors to assess papers or people; and calls for their explicit exclusion from some research assessments (REF 2014).

A more fundamental issue is that citations may not reflect the way that academics rank the journals in their field (although using citation data in promotion or employment decisions may make that alignment become a reality). This is a motivation for studies which directly elicit peers' journal assessments. Revealed-preference data have on occasion been analyzed. For example, Lusk and Hudson (2009) use data on authors' submission sequences for papers to infer their preferences among journals in agricultural economics. Such preference data are more commonly derived from surveys in which respondents are asked to allocate journals to predefined quality tiers.

Axarloglou and Theoharakis (2003) invited American Economic Association (AEA) members to allocate 15 journals to both a top and second quality tier. The authors then derived a single measure of quality by combining several measures of rank. Rousseau (2008) invited participants at the World Conference of Environmental and Resource Economics to allocate 11 journals into a "top ranked" or "subtop" grouping. A journal ranking was generated based on the percentage of respondents who placed a journal in the top category. In preparation for the national research assessment, the Economic Society of Australia conducted a peer journal ranking study (Abelson 2009) in which economics professors allocated journals to four tiers. Herrmann et al. (2011) deviate from this allocation approach, instead asking agricultural economists in Germany, Austria, and Switzerland to rate journals based on the the scientific requirements for submission, and the scientific quality of the papers published. These two scores, equally weighted, were used to provide an overall measure of quality.

The methodology of Rousseau and Rousseau (2012) stands out, as they use a discrete choice experiment in which respondents chose where they would submit an article from sets of experimentally-constructed journal options. These differed in terms of the quality of the editorial board, the quality of referee reports, the probability of being accepted, the impact factor, the time before a decision was reached, and the journal's standing among peers. The study uses waiting time as a numeraire to calculate the tradeoffs that respondents are prepared to make for marginal changes in the quality of the journals they might submit to. Their choice options, however, are unlabelled, hypothetical journals, and so no ranking of real journals results from the study.

We use Best-Worst Scaling (BWS) to investigate this issue—to our knowledge Louviere et al. (2013) are the only others to apply the technique to journal ranking (their application was in the field of marketing). The nature of the journal ranking data allow for the econometric investigation of the degree of observed and unobserved heterogeneity in journal assessments. In addition, the sample size (936) far exceeds that achieved in any previous study in the area of agricultural, resource, and environmental (ARE) economics. Moreover, we obtain multidimensional journal rankings based on two different perceived dimensions of quality, career impact, and "real world" impact beyond academia, and compare these to citation-based rankings. We now outline our methodology and the models estimated on the journal choice data before describing the sample characteristics and results.

Best-Worst Scaling

We derive journal rankings using a case 1 Best-Worst Scaling (BWS Flynn 2010) approach. The BWS is a form of choice experiment analysis developed by Louviere and Woodworth (1990) as an extension of Thurstone's Method of Paired Comparisons for the elicitation of trade-offs between paired items (Thurstone 1927). Within a BWS study, each participant is shown a number of sets comprising items selected from a larger set. Each subset typically contains four or five of the items, and the participants are asked to make a choice, selecting the "best" and "worst" item in each subset. If, within a subset of four, the participant selects "Item 1" as the best and "Item 2" as the worst, it is known that Item 1 is preferred to Items 2, 3, and 4, and Items 2 and 3 are preferred to Item 4. The only preference ordering that cannot be inferred is between Items 2 and 3. Respondents make choices from multiple subsets of items in combinations determined by an experimental design. The resulting best-worst data can be analyzed in a number of ways to provide a full, scaled ranking of the items.

Best-Worst Scaling is typically used when there is a large list of items and the researcher seeks to understand their relative importance to respondents. As the participant is not asked to rank the full list, it is argued to be less cognitively demanding than other ranking methods. Best-Worst Scaling has been argued to have advantages compared to more traditional forms of ranking, including the following: having to make trade-offs means that participants cannot rate all/several items at equal importance as is possible with a Likert scale; the absence of a scale eliminates interpretive scale bias; and participants are better at judging at the extremes of preference (Cohen 2003; Sawtooth_Software 2007). The BWS method has been used to explore relative importance in diverse settings including, *inter alia*, relative concern associated with public policy issues (Finn and Louviere 1992), relative importance of food values (Lusk and Briggeman 2009), relative effectiveness of pathogen control measures (Cross, Rigby, and Edwards-Jones 2012), and relative perceptions of concern and control over risks (Erdem and Rigby 2013).

Analysis of the best-worst choices is based on Random Utility Theory. A number of alternative models can be derived based on the assumptions made about the cognitive process by which the best and worst are selected (Flynn and Marley 2014). We employ the sequential best-worst framework, first proposed by Marley and Louviere (2005), and implemented in Latent Gold Choice 5.0.

We define the latent utility (y^*_{ism}) associated with journal m by individual i, as having a deterministic component, β_m, and a stochastic element captured by the error term (ε_{ism}):

$$(1) \qquad y^*_{ism} = \beta_m + \varepsilon_{ism}.$$

We allow for heterogeneity in the standard deviation of the error process due to observable characteristics (e.g., of individuals or information treatments), and between worst and best choices, such that:

$$(2) \qquad y^*_{ism} = \beta_m + \varepsilon_{ism}$$

where $\exp(\mathbf{w}'_{is}\gamma)$ is the scale factor that is inversely proportional to the standard deviation of the errors, s indicates whether a best or worst choice is being made, and $\mathbf{w}$ is a vector of individual specific characteristics. The exponential functional form in equation (2) ensures that error variance is positive (Vermunt 2013).

We assume a sequential best-worst ranking model in which the probability that option m is selected as best (assuming the stochastic element follows a type I extreme value IID distribution) is:

$$(3) \qquad \pi_{ism_1} = \frac{\exp\left[\beta_{m_1} \exp\left(\mathbf{w}'_{is}\gamma\right)\right]}{\sum_{r=1}^{M} \exp\left[\beta_r \exp\left(\mathbf{w}'_{is}\gamma\right)\right]}$$

$$s = best$$

and the probability that option m is selected as worst, conditional upon the choice of best, is given by

$$(4) \qquad \pi_{ism_2|m_1} = \frac{\exp\left[-\beta_{m_2} \exp\left(\mathbf{w}'_{is}\gamma\right)\right]}{\sum_{r\neq m_1}^{M} \exp\left[-\beta_r \exp\left(\mathbf{w}'_{is}\gamma\right)\right]}$$
$$s = worst$$

in which the sign of the deterministic component is scaled by -1 since it is the least-preferred option being chosen.

The probability of selecting m_1 as the best and m_2 as the worst is given by

$$(5) \qquad \pi_{ij,m_1,m_2} = \pi_{ij,m_1}\pi_{ij,m_2|m_1}.$$

The model in equations (1)–(5) does not accommodate preference heterogeneity, but it does allow for differences in error variance over sets, people, experimental conditions (such as information treatments), or choices. The latter is of particular interest in this paper since the scale might differ between best and worst choices.

This heteroscedastic sequential conditional logit model can be extended to a Heteroscedastic Scale Adjusted Latent Class Model (Vermunt 2013) in which both latent scale classes and preference classes are accommodated. Given a total of C latent preference classes and D latent classes for error variance, the probability of selecting best and worst becomes

$$(6) \qquad \pi_{ism_1|cd} = \frac{\exp\left[\beta_{m_1c} \exp\left(\mathbf{w}'_{is}\gamma_d\right)\right]}{\sum_{r=1}^{M} \exp\left[\beta_{rc} \exp\left(\mathbf{w}'_{is}\gamma_d\right)\right]}$$
$$s = best$$

and

$$(7) \qquad \pi_{ism_2|m_1cd} = \frac{\exp\left[-\beta_{m_2c} \exp\left(\mathbf{w}'_{is}\gamma_d\right)\right]}{\sum_{r\neq m_1}^{M} \exp\left[-\beta_{rc} \exp\left(\mathbf{w}'_{is}\gamma_d\right)\right]}$$
$$s = worst.$$

The probability of selecting m_1 as the best and m_2 as the worst is given by

$$(8) \qquad \sum_{cd} P_{cd}\pi_{ij,m_1,m_2|cd} = \sum_{cd} P_{cd}\pi_{ij,m_1|cd}\pi_{ij,m_2|m_1cd}$$

where P_{cd} is the probability that an individual is a member of preference class c and scale class d. Membership of preference and scale classes can be explicitly modeled probabilistically as a function of individual specific characteristics using a multinomial logit functional form:

$$(9) \qquad P_{ic} = \frac{\exp\left[\mathbf{z}'_i\phi\right]}{\sum_{r=1}^{C} \exp\left[\mathbf{z}'_{ir}\phi\right]}$$

$$(10) \qquad P_{id} = \frac{\exp\left[\mathbf{z}'_i\varphi\right]}{\sum_{r=1}^{D} \exp\left[\mathbf{z}'_{ir}\varphi\right]}$$

where $\mathbf{z}_i$ is a vector of individual specific characteristics, and identification is achieved by imposing that

$$(11) \qquad \sum\phi = \sum\varphi = 0.$$

In summary, we model the BW journal choices probabilistically. We do so by estimating random utility models on respondents' BW choice data. Rankings of journals are revealed by the relative size of the logit coefficients (βs). The zero-meaned logit coefficients can be transformed into ratio-scaled "importance scores" using the transformation:

$$(12) \qquad \frac{\exp\beta_m}{[\exp\beta_m + (\lambda - 1)]}$$

where λ is the number of items comprising each set.

We allow for preference heterogeneity in journal rankings by estimating heteroscedastic scale-adjusted latent class models in which class membership, and hence preferences, are a function of individual characteristics. These models include scale classes in addition to preferences classes, and allow for differences in error variance, across all scale classes, between respondents' best and worst choices.

Implementation

Implementing the BWS approach requires specification of both the criteria respondents use when making their best/worst choices, and the items (journals) that populate the sets. Many candidate criteria were considered and pre-tested. A criterion was sought for the underlying scale that was unambiguous so that variation in choices arising from varying interpretations was minimized. After consultation and piloting, the criterion used was Career Progression: “A paper in which journal would most/least enhance your career progression, whether at your current institution or another at which you would like to work.” An advantage of this criterion over asking about the quality of the papers in journals was that some researchers, particularly PhD students, would be able to assess the desirability (by reputation) of having a paper appear in a particular journal even if they were not directly familiar with (many) papers within it.

Given the possibility that people may have different evaluations for the impact of journals, a second criterion was also included with respondents asked to choose “The journal whose papers you think have most/least impact beyond academia (i.e., on policy makers, business community, etc.).” This second criterion was included in part because of a shift toward impact in research assessments. For example, in the UK the REF (2014) introduced an explicit element to assess the impact of research linking “excellent research and … demonstrable benefits to the wider economy and society.”

The selection of journals to include in the study was based upon a number of criteria. The first requirement was to include all the key journals in ARE economics. In addition, it was desirable that all journals were relevant for all potential respondents, which meant that journals focusing on a single resource (water, energy), or a particular methodological scope (e.g., econometrics or choice modeling only), were excluded. In order to locate the journal rankings in the broader journal landscape in which ARE Economics researchers are publishing, a set of non-ARE journals was included. Similarly, a set of non-economics journals that may be relevant to the area of ARE economics (and which publish interdisciplinary papers) was included. The set of journals, post piloting, is shown in table 1. The list was constrained by the time and cognitive costs associated with the additional choice tasks required to accommodate larger numbers of journals.

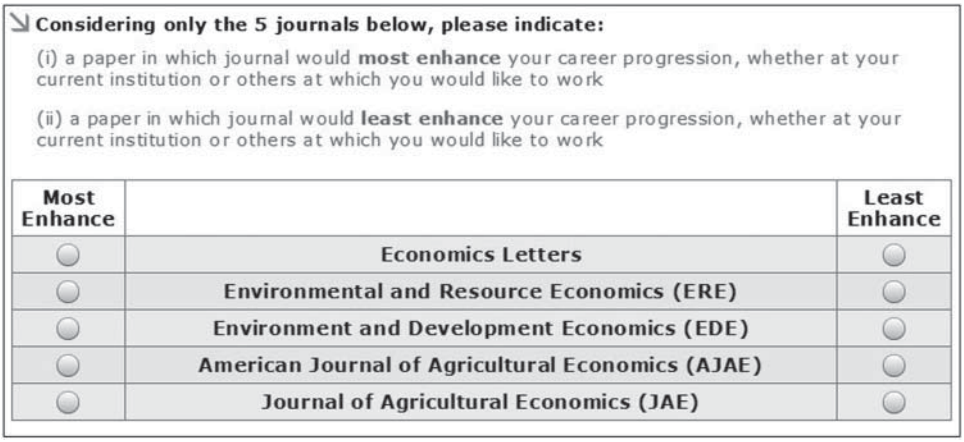
An experimental design was generated using Sawtooth Software’s Maxdiff Designer (Sawtooth_Software 2013). The cyclical design algorithm searches for designs that balance how often each attribute is shown and how often each attribute is shown with each other attribute. The design also sought to balance the position of the item in the set to avoid order effects. The employed design comprised 30 blocks to which respondents were assigned at random, with each respondent completing 15 sets of 5 journals ($\lambda = 5$), meaning that each respondent saw each of the 23 journals, on average, 3.3 times.[2] The design’s patterns of occurrence and co-occurrence are shown in the online appendix. The same experimental design was used for both Career Progression and Impact beyond Academia criteria. Figure 1 shows an example of a Career Progression BWS set used in the survey.

Table 1. The Set of Journals

Journal	Label
Agricultural Economics	*AgEc*
American Journal of Agricultural Economics	*AJAE*
Australian Journal of Agricultural & Resource Economics	*AJARE*
Ecological Economics	*EE*
Environment and Development Economics	*EDE*
Environmental and Resource Economics	*ERE*
European Review of Agricultural Economics	*ERAE*
Journal of Agricultural Economics	*JAE*
Journal of Environmental Economics & Management	*JEEM*
Land Economics	*Land*
Review of Environmental Economics and Policy	*REEP*
Applied Economic Perspectives & Policy	*AEPP*
Journal of Agricultural and Resource Economics	*JARE*
Science	*Sci*
Food Policy	*Fpol*
Journal of Environmental Management	*JEM*
Journal of Risk and Uncertainty	*JRU*
RAND Journal of Economics	*RAND*
World Bank Economic Review	*WBER*
Review of Economics and Statistics	*REStat*
Applied Economics	*AppEc*
Economics Letters	*ELett*
The B.E. Journal of Economic Analysis & Policy	*BE*

Note: The *BE* journal has 4 quality-rated tiers (*Frontiers*, *Advances*, *Contributions*, *Topics*) and in the sets was specified as *Contributions*.

[2] To address potential fatigue, after completing the career progression sets participants were asked whether they would also complete the impact choice tasks, with the option of skipping to the final stages of the survey.



Considering only the 5 journals below, please indicate:

(i) a paper in which journal would **most enhance** your career progression, whether at your current institution or others at which you would like to work

(ii) a paper in which journal would **least enhance** your career progression, whether at your current institution or others at which you would like to work

Most Enhance		Least Enhance
○	Economics Letters	○
○	Environmental and Resource Economics (ERE)	○
○	Environment and Development Economics (EDE)	○
○	American Journal of Agricultural Economics (AJAE)	○
○	Journal of Agricultural Economics (JAE)	○

Figure 1. A career progression choice set

The survey was hosted online, and the recruitment process was facilitated by seven academic societies and associations: AARES, AAEA, AERE, AES, EAAE, EAERE, IAAE. These associations sent out invitation emails, including the survey URL, to their members. The survey was open between July and September 2011. A sample of 936 respondents completed the Career Progression sets and the rest of the questionnaire. Of these, 285 people also completed the optional impact beyond academia sets.

Table 2. Sample Membership Characteristics

Membership	N	Percentage
AARES	88	9.39
AAEA	519	55.39
AERE	254	27.11
AES	98	10.46
EAAE	196	20.92
EAERE	179	19.10
IAAE	158	16.86

Note: many respondents were members of more than one organization; 28 respondents reported no affiliation.

Sample Characteristics

A full set of descriptive statistics is included in the supplementary appendix online. The sample was predominantly male (78%), and aged between 30 and 49 (61%), with a mean age of 44. Just under one-third of the sample were professors, and a similar proportion were either assistant or associate professors, with 87% holding a PhD, and 90 respondents (10%) studying for a doctorate at the time of the survey. Most of the respondents were from North America (58%) and Europe (32%), with far fewer responses from Africa, Asia, and Central and South America.

Over three-quarters (79%) of the sample were based in universities, with research institutes (10%) and government/regulatory bodies (7%) represented much less frequently. Most respondents (43%) were based in agricultural economics departments, with approximately equal numbers from economics (23%) and environmental economics (20%) departments. The rest of the sample were employed in schools of business (1.9%), marketing (1.0%), fishery/marine economics (0.9%), agriculture (2.4%), fisheries (0.1%), and environment (2.4%), with 5% in unspecified "other" departments.

At the time of the survey, 6% of the sample had published no papers, and 32% had published less than 10 papers; 70% of the sample had published less than 30 papers. The membership affiliations of the sample are shown in table 2, which indicates that U.S. societies (AAEA, AERE) dominated the sample.

The gender and age characteristics of the Impact beyond Academia sample of 285 were similar to the larger sample—mostly male and aged between 30 and 49. There was a difference in that the Impact sets were completed by fewer PhD students (4.2% as opposed to 9.6% of the full sample) and more professors (38.6%; 31.1%). As with the main sample, most of the respondents were from North America (59%) and Europe (31%). The proportion of the sample from universities was stable across the

Impact (75%) and Career Progression (79%) samples.

Weighting the Sample

It is necessary to weight the sample by membership in order to produce results that represent the population of agricultural and environmental economists, as defined by society membership. Respondents provided data on their membership of the 7 societies (table 2). Since respondents were members of multiple societies, and we have no data on the population cross-membership numbers, we generate weights via an optimization process (see supplementary appendix for more details). We identify 65 unique cross-membership profiles within the sample from the 127 possible combinations from 7 societies. We know the sample numbers for each profile (S_k, $k = 1$–65) and the proportion of the sample with each profile ($R_k = \frac{S_k}{908}$). We seek an estimate $\widehat{P}_k$ of the true population for each membership profile, given by the sum of sampled and additional, unsampled, people ($\widehat{A}_k$) of that profile: $\widehat{P}_k = S_k + \widehat{A}_k$. We require that the predicted number of members of a society (which is the sum of all members of profiles that contain that society) equals the observed aggregate society membership numbers, (M_t, $t = 1$–7), for each society. To this end, we solve for the unsampled numbers of each membership profile, $\widehat{A}_k$ which provide the (known) aggregate society membership numbers, while minimizing the implied sampling bias, $\sum\left[\frac{\widehat{R}_k}{R_k} - 1\right]^2, \widehat{R}_k = \frac{\widehat{P}_k}{\sum \widehat{P}_j}$, specifying A_k as control variables. The mean squared error at the solution is 8.3%, with sampling weights for each of the 65 cross-membership profiles given by $\frac{\hat{p}_k}{s_k}$, with a mean sampling weight of 5.2. This mean weight was assigned to those who reported no affiliations.

Results: Career Progression and Impact beyond Academia

Choice models are estimated to derive rankings in terms of both Career Progression and Impact beyond Academia assuming a single preference class. Table 3 shows results from estimating the heteroscedastic sequential conditional logit model on the Career Progression data. The logit coefficients are scaled to have a zero mean, so a positive coefficient indicates the sample regard a paper in that particular journal to have an above average impact on career progression.[3] Table 3 also reports ratio-scaled importance scores for each journal, and the estimate of the differential scale effect between best and worst choices. The scale estimate is highly significant, indicating that choice inconsistency is greater when respondents make worst choices than when making best choices.

These zero-meaned coefficients are graphed in figure 2, ranked by score; they reveal that, when considered in aggregate, the journal within the sample regarded as having the biggest career payoff was *AJAE*, followed by *REStat*, *Science*, and *JEEM*. *The RAND Journal*, *Land Economics*, and *ERAE* were the next most highly ranked in terms of career progression, all of them being regarded as having an effect greater than the sample average. The ratio-scaled scores[4] in table 3 reveal that a paper in *AJAE* was seen as having more than twice the career payoff as a paper in *Land Economics* and the journals ranked below it. The ranking of agricultural economics journals after *AJAE* was *ERAE*, *JAE*, *AgEc*, *JARE*, *AEPP*, and *AJARE*. Within environmental economics, the resulting hierarchy was *JEEM*, *Land*, *ERE*, *EE*, *REEP*, and *EDE*.

Results from a heteroscedastic sequential conditional logit model estimated on the Impact beyond Academia choice data are reported in table 4 and figure 3. These results indicate that *Science* is the highest-performing journal in terms of Impact beyond Academia. The top-ranked ARE journals on this criterion are *AJAE*, *REEP*, and *JEEM*. The ratio-scaled scores indicate that papers in *Science* are considered to have more than twice the impact of those in *AJAE* and those journals ranked beneath it, and nearly five times that of papers in *REStat*, which was the top-ranked general economics journal in terms of career progression. As was the case for the Career Progression data, scale is lower, and hence error variance significantly greater, for worst as opposed to best choices.

[3] The mean is determined by the set of journals included in the study, and so the above/below average interpretation applies only relative to that set, rather than the population of all possible journals.

[4] These scores have been rescaled to sum to 100 for ease of interpretation.

Table 3. Career Progression Results: Heteroscedastic Sequential Best-Worst Conditional Logit Model

	Coefficient	s.e.	z-value	Ratio Scaled Importance Scores
Preference parameters:				
AJAE	1.702	0.054	31.766	11.00
REStat	1.520	0.066	23.156	10.15
Sci	1.504	0.073	20.562	10.07
JEEM	1.218	0.058	21.006	8.72
RAND	0.790	0.066	11.905	6.76
Land	0.355	0.059	6.033	5.00
ERAE	0.240	0.072	3.346	4.59
JAE	0.134	0.059	2.280	4.23
ERE	0.102	0.057	1.781	4.13
AgEc	0.050	0.063	0.790	3.96
JARE	−0.011	0.062	−0.184	3.77
ELett	−0.120	0.071	−1.695	3.45
JRU	−0.229	0.073	−3.148	3.16
AppEc	−0.384	0.064	−5.967	2.77
EE	−0.388	0.076	−5.138	2.76
REEP	−0.453	0.063	−7.184	2.61
WBER	−0.535	0.080	−6.702	2.43
Fpol	−0.804	0.132	−6.106	1.91
AEPP	−0.810	0.075	−10.842	1.90
EDE	−0.869	0.080	−10.828	1.81
JEM	−0.925	0.086	−10.767	1.72
AJARE	−0.953	0.100	−9.571	1.67
BE	−1.132	0.090	−12.610	1.42
Scale parameter:				
worst	−0.851	0.073	−11.647	

$N = 28080$; $LL = -38038.56$.

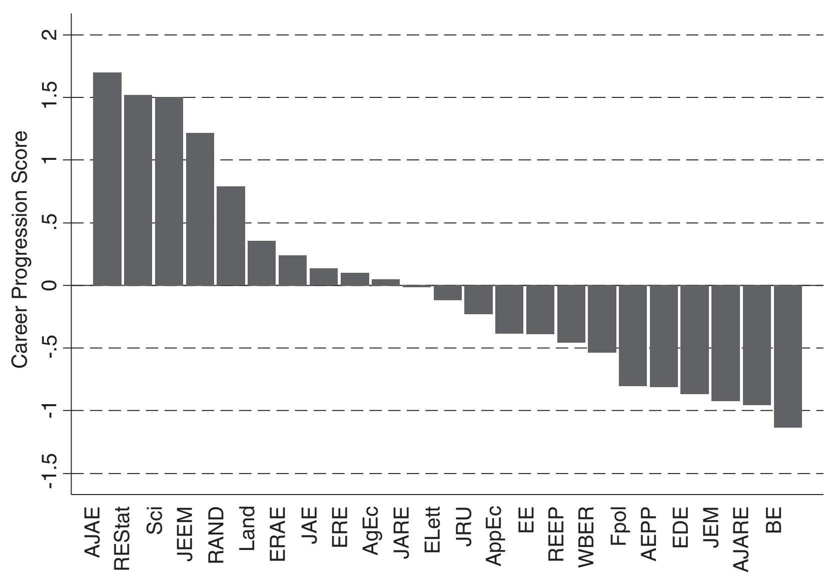


Figure 2. Career progression results

Table 4. Impact Beyond Academia Results: Heteroscedastic Sequential Best Worst Conditional Logit Model

	Coefficient	s.e.	z-value	Ratio Scaled Importance Scores
Preference parameters:				
Sci	2.6914	0.0776	34.6755	14.90
WBER	1.6681	0.0657	25.3943	10.79
Fpol	1.2278	0.0655	18.7412	8.72
AJAE	0.768	0.0698	11.0073	6.63
REEP	0.5219	0.0701	7.4398	5.61
JEEM	0.5061	0.0718	7.0453	5.55
AEPP	0.3879	0.0727	5.3387	5.10
RAND	0.1384	0.076	1.8224	4.22
Land	0.0676	0.0746	0.9056	4.00
EE	−0.0782	0.0795	−0.9831	3.56
REStat	−0.268	0.0857	−3.1262	3.04
ERAE	−0.2705	0.0816	−3.316	3.03
JEM	−0.2946	0.0829	−3.554	2.97
AgEc	−0.3511	0.0833	−4.2169	2.83
ERE	−0.3628	0.0847	−4.284	2.81
BE	−0.4127	0.0853	−4.8363	2.69
JARE	−0.4196	0.084	−4.9946	2.67
JAE	−0.4497	0.0843	−5.3344	2.60
EDE	−0.5424	0.0877	−6.1825	2.40
AppEc	−0.6958	0.0897	−7.7598	2.10
AJARE	−0.9793	0.0943	−10.3849	1.63
ELett	−1.4194	0.1054	−13.4682	1.08
JRU	−1.433	0.1067	−13.4269	1.07
Scale parameter:				
worst	−0.753	0.065	−11.512	

N = 8550; LL = −11151.26.

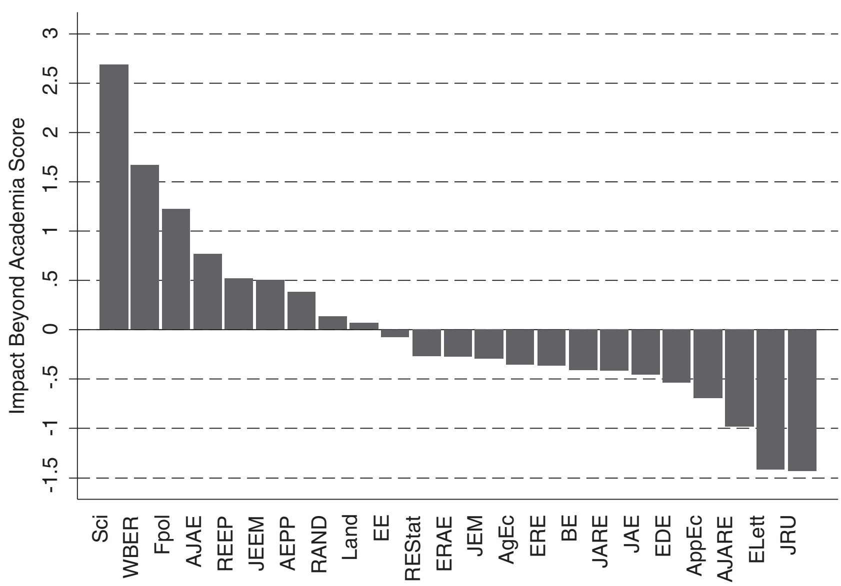


Figure 3. Impact beyond academia results

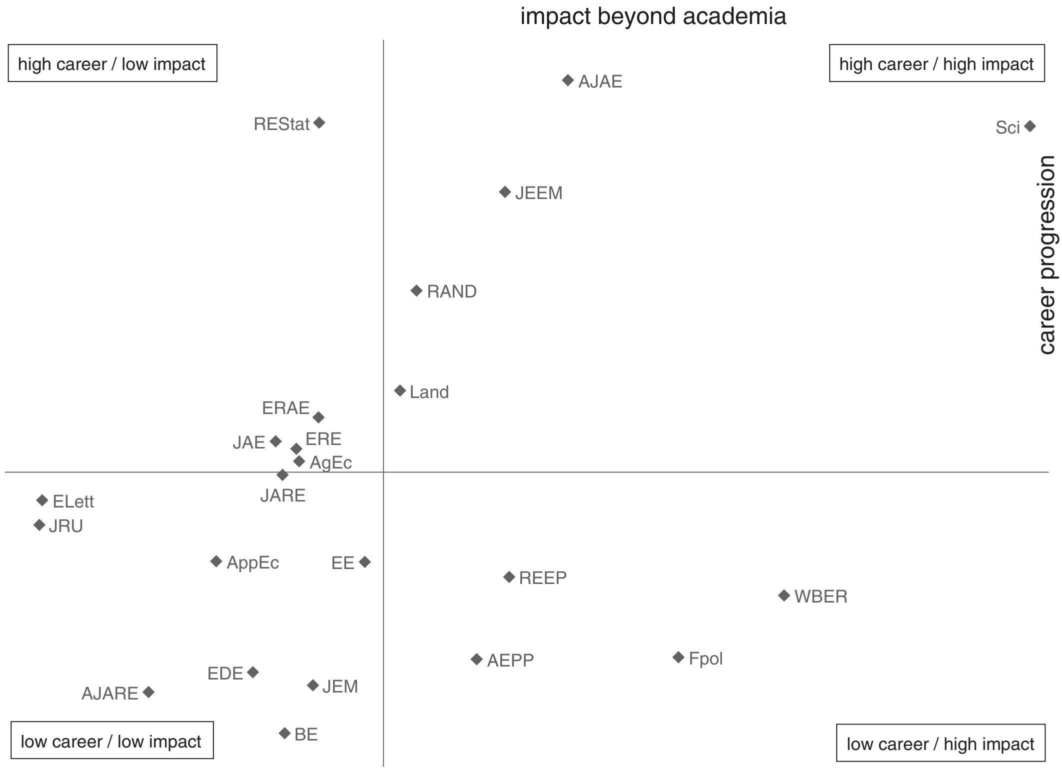


Figure 4. Journals located in Career Progression – Impact beyond Academia space

The respondents' assessment of the journals on both dimensions are shown in figure 4, with the journals located in a space defined by Career Progression and Impact beyond Academia scores, with both axes defined at zero (the mean score for both criteria). Some journals score strongly on both criteria (e.g., *Science*, and *AJAE* to a lesser extent), while others score below average on both criteria (*AJARE*, *EDE*). Nine journals (*REStat*, *AgEc*, *ERAE*, *ERE*, *JAE*, *REEP*, *AEPP*, *Fpol*, *WBER*) score above average on one criteria and below average on the other. In some cases the divergence in assessment between the two criteria is marked: *Fpol* is ranked 6th from bottom in terms of career effect, but 3rd on impact; *REStat* is ranked 2nd on career but 11th on impact. The correlation between the two sets of zero-meaned logit scores (0.142) is insignificant at the 95% level, meaning that these are indeed different dimensions of quality.

Comparison of BWS Scores and Impact Fctors

Since citation metrics are increasingly used to measure the standing of journals, papers, and people, we compare the direct assessment of the journals revealed in the BWS choice data with a series of citation-based measures of the journals' quality. The relationship between the Career Progression scores and 2011 Impact Factor (IF) values is shown in figure 5, in which both sets of values have been zero meaned.[5] The plot indicates that while journals such as *JEEM* and *REStat* score highly on both measures, there is a set of high IF journals which are regarded relatively poorly in terms of the career impact of publishing in them (*JEM*, *EE*, *REEP*, *Food Policy*). The *AJAE* had a below average IF, yet was seen as the most prestigious journal in terms of career progression. *Land*, *ERAE*, and *AgEc* also had below-average IF values but above average career progression scores. Figure 5 illustrates the weakness of the Impact Factor in capturing peer esteem of journals among researchers in ARE.

The relationship between peer assessment of journals and citation measures is extended

[5] Science is excluded from the calculation of the mean IF since it is such an outlier (31.2 compared to the next highest IF of 3.3); its position on the IF dimension in figure 5 is nominal.

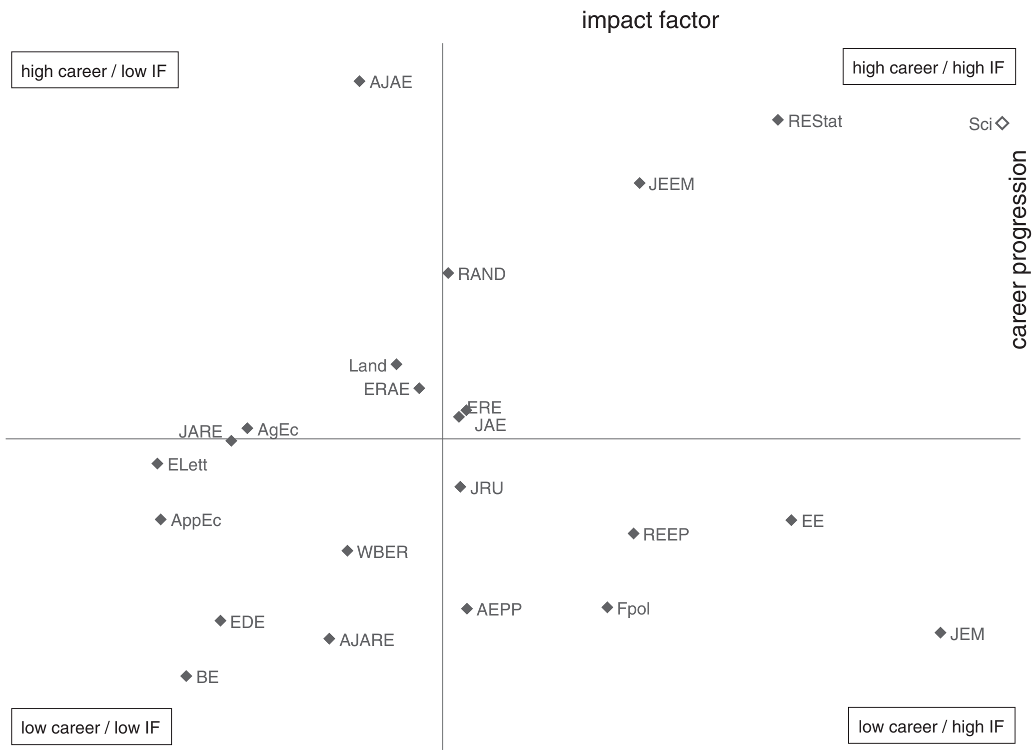


Figure 5. Journals located in Career Progression – Impact Factor space

to correlation analysis with citation metrics from 2011 and 2012. These measures comprise the journals' one-year impact factor (IF), five-year impact factor (5YrIF), Immediacy Index, Eigenfactor, and Article Influence scores.

Because *Science*'s IF is such an outlier (2011 value = 31.2, next highest is *JEM* at 3.3), we exclude it from the analysis here (the fundamentals of the results are unchanged by this exclusion). The correlation coefficients between the Career Progression logit scores and the 2011 and 2012 IFs are 0.198 and −0.001, respectively, and not significant at the 5% level in either case. The absence of significant correlation holds for the 2011 and 2012 values of the 5YrIF [0.196, 0.119] Immediacy Index [0.061, 0.020] and Eigenfactor [0.240, 0.174]. There is a positive significant correlation between the Career Progression scores and the Article Influence scores, for both 2011 and 2012 [0.477, 0.454]. There is a similar absence of correlation between the Impact beyond Academia logit coefficients and citation-based measures: the only significant correlation being with the 2012 5YrIF [0.430].

If *Science* is included, the absence of correlation between Career Progression scores and citation metrics holds (except for Article Influence). However, the impact beyond academia scores become significantly positively correlated with all citation measures, since *Science* scores so highly on citations and was most positively regarded for impact beyond academia. The lack of correlation between impact factor and perceptions of both career progression effects and broader impacts suggests that journal quality is multideminsionsal and not easily captured in a single metric; either that, or it implies a disconnect between perceptions and reality regarding the effects of papers in journals.

Heterogeneity in Career Progression Journal Preferences: Latent Class Analysis

Latent heterogeneity in preferences and scale in the Career Progression data is investigated by estimating the Heteroscedastic Scale Adjusted Latent Class Model outlined previously. The number of classes in this model must be specified *ex ante*, with the preferred number of classes decided upon *ex post* via judgment, typically informed by various information criteria [Akaike information criterion, consistent Akaike information criterion, Bayesian information criterion (BIC), etc.]. For a given number of preference classes, the BIC and other information criteria were unambiguous in suggesting that 3 scale classes were appropriate. However, these criteria implied ever-increasing numbers of preference classes (>20), although the improvements in the BIC exhibited diminishing returns. In order to keep the exposition tractable, we limit ourselves in this section to results from a 6 preference class, 3 scale class model, which fits the data well (61% correct predictions[6]), and which provides intuitive results in terms of the relationship between covariates and journal preferences. The preference parameter estimates, and the estimated class membership covariate effects from the latent class model, are shown in table 5.

We confine our discussion of scale heterogeneity to noting that there remains a significant difference in scale between best and worst choices: there was greater noise (choice inconsistency) for worst as opposed to best choices. Covariates were found to significantly affect membership of both preference and scale classes. Whether respondents are based in North America (Nam = 1), and whether their home department is an economics department (Econ = 1) or an environmental economics department (EnvEcon = 1), all significantly affect their journal preference class membership probabilities.

The journal preference estimates from the Heteroscedastic Scale Adjusted Latent Class models are summarized in figure 6, in which the journals' career progression logit scores are plotted for each of the six classes. Because scale differences have been accounted for, and the scores within each class are zero meaned, the scores are directly comparable.

For some of the top journals in the aggregate rankings, the latent class results reveal a pattern of consistent high esteem, while for others there is considerable variation. *AJAE* is the top-ranked journal in Classes 4 and 6, and in the top 3 journals for all but Class 2, where it is ranked 5th in terms of career progression.

REStat is the top journal for Classes 2 and 5, and 2nd for Class 6 but, in marked contrast, is not in the top 10 journals for the other 3 classes. Similarly, the *RAND journal* (5th in the aggregate analysis) is outside the top 10 for Classes 1, 3, and 4. A similar pattern is observed for *JEEM*: it is in the top 2 for Classes 1 and 2, but outside the top 10 for Classes 4 and 6. The impact on career progression of a paper in *Science* exhibits even more marked variation: it is in the top 3 journals for 4 classes, but at the bottom of the set for Class 4.

While *AJAE* is consistent in its position within the rankings, there is considerable variability in the assessment of the career impacts of publishing within other agricultural economics journals. These journals are best regarded by members of Classes 3, 4, and 6. Regarding the non-economics journals, *JEM* fared poorly in terms of its career impact, scoring below average for all but Class 1, where it ranked 8th. *Food Policy* was better regarded in some segments, despite appearing towards the bottom of the rankings in the aggregate analysis: it appeared among the top 10 journals for Classes 3, 4, and 6.

Having identified some of the consistencies and variability by journal, we now characterize the classes more systematically in terms of the covariate effects and the pattern of journal preferences within them. The marginal effects of covariates on preference class membership probabilities (see Greene (2008)) are summarized in table 6. In categorizing the six preference classes, we limit consideration to covariates which shift class membership probabilities substantially, using a threshold of 10 percentage points.

In looking at the ranking structure by class, it is useful to categorize journals into broad groups: Economics (*REStat*, *RAND*, *ELett*, *JRU*, *AppEc*, *WBER*, *BE*), Agricultural Economics (*ERAE*, *JAE*, *AgEc*, *JARE*, *AEPP*, *AJARE*), and Environmental Economics (*Land*, *ERE*, *REEP*, *EE*, *EDE*). We keep *AJAE*, *JEEM*, and *Science* outside of these groupings because the way they enter the rankings seems quite different from the broader groupings to which one might allocate them. We now interpret the class-journal rankings on this basis (the supplementary appendix includes a color coded classification of these ranking by class).

[6] This is compared to a 20-class model that predicts 66% of choices but with an additional 392 parameters.

Table 5. Career Progression Results: Heteroscedastic Scale Adjusted Latent Class Model

Attributes	Class1	s.e.	Class2	s.e.	Class3	s.e.	Class4	s.e.	Class5	s.e.	Class6	s.e.
AgEc	−0.489	0.364	−2.982	0.357	1.860	0.409	2.900	0.403	−0.356	0.256	1.878	0.475
AJAE	2.748	0.388	1.853	0.343	4.418	0.758	5.115	0.734	4.085	0.619	4.674	1.032
AJARE	−0.186	0.581	−4.475	0.473	−1.156	0.745	1.179	0.606	−1.916	0.322	−0.347	0.541
EE	1.884	0.388	0.318	0.209	1.175	0.555	−1.656	0.611	−2.423	0.681	−3.871	0.763
EDE	0.015	0.419	−0.470	0.291	−2.088	0.513	−0.487	0.573	−2.895	0.517	−2.480	0.440
ERE	2.455	0.284	1.748	0.207	−0.083	0.251	0.210	0.384	−1.467	0.422	−2.345	0.514
ERAE	−0.704	0.432	−2.658	0.313	2.979	0.654	2.925	0.669	0.094	0.338	2.162	0.594
JAE	0.312	0.477	−2.461	0.289	1.258	0.501	3.253	0.465	−0.677	0.281	2.299	0.810
JEEM	3.838	0.515	4.704	0.456	2.092	0.858	0.147	0.474	2.533	0.671	−3.075	0.654
Land	2.685	0.413	1.550	0.212	0.391	0.466	−1.314	0.566	1.168	0.299	−2.019	0.917
REEP	1.033	0.295	0.895	0.266	−1.340	0.477	−0.316	0.333	−2.589	0.530	−2.230	0.524
AEPP	−1.279	0.295	−3.384	0.412	−2.085	0.604	0.629	0.393	−1.644	0.388	0.940	0.422
JARE	0.852	0.470	−2.125	0.310	0.084	0.869	2.831	0.480	−0.999	0.487	1.450	0.637
Sci	3.032	0.729	4.593	0.522	4.781	0.962	−4.780	1.219	5.076	0.984	1.479	1.005
Fpol	−4.492	0.630	−5.897	0.643	1.645	0.682	1.294	0.577	−1.109	0.517	1.228	0.603
JEM	0.962	0.455	−1.898	0.358	−0.530	0.396	−0.930	0.404	−2.405	0.475	−3.897	0.729
JRU	−1.918	0.514	1.420	0.270	−1.511	0.853	−2.308	0.830	−0.068	0.373	−0.879	0.606
RAND	−1.428	0.831	4.041	0.494	−2.547	0.842	−1.742	0.572	3.800	0.626	1.093	1.253
WBER	−2.836	0.481	−0.272	0.285	−1.496	0.728	−2.230	0.494	−0.910	0.562	0.562	0.675
REStat	−0.656	1.038	5.482	0.609	−0.085	1.035	−0.840	0.695	5.709	0.917	2.702	0.866
AppEc	−1.076	0.352	−0.894	0.259	−1.151	0.534	0.537	0.284	−1.394	0.440	1.165	0.408
ELett	−1.946	0.379	1.087	0.224	−2.169	0.926	−2.277	0.798	0.266	0.316	0.938	0.519
BE	−2.805	0.518	−0.171	0.270	−4.442	0.939	−2.138	0.448	−1.878	0.457	−1.427	0.878
Preference Class Membership Terms												
Intercept	−0.638	0.252	−0.761	0.242	0.730	0.168	0.517	0.264	0.082	0.259	0.069	0.301
EnvEcon	2.723	0.418	3.314	0.337	−0.617	1.287	−0.744	0.667	0.154	0.481	−4.830	0.490
Nam	0.114	0.297	0.588	0.207	−1.583	0.424	−0.603	0.301	1.089	0.292	0.395	0.342
Econ	0.550	0.391	2.275	0.276	−1.893	0.826	−0.928	0.473	0.284	0.306	−0.289	0.470
Scale Estimates												
	Class1	s.e.	Class2	s.e.	Class3	s.e.						
scale	0	–	−0.548	0.061	−1.311	0.169						
	best		worst	s.e.								
worst	0	–	−0.326	0.049								
Scale Class Membership Terms												
Intercept	0	–	0.821	0.538	−0.797	0.882						

N = 28080; LL = −31327.90.

- Class 1 (EnvEcon) rank *JEEM*, *Science*, *AJAE*, *Land*, and *ERE* as their top 5, followed by the Environmental Economics, then Agricultural Economics journals, with Economics journals largely at the bottom.
- Class 2 (North America, EnvEcon or Econ) rank *REStat*, *JEEM*, *Science*, *RAND*, *AJAE* in the top 5. The Agricultural Economics journals dominate the tail, with Economics and Environmental Economics journals interspersed in the middle.
- Class 3 (non North America, non EnvEcon, non Econ) rank *Science*, *AJAE*, *ERAE*, *JEEM*, and *AgEc* as the top 5. Tendency to rank Agricultural Economics above Environmental Economics journals in the middle order, with Economics journals in the lower positions.
- Class 4 (non North America, non EnvEcon, non Econ) has similar characteristics to Class 3 and a very similar top ranking (*AJAE*, *JAE*, *ERAE*, *AgEc*, *JARE*) except *Science* falls from 1st in Class 3 to 23rd in Class 4, and JEEM from 4th to 11th. Agricultural Economics journals dominate the top of this ranking, more so than for Class 3.

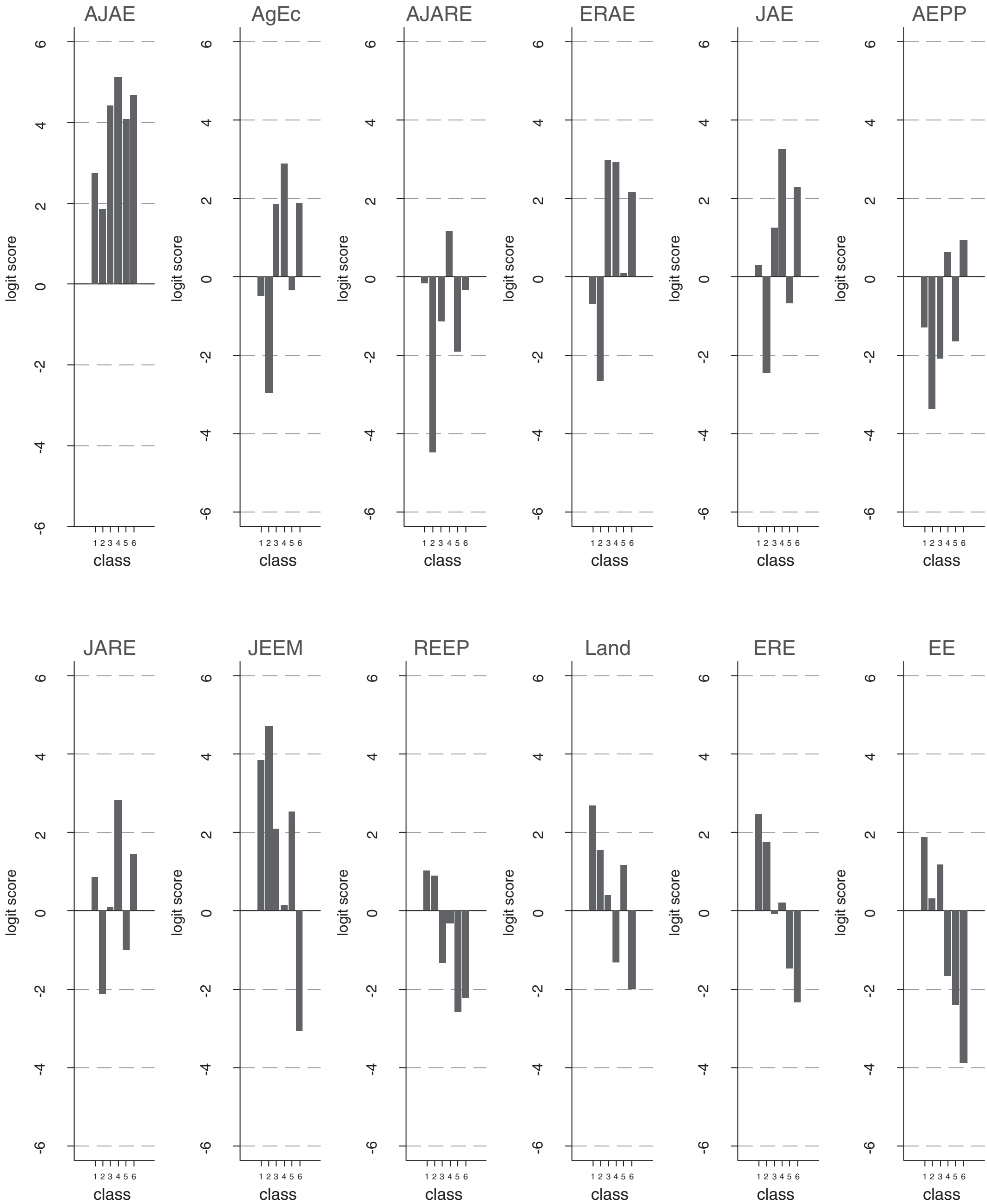


Figure 6. Journal preference scores by class: Career Progression

- Class 5 (N. America, non EnvEcon) rank *REStat*, *Science*, *AJAE*, *RAND*, *JEEM* in the top 5. This is similar to Class 2, but they differ in that Environmental Economics journals (apart from *JEEM* and *Land*) appear in the tail for Class 5, whereas in Class 2 Agricultural Economics journals dominate the tail.
- Class 6 (non EnvEcon) ranks *AJAE*, *REStat*, *JAE*, *ERAE*, *AgEc* top, with the 7 Environmental Economics journals, including *JEEM* and *Land Economics*, taking the bottom positions.

The correlation analysis between career progression logit scores and citation metrics,

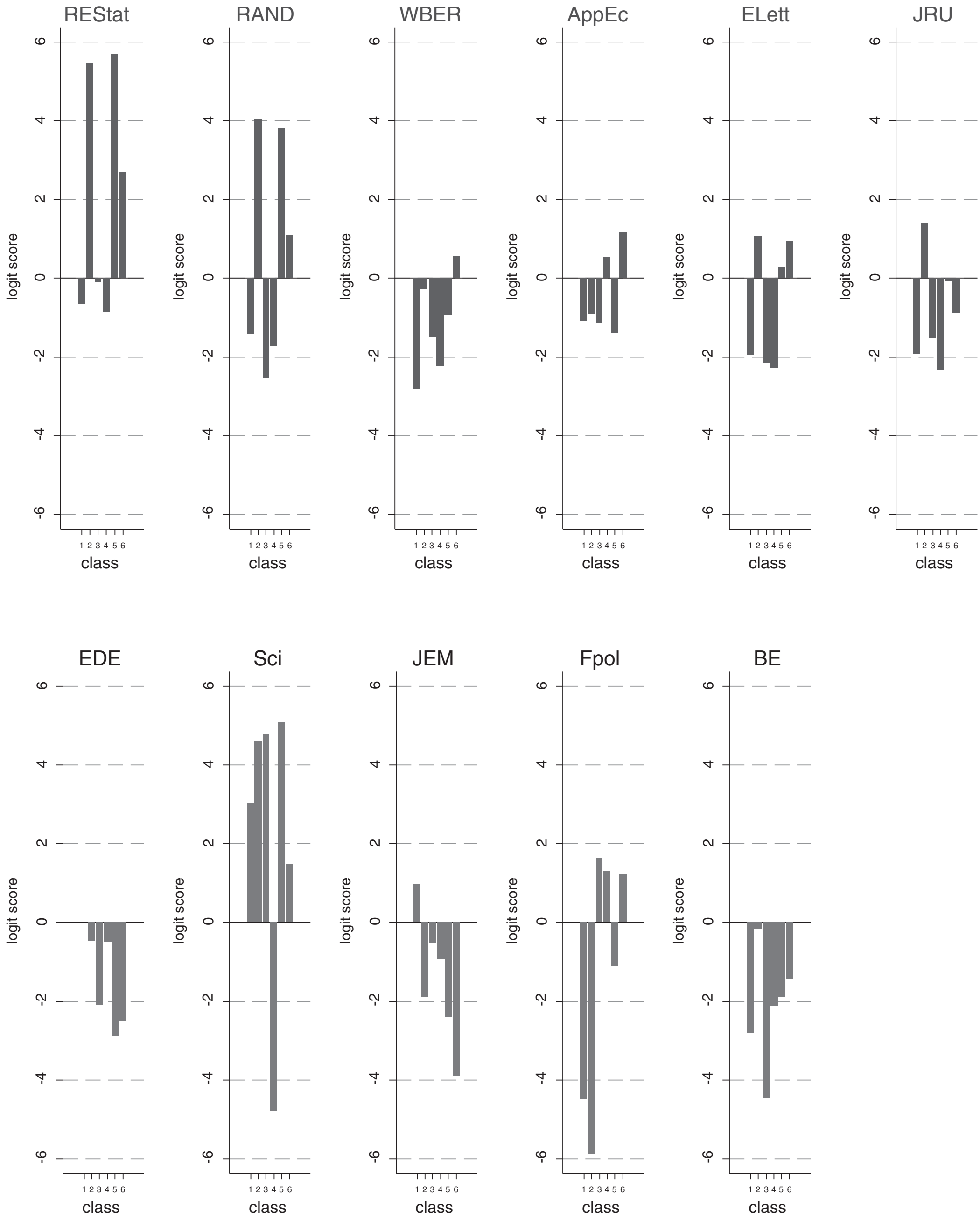


Figure 6. Continued

previously undertaken at the aggregate level, is repeated for each of the 6 classes (see supplementary appendix online). Only 6 of the 60 correlations are significant, and in all but one case these are correlations for Classes 2 and 5. Class 4 has a single significant correlation with 2011 Article Influence, but this is negative. Classes 1, 3, and 6 exhibit no significant correlation between career progression assessments and any citation measure. Thus, we find no subsection of the sample whose assessment of the career effects of publishing in the journals consistently aligns with the citation metrics.

Table 6. Preference and Scale Class Sizes and Covariate Effects

Preference Class	1	2	3	4	5	6
Size	0.13	0.29	0.11	0.12	0.23	0.12
Scale Class	1	2	3			
Size	0.269	0.610	0.121			
Covariate Marginal Effects (%)						
EnvEcon	27	79	−13	−16	−10	−67
Nam	−2	10	−20	−10	20	2
Econ	1	53	−26	−17	−4	−9

Conclusions

Some argue that journal rankings are flawed by nature and that papers should be assessed on their fundamental merit rather than the outlet in which they appear. However, given that journals' reputations are taken as proxies of the quality of the individual papers they publish, understanding the peer esteem associated with them matters. If journal rankings are to be used, then they should be explicit, transparent in derivation, robust, and widely accepted. The absence of explicit rankings does not guarantee that research is not being assessed via journal publication profiles since unarticulated journal rankings may be in use instead. Transparency in the assessment process, and any journal hierarchies within it, seems more equitable than one based on unarticulated rankings that are opaque to the researcher and may well vary over assessors. This at least allows informed disagreement and debate. This is particularly pertinent for research in subfields such as agricultural, resource, and environmental economics since this work is often assessed by researchers external to it—for example, economists or natural scientists. As a result, assessors' understanding of the relative esteem associated with ARE journals may deviate markedly from that of those working in the field.

Previous journal rankings in economics have typically been derived from the results of external research assessments or have been based upon citation data, or, in a few cases, resulted from peer surveys. Previous peer surveys have not typically taken advantage of stated preference methods available to derive preference measures, and have been limited in geographical scope and sample size. This study develops the literature by using case 1 Best-Worst Scaling with a large, international sample using 2 criteria: the career impacts of publishing in journals, and the impact beyond academia of papers published therein.

The estimation approach has focused on heterogeneity in both scale (choice inconsistency) and journal preferences. While a few studies have employed scale-adjusted latent classes (e.g., Burke et al. 2010) as interest in scale heterogeneity has grown, this paper has extended the analysis to test for systematic differences in error between different types of choices. In both the career and impact choice data, we have found significantly higher error variance for worst as opposed to best choices. This finding has remained even when latent scale classes are included within the model. This is perhaps intuitive: we are used to picking most preferred options, but less accustomed to choosing least preferred options. The finding is of general significance for researchers as best-worst approaches are increasingly used, and the assumption that scale is constant across both types of choices is one that warrants testing. A related question concerns the degree of stability in preferences between best and worst choices, and this is an issue we believe merits further investigation.

The substantive results indicate that the *AJAE* is regarded as outperforming prestigious journals in environmental economics (*JEEM*), economics (*REStat*), and natural sciences (*Science*) in terms of career progression. The career impacts of a paper in *AJAE* are regarded as twice that of a paper in *Land Economics*, and more than 3 times the effect of a paper in *REEP*, *JRU*, and *EE*. Considerable heterogeneity is evident from scale-adjusted latent class analysis. However, the *AJAE* is consistent in its standing across the 6 classes identified (always in the top 5 journals). This is largely also true for *Science* (top 3 in 4 classes) and *JEEM* (top 5 in 4 classes), albeit with some marked exceptions (see classes 4 and 6) for these otherwise leading journals.

Setting aside the top journals considered (*AJAE*, *JEEM*, *Science*), there is great variability in what researchers understand as the hierarchy of journals in which they should aspire to publish to best develop their career. This variation is influenced by researchers' geographical and institutional locations, but there is still marked variation over and above that. Classes 3 and 4 have similar membership covariate effects, yet Science switches from top to bottom between them. These results suggest that either the incentives for researchers to publish in the journals differ markedly, or instead that their understanding of those incentives is uncertain and variable.

Impact factors exhibit no correlation with these directly-elicited journal assessments at either the aggregate level or for individual classes. The only citation metric that does correlate with peer assessment of career impacts, in aggregate and for some latent classes, is Article Influence. This suggests that using impact factors and most other citation metrics to assess the research of individuals and organizations seriously fails to capture the relative peer esteem associated with journals in agricultural, environmental, and resource economics.

The ordering of journals is markedly different when the criterion is impact beyond academia. Journals towards the bottom of the ranking in terms of career progression are top-ranked in terms of broader impact. The correlation between the 2 sets of journal scores was not close to significant at either the aggregate level or within any of the latent classes. Researchers do not perceive that publishing in journals that have a broader impact will advance their career, despite recent attempts to incorporate impact into research assessments.

Supplementary Material

Supplementary material is available at http://oxfordjournals.org/our_journals/ajae/online.

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