High-Ranked Social Science Journal Articles Can Be Identified from Early Citation Information

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Abstract

Do citations accumulate too slowly in the social sciences to be used to assess the quality of recent articles? I investigate whether this is the case using citation data for all articles in economics and political science published in 2006 and indexed in the Web of Science. Surprisingly, citations in the first one to two years after publication are highly predictive for cumulative citations received over a longer period. Journal impact factors improve the correlation between the predicted and actual future ranks of journal articles when using citation data from 2006 alone but the effect declines sharply thereafter.
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A 12, A 14

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Abstract

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JEL Codes: A12, A14

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1. Introduction

I show that, surprisingly, citations received by journal articles in the social sciences in the first one to two years after publication are predictive for citations received in future years. This finding is of interest because it is usually assumed that citations accumulate too slowly in social sciences apart from psychology to be useful for short-term research assessment (Anderson and Tressler, 2013). For example, the Australian Government’s Excellence in Research for Australia (ERA) exercise, which attempts to assess the research quality of universities in the previous 5 years, uses peer review in social science disciplines apart from psychology for this reason but uses citation analysis for psychology and all natural sciences. On the other hand, the Research Evaluation Framework (REF) in the United Kingdom uses peer review for all disciplines.¹ If it is actually possible to predict citations fairly reliably in social science disciplines, then it should also be easy to predict them in the natural sciences. If so, it would be possible to expand bibliometric analysis in such evaluation exercises to all disciplines apart from the humanities and arts.

There is an alternative to peer review and citation counting - using journal metrics such as the impact factor, which is widely used in many disciplines including economics to assess the potential quality of recently published papers (Stern, 2013). However, correlations between impact factors and the citations received by individual articles in the respective journals are low (Lozano et al., 2012) and have been much criticised (Vanclay, 2012). Hegarty and Walton (2012) show that article and reference list length are better predictors of citations to an individual article than the journal impact factor. On the other hand, Bertocchi et al. (2013) show that, at least in economics, there is a strong correlation between peer review assessment of an article’s quality and the impact factor of the journal it was published in.

In this paper, I use simple methods to test how well initial citations and journal impact factor can predict the future citations rankings of journal articles. I apply these methods to all journal articles included in the economics and political science categories in the Web of Science in 2006, tracking cumulative citations through 2012. These two fields represent a field where journal articles reign supreme (economics) and a field where books are also important (political science).

¹ Research evaluation exercises in other countries use different combinations of peer review
The absolute number of citations received by articles is much less important for evaluation purposes than determining which articles rank as high or low quality. Therefore, I compute the rank correlation between cumulative citations from 2006 to 2012 and the partial sums of citations for earlier years. Obviously, as citations accumulate, the rank correlation will increase, but how fast the correlation rises is of interest. As there is particular interest in whether we can predict which papers will be in the top quality categories, I also compute how many papers that were in various top quantiles in 2012 were already in those quantiles in earlier periods. Finally, I test whether adding information about the journal in which an article is published can help predict its future rank. Sgroi and Oswald (2013) suggest that though the impact factor is a very imperfect predictor of individual article citations it can serve in a similar fashion to a Bayesian prior before citation data arrives. Therefore, I estimate a series of simple regressions using the number of citations accumulated in a given initial period and impact factors to predict cumulative citations over the entire seven-year period. The regression coefficient of the impact factor should decline as the initial period is extended as suggested by Laband (2013). I test the predictive quality of these models by computing the rank correlation of their predicted citations and actual cumulative citations. The results show that using just citation data from the year of publication and the following year can explain more than half the variation in ranks after six years. Using data from the second year after publication as well increases the proportion of explained variance in ranks to more than three quarters. The results also show that the impact factor of the journal in which an article was published dramatically improves the correlation between predicted and actual ranks when using just data from the year of publication and also improves the predictions based on data accrued to one year after publication, but after that it adds little information. Finally, more than half of the papers in the top 20% in 2012 were already in the top 20% using just data for the year of publication (2006) and the following year (2007).

The remainder of the paper is structured as follows. After reviewing the existing literature on predicting future citations, I describe the data and the methods used. Then I present the results of the analysis and follow on to conclusions.
2. Review of Literature on Predicting Citations

Adams (2005) is the only previous study that uses a similar approach. Adams used citations to articles in the first two years after publication to predict citations in the next 3-10 years for all articles published in 1993 by UK researchers in six life and physical science fields. Correlations between 1993-94 and 1995-2002 citations ranged from 0.94 in biochemistry and biophysics to 0.617 for optics and acoustics. Our sample has a correlation of 0.692 between 2006-7 and 2008-12 citations for economics and 0.718 for political science. This shows that early citation numbers can have similar predictive power in the social sciences as in the natural sciences.

Bertsimas et al. (2014), use data on citations in the first five years following publication. They use indices of a scholar’s centrality in the coauthorship and citation networks to help predict citations to new papers in the management and information systems literature. They find that the most cited papers have much higher betweenness centrality in the citation network than do other papers. They use a logistic regression model to predict whether a paper will be in the top 0.1%, 0.5%, or 1% of cited papers in 2012 using the various centrality indices as predictors. They do not use the actual number of citations as a predictor.

There is a larger literature on predicting citations to articles based on factors knowable at the time of publication or prior to publication but not including initial citations (Fu and Aliferis, 2008; Ibañez et al., 2009; Lokker et al., 2009; Lovaglia, 1999; Walters, 2006). Additional indicators could be derived from this literature in a real world research assessment exercise. However, collecting information on authors or even the length of reference lists was prohibitively expensive for a journal article such as this and, therefore, I only use journal level information in addition to actual citations.

There are also papers that attempt to predict the number of citations that will be received by individual scientists in the future. Hirsch (2007) predicted the citations of 50 physicists at year 24 in their careers using data up till year 12. The h-index and the (square root of) total citations at year 12 both had a correlation of 0.89 with the (square root of) total citations at year 24. The h-index at year 12 had a correlation of 0.60 to the (square root of) number of citations to papers published only after year 12 at year 24.

Mazloumian (2012) followed this up using data from the Web of Science on the careers of around 150,000 scientists with non-ambiguous names. He finds that the annual rate of total
citations explains 80% of the variance in future citations to existing papers in the next year and 65% of the variance in the next ten years. These are somewhat more than that predicted by the h-index and the average number of citations per paper. Contrary to Hirsch (2007), none of these are good predictors of the citations received by as yet unpublished papers at the time of prediction.

Van Leeuwen (2012) investigates the correlation between the cumulative citations per article received by a journal for articles published in a given year in the year of their publication and each following year. Economics is one of the five Web of Science subject categories considered. The universe of journals is split into six groups according to the number of articles published in those journals. Correlations between citations in the year of publication and the cumulative citations in year two range from 0.28 to 0.89. But the correlations between cumulative citations in years two and three range from 0.94 to 0.99. This quick convergence suggests that year one and two citations are sufficient for prediction. It must be emphasized though that these correlations are at the journal level, not the article level; though the journals are sorted by size, total citations rather than impact factors are used; and cumulative citations rather than citations in each year are used. These choices will all increase the correlations relative to the alternatives.

Wang et al. (2013) ask whether there is long-term predictability in citation patterns. They derive a mechanistic model for the citation dynamics of individual papers, allowing them to collapse the citation histories of papers from different journals and disciplines into a single curve, indicating that all papers tend to follow the same universal temporal pattern. Their approach is to fit a model for the probability of a paper being cited at time \( t \):

\[
\Pi_i(t) \sim \eta_i c_i P(t),
\]

where \( \eta_i \) is a measure of the paper’s fitness, \( c_i \) is the citations it has already accumulated and \( P(\cdot) \) is a log-normal survival probability which depends on another two parameters \( \mu \) and \( \sigma \). The former measures “immediacy”, governing the time for a paper to reach its citation peak; and \( \sigma \) is longevity, capturing the decay rate. The model then can be solved to derive a time path for \( c_i \), for each individual paper \( i \) at time \( t \). This model can fit the data on paper citation histories extremely nicely as many different citation patterns can be modelled. However, it seems that a considerable number of data points are needed for each paper to get good estimates of the parameters. The authors make some predictions of future citations using 5 or
10 years of “training data”, but they use data with much higher than annual frequency. Still, predictions from the 5 years of data do not seem that good compared to those with ten. So, this does not seem to be a practical method of generating forecasts from very narrow early citation windows.

Stringer et al. (2008, 2010) show that in the long run the cumulative citations to articles cited at least once published in a given year in a given journal converge to a lognormal distribution. The distribution when no further citations are accumulating is termed the steady state. At any point in time, the distribution of citations to articles cited at least once follows a lognormal distribution truncated at zero. Over time the mean increases but the standard deviation stays constant. More specifically, the steady state citations of an article $i$ are given by:

$$C_i = 10^{q_i} \text{ if } C_i > 0,$$

where $q$ is the measure of quality or popularity that explains citations. $q$ follows a truncated normal distribution, truncated at zero from below with mean $\mu_j$ and standard deviation $\sigma_j$ where the subscript $j$ refers to a specific journal. Therefore, articles published in a specific journal share a common distribution of citations. Their analysis is based on data for more than 10 million articles from the Web of Science database. Stringer et al. (2010) find that only 30 of the 2184 journals they analyse do not follow this lognormal distribution. It seems that several of these are large multidisciplinary journals. These findings are useful in constructing a parametric model for forecasting cumulative citations.

3. Data

I collected from the Web of Science all citations from 2006 to 2012 to each article published in 2006 in all journals included in the 2012 JCR economics and political science subject categories that had articles published and an impact factor in 2006 and remain in the index to the present as indicated by having a 5 year impact factor for 2012. This sample period should be sufficient as McCabe and Snyder (in press) find that for economics journals the annual citation rate peaks five years after publication. I dropped two political science journals that had a zero impact factor in one year. Using “advanced search”, I restricted the search to the document type “articles” for items published in 2006 with results limited to 2006 to 2012. For some journals such as the Journal of Economic Literature or Journal of Economic Surveys this excludes a number of what are regular articles that are classified as “reviews”
but I decided not to make *ad hoc* changes to the sample. It also excludes proceedings papers from journals such as the *American Economic Review* and of course, book reviews, editorials etc. The advantage of restricting attention to the article category is that I have a presumably more homogenous dataset as far as type of article is concerned. I then requested a “citation report” from the database and downloaded the resulting file. In total the sample includes 184 economics journals, which published a total of 8,715 articles in 2006 that received a cumulative total of 95,771 citations in the *Web of Science* by 2012. There are also 79 political science journals, which published a total of 2,983 articles in 2006, which received a total of 25,260 citations in the *Web of Science* by 2012.

4. Methods

**Simple rank correlation**

I compute the cumulative citations from 2006 to 2012 for each article and the partial sums for 2006, 2006-7, …, and 2006-11. I then rank all articles in each year in each discipline separately by the partial sum of citations they received up to and including that year, giving a common rank to articles with a common number of accumulated citations. I then compute the rank correlations between the 2006-2012 cumulative citations and each of the partial sums.

**Regression Models**

I use a regression model to update an initial prediction based on the impact factor with incoming citation data as suggested by Sgroi and Oswald (2013). I use three functional forms to test the sensitivity to different specifications, though many more are obviously possible. The models are loosely based on the results of Stringer *et al.* (2008). The first regression model assumes that:

$$\ln(1 + C_{i,t}) = \beta_0 + \beta_1 \ln F_{i,t} + \beta_2 \ln(1 + C_{i,t}) + \epsilon_i \quad \text{For all } t = 1 \text{ to } T-1,$$

(3)

where $C_{i,t}$ is the partial sum of citations to article $i$ up till and including year $t$ and $F_{i,t}$ is the impact factor of the journal, $j$, in which the article was published in year $t$. Therefore, I update the impact factor as new information comes in. I add one to the citation variables in order to include articles with zero citations in the regression. I found that this model yields residuals whose absolute value is inversely related to the fitted values. An alternative model, which is often recommended for count data (e.g. McCullagh and Nelder, 1989), is to use the square root transformation instead of the logarithmic transformation:
\[ C_{it}^{0.5} = \beta_0 + \beta_1 F_{it}^{0.5} + \beta_2 C_{it}^{0.5} + \epsilon_{it} \quad \text{For all } t=1 \text{ to } T-1, \]  

This produces less heteroscedastic residuals, though the White (1980) and Breusch-Pagan (1979) heteroscedasticity tests are extremely significant for all models. As a result, I use robust standard errors clustered by journal for all regressions. Of course, if it is important to obtain more precise estimates for articles with high numbers of citations then the heteroscedastic nature of the logarithmic model is actually advantageous because the residuals for articles with high citations are proportionally smaller. For articles with low numbers of citations, a model that explicitly takes into account the count nature of the data might be more appropriate. I fit the Poisson model to the data to see how well this works in comparison to the models that assume that the dependent variable is continuous. Again loosely based on Stringer et al. (2008), for all those articles with at least one citation by year \( t \), I assume that the log of the mean of the distribution of the dependent variable can be modelled using:

\[ \ln E(C_{it}) = \beta_0 + \beta_1 \ln F_{it} + \beta_2 \ln C_{it} \quad \text{For all } t = 1 \text{ to } T-1 \text{ and } C_{it} \geq 1. \]  

For those articles with zero citations accumulated by year \( t \), I assume:

\[ \ln E(C_{it}) = \gamma_0 + \gamma_1 \ln F_{it} \quad \text{For all } t = 1 \text{ to } T-1 \text{ and } C_{it} = 0. \]  

I use the RATS command DDV to estimate these models. More sophisticated models such as the negative binomial could also be fitted to the data, but this should not substantially affect the estimated regression coefficients (Berk and Macdonald, 2008). As explained above, I use standard errors that take the heteroskedasticity into account.

For all these models, I predict the number of citations each article will accumulate by 2012 and I then round these predictions to the nearest integer. These rounded predictions are used to rank the articles. I then compute the rank correlation coefficients for the predicted cumulative citations in 2012 for each regression estimate and the actual 2012 cumulative citations.

Quantiles

I determined how many articles that were in the various top quantiles by cumulative citations in 2012 in each discipline were already in that top quantile in each previous year. The top 20%, 10%, 5%, 2%, 1%, and 0.5% of papers are considered.
5. Results

Table 1 presents the rank correlation coefficients and some additional statistics. The results for economics and political science are remarkably similar. From the fourth year on, the rate of additional citations a year is fairly constant at 20,000 for economics and 5,000 for political science. So, the citation rate seems to have settled into a steady state though total citations are of course far from the steady state as defined by Stringer et al. (2008). Not surprisingly, the cumulative citations in 2010 and 2011 are highly correlated with cumulative citations in 2012. The high correlation coefficients achieved early on when only a small fraction of the 2012 cumulative citations have accumulated are surprising. By the end of 2007, the correlation coefficient is 0.723 for economics when only 8.0% of citations have accumulated and is 0.724 for political science with only 8.5% of citations accumulated. These imply that 52-53% of the variance in ranks in 2012 can be explained with less than two years on average of citation data (as the average article was published in the middle of 2006). By the end of 2008 when only 22% of citations have accumulated the correlation coefficients are 0.880 and 0.871 implying that 76-77% of the variance in final ranks can already be explained. By the end of 2009 with only 40% of citations accumulated, 88-90% of the variance in final ranks can be explained.

Table 2 presents regression results for the logarithmic model for economics. As expected, the coefficient of the journal impact factor declines sharply as more citation data accumulates, whereas the coefficient of the log of the partial sum of citations is fairly constant and close to unity. This implies that a paper that has 1% more citations already in 2006 than another paper can be expected to have 1% more cumulative citations in 2012. Given that the elasticity with respect to the partial sum of citations is unity then the intercept term is the log of the ratio of expected cumulative citations in 2012 to the partial sum of citations in the given year for an article in a journal with an impact factor of 1. The R-squared rises strongly as expected. By the end of 2008, 70% of the variance in 2012 citations can be explained by the data accumulated to date.

Table 3 presents results using the square root transformation. These are similar to the results in Table 2. The intercept here is the expected square root of 2012 cumulative citations for an article with zero citations in the given year and a zero impact factor. This number is insignificantly different from zero in 2006 and in the last two years, but is significant in 2007-2009. Also, unlike the logarithmic model, the coefficient of cumulative citations
declines over time. This is because the multiplier of partial citations on cumulative citations must be time varying and declining to unity over time if the elasticity of cumulative citations with respect to partial citations is constant as we found above.

The Poisson regression models in Tables 4 and 5 are comparable to the logarithmic models in Table 2 as the model is for the log of the mean of the 2012 cumulative citations. However the dependent variable for the Poisson model is simply the number of cumulative citations and as explained above, there are separate models for articles that already received some citations and those that did not. The elasticity of the partial sum of citations rises towards unity over time and as a result the intercept needs to be larger. This suggests that articles that get some but not very many initial citations catch up with those that get more initial citations to some degree. The models for those articles without any citations in Table 5 also show a steep decline in the predictive power of the impact factor as shown by both the regression coefficient of the impact factor and the R-squared of the regression. The intercept term shows that an article that received no citations in 2006 published in a journal with an impact factor of 1 can still expect to receive a total of 10 citations by 2012. However, by 2009 we can predict that such an article will only get one citation.

Tables 6 to 9 present the regression results for political science. These are similar to those for economics, though, of course, the sample sizes are smaller and the standard errors larger. Comparing Table 6 to Table 2, the main difference is that the effect of the impact factor declines more slowly in political science. There is a similar pattern when using the square root model (Table 7 and Table 3). The greatest differences are for the Poisson models (Tables 8 and 4 and Tables 9 and 5). The R-squared in 2006 for equation (5) for political science is almost twice as large as that for economics. This is likely due to the slower rate of accumulation of citations in political science. Articles that already got any citations in the first year in political science are more clearly destined to be outstanding. The coefficient of the log of the partial sum of citations is also much larger in 2006 for political science than for economics. Here there is no catch-up effect for slow starting articles. There is a catch up effect in following years, but it is weaker than in economics. The results for equation (6) are even more different. For political science, the explanatory power of the impact factor for papers that did not yet receive any citations actually rises until 2008 and the size of the effect remains stronger than in economics though the R-squared eventually falls to a similar level in 2011. It seems that despite the lack of a catch-up effect among articles that already received
some citations in 2006 there are some high quality papers published in the higher impact journals, which are slow to receive citations. This effect is much weaker in economics.

Table 10 presents the correlations between the predicted ranks in 2012 using data up to the year given and the actual ranks. The correlations are similar to those in Table 1 with the exception of that for 2006. The results are remarkably similar across functional forms and disciplines despite the differences in the regression results documented above. Comparing Table 10 with Table 1, the R-Squared more than doubles for 2006 when the impact factor data is also used. However, in 2007 the additional information only adds 5-6% to the explained variance. By 2008 the additional explanatory power is only 2%. So while impact factors are useful in predicting future citations in the first year or two after publication, they add little explanatory power after that. An obvious criticism of the regression analysis in this paper is that if we want to carry out an evaluation exercise of a set of papers not long after they are published we will not have the information on future cumulative citations, which was used to estimate these regression models. But because the explanatory power of the impact factor declines rapidly, just using the rank analysis in Table 1 will be an adequate predictor of the future ranks of papers after a couple of years of information are acquired. It is not necessary to fit a model to data as we have done in Table 10 in order to generate good predictions. Even if a model is used, the exact functional form and parameter values do not seem to be important.

Table 11 shows what fraction of the papers in each indicated quantile was already in that quantile in earlier years. Because many papers have the same small number of citations, it is not possible to carry out the analysis for most quantiles in 2006. The fraction of the top 20% of articles in 2012 that were already in this quantile in 2006 is 28.7% for economics. This doubles after one year to 59% in 2007. It seems that it is more difficult to predict which papers would be in the very top quantiles in that year, though the sample size is, of course, much smaller for the higher quantiles. By 2008, three quarters of the top 20% papers can be predicted. Therefore, this seems a fairly useful tool for assessing which departments, for example, have publications in the top 20% only 2-3 years after publication.

Again, the results for political science are similar to those for economics (Table 10) though there seems to be a little less predictability in the earlier years or for the top 0.5% quantile.
6. Conclusions

The desire to rank articles, researchers, and institutions (Stern, 2013) is not likely to diminish, as ranking behaviour is inherent in humans (Heffetz and Frank, 2011) and, of course, other primates (Seyfarth, 1981). The question is how to carry out a ranking in an accurate and cost-effective way. I find in this paper that it is possible to forecast the future citations rank of journal articles in two social science disciplines to a fairly high degree of accuracy using data available within the first two to three years following publication. This data is available to subscribers to the Web of Science database and only takes at most a couple of days work for a single researcher to download and process for one discipline. This is obviously much more cost effective than the large secondary peer review based research assessments carried out regularly in the UK, Australia, and other countries. I also found that the journal impact factor is quite useful in predicting future citations and rank in the first two years following publication. However, its usefulness drops steeply as more actual citations data accumulates. It more than doubles the explained variance in rank in 2012 using just data from 2006. But by the third year it only adds 2% to the explained variance. This means that ranking by accumulated citations in the first 2-3 years following publication should be sufficient to predict the future citation ranking of journal articles in these disciplines.

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Table 1. Rank Correlations

|                     | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 |
|---------------------|------|------|------|------|------|------|
| **Economics**       |      |      |      |      |      |      |
| Rank Correlation Coefficient | 0.359 | 0.729 | 0.880 | 0.949 | 0.977 | 0.993 |
| R-Squared           | 0.129 | 0.532 | 0.774 | 0.900 | 0.955 | 0.985 |
| Number of Cumulative Citations | 1,379 | 7,705 | 20,570 | 37,586 | 56,052 | 75,802 |
| Percentage of Final Citations | 1.4% | 8.0% | 21.5% | 39.5% | 58.5% | 79.1% |
| **Political Science** |      |      |      |      |      |      |
| Rank Correlation Coefficient | 0.380 | 0.723 | 0.871 | 0.939 | 0.973 | 0.991 |
| R-Squared           | 0.144 | 0.523 | 0.758 | 0.882 | 0.947 | 0.983 |
| Number of Cumulative Citations | 417 | 2,140 | 5,648 | 10,124 | 14,811 | 19,936 |
| Percentage of Final Citations | 1.7% | 8.5% | 22.4% | 40.1% | 58.6% | 78.9% |
Table 2. Regression Results, Logarithmic Model: Economics

|       | Constant (std) | Log Impact Factor (std) | Log of Partial Sum of Citations (std) | R-Squared |
|-------|----------------|-------------------------|---------------------------------------|-----------|
| 2006  | 1.998 (0.027)  | 0.680 (0.037)           | 1.004 (0.040)                         | 0.302     |
| 2007  | 1.580 (0.026)  | 0.438 (0.026)           | 1.008 (0.019)                         | 0.500     |
| 2008  | 1.029 (0.021)  | 0.269 (0.019)           | 1.028 (0.012)                         | 0.701     |
| 2009  | 0.611 (0.015)  | 0.125 (0.012)           | 1.044 (0.008)                         | 0.839     |
| 2010  | 0.330 (0.010)  | 0.069 (0.008)           | 1.035 (0.005)                         | 0.922     |
| 2011  | 0.142 (0.008)  | 0.031 (0.004)           | 1.016 (0.003)                         | 0.969     |

Standard errors in parentheses

Table 3. Regression Results, Square Root Model: Economics

|       | Constant (std) | Square Root of Impact Factor (std) | Square Root of Partial Sum of Citations (std) | R-Squared |
|-------|----------------|-----------------------------------|-----------------------------------------------|-----------|
| 2006  | 0.048 (0.137)  | 2.687 (0.161)                     | 1.458 (0.081)                                 | 0.325     |
| 2007  | 0.343 (0.101)  | 1.627 (0.115)                     | 1.469 (0.042)                                 | 0.535     |
| 2008  | 0.159 (0.066)  | 0.917 (0.062)                     | 1.422 (0.029)                                 | 0.734     |
| 2009  | 0.100 (0.044)  | 0.393 (0.040)                     | 1.337 (0.018)                                 | 0.863     |
| 2010  | 0.022 (0.027)  | 0.179 (0.026)                     | 1.217 (0.009)                                 | 0.937     |
| 2011  | -0.017 (0.013) | 0.080 (0.013)                     | 1.098 (0.004)                                 | 0.978     |

Standard errors in parentheses
Table 4. Regression Results, Poisson Model, Equation (5): Economics

| Year | Constant (SE) | Log Impact Factor (SE) | Log of Partial Sum of Citations (SE) | R-Squared |
|------|---------------|------------------------|--------------------------------------|-----------|
| 2006 | 2.938 (0.039) | 0.714 (0.069)          | 0.670 (0.079)                        | 0.278     |
| 2007 | 2.340 (0.026) | 0.415 (0.037)          | 0.773 (0.022)                        | 0.546     |
| 2008 | 1.595 (0.020) | 0.259 (0.019)          | 0.861 (0.012)                        | 0.775     |
| 2009 | 0.973 (0.014) | 0.121 (0.013)          | 0.949 (0.007)                        | 0.897     |
| 2010 | 0.540 (0.011) | 0.063 (0.009)          | 0.984 (0.005)                        | 0.955     |
| 2011 | 0.227 (0.007) | 0.024 (0.004)          | 0.998 (0.003)                        | 0.987     |

Standard errors in parentheses

Table 5. Regression Results, Poisson Model, Equation (6): Economics

| Year | Constant (SE) | Log Impact Factor (SE) | R-Squared |
|------|---------------|------------------------|-----------|
| 2006 | 2.321 (0.027) | 0.859 (0.044)          | 0.185     |
| 2007 | 1.799 (0.030) | 0.608 (0.039)          | 0.124     |
| 2008 | 1.027 (0.034) | 0.459 (0.048)          | 0.059     |
| 2009 | 0.250 (0.048) | 0.290 (0.059)          | 0.024     |
| 2010 | -0.548 (0.065)| 0.286 (0.077)          | 0.014     |
| 2011 | -0.537 (0.067)| 0.276 (0.068)          | 0.014     |

Standard errors in parentheses
Table 6. Regression Results, Logarithmic Model: Political Science

|      | Constant | Log Impact Factor | Log of Partial Sum of Citations | R-Squared |
|------|----------|-------------------|---------------------------------|-----------|
| 2006 | 1.948    | 0.710             | 1.060                           | 0.397     |
|      | (0.064)  | (0.093)           | (0.071)                         |           |
| 2007 | 1.525    | 0.597             | 1.069                           | 0.594     |
|      | (0.053)  | (0.075)           | (0.034)                         |           |
| 2008 | 0.981    | 0.385             | 1.045                           | 0.765     |
|      | (0.038)  | (0.046)           | (0.022)                         |           |
| 2009 | 0.538    | 0.211             | 1.068                           | 0.860     |
|      | (0.056)  | (0.023)           | (0.029)                         |           |
| 2010 | 0.289    | 0.096             | 1.057                           | 0.930     |
|      | (0.043)  | (0.011)           | (0.020)                         |           |
| 2011 | 0.106    | 0.032             | 1.034                           | 0.974     |
|      | (0.024)  | (0.007)           | (0.011)                         |           |

Standard errors in parentheses
Table 7. Regression Results, Square Root Model: Political Science

| Year | Constant     | Square Root of Impact Factor | Square Root of Partial Sum of Citations | R-Squared |
|------|--------------|-----------------------------|---------------------------------------|-----------|
| 2006 | -0.216 (0.349) | 2.851 (0.419)               | 1.606 (0.224)                         | 0.361     |
| 2007 | -0.304 (0.237) | 2.201 (0.267)               | 1.510 (0.074)                         | 0.590     |
| 2008 | -0.203 (0.127) | 1.217 (0.145)               | 1.418 (0.047)                         | 0.770     |
| 2009 | -0.141 (0.081) | 0.604 (0.080)               | 1.325 (0.031)                         | 0.873     |
| 2010 | -0.071 (0.037) | 0.287 (0.041)               | 1.208 (0.017)                         | 0.941     |
| 2011 | -0.018 (0.015) | 0.066 (0.022)               | 1.105 (0.008)                         | 0.980     |

Standard errors in parentheses

Table 8. Regression Results, Poisson Model, Equation (5): Political Science

| Year | Constant     | Log Impact Factor     | Log of Partial Sum of Citations | R-Squared |
|------|--------------|-----------------------|---------------------------------|-----------|
| 2006 | 2.777 (0.090) | 0.687 (0.089)         | 1.164 (0.217)                   | 0.498     |
| 2007 | 2.283 (0.060) | 0.489 (0.065)         | 0.845 (0.054)                   | 0.584     |
| 2008 | 1.510 (0.051) | 0.268 (0.046)         | 0.908 (0.046)                   | 0.813     |
| 2009 | 0.908 (0.042) | 0.160 (0.025)         | 0.971 (0.023)                   | 0.904     |
| 2010 | 0.528 (0.032) | 0.080 (0.015)         | 0.991 (0.014)                   | 0.959     |
| 2011 | 0.215 (0.015) | 0.028 (0.007)         | 1.005 (0.006)                   | 0.990     |

Standard errors in parentheses
Table 9. Regression Results, Poisson Model, Equation (6): Political Science

| Year | Constant (SE) | Log Impact Factor (SE) | R-Squared (SE) |
|------|---------------|------------------------|---------------|
| 2006 | 2.286 (0.070) | 0.850 (0.122)          | 0.153         |
| 2007 | 1.742 (0.066) | 0.893 (0.135)          | 0.169         |
| 2008 | 0.961 (0.069) | 0.930 (0.145)          | 0.179         |
| 2009 | 0.129 (0.013) | 0.894 (0.021)          | 0.096         |
| 2010 | -0.726 (0.189)| 0.811 (0.253)          | 0.067         |
| 2011 | -1.996 (0.378)| 0.600 (0.179)          | 0.013         |

Standard errors in parentheses
Table 10. Predicted Rank Correlations

|                      | 2006  | 2007  | 2008  | 2009  | 2010  | 2011  |
|----------------------|-------|-------|-------|-------|-------|-------|
| **Economics**        |       |       |       |       |       |       |
| **Logarithmic**      |       |       |       |       |       |       |
| Rank Correlation     | 0.543 | 0.765 | 0.890 | 0.952 | 0.978 | 0.993 |
| R-Squared            | 0.295 | 0.586 | 0.792 | 0.906 | 0.957 | 0.985 |
| **Square Root**      |       |       |       |       |       |       |
| Rank Correlation     | 0.547 | 0.744 | 0.879 | 0.952 | 0.975 | 0.992 |
| R-Squared            | 0.300 | 0.553 | 0.773 | 0.906 | 0.952 | 0.983 |
| **Poisson**          |       |       |       |       |       |       |
| Rank Correlation     | 0.554 | 0.762 | 0.886 | 0.949 | 0.977 | 0.991 |
| R-Squared            | 0.307 | 0.580 | 0.786 | 0.901 | 0.954 | 0.983 |
| **Political Science**|       |       |       |       |       |       |
| **Logarithmic**      |       |       |       |       |       |       |
| Rank Correlation     | 0.540 | 0.765 | 0.879 | 0.941 | 0.974 | 0.991 |
| R-Squared            | 0.291 | 0.585 | 0.772 | 0.886 | 0.949 | 0.983 |
| **Square Root**      |       |       |       |       |       |       |
| Rank Correlation     | 0.528 | 0.753 | 0.873 | 0.939 | 0.973 | 0.991 |
| R-Squared            | 0.279 | 0.567 | 0.762 | 0.881 | 0.946 | 0.982 |
| **Poisson**          |       |       |       |       |       |       |
| Rank Correlation     | 0.530 | 0.764 | 0.881 | 0.941 | 0.973 | 0.990 |
| R-Squared            | 0.281 | 0.584 | 0.776 | 0.886 | 0.947 | 0.979 |
Table 11. Quantile Persistence: Economics

| Top  | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 |
|------|------|------|------|------|------|------|
| 20%  | 0.29 | 0.59 | 0.75 | 0.80 | 0.88 | 0.93 |
| 10%  | n.a. | 0.55 | 0.74 | 0.78 | 0.89 | 0.91 |
| 5%   | n.a. | 0.54 | 0.66 | 0.84 | 0.91 | 0.94 |
| 2%   | n.a. | 0.57 | 0.71 | 0.81 | 0.87 | 0.94 |
| 1%   | 0.17 | 0.48 | 0.70 | 0.80 | 0.88 | 0.92 |
| 0.5% | n.a. | 0.46 | 0.70 | 0.81 | 0.81 | 0.88 |

Table 12. Quantile Persistence: Political Science

| Top  | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 |
|------|------|------|------|------|------|------|
| 20%  | n.a. | n.a. | 0.84 | 0.82 | 0.90 | 0.96 |
| 10%  | 0.45 | n.a. | 0.62 | 0.77 | 0.87 | 0.89 |
| 5%   | n.a. | 0.48 | 0.65 | 0.78 | 0.85 | 0.94 |
| 2%   | n.a. | n.a. | 0.66 | 0.79 | 0.91 | 0.91 |
| 1%   | n.a. | 0.37 | 0.67 | 0.73 | 0.90 | 0.97 |
| 0.5% | n.a. | 0.40 | 0.53 | 0.73 | 0.73 | 0.80 |