Academic Productivity and Quality –How Do They Change with Age?

Andrew Pirola-Merlo

Department of Management

Monash University

andrew.pirola-merlo@buseco.monash.edu.au

Abstract

A study of the relationship between age and innovative productivity among organizational psychology researchers was conducted. The study analysed the publication records of a sample of organizational psychologists, and focused on the outcome measures of productivity (number of articles published per 2-year period) and research impact (number of times each article was cited within five years of publication). Regression and Hierarchical Linear Modeling (HLM) analyses identified a trend of decreasing productivity over time, consistent with previous research. However, research impact showed an early-career peak, followed by a decline to a minimum approximately 21 years after first publication, followed by a dramatic increase over approximately the last decade of a researcher's career.

The workforce in Australia is ageing at one of the fastest rates among OECD countries. The impact of this is an issue of national significance, as reflected in the Australian Research Council (ARC) national priorities and in the recent report by the Productivity Commission on the economic impact of an ageing workforce. The Productivity Commission's report concluded that Australia needs to continue to increase its productivity rates if it is to meet the health and welfare implications of an older population (Productivity Commission, 2004). Therefore, with an ageing workforce an important question is how productivity changes with age.

The Relation Between Age and Innovative Productivity

The major approach by behavioural scientists to studying how productivity changes with age has been to examine innovative outputs. By innovation, I mean the application or implementation of something that is new and useful (Ford, 1996; West & Farr, 1990). Thus, researchers have examined how age relates to outputs that represent major career milestones, such as musical compositions (Simonton, 2000) or poems (Lehman, 1953). The most significant work in this area was conducted by Lehman (1953), who collected data concerning the ages at which professionals in a range of fields made their most significant achievements. Lehman's data included research publications by mathematicians, chemists, physicists and psychologists, literary works by poets, patents filed by inventors, etc. Lehman's data shows a remarkable consistency in the general shape of the relation between age and productivity (of innovative and non-innovative types). In all of the fields studied, the data shows an increase in productivity with age up until a peak is reached, which is followed by a decline in later years. The rise in productivity tends to be more rapid than the decline, resulting in a single-modal, positively skewed shape. Although the general form of the shape is consistent across fields, the age at which the peak is reached varies from field to field. Even among different scientific disciplines there is variation. For example, mathematicians peak at an earlier age than geologists (Simonton, 1997).

Simonton (1997) developed a mathematical formula linking age with innovative productivity. This shows innovative productivity as a function of two profession-related parameters, rate of ideation and rate of elaboration or conversion into products, and two individual difference parameters, namely age of career onset and initial creativity potential. The model is shown in Figure 1. This model has a number of merits. Firstly, it accounts for variation both between fields of endeavour, and between individuals within fields. Secondly, although it is consistent with empirical evidence, this is a theoretical model rather than an empirical (e.g. regression) model. This means that the parameters, unlike those of a polynomial regression which shows the same curve, are substantively interpretable.

[INSERT FIGURE 1 ABOUT HERE]

The major limitation of Simonton's (1997) approach, which forms the basis of this paper, is that it does not easily enable analysis of the types of external factors that impact on individuals during their careers. Simonton notes that studying aggregated data, made up of the career profiles of a sample of people, is preferable to studying individual career profiles, which may or may not reflect the general trend shown in Figure 1. He points out that studying individual profiles introduces random confounds in the way of life events and external influences that are difficult to control for. However, to draw general conclusions about career trajectories on the basis of average productivity data from a sample of individuals risks committing the compositional fallacy (Kozlowski & Klein, 2000). That is, the relationship that holds at the group level may not apply to any of the individuals within the group. In other words, the question remains as to whether the pattern shown in Figure 1 is recognizable among individual career trajectories. This paper attempts to identify the extent to which individuals vary in their age-innovation trajectories.

Another contribution of this study is the analysis of two different criteria relating to innovative productivity, namely quantity and quality. A great deal of the research on age and productivity among academics (e.g. Horner, Rushton, & Vernon, 1986; Howard & Curtin, 1993; Over, 1982, 1989; Simonton, 1997) has used numbers of published works to measure productivity. However, quantity and quality of published works may be two independent criteria. This is supported by Dewett & Denisi (2004), who showed that quantity and quality of management scholars' works make independent contributions to explaining their scholarly reputation. Additionally, Over (1989) showed that significantly more high-impact publications are produced by young psychologists than older psychologists. However, when accounting for relative numbers of publications by different age groups, there was no evidence that publications from older scientists have less impact.

Thus, the quality and quantity of research outputs should be examined together, if valid conclusions about creative ability and innovative productivity are to be reached. In this author's view, analysis of the quality of research lends itself more readily to conclusions about how creativity changes throughout adulthood. Analysis of quantity produced, on the other hand, arguably relates in part to other factors, such as an individual's resources and ability to efficiently convert ideas into published works. That is, quantity relates more to the implementation aspect of innovation and quality relates more to the creativity aspect of innovation. I view these distinctions as a matter of emphasis rather than absolutes, but assert that consideration of both criteria leads to a more complete understanding of this topic. It is worth noting that in making the above argument, I implicitly reject two of the assumptions of Simonton's (1997) mathematical model of innovative productivity: specifically, Simonton's assumptions that both an individual's ideation rate and also their rate of conversion of ideas into products are constant throughout adulthood. Consistent with my argument, McCrae, Arenberg, and Costa (1987) report empirical evidence of a decline in ideational fluency with age.

Using HLM to Examine Age-Innovation Profiles

Hierarchical linear modeling (HLM) is an analytical technique that allows researchers to fit regression models at multiple levels of aggregation in a single analysis. In many applied settings individuals are nested within groups. As such, questions such as how group characteristics impact on individuals cannot be tested using traditional regression techniques, which assume independence of observations. HLM analyses allow for nested observations. For example, Pirola-Merlo (2004) used

HLM to test a multi-level model of team creativity, by analyzing the relations between team climate, team innovation and individual (team member) innovation.

The most common use of HLM is to analyse ratings of a group phenomenon (e.g. team or organisational climate) together with individual ratings (e.g. individual/team member motivation or performance). However, HLM can also be used to analyse stability and change in longitudinal data (Bryk & Raudenbush, 1992). By identifying individual identity as a higher-level category within which several observations at different points of time are collected, HLM views repeated observations as being nested within individuals.

In this context, the level-1 model describes the intra-individual pattern of change over time. The analysis fits a separate regression separately for each individual. The extent to which regression parameters vary *between* individuals can then be examined. For example, Deadrick, Bennett and Russell (1997) showed that over a 24-week period, a sample of sewing machine operators showed a systematic linear change in performance over time. However, there were also significant inter-individual differences in performance trends (operators with lower initial performance improved faster), and rates of improvement were also predicted by individual characteristics (specifically, cognitive ability and experience). Similarly, Hofmann, Jacobs and Baratta (1993) showed a curvilinear relationship between time and performance of sales personnel. In this study also, individuals varied significantly in their performance trajectories.

A study that utilized HLM to analyse longitudinal data of innovative productivity was conducted by Zickar and Slaughter (1999). These authors examined the critical reviews received for the films directed by 73 directors during their careers. The order of each film within a director’s career was used instead of calendar time as an independent variable. The results showed that the typical director’s creative performance improved over the beginning of their career and tended to significantly decline after about ten films. These results are similar to Lehman’s (1953) research findings that indicated performance generally increased initially and eventually declined. Zicker and Slaugter’s results also indicated that performance trajectories significantly differed intra-individually (i.e., individuals varied in their initial performance level and their rate of increase/decrease). It was also found that directors who directed a greater number of films per year tended to improve their creative performance when compared to those who directed fewer films per year.

HLM analysis provides a means to investigate intra-individual change patterns in performance across time and to determine whether inter-individual differences exist in these change patterns (Hofman et al., 1993). Through implementing HLM analyses, this study aimed to extend our understanding of the innovative performance trajectories of academics, specifically organizational psychologists.

A Study of the Innovative Productivity of Organisational Researchers

This paper describes a study that attempts to contribute to Simonton's work in two ways. Firstly, it takes advantage of the HLM technique to estimate the extent to which individuals vary in their age-innovation trajectories. Secondly, it extends previous work on the age-productivity relation by incorporating measures of both innovative productivity *and* innovative quality.

Previous studies of age and innovative productivity of academic researchers (e.g. Lehman, 1953) have used the publications records of deceased researchers, in order to ensure data pertain to the entire careers of the researchers. One of the advantages of HLM is its ability to deal with missing data (Zickar & Slaughter, 1999). This enables publication data from still-living researchers to be analysed, because some individuals in the sample will be early-career researchers and others will be in the twighlight of their careers. HLM will simply estimate regression parameters based on non-missing data.

Method

Data

In order to examine career trajectories, a 20-year period was selected: 1983 – 2002. This was used because, at the time this study was conducted (during 2005) it was the most recent 20 year period that still allowed a 2-year gap (from 2003 – 2004) to ascertain the impact of the most recent works. A two-step process was used to obtain data. Firstly, a sample of researchers actively publishing in the area of organizational psychology during this period was obtained. Secondly, measures of research productivity and impact (relating broadly to quantity and quality) were obtained for these researchers via Social Sciences Citation Index (SSCI). These steps are described below.

The sample was obtained by searching for a range of subject headings and key terms relating to organizational psychology in the PsychInfo database. Appendix A shows the search terms used. The search was limited to journal articles, published in the English language, from 1983-2002. This resulted in 20,997 articles (after removing duplicates). From this list, the first author's names were extracted into a database. This was then further analysed to identify authors who published at least one first-authored journal article in *each* of the following five-year periods: 1983-1987; 1988-1992; 1993-1997; 1998-2002. This resulted in identification of a mere 158 individuals.

A sample of 44 of these individuals was selected. This represents 28% of the total population of organizational psychology researchers who actively published in English during the period 1983-2002 (according to the criteria outlined above). For this sample, the entire publication record (i.e., including pre-1983 and post-2002) was obtained from the SSCI, and manually screened to ensure records did not confuse different individuals with the same surname and initials. Additionally, the citation information (number of times each publication was cited) was also obtained from the SSCI for a subset of 23 of these researchers.

Only the citation records for articles published in the period 1983-2002 was obtained. From this, two measures of scholarly impact were obtained: the number of citations within 2 years after the publication year; and the number of citations within 4 years after the publication year. These periods were chosen because citations within 2 years is equivalent to the "impact factor" used to rank journal articles. However, it was observed that many articles were only just beginning to be cited after 1-2 years, and so citations within 4 years were also measured. For the purpose of clarity only analyses using the 5-year impact (i.e. number of citations in the publication year plus the next four years) is reported here. Thus, citation data were based on articles published between 1983 and 2000.

The publication data were collapsed into 2-year intervals (from 1983 – 2000), in order to reduce the amount of random fluctuation in productivity from one time interval to the next. Consistent with previous research (c.f. Simonton, 1987), career-age rather than chronological age was examined. Accordingly, each person's publication data was coded relative to the year of their first publication, rather than chronological time. Time was coded such that the first year that an author ever published an academic journal article (as first or subsequent author) became time = 0 for that individual. So for example, for one researcher, 1985 might be time = 3 (if they had first published in 1979 (ie, 3 x 2 year blocks previously). For another researcher, their publications from 1985 would be coded as time = 0, if this was the first year they had published. Centering the time variable in this way means that in a regression analysis, the intercept term represents the *initial* publication rate –that is, how many publications a researcher produced in the first two-year block of their publication history.

Analyses

Publication and impact (citation) data were analysed using traditional (OLS) hierarchical regression, using year, year-squared and year-cubed as independent variables. This analysis was conducted using a data file aggregated by year, in order to show the average career trajectory (i.e. how many publications are produced per year per person on average). The aggregated data contained only 17 data points (corresponding to 17 x 2-year blocks), and thus the regression analysis lacked sufficient power to test the significance of individual predictors (the three polynomial effects of time). Therefore, the regression models were assessed using the criteria that each should be significant overall according to the F-value, and that each addition of a predictor should be accompanied by an increase in the R-squared value.

Following the OLS regression, a series of HLM analyses were conducted, using the following procedure: Firstly, the number of first-authored journal articles was entered as the (level-1) dependent variable. This model, sometimes referred to as a one-way analysis of variance model, predicted productivity at any given time by the average productivity of the entire sample, and also by a residual term representing the deviation of the individual's (across-time) average productivity from the sample's average productivity. The variation of the residual term indicated the amount of inter-individual variation in productivity. Secondly, a process similar to backwards regression was performed, in which year, year-squared and year-cubed were entered as level-1 predictors, with each predictor freed to vary between individuals (that is, each predictor was analysed as a random effect). If any of the random effects were non-significant, they were removed one at a time, in order of their level of significance (least significant removed first), until only significant random effects remained in the model.

In his analysis of journal citations, Simonton found citations to be very skewed, and applied a log transformation before analysis. Similarly, the impact variable in this study was very skewed, and so a log transformation was applied. However, analyses conducted using both the transformed and un-transformed variables yielded essentially the same results. The results for the un-transformed variable are reported as they are easier to interpret and are consistent with the transformed results.

Results

OLS Analyses

The results of the OLS regressions using the aggregated productivity data are shown in Table 1. These indicate that time and time-squared contribute to the R-squared of .63, but time-cubed adds no further contribution to R-squared. The observed data as well as the regression line using time and time-squared are shown in Figure 2.

[INSERT TABLE 1 ABOUT HERE]

[INSERT FIGURE 2 ABOUT HERE]

The results of the OLS regressions using the aggregated impact (i.e. citation) data are shown in Table 2. Unlike the previous analysis using productivity data, the regressions on impact showed that all three polynomials make large contributions to predicting performance across time. The observed data as well as the regression line using time and time-squared are shown in Figure 3.

[INSERT TABLE 2 ABOUT HERE]

[INSERT FIGURE 3 ABOUT HERE]

HLM Analyses

The HLM analyses of the productivity data showed that 12% of variation in productivity was attributable to inter-individual differences. That is, the intraclass correlation coefficient (ICC(1)) value was .12. The analysis indicated that only two random factors were significant: those for the intercept (Chi-square (39) = 114.40, $p < .01$) and the linear function of time (Chi-square(39) = 75.40, $p < .01$). The results indicated that 63% of the variation in the intercept term and 39% of variation in the linear (function of time) term was systematic across individuals. The intercept was the only significant fixed effect, with a coefficient of 2.14 ($t(40) = 7.11$, $p < .01$), indicating that on average individuals published 2.14 articles within an initial 2-year period. The effect of time on productivity varied significantly between individuals, with some individuals showing increases in productivity over time and some showing decreases (indicated by positive and negative coefficients). The average coefficient for the linear function of time was -.09, but the standard deviation was .11. Thus, an individual one-standard deviation below the average would show a decrease of .20 publications per two-year period.

The HLM analysis for publication impact showed that 41% of variation in publications was attributable to inter-individual differences. That is, there was an ICC(1) value of .41. When all four random effects were added to the model (that is, the intercept and the three polynomial functions of time) all random effects were significant. The results indicated that the percentage of systematic variation between individuals in the regression terms was 37% for the intercept, 33% for time, 17% for time-squared and 6% for time-cubed. The null hypothesis that individuals do not vary in these parameter estimates was rejected according to chi-square tests. The variance components and chi-square values are shown in Table 3. The fixed effects were all non-significant, except for the intercept, which had a coefficient of 2.53 ($t(40) = 2.05$, $p < .05$). This indicates that on average, researchers achieved a total of 2.53 citations (within 5 years of publication) for works produced in the first two years of their publishing career. The average coefficients for time, time-squared and time-cubed were 5.96, -1.96 and .15 respectively, confirming the general shape of the average career trajectory shown in Figure 3, with an initial increase, followed by a decrease which eventually levels and increases once more.

[INSERT TABLE 3 ABOUT HERE]

Discussion

The results of the OLS regression analyses indicated that when focusing on first-authored journal articles as a productivity measure, the average career trajectory shows a decline in productivity over time, but that this decline levels off and eventually begins a slight incline approximately 26 years after first publication. However, of particular interest is the significant variation between individuals in their productivity profiles. There was significant variation between individuals in the initial rate of productivity (as indicated by the intercept term in the HLM). Further, the extent to which individuals increased or decreased in their productivity over time varied significantly from person to person.

The results of the OLS regression for impact showed an average trend that initially increased to a peak within approximately 7 years, followed by a decline towards a trough over the next 14 years, after which research impact increased quite dramatically over the final 11 years analysed in this study. Again, however, the variation between individual profiles was considerable –even more so than for productivity. Individuals varied significantly in the intercept, representing the impact of a researcher's initial work. Further, individuals varied significantly in the three functions of time: the linear, square and cube functions of time. This indicates that there were large individual differences in the extent to which researchers showed an initial increase or decrease in their impact, and also in the rate and extent of any reversal of an initial increase or decrease.

The pattern of an early-career peak in innovative productivity followed by a decline, as found here, is consistent with previous research (e.g. Horner, Rushton, & Howard & Curtin, 1993; Lehman, 1953; Over, 1982, 1989; Simonton, 1997; Vernon, 1986). However, the eventual increase in performance in later years, particularly for the impact measure, is inconsistent with previous analyses of researcher productivity. As discussed above, previous studies have focused on productivity, without also examining research impact. Alternatively, researchers such as Lehman (1953) have selected only high-impact publications, and have matched these against the age of the person producing them. However, to date an analysis that examines research impact among a representative sample of researchers within a field has been lacking.

This increase in research impact during later years of a researcher's career is particularly noteworthy in the context of the very small change in number of articles published (compare Figures 2 and 3). This indicates that on a per-publication basis, researchers do greatly increase in their research impact in the period after approximately 26 years. If we assume that most academics begin their publishing career at around 28-30 years of age, then the period where impact greatly rises corresponds to an individual aged approximately 60 years. This is a period when many academics experience a lighter administrative load and in some cases retire from teaching duties in order to focus on research.

This highlights the potential impact of external events in shaping researchers' career profiles. It also highlights the strength of the HLM approach to this topic: if data pertaining to events such as promotion, change of institution, teaching/administrative load and success in research grants were collected, these could be incorporated as level-1 variables in the HLM, to ascertain their impact on individual researcher productivity and impact. Additionally, factors such as personality, age, country, and methodological/theoretical orientation could be analysed as level-2 (between persons) variables. HLM would enable the impact of these on the career trajectories of researchers to be estimated.

One of the limitations of the present study is the relatively small sample, with publication records analysed for only 44 individuals, and research impact (citations) analysed for only 23 of these. Although the data are available via citation databases, they are difficult to extract. For example, the current data pertaining to 44 researchers includes data for 1469 individual publications. Obtaining the number of citations –only those within 4 years of the publication itself – for each of those 1469 publications is very time consuming. However, given the small size of the population -158 active researchers in organizational psychology between 1983 and 2002 –it is very feasible to administer biographical and personality data to the entire population, and to continue collecting complete citation data.

The present study has established the usefulness of HLM for the analysis of researcher productivity and impact data. By showing that large between-person variation exists in publication trajectories, and that there are systematic effects of time, this study provides a first-step towards a comprehensive model of age and innovative productivity that includes intra-individual (e.g. personality) and external (e.g. teaching load; organizational climate) predictors.

At a practical level, this study also makes the important contribution of identifying a trend towards high impact work in the later years of researchers' careers. This is a welcome corollary to previous publications in a range of forums (e.g. Productivity Commission, 2004) which conclude that older workers are less productive than their younger counterparts.

Figures and Tables

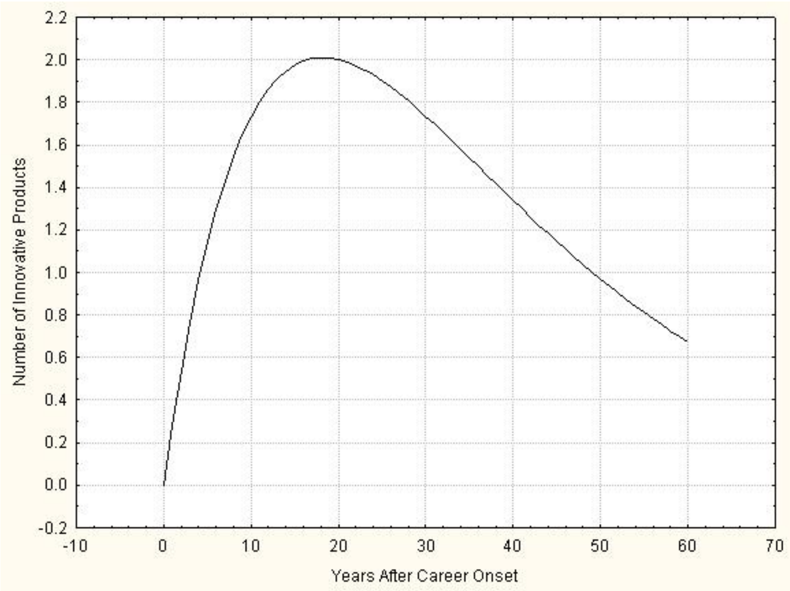

Figure 1. *Simonton's (1997) Mathematical Model of Age and Innovative Productivity.*

Table 1: *OLS regression of effects of time on number of journal articles authored.*

					Regression coefficients			
Predictors	R^2	F	d.f.	p	intercept	time	$time^2$	$time^3$
time	.59	21.92	15	.000	2.10	-.05		
time $time^2$	.63	11.96	14	.001	2.21	-.09	.00	
time $time^2$ $time^3$	.63	7.41	13	.004	2.22	-.10	.00	-.00

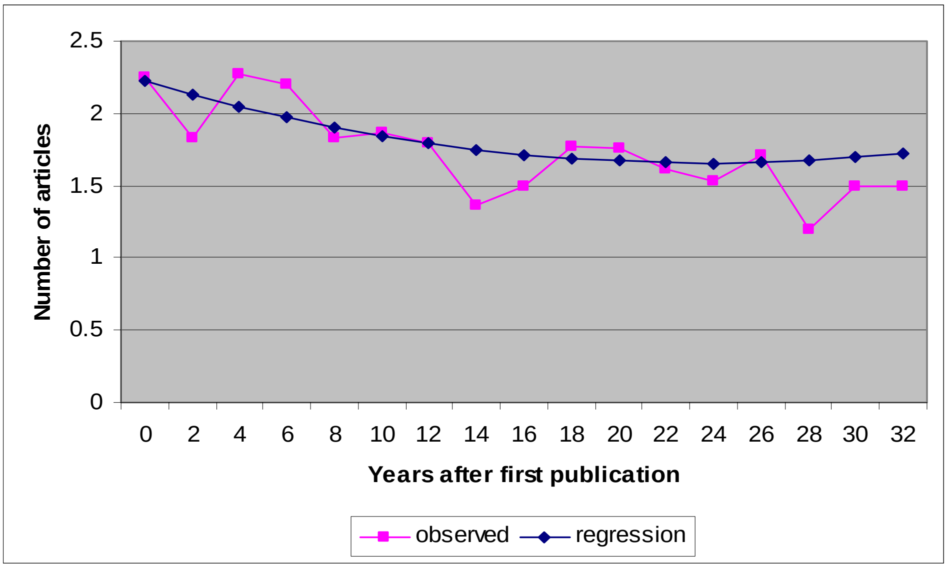

Figure 2. *Observed data and the regression trend predicting productivity (journal articles) with number of years since author's first publication.*

Table 2: *OLS regression of effects of time on impact of journal articles.*

					Regression coefficients			
Predictors	R^2	F	d.f.	p	intercept	time	$time^2$	$time^3$
time	.02	.27	15	.61	3.50	.06		
time $time^2$	.31	3.12	14	.08	5.71	-.83	.06	
time $time^2$ $time^3$	.70	9.87	13	.00	3.18	1.42	-.31	.02

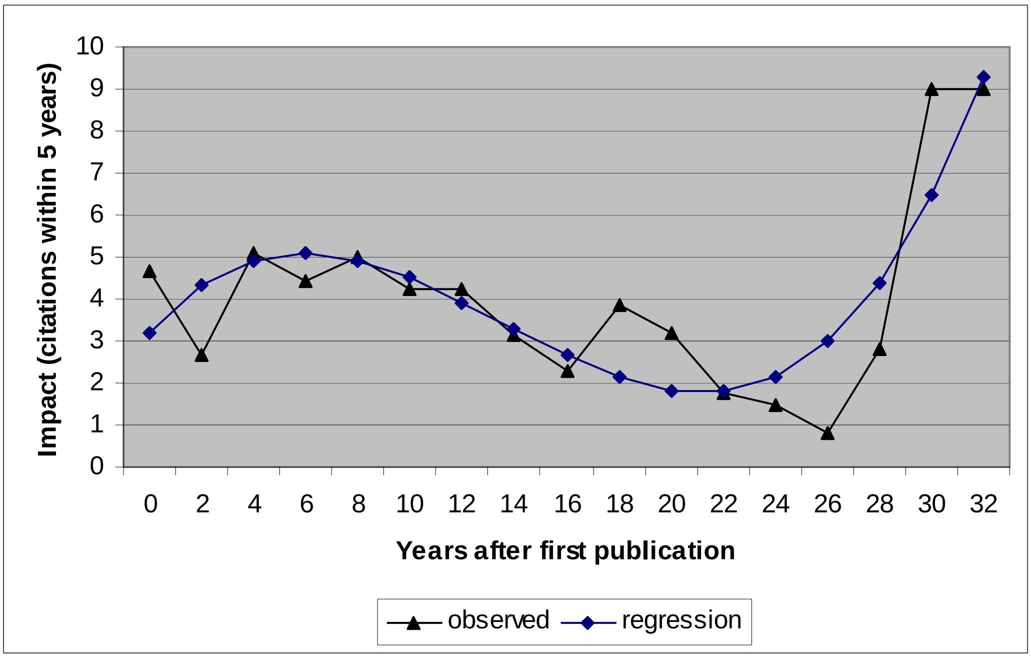

Figure 3. *Observed data and the regression trend predicting impact with number of years since first publication.*

Table 3. Variance components of the random coefficients, predicting researcher impact.

Coefficient	Variance	Chi-squared value	d.f.	p
Intercept	20.642	40.39	6	< .001
Time (slope)	30.654	69.85	6	< .001
$Time^2$ (slope)	1.537	48.48	6	< .001
$Time^3$ (slope)	0.004	3255	6	< .001

Note: the variance of the level-1 residual was 40.048.

References

Bryk, A. S. & Raudenbush, S. W. (1987). Application of hierarchical linear models to assessing change. *Psychological Bulletin,* 101(1), 147-158.

Deadrick, D. L., Bennett, N. & Russell, C. J. (1997). Using hierarchical linear modeling to examine dynamic performance criteria over time. *Journal of Management,* 23(6), 745-757.

Dewett, T. & Denisi, A. S. (2004). Exploring scholarly reputation: It's more than just productivity. *Scientometrics,* 60(2), 249-272.

Ford, C. M. (1996). 'A theory of individual creative action in multiple social domains', *Academy of Management Review,* 21(4): 1112-1142.

Hofmann, D. A. Jacobs, R., & Baratta, J. E. (1993). Dynamic criteria and the measurement of change. *Journal of Applied Psychology*, 78(2), 194-204.

Horner, K. L., Rushton, P. & Vernon, P. A. (1986). Relation between aging and research productivity of academic psychologists. *Psychology and Aging,* 1(4), 319-324.

Howard, G. S. & Curtin, T. D. (1993). Individual productivity and impact in counselling psychology. *The Counseling Psychologist*, 21(2), 288-302.

Kozlowski, S. W. & Klein, K. J. (2000). 'A multilevel approach to theory and research in organizations: Contextual, temporal and emergent processes' in K. J. Klein & S. W. Kozlowski (Eds) *Multilevel Theory, Research and Methods in Organizations: Foundations, Extensions and New Directions*. (pp 3-90. Jossey-Bass, San Francisco.

Lehman, H. C. (1953). *Age and Achievement*. Princeton, N.J: Princeton University Press.

McCrae, R. R., Arenberg, D. & Costa, P. T. (1987). Declines in divergent thinking with age: Cross-sectional, longitudinal, and cross-sequential analyses. *Psychology and Aging,* 2(2), 130-137.

Over, R. (1982). Is age a good predictor of research productivity. *Australian Psychologist*, 17(2), 129-139.

Over, R. (1989). Age and scholarly impact. *Psychology and Aging*, 4(2), 222-225.

Pirola-Merlo, A. & Mann, L. (2004). The relationship between individual creativity and team creativity: aggregating across people and time. *Journal of Organizational Behavior*, 25, 235-257.

Productivity Commission (2004). *Economic Implications of an Ageing Australia*, Draft Research Report, Productivity Commission, Canberra.

Simonton, D. K. (1997). Creative productivity: A predictive explanatory model of career trajectories and landmarks. *Psychological Review*, 104(1), 66-89.

Simonton, D. K. (2000). Creative development as acquired expertise: Theoretical issues and an empirical test. *Developmental Review*, 20(2), 283-318.

West, M. A. & Farr, J. L. (1990). 'Innovation at work', in M. A. West & J. L. Farr (Eds.) *Innovation and Creativity at Work: Psychological and Organizational Strategies* (pp. 3-14). Chichester: Wiley.

Zicker, M. J. & Slaughter, J. E. (1999). Examining creative performance over time using hierarchical linear modeling: An illustration using film directors. *Human Performance,* 12(3/4), 211-230.

Appendix A: Search Terms Used in PsychInfo.

1 exp BUSINESS/
2 exp Business Management/
3 exp Business Organizations/
4 exp Management Methods/
5 exp Management Personnel/
6 exp Work Teams/
7 exp LEADERSHIP/
8 exp Management Decision Making/
9 exp Human Resource Management/
10 exp ORGANIZATIONS/
11 exp Organizational Behavior/
12 exp Organizational Structure/
13 (industrial and organizational psychology).mp. [mp=title, abstract, subject headings, table of contents, key concepts]
14 exp "Industrial and Organizational Psychology"/
15 1 or 2 or 3 or 4 or 5 or 6 or 7 or 8 or 9 or 10 or 11 or 12 or 14 (63068)
16 limit 16 to (peer reviewed journal and english)