LIFE CYCLE AND COHORT PRODUCTIVITY IN ACADEMIC ECONOMIC RESEARCH: EVIDENCE FOR GERMANY AND MANAGEMENT CONSEQUENCES

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Abstract

In this paper we investigate the research productivity of German academic economists over their life cycles. We find that that the career-pattern of research productivity as measured by journal publications is cohort and ability specific. Moreover, we find that not only overall productivity, but also the quality of research follows distinct life cycles. Our study is based on a fairly comprehensive sample of German academic economists and employs econometric techniques that are likely to produce estimates that are more trustworthy than previous estimates. We point out the ramifications of the received results for the academic labor market, in particular for the design of salary schemes that rely on dynamic incentives.

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1. Introduction

The sciences in general and the economics profession in particular have in recent times become subjects of economic inquiry. Up to date surveys on the *economics of science* and on the literature dealing with economics as a science are to be found in Stephan (1996) and Coupé (2004), respectively. Among the characteristics that have been examined in some detail is the development of research productivity over the researchers' life cycles. Studying the dynamics and heterogeneity of productivity in the context of academic labor markets makes good sense because research productivity can be measured in a comparatively easy manner in this setting. The academic market therefore lends itself in a natural way to positive and normative investigations of the nexus between labor productivity and remuneration.

The positive literature clearly indicates that research productivity as measured by publications and/or citations is a crucial determinant of salary (cf., for example, Kenny and Studley, 1996, and Moore et al., 2001), tenure and rank (cf. Coupé et al., 2003a), and the obtainable job status in terms of the employing university's reputation (cf. Grimes and Register, 1997, Coupé et al., 2003a). When it comes to identifying the pattern of research productivity over career time, the empirical evidence becomes less clear-cut. Human capital theory suggests a hump-shaped progression of individual research productivity the human capital stock, which is a prerequisite of high productivity, needs to be built up at the beginning of the career, and obsolescence of knowledge is likely to dominate the positive effect of increased experience towards the end of professional life.[1] The standard hump-shaped productivity curve indeed emerges in some empirical studies (cf. Kenny and Studley, 1996, Oster and Hamermesh, 1998, Baser and Pema, 2004). It is, however, conceivable that the identified hump-shape represents an artifact of the *quadratic* specification of elapsed career time in the employed regressions of research productivity. Goodwin and Sauer (1995) identify a more complex career productivity profile that follows a fifth degree polynomial, whereas evidence uncovered by Hutchinson and Zivney (1995) and Hartley et al. (2001) do not indicate any significant decline in productivity as experience increases - a result that is compatible with the view that research behaviour is rather determined by sociological factors related to social imprinting than by human capital considerations.

The social imprinting hypothesis suggests that significant variations in research behaviour may be observed when comparing different cohorts of researchers. So far, however, the empirical evidence does not point to strong cohort effects in the economics profession: Basar and Pema (2004) do not find any cohort effects at all, and Goodwin and Sauer (1995) report only marginally significant effects that, moreover, may well reflect the fact that the members of the analyzed cohorts differ in age, implying that the older cohorts are composed of academic survivors and thus liable to have been more productive on the average. Notice, however, that the hitherto available empirical evidence relates to the United States; studies relating to countries with different experiences in the development of academic institutions may exhibit substantially different cohort effects.

In explaining academic labor market success (with respect to job status, tenure, rank and salary) there is general agreement that publications need to be adjusted for quality if they

[1] For a survey of the literature dealing with life cycle productivity changes caused by changes in cognitive abilities see Skirbekk (2003).

are used as indicators of research productivity. Two ways of controlling for publication quality have been used in the literature: some scholars (for example Goodwin and Sauer, 1995) restrict themselves to articles published in a select list of highly reputable journals, whereas others (for example Kenny and Studley, 1996, and Coupé et al., 2003a) base their measure of research productivity on a more encompassing list of journals and use explicit quality weights that are somehow based on the respective journals' scientific impact. Hybrid approaches with two or more quality classes of journals are also quite common (see, for example, Grimes and Register, 1997, Oster and Hamermesh, 1998, and Moore et al. 2001).

Since research productivity consists of a quantity and a quality component, the identified career patterns can, in principle, be decomposed into a quantity and a quality cycle. Particularly interesting insights from quality-quantity decompositions were gained by taking heterogeneity in research ability into account. It transpires that quality publishers are in general also quantity publishers (cf. Hutchinson and Zivney, 1995) and that the post-peak decline of the most prolific economists is much smaller than the decline of the less productive (Grimes and Register, 1997). Oster and Hamermesh (1998) show that top producers keep on producing high-quality research, but at a slower rate, whereas the slowdown of second-rate economists leads them to publish in lower quality outlets. Really creative economics at the highest level is, however, mainly undertaken by the young (cf. Oster and Hamermesh, 1998, van Dalen, 1999).

A related strand of the literature investigates the impact of institutional features on the pattern of research productivity. Of special interest are the influence of entry barriers (such as the continental European institution of the "habilitation"), mid-career hurdles such as tenure and rank promotions, and also institutional provisions that affect the mobility of academic researchers between universities.[2] Entry and promotion barriers have typically been portrayed as contest devices designed to induce higher research effort via increased competition (cf. Coupé et al., 2003b, Backes-Gellner and Schlinghoff, 2004, Kolmar and Wagener, 2004). The empirical evidence indicates that these institutional provisions indeed do work as incentive schemes and thus influence the pattern of research productivity: those life-cycle studies that identify hump-shaped productivity patterns usually find that research productivity peaks about six years into the professional career, i.e. around the time when professors can apply for tenure. The post-tenure decline in productivity appears however to be rather small (cf. Bell and Seater, 1978, Hutchinson and Zivney, 1995). Somewhat more informative results emerge from micro-econometric studies using information about when exactly the individual researchers were promoted: Backes-Gellner and Schlinghoff (2005) uncover strong evidence for the United States and Germany indicating that promotion tournaments give rise to an increase in research productivity in time periods preceding promotion and a lapse of productivity afterwards. Moreover, they show that the career profiles of German economists is characterized by a more pronounced post-tenure decline than the profiles of their American colleagues, the reason being that the German university system lacks a second career step, namely promotion to full professor. Using data on 650 out of the top-1000 economists according to a world-wide ranking, Coupé et al. (2003a) corroborate the result that promotions cause cyclical deflections in research productivity: pre-promoted economists not only are more productive than post-promoted ones, the spikes also

[2] Such provisions can either be designed to curb mobility (examples are lock-ins via retirement benefits and cartel agreements among university presidents or their superiors in the respective governments) or to increase it (international mobility of researchers is promoted, for example, with the help of the Marie Curie Actions organized and financed by the European Commission).

become less pronounced as the career progresses, probably because the signal provided by publications becomes less informative.

The significance of these institution-induced effects is, from a management point of view, quite clear-cut. Promotion steps can be designed such that the objectives of the principal are best suited. Whether the established institutions reflect controlled tournaments or serve to impose quality standards is hard to determine; the available evidence so far appears to favor the latter (cf. Coupé et al, 2003b). In any event, tournaments and quality standards represent only one type of management instrument to induce incentives. More direct measures are incentive compatible salary contracts.

Salary schedules generate *dynamic incentives*, i.e. incentives that aim at the whole career prospects of the employees. Such schemes also work in the absence of promotion barriers and are thus of special interest for human resource mangers in academic systems that are not based on the Anglo-Saxon tenure and promotion system but rather rely on one large career step. Precisely because these “German-type” with extremely flat hierarchical structures are rather inflexible, they may profit from a clever design of the post-tenure salary schedule.

When designing performance-related salary schedules in order to stimulate research, it is of prime importance to consider the dynamic implications of the incentives set, the reason being that research production heavily relies on the researchers’ stock of human capital. Research related human capital is, however, augmented by on-the-job experience on the one hand, and subject to high rates of obsolescence on the other. These dynamic aspects of research production thus imply that all incentives schemes bring their influence to bear on future behavior and, since the principal can commit to implementing the incentive scheme, also on the behavior taking place long before the contingent rewards are paid out. The objective of this paper is to lay some foundations for the design of a performance-related post-tenure salary scheme whose objective is to generate the optimal research output under given budgetary restrictions.

The design of incentive-compatible salary schemes for researchers needs to be based on two foundations: first, on a thorough understanding of the technology of research production and, second, on firm information about the quantitative impact of the identified factors of production. The latter can be gleaned from empirical studies of the life cycles of researchers producing under the pertinent conditions. In this paper we cover the theoretical aspect as well as the empirical one. In the next section we present a very simple two-period model that portrays two crucial dynamic forces of research production, namely obsolescence and experience-based accumulation of the human capital stock that is arguably the most important factor of research production. In the absence of any performance-related salary scheme, the pattern of research production over the two periods depends only on the relative strength of the two modeled effects. In a second step we then go on to ask ourselves how a dynamic incentive scheme influences the life cycle of research production if the agents' salaries are made contingent on current research output. We thereby assume that rewards cannot be conditioned on the researchers' ability as measured by their (unobservable) respective stock of human capital, nor do we consider non-linear reward-schemes that may substitute for ability based systems; such schemes would probably not be viable for ethical reasons. We only consider rewards that are contingent on observable career age. We show that a purely static incentive schemes that do not take the heterogeneity in experience into account is, in general, not optimal in the sense that it does not maximize total research output. An optimal dynamic incentive scheme rather conditions rewards on the career age. If, in the absence of any performance related rewards, the life cycle of research productivity shows a decline in the second part of the career, it may well be optimal to reward older researchers more for their research results than younger ones because such a top-loading of rewards not only generates *static* incentives in the second stage of a researcher's career but also *dynamic* incentives to work hard in the beginning of one's career since this is a prerequisite for being well equipped later on when rewards are to be had.

In section 3 we present our data set on academic economic research in Germany and in section 4 our base-line estimates of the life cycles in research productivity. We identify life cycles that are akin to, but rather flatter than the ones uncovered by Goodwin and Sauer (1995). Moreover, we arrive at the result that the German profession is characterized by significant cohort effects in research productivity. We also find that the shape of the life cycles depends on the individual researchers' ability. Studies focusing on aggregates thus miss an essential part of the story that has to do with heterogeneity. We then go on to investigate in section 5 cycles in the constituent parts of our measure of research productivity. Again it turns out that it is important to allow for heterogeneity of the labor force: the identified cycles in the *quality* of research not only display a markedly different shape than the cycles in overall research productivity, their shape also crucially depends on the respective researcher's ability. In the end of this section we also investigate the incidence of joint research along the life cycle. Section 6 concludes.

2. Research production over time and incentive compatible work contracts

In this section we derive the production decision of a researcher in a simple two period setting. Using the portrayed research behavior we then go on to show how the researcher's principal can design a salary scheme that induces the researcher to behave in a manner that maximizes the principal's objectives.

2.1 Research technology and research production

Our model is based on the seminal work by Levin and Stephan (1991). We assume that the individual researcher chooses to allocate his time between research and an alternative activity, such as teaching, consulting or leisure. The researcher's utility U_i in period i varies positively with his research output R_i and the time spent on the alternative activity. Denoting time spent on research by s_i, we specify the linear period utility function

$$U_i = \theta_i R_i - s_i .$$

Research output is produces by research time s_i and the researcher's stock of knowledge P_{t-1} at the beginning of period t:

$$R_i = \sqrt{s_i P_{i-1}} .$$

At the beginning of his career the researcher is endowed with a stock of knowledge P_0 that reflects his innate ability and (graduate) education. The stock of knowledge P changes over time; it decreases with an exogenous depreciation rate of δ and increases as a by-product in the course of undertaking research:

$$\Delta P = \alpha R_i - \delta P_i .$$

A researcher's time horizon of research activity encompasses two periods, period 1 and period 2. Maximizing U_2 immediately yields

$$s_2 = \frac{\theta_2^2}{4}\left[\alpha\sqrt{s_1 P_0} + (1-\delta)P_0\right],$$

and maximizing lifetime utility $U=U_1+U_2$ subject to the above second-period behaviour results in

$$s_1 = \left(\frac{\varphi}{2}\right)^2 P_0, \text{ where } \varphi = \theta_1 + \frac{\theta_2^2}{4}\alpha.$$

Thus, $s_2 = \frac{\theta_2^2}{4}\left[\frac{\alpha\varphi}{2} + (1-\delta)\right]P_0$ and substitution into definition of research output R_i finally yields

$$R_1 = \frac{\varphi}{2}P_0 \text{ and } R_2 = \frac{\theta_2}{2}\left[\frac{\alpha\varphi}{2} + (1-\delta)\right]P_0. \tag{6}$$

If the marginal utility of research output is constant over time, i.e. if $\theta_1=\theta_2=\theta$, we arrive at the conclusion that research output decreases over time if

$$\delta > \frac{\theta}{4}\left(\alpha + \frac{\theta}{2}\alpha^2\right). \tag{7}$$

Research output increases over time if δ falls short of the expression on the right hand side of the above inequality and remains constant if δ equals this expression. Figure 1 summarizes this result.

If the marginal utility θ of conducting research and/or the learning effect α of research is sufficiently small as compared to the rate of knowledge depreciation δ, the career of a researcher follows the standard life cycle: $R_1>R_2$. Under these circumstances the decrease in research productivity can only be countered if the incentives to engage in research activities in the second part of the career are somehow strengthened.

2.2 Incentive compatible work contracts for researchers

An incentive scheme that increases the marginal utility θ_2 of research in the second period and thereby increases research productivity in the second part of the researchers' careers via equation (6), can readily be designed. It would entail a reward in terms of salary that depends on the researcher's output R_2. Assume, for example, that each unit of research output is rewarded by a certain sum of money. Furthermore assume that this reward cannot be made contingent on ability as portrayed in our model by the stock variable P, be it because of incomplete information or ethical standards. However, the rewards can be made contingent on the researcher's age. Denoting the intrinsic motivation of undertaking research by $\overline{\theta}$, we thus arrive at

$$\theta_i = \overline{\theta} + B_i \quad \text{for } i=1,2.$$

Since the sum of the rewards needs to be restricted somehow, we assume that the principal caps the sum of per unit rewards over the two periods, i.e.

$$B_1 + B_2 = \overline{B}.$$

Subject and the non-negativity constraints $B_1 \geq 0$ and $B_2 \geq 0$, the principal is now assumed to maximize lifetime research output $R=R_1+R_2$ which can be written as follows if the above pseudo budget constraint is taken into account:

$$R = \left[\left(1+\frac{\alpha}{2}\left(\overline{\theta}+B_2\right)\right)\left(\left(\overline{\theta}+\overline{B}-B_2\right)-\frac{\alpha}{4}\left(\overline{\theta}+B_2\right)^2\right)+\left(\overline{\theta}+B_2\right)\left(1-\delta\right)\right]\frac{P_0}{2}$$

$$\equiv \xi(B_2)\frac{P_0}{2}. \tag{10}$$

For an interior solution one obtains in a straightforward manner

$$B_2 = \frac{2}{3\alpha} - \overline{\theta} - \frac{2}{3\alpha}\sqrt{1+6\delta-3\alpha\left(2\overline{\theta}+\overline{B}\right)}. \tag{11}$$

Notice, that our reward scheme presupposes that the market for researchers is *incomplete* in the sense that young researchers cannot easily be poached by another employer if the present employer grants a relatively small first-period reward B_1.

The comparative-static properties of our reward-scheme with respect to the research-production parameters α and δ are the following: the higher the depreciation δ of the stock of scientific knowledge, the more should the research output of young researchers be rewarded $\left(\frac{\partial B_2}{\partial \partial} < 0\right)$, and the larger the learning effect of research as measured by the parameter α, the more should the research output of old researchers be rewarded $\left(\frac{\partial B_2}{\partial \alpha} > 0\right)$. Because of the imposed non-negativity constraints, the relationship between the reward B_2 and the research-production parameters α and β is not everywhere governed by equation (11). For sufficiently small values of δ the function $B_2(\alpha)$ has the appearance shown in Figure 2a, i.e. the function is continuous but constant for sufficiently small and large values of α. If, on the other hand, δ becomes sufficiently large, B_2 is zero for values of α falling short of a certain critical value $\hat{\alpha}$, and $B = \overline{B}$ if α exceeds this critical value (cf. Figure 2c). For intermediate values of δ, finally, B_2 increases with increasing values of α before jumping to $B = \overline{B}$ at a critical value $\tilde{\alpha}$ (cf. Figure 2b).

The complex relationship between the optimal reward B_2 and the characteristics of research production is due to the fact that an individual researcher's total research output R as given in equation (10) is a polynomial of degree three in B_2, implying that increasing the reward for research output in the second period may increase total research output as long as B_2 is small, decrease R if B_2 becomes larger, and finally increase total research again for B_2 close to the upper limit $\overline{B}$. This reversal of influence may occur because increasing the reward B_2 in the second period implies that that research in the first period is rewarded less, with the consequence that the research output in the first period declines. Less research in the first period, however, implies that the stock of knowledge becomes smaller in the second period which, in turn, makes research in the second period more costly in opportunity terms. It is thus not surprising that this indirect effect may be so strong that, together with the reduction in the first period, total research output R declines. The relationship between the function $R=R(B_2)$ and the characteristics of research production as portrayed by the parameters α and δ is depicted in Figure 3.

Figure 3, in principle, shows what an optimal salary scheme for researchers looks like. In order to get a feeling for the size of the underlying parameters we investigate in the remainder of this paper the life cycles in research productivity of (German academic) economists because these life cycles are determined by the very same parameters.

3. The Data

3.1 The sample

Our dataset encompasses 567 German economists who received their doctoral degrees between 1969 and 1998 and who were employed at a German university in the year 2004 or had retired briefly before.[3] The youngest economists in our sample thus have a minimum of six years of post Ph.D. experience. The starting year of 1969 was chosen because we rely in our study on the data base EconLit that contains publication records from 1969 to the present. Whereas many other bibliometric studies focus on researchers who publish frequently, our dataset compromises, in principle, all German academic economists.

We collected all EconLit-listed journal publications authored or co-authored by economists included in our sample up to the year 2004 and linked these publications to

[3] We gathered information on more than one thousand German economist. Our sample comprises however only those economists who obtained their doctoral degrees between 1969 and for whom we could actually ascertain the exact year in which they obtained their doctoral degree.

their respective authors.[4] Although measuring research output by focusing on the journal literature neglects other types of research outlets such as monographs, collected volumes and proceedings, we are in accord with most scholars in the field who are confident that EconLit records the most important journals of the economics profession and that the articles published in these journals together constitute the lion's share of economic research (cf. Hartley et al., 2001, Combes and Linnemer, 2003, Coupé, 2003). Merging the annual records of individual publication activities with the year in which the respective researchers obtained their doctoral degrees, we were thus able to establish individual lifecycles of research productivity for a large number of German economists. These life cycles represent the basic input for our empirical study.

Some descriptive statistics of our data set are presented in Table V in the Appendix. Only 34 or 6 percent of the 567 researchers are women. 83 economists in our sample specialize in microeconomics, 158 in macroeconomics, 193 in public economics and 81 in econometrics. Economists who could not be assigned to one of these fields were assigned to the field OTHER. Interestingly, 68 or about 12% of the economists in our sample have never published in an EconLit listed journal.

3.2 The dependent variable: Individual annual research productivity

Since the EconLit database indexes nowadays over 800 journals, the quality standards set by these journals are quite diverse. We do not believe that controlling for journal quality by restricting the set of journals is a viable strategy of measuring research output because a robust measures needs to draw on all available information. Using, for example, only a relatively small number of top-journals would bias the productivity measure in favor of

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[4] Whenever EconLit reported "et al." we identified the hidden co-authors by tracing the article.

top-researchers specializing in hot topics. Moreover, life cycle patterns in research quality (as compared to cycles in overall output) can only be properly identified if the whole quality range of research products is taken into account.

To control for the quality of all journals indexed in *EconLit* we settled for a standard method and use the "CLpn" scheme proposed by Combes and Linnemer (2003). The CL-scheme weighs journal quality according to their relative reputation and impact, and converts research output in standardized units of AER-page equivalents. The imputed weights lie between one for top journals and one twelfth for journals with the lowest quality standards. The top-tiered journals that receive the weight of unity are the *American Economic Review*, *Econometrica*, the *Journal of Political Economy*, the *Quarterly Journal of Economics* and the *Review of Economic Studies*. Thereafter sixteen journals receive a weight of two thirds. Weights then decline in discrete steps (one half, one third, one sixth) down to the minimum weight of one twelfth.[5]

To construct our dependent variable, we multiplied the number of pages of each article with the respective journal weight and divided this product by the number of authors. Adding the scores calculated according to this rule over all articles published by researcher i in year t we arrive at our basic research productivity measure.

3.3 The explaining variables

To identify life cycle patterns in research productivity we regress our dependent variable, research productivity of researcher i at time t, on several independent variables, the most important one being experience or career-time.

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[5] One disadvantage of this method is that journal quality is kept constant over the period of investigation that covers, after all, a time-span of 36 years.

Experience

In accordance with the literature we align all individual life cycles by using the reference year in which the researcher obtained his or her doctoral degree. Notice, however, that we also include the research output generated in the pre-Ph.D. years in our regressions. The life cycle thus begins five years before the reference year 0 and ends for the oldest cohort 35 years thereafter. To estimate the shape of the lifecycle we include career-time polynomials of different orders in the regressions. Simple t-tests as well as likelihood ratio-tests were used to determine the optimal degree of the polynomial. In most cases a 4th degree polynomial has proven to fit the data best.

Individual heterogeneity: Ability, field and gender

More able researchers (almost by definition) produce more research output than less able ones. To control for this unobserved heterogeneity, we followed the approach advocated by Goodwin and Sauer (1995) and ranked the researchers according to their average life-time productivity within the distribution of a three years cohort.[6] We then defined quintile ranks within the distribution for each cohort and assigned each researcher the appropriate rank. The top publishers were assigned rank 5 because they lie within the highest quintile of their cohort, whereas the bottom group was assigned rank 1. Even though their overall productivity might be quite different in absolute terms, the most productive economists of the youngest cohort therefore have the same rank as the most productive economists of the oldest cohort. This expresses their similarity with respect to

[6] A similar approach was employed by Hausman, Hall and Griliches (1984) in a study dealing with patents and by Vella and Verbeck (1997) who use regression residuals to rank individuals according to their unobserved heterogeneity to identify returns to education.

unobserved ability and motivation.[7] Our RANK variable enters the regression as a dummy variable for each rank, allowing for a possible non-linear relationship between ability and research productivity.

The specific field of research is included for similar reasons. First, it cannot be ruled out that publishing habits vary across different fields of research. A simple comparison of the average yearly per capita research productivity across different fields reveals that this conjecture cannot be easily dismissed: these productivities range between 2.11 AER equivalent pages in microeconomics and 0.78 AER equivalent pages in econometrics. We decided therefore to include the *field of research* as dummy variable to allow for different research cultures across fields. A second reason for including field dummies is that these variables would also capture any bias stemming from an uneven coverage of the research fields in the EconLit data base as a whole and/or within each quality-group of journals. The interpretation of field-specific effects on research productivity is therefore not straight-forward.

Finally, we also included a gender variable that may capture gender specific differences in research productivity.

Cohort effects and historical time

Research productivity may not only vary across different fields of economic research but also across time. To allow for vintage effects we include six-year cohort dummy variables in our regressions. They are constructed by using the reference year in which the

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[7] Other Fixed Effects estimation procedures can be found in the literature, e.g. Honore (1992). They do however not allow a separate identification of the effect of variables that do not change across time. Since many of the variables we are interested in are dummy variables that do not vary across time, we had to stick to the approach described above, even though we realize that we thereby control for individual heterogeneity in a rather imperfect manner.

researchers obtained their doctoral degrees, starting in 1969. We also experimented with different cohort lengths; our results proved to be rather insensitive to such changes.

A second approach is to include a time trend in the regressions. Just as cohort dummies, a time trend will capture changes of research behavior across historical time. Whereas cohort dummies portray changes in research behavior that are peer-group specific (they could, for example, portray different cultural imprinting patterns across time), a time trend indicates that individual research productivity does change over time for *all* researchers and this change is independent of experience. Such time trends might capture changes in publication customs, for example a substitution away from monographs towards journal articles. Unfortunately, a separate identification of pure cohort effects and time-trend effects appears not to be possible since the difference between historical time and career age is used to assign the individual researcher to a cohort. Employing cohort dummies and a time trend together in a regression thus results in collinearity problems. Imposing specific functional forms on the cohort and pure time dummies to identify the individual effects appears to be a rather dubious strategy because there are no obvious restrictions that could be imposed. We therefore decided to present specifications with cohort dummies as well as specifications with time dummies in order to document the robustness of our results.

4. Results

4.1 Identifying life cycles in research productivity

To begin with, we present some lifecycle regressions that do not account for the circumstance that our sample of academic economists may be rather heterogeneous. We thus restrict our set of explaining variables to a time polynomial, the cohort dummies, the gender dummy, and on a constant. The dependent variable $SCORE_{it}$ represents individual i's research productivity at career-time t as measured by the CLpn index. Because of the high degree of censoring (about ¾ of our SCORE-observations are zeros) we cannot apply OLS and have to rely on other techniques which can accommodate this heavy censoring situation properly.

The results are summarized in Table I. In the first column standard Tobit estimates are shown and in the second column Powell's Censored Least Absolute Deviation (CLAD) estimates for the 0.75 Quartile. In column three the results obtained from a log linear model estimated via OLS are shown; in this regression the logarithm of the score is regressed on the independent variables and a dummy variable for observations with a zero score.[8] In the fourth and fifth columns we finally present estimates of a hurdle model.[9] The hurdle model assumes that the decision to undertake research at all might be driven by other forces than the decision with respect to how much research effort is expended by an active researcher. We therefore model both stages of the decision making process in different ways. For the decision to undertake research at all we use a Probit specification and for the determination of effort, given that the respective economist has already decided to be an active researcher, we use a truncated Negative Binomial model.[10] The Negative Binomial model appears to be appropriate since the observed density distribution of our dependent variable resembles the pattern of count data. This resemblance (spikes at steps of 1/12) emerges because the CLpn index is based on journal weights that are multiples of 1/12. To arrive at proper count data we divided

[8] Note that for this regression we transformed the score by adding 1/24 to avoid the ln(0) trap.
[9] For a similar application of the hurdle model, see Pohlmeier and Ulrich (1995), and for a censored quantile regression Fitzenberger et al. (2001).
[10] We estimated also zero truncated Poisson models to check for the robustness of our NegBin II specification. We choose the NegBin II as our preferred specification because the LR-tests rejected alpha=0 and because a closer look to the data reveals that the dispersion increases with the mean.

our SCORE variable by one twelfth and rounded to the next integer. The variable transformed in this manner can then, of course, be analyzed by using a count data model. One count can be interpreted as 1/12 of an AER equivalent page or one page in a journal of lowest quality.[11]

All four estimation techniques used give rise to estimates that are not obscenely at variance with the standard life cycle hypothesis. The estimated career-time polynomial implies in each case a hump-shaped curve of research productivity over career time (cf. Figures I/1-I/5). The Tobit, CLAD and Hurdle models fit best with a life cycle polynomial of degree four, the log-linear model works best with a polynomial of degree three. Even though the standard life cycle hypothesis does not do that badly, we do not find a marked and final decline in research productivity after a peak occurring around the career-time when academic economists are usually promoted to full professor in Germany. Research productivity rather appears to remain constant over a substantial part of the lifecycle which implies that our estimates may just as well be construed to support the sociological hypothesis of imprinting. The odd increase in research productivity identified by the Tobit and Hurdle models towards the end of the researchers' careers is in line with the results presented by Godwin and Sauer (1995). Their estimates for American economists show however a more substantial decline in research productivity during the mid-career years. Interestingly, our hurdle model indicates that there are significant

[11] We also used ½ and ¼ of an AER equivalent page as units without obtaining significantly different results. However, since the underlying density has spikes at steps of one twelfth the applied scheme appears to be more natural and precise.
To further check for the robustness of our model we estimated a hurdle model which assumes a lognormal distribution of the positive scores (Wooldridge (2002)). The results are similar to the count data hurdle model presented above.

differences between the time polynomials of the Probit and NegBin part, thereby hinting at different underlying forces governing the two respective processes.[12]

Although the Tobit estimates seem to be in line with the results of the other estimators, a Pagan and Vella (1989) conditional moment test on normality of the underlying disturbance term rejects this hypothesis which casts doubt on the applicability of this estimator. This caveat probably does not come as a surprise, considering the count data character of the publication process. Nevertheless, the estimates turn out to compare well with the estimates received with moiré appropriate techniques and therefore lend support to the robustness of our results.

The coefficient of the Gender dummy indicates that female economists publish significantly less than their male peers. The hurdle model reveals however that this negative effect is mainly due to the decision to publish at all rather than a consequence of the productivity of female economists who are active researchers. The log linear model, on the other hand, does not reveal any significant differences between male and female researchers.

As expected, the coefficients of the cohort dummies increase over time. We interpret this result to imply that members of younger cohorts are more productive researchers than their older colleagues. About the reasons for this phenomenon we can only speculate: the evidence certainly does not contradict the hypothesis that over the last thirty years the German economics profession has increasingly been exposed to the Anglo-Saxon research tradition that stresses the requirement to document one's research efforts on a continuous basis. Many economists who returned in the 1970s and 1980s

[12] For statistical reasons we used the hurdle specification due to Cragg (1971) that nests the Tobit, and conducted a likelihood ratio test: the LR-test statistic that is distributed χ^2_{10} amounts to 862. Therefore the H0 of a single decision making process can be rejected on the 1 percent level and the hurdle specification is favoured.

from the United States helped to internalize this research culture which nowadays characterizes the academic environment at German graduate schools and also the increasingly competitive hiring strategy employed by the leading departments.

We admit, however, that our preferred interpretation of the cohort effects is debatable. Table II shows estimates using a linear time trend as independent variable instead of the cohort dummies. The estimates of the life-cycle variables prove to be stable with respect to this specification, although the coefficient of the linear term is reduced. The coefficient of the linear trend picks up some of the impact of the linear career-time variable. Both of the two alternative specifications thus appear to capture the same joint effect that is composed of cohort effects and a real-time effect. Even though it is not possible to discriminate between the two kinds of effects without imposing further restrictions (that would, in any event, be hard to justify), we decided to stick to the specification that employs cohort dummies.[13] In accordance with most scholars in the field we feel quite confident that the influence of these dummy variables can indeed be interpreted to constitute mainly vintage effects. We admit however that we cannot offer much more in the line of justification than economic gut feeling and introspection.

4.2 Enter Heterogeneity

So far we have neglected any kind of heterogeneity in ability in our sample of academic economists. Our strategy of identifying life cycles in research productivity only makes sense if the pattern of the individual life cycles do not depend on research ability. Since there are good reasons to believe that this homogeneity assumption is not satisfied, we

[13] We also ran all of our regressions with the trend specification without obtaining significantly different estimates.

included in the regressions summarized in Table III our measures of individual research ability. Again we estimated the Hurdle, Tobit, and the Log Linear Model.[14]

The first two columns of Table III present the estimates for the Hurdle model that now also includes variables capturing sample heterogeneity. The additional variables are the ability indicators RANK and the field indicators. As expected, the rank dummies are highly significant and a higher rank is associated with a higher research productivity. Concerning our field dummies, we find that economists specializing in microeconomics and public economics publish more than their peers in other fields. This might be the consequence of a more competitive academic environment in these fields; alternatively the positive coefficient might simply capture a hidden imbalance in our productivity measure.

The career time polynomial identified by the NegBin regression now has a somewhat different shape: in the second half of the career of an active researcher productivity now appears to decline (see Figure III/1b). As documented in Figure III/1a, the probability to undertake research does, however, not change as compared to our base-line estimate presented in Table I: we still observe a bi-modal distribution that hints at a "second wind" in research activity. The different shapes of the two distributions are compatible with the interpretation that economists "in their best" years (say in their 50s) tend to return to research (maybe because of disengagements in their family lives) but do then, because their research-specific human capital stock suffered from obsolescence and lack of maintenance, produce research of lesser quality. We will investigate this hypothesis in more detail in the following section. Note also that the fit of the model increases noticeably.

[14] The quantile regressions, unfortunately, did not converge.

The estimates of a second, more general specification are presented in columns three and four of Table III. In these regressions we allow the life-cycle polynomials to differ across ability ranks. To estimate the time polynomials we grouped rank one, two and three together. This was necessary due to the high degree of censoring within the lowest ranks. Nevertheless, we still allow for different intercepts for each rank. Figures III/2 show that the time polynomials differ across ability ranks. This is also confirmed by a likelihood ratio test between both specifications. Our results indicate that the most productive researchers manage to increase their publication incidence over time (this may reflect a reputation effect) while their research productivity declines only very little in the second half of their careers.[15] As compared to the rank-5 top-researchers, the rank-4 run of the mill researchers' publication incidence and research productivity declines more sharply over the lifecycle. The "hobby researchers" who are ranked together in the bottom group have rather flat and nondescript life cycles: productivity probably also somewhat declines with career age, whereas the probability of engaging in presentable research activities at all appears to slightly increase towards the end of their careers.

It is also worth pointing out that our estimates of the log-linear model (see Figure III/4) indicate that the burn-out of the run of the mill researchers is so strong that they are, in their 50s, overtaken by the bottom group economists. A daring interpretation might maintain that the middle group is able to redirect their professional careers when they reach their 50s towards consulting or administration, whereas the bottom group members, nolens volens, have to continue on their adopted career paths up to the bitter end.

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[15] The log linear model however predicts even for top-researchers a decline of productivity toward the end of their careers (see Figure III/4).

5. An exercise in deconstruction: Quality, quantity and co-authorship

Up to now we have treated research productivity as measured by the CLpn index as a preordained unit of account. The shapes of the identified life cycles suggest however that the constituent parts of this productivity measure might follow quite different patterns that cannot be uncovered by an investigation at the aggregate level. In this section we therefore deconstruct the employed index and focus our investigation on the constituent parts thereof, namely on quality, quantity and the number of collaborators. In order to identify life-cycle patterns in these constituent parts of research productivity we "deconstruct" the density of our dependent variable SCORE in the following way:

$$f(S) = f_E(E \mid \theta_E) \cdot f_N(N \mid \theta_N, E=1) \cdot f_C(C \mid \theta_C, N, E=1) \cdot f_Q(Q \mid \theta_Q, C, N, E=1)$$

The first factor on the RHS captures whether economist i has been involved in producing a research output in year t or not. The second marginal density represents the *number of publications* given that at least one publication has been produced in t. The third factor denotes the average quantitative *contribution* per article (number of pages per coauthor) and the fourth factor the average *quality* of the articles authored or co-authored by economist i in year t. An exemplary deconstruction of the score can be found in the Appendix.

The first column in Table IV presents the regression for the number of authored or co-authored journal articles (NUMBER). As can be seen from Figure IV/1, this number reaches a first maximum approximately seven years after economists are granted their doctoral degrees and declines thereafter very slightly. Around the middle of the career it once again begins to rise and continues to do so until about five years before retirement. We will show below that this second increase is due to a higher co-authorship incidence of older economists. Whereas young economists appear to write most of their articles by themselves (and therefore publishing only a few), older researchers tend to publish together with others and therefore a larger number of papers. This increase in co-authorships might be due to network effects or co-authorship with ones doctoral students. In the second column we regress the logarithm of the average (quantitative) contribution (AVCONTR) on our independent variables and on the number of articles authored or coauthored (NUMBER). An inspection of Figure IV/2 reveals that the average contribution is steadily declining after the early career peak. The increased incidence of co-authorships of course contributes to this decline. It thus transpires that at the beginning of their careers, economists, conceivably for reputation reasons, focus their research activity on relatively few projects that are pursued without collaborators, whereas at later stages they tend to spread themselves wider and prefer to engage in more collaborative research endeavors.

The third and arguably most important constituent part of our measure for research productivity is (average) quality. Our regression results for the average research-quality variable are summarized in the third column of Table IV. The density of AVQUALITY is heavily centered on the discrete steps of the underlying weighting scheme (see Figure A3 in the appendix). We therefore transformed this variable into a variable that can assume six different values that correspond to the original journal quality weights. We then apply an ordered probit model to estimate the underlying quality lifecycle. This method is especially appealing because the original weights enter the analysis only in an ordinal fashion. The estimated lifecycle polynomial is depicted in Figures IV/3 and IV/4.[16] Our results corroborate the received wisdom that top-performers

[16] The regression on which Figure IV/4 is based is not presented in Table IV. It's available from the authors upon request.

continue to produce high-quality research throughout their active lives but tend to slow down with respect to quantity as they grow older, whereas less gifted researchers substitute in the course of their careers quality by quantity (cf. Oster and Hamermesh, 1998).

As far as the "average economist" is concerned, it is fair to say that not only *overall research productivity* but also *average research quality* follows a hump-shaped life cycle: the probability of publishing articles in highly reputed journals sharply increases at the very beginning of the career as the budding economists become increasingly accomplished but begins to declines already about six years after economist reach their first career step, the conferral of the doctoral degree. This result further reinforces our notion that when measuring research productivity over the lifecycle it is imperative to include all types of journals; bibliometric approaches that focus on a subset of prime-rate journals will give rise to estimates of the research productivity of older economists that are downward biased.

We now return to our hypothesis maintaining that co-authorships become more attractive in the course of the average economists' careers.[17] To explore this hypothesis in more detail we constructed a co-author index measuring each economist's average number of collaborators (including him- or herself), by using the number of pages as the respective weight for each journal article published in the respective year. The regression explaining the average number of co-authors is presented in the forth column of Table IV. The implied life-cycle is depicted in Figure IV/5. This figure reveals that the number of co-authors is relatively high for graduate students and reaches a minimum about three years after economists are conferred their doctoral degrees. Afterwards the number of co-

[17] There is a small literature on the topic of co-authorship; see, for example, McDowell and Smith (1992), Hollis (2001) and Laband (2002).

authors steadily increases over the whole life-cycle. This piece of evidence points towards network advantages of more mature economists and, as far as the odd early-career twist is concerned, to a high incidence of collaborative efforts between graduate students and supervisors.

The last regression presented in Table IV re-estimates the impact of our explanatory variables on the average quality of research; as compared to the third regression we also included here our index of the average number of co-authors. It transpires that quality indeed depends on the number of collaborators: working with collaborators appears to increase research quality.

6. Conclusions

In investigating the careers of German academic economists we have come across two characteristics that we regard to be essential for our understanding of the profession. First, we discovered that the pattern of research productivity over the life cycle is co-determined by economic incentives and by sociological factors. The influence of the economic incentives is reflected in the hump-shape of the identified life cycles, the sociological factors show up in the marked cohort effects. As compared to those of their American peers, the life cycles of German economists turn out to be flatter and the level of research productivity appears to be much more strongly influenced by cohort specific factors. We do, however, not interpret these finding as evidence supporting the hypothesis that the American profession is mainly driven by economic incentives and the German profession by sociological factors. Our results simply reflect the fact the academic environment in Germany has changed much more dramatically over the period of our investigation than the science system in the United States. That sociological factors are also at work in the U.S. transpires for example from studies that have identified significant pedigree effects of research productivity (see, for example, Moore et al., 2001).

The second uncovered characteristic of the economics profession that deserves special attention is the fact that lifecycles in research productivity are ability specific. Studies that attempt to identify the research behavior of the "representative" economist miss a large part of the story. The economics profession is very heterogeneous and neglecting this heterogeneity may give rise to severe misinterpretations. It is worth emphasizing that this heterogeneity in ability not only affects the variance of the *level* of individual research productivity (this we have known for a long time from various ranking exercises), it has also distinct effects on the dynamic dimension of research productivity, i.e. on the *shape* of the individual life cycles. The ability induced variation in life cycle patterns is especially striking when one compares life cycles in the *quality* of research.

The fact that the life cycles in research productivity turn out to be rather flat in the German profession and thus lend implicit support to the sociological imprinting hypothesis, does not imply that economic incentives are of second-order importance. Incentives provided, for example, by career hurdles may very well have a great deal of influence: since we find early career peaks that appear to coincide with the timing of the only career hurdle in Germany our results are certainly compatible with the existence of *tenure kinks* and thus with the results derived by Backes-Gellner and Schlinghoff (2004). As a matter of fact, we are confident that we will be able to replicate the tenure-kink result obtained by Backes-Gellner and Schlinghoff after having extended our data set with further details of the included economists' resumes, in this particular case with the dates of the first job offer.

Further routes of investigation that we plan to follow up after having completed the extension of our data set include testing the *pedigree hypothesis* that maintains that the graduate school environment has, ceteris paribus, a distinct life-long influence on the students' research behavior. In this study we only touched the gender issue, and we did so mainly because the gender variable is so easily available (at least as long as the Chinese do not make a more substantial inroad on the German profession). In our follow up study we will, however, be able to present some more far-reaching results, namely on how mothering affects the research careers of economists. A third line of investigation we have embarked upon concerns peer-group effects in research: the main question to be answered in this context is whether new members of an economics department are likely to be affected by the research environment they encounter.

What are the management consequences that arise from this study? Our theoretical model was intended to show how, in principle, optimal salary schemes that generate dynamic incentives would have to be designed. Our model indicates that rewards (for research achievements) that are independent of career-age are, in general, not optimal. It is, however, not possible to glean from our empirical study enough information that would help us to design an optimal reward scheme. In our two-period model with three essential parameters (θ, α and δ) we can only derive one constraint that can be estimated empirically.[18] Getting rid of one degree of freedom, however, still leaves our model underdetermined. In order to arrive at a practicable optimal scheme that allows for age-dependent rewards, one would have to set up a richer theoretical model that can

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[18] We refer here to equation (7) that implies $\frac{R_2}{R_1} = \frac{\theta}{4\delta}\left(\alpha + \frac{\theta}{2}\alpha^2\right)$.

produce life cycles that resemble the ones we identified empirically. We realize, of course, that optimizing a management objective function under the constraint of a fully-fledged research production model is beyond the reach of analytical methods. Resorting to numerical methods may prove to be a feasible alternative; after all, even research production models that do not imply any mechanism design have been analyzed in this manner (see Thursby et al., 2005, for a recent study). In any event, our objective in this paper was not to derive any practicable management results but rather to point out a potentially fruitful route of investigation.

Finally, we would like to highlight a further management consequence that arises from this study. Since life-cycle and cohort effects turn out to represent major determinants of research production in Germany, this information should be taken into account not only on the occasion of evaluating individual researchers, but also when one attempts to rank university departments, the reason being that the exogenous age and cohort structure of the departments significantly affects the observed research productivity. It therefore appears to be obvious that these effects should be deducted from the gross amount of research produced if one attempts to fairly represent a department's research standing. Even though adjustments for career-age have been made in the ranking literature (see, for example, Combes and Linnemer, 2003), these adjustments were up to now based on an ad hoc reckoning. Our empirical study provides the kind of information that would have to be used in more sophisticated rankings.

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Table I	Tobit	CLAD 0.75 Quartile	Log Linear Model	Hurdle Model Probit	Hurdle Model NegBin
T	0.3987***	1.5963***	0.0119***	0.2244***	0.1711***
	(25.67)	(3.92)	(7.61)	(21.68)	(8.52)
T^2	-0.0432***	-0.1852***	-0.0008***	-0.0236***	-0.0215***
	(17.35)	(2.96)	(4.68)	(15.16)	(7.59)
T^3	0.0018***	0.0086***	$1.31E^{-5}$***	0.0009***	0.001***
	(12.87)	(2.35)	(3.01)	(11.33)	(6.50)
T^4	$-2.49E^{-5}$***	-0.0001**		$-1.32E^{-5}$***	$-1.46E^{-5}$***
	(10.41)	(1.95)		(9.03)	(5.84)
C7580	0.3593***	1.0538***	0.0266***	0.1845*	0.1602
	(5.99)	(2.25)	(1.19)	(1.90)	(0.96)
C8186	1.1156***	2.6962***	0.0557**	0.5172***	0.2374
	(17.00)	(4.42)	(1.99)	(5.03)	(1.56)
C8792	1.7307***	3.7218***	0.0978***	0.7189***	0.3652***
	(26.15)	(6.04)	(3.45)	(8.56)	(2.63)
C9398	2.1491***	5.1297***	0.1246***	0.8596***	0.3887***
	(30.25)	(7.34)	(5.29)	(10.34)	(3.03)
FEMALE	-0.4301***	-1.6072**	-0.0259	-0.3191***	-0.1138
	(4.20)	(1.92)	(0.94)	(3.16)	(0.83)
CONSTANT	-2.58***	-4.2129***	1.0151***	-1.4533***	3.530***
	(36.73)	(4.21)	(27.42)	(22.20)	(26.84)
DUMMY			-4.2478***		
			(126.56)		
Observations	14300	12550	14300	15812	3585
(Pseudo)-R^2	0.0507	0.0662	0.93	0.1080	
Log Likelihood	-16806.7			-7183.1	-18142.2

Note: Absolute t-value in parentheses
Tobit : Marginal Effects on Unconditional Expected Value are reported
CLAD: 0.75 Quartile, S.E. bootstrapped (100 replications), only researchers with at least one publication in sample

*** denotes significant on the 1 percent level, ** on the 5 percent level and * on the 10 percent level.

Table II	Tobit	CLAD 0.75 Quartile	Log Linear Model	Hurdle Model Probit	Hurdle Model NegBin
T	0.3353***	1.4017***	0.0068***	0.1877***	0.1494***
	(21.77)	(4.49)	(5.18)	(18.16)	(6.77)
T^2	-0.0422***	-0.1829***	-0.0008***	-0.0231***	-0.0206***
	(17.12)	(3.65)	(4.68)	(14.59)	(6.81)
T^3	0.0017***	0.0080***	$1.39E^{-5}$***	0.0009***	0.0009***
	(12.45)	(2.82)	(3.08)	(10.56)	(5.86)
T^4	$-2.34E^{-5}$***	-0.0001***		$-1.24E^{-5}$***	$1.39E^{-5}$***
	(9.89)	(2.25)		(8.25)	(5.35)
TREND	0.0642***	0.2214***	0.0055***	0.0372***	0.0189***
	(23.60)	(7.25)	(6.12)	(11.72)	(3.99)
FEMALE	-0.4482***	-1.6070***	-0.0284	-0.3310***	-0.1360
	(4.37)	(2.05)	(1.02)	(3.29)	(0.99)
CONST	-2.8139***	-5.2357***	0.9896***	-1.5849***	3.4476***
	(37.41)	(5.14)	(26.03)	(24.29)	(26.62)
DUMMY			-4.2468***		
			(127.09)		
Observations	14300	12550	14300	14300	3585
(Pseudo-)R^2	0.0516	0.057	0.92	0.1072	
Log Likelihood	-16791.5			-7189.1	-18136.4

Note: Absolute t value in parentheses
Tobit : Marginal Effects on Unconditional Expected Value are reported
CLAD: 0.75 Quartile, S. E. bootstrapped (100 replications), only researchers with at least one publication in sample

*** denotes significant on the 1 percent level, ** on the 5 percent level and * on the 10 percent level.

Table III

	Hurdle (1) Probit	Hurdle (1) NegBin	Hurdle (2) Probit	Hurdle (2) NegBin	(3) Tobit	(4) Log-Linear Model
whole samplel/ infreq. publ.						
T	0.2648***	0.1619***	0.2147***	0.0969***	0.2046***	0.0019***
	(21.46)	(9.45)	(10.97)	(4.41)	(13.25)	(3.89)
T^2	-0.0280***	-0.0196***	-0.0255***	-0.01***	-0.024***	
	(14.98)	(8.03)	(8.46)	(3.07)	(9.39)	
T^3	0.0011***	0.0008***	0.0010***	0.0003*	0.001***	
	(11.24)	(6.45)	(6.44)	(1.89)	(6.79)	
T^4	-1.54E^{-5}***	-1.19E^{-5}***	-1.4E^{-5}***	-3.9E^{-6}	-1.32E^{-5}***	
	(9.02)	(5.47)	(5.04)	(1.23)	(5.20)	
frequent publishers						
T			0.2742***	0.1945***	0.2759***	0.0175***
			(14.82)	(5.51)	(14.45)	(5.65)
T^2			-0.026***	-0.0222***	-0.0277***	-0.0015***
			(8.48)	(4.45)	(8.99)	(4.10)
T^3			0.0009***	0.0009***	0.001***	2.56E^{-5}***
			(5.34)	(3.50)	(5.93)	(2.52)
T^4			-1.06E^{-5}***	-1.21E^{-5}***	-1.26E^{-5}***	
			(3.65)	(3.01)	(4.27)	
top publishers						
T			0.2774***	0.1811***	0.3229***	0.0617***
			(13.71)	(6.27)	(21.09)	(11.45)
T^2			-0.0268***	-0.023***	-0.0347***	-0.0044***
			(8.51)	(6.08)	(13.88)	(7.50)
T^3			0.0011***	0.001***	0.0015***	7.42E^{-5}***
			(6.49)	(5.33)	(10.58)	(5.33)
T^4			-1.67E^{-5}***	-1.52E^{-5}***	-2.15E^{-5}***	
			(5.62)	(4.73)	(8.91)	
C7580	0.2114***	0.1754*	0.218***	0.1765*	0.251***	0.0314
	(4.31)	(1.76)	(4.38)	(1.77)	(6.42)	(1.53)
C8186	0.5927***	0.2345**	0.605***	0.2409***	0.7916***	0.0665***
	(10.59)	(2.52)	(10.69)	(2.58)	(18.88)	(3.03)
C8792	0.7951***	0.46***	0.7967***	0.4588***	1.2451***	0.1093***
	(14.34)	(5.85)	(14.74)	(5.71)	(29.93)	(4.70)
C9398	0.9651***	0.4847***	0.9603***	0.4828***	1.5556***	0.1418***
	(17.67)	(6.17)	(17.96)	(6.07)	(35.09)	(7.21)
MICROECCONOMICS	0.1732**	0.1331*	0.15*	0.138*	0.2127***	-0.0044
	(2.05)	(1.72)	(1.91)	(1.80)	(3.30)	(0.19)
MACROECONOMICS	0.0742	0.0743	0.0584	0.0755	0.0886	-0.0228
	(0.94)	(0.86)	(0.79)	(0.89)	(1.44)	(1.28)
PUBLIC ECONOMICS	0.15**	0.0139	0.1403**	0.0183	0.1393**	-0.0229
	(1.96)	(0.19)	(1.97)	(0.25)	(2.30)	(1.52)
ECONOMETRICS	0.1010	-0.069	0.0904	-0.0612	0.058	-0.0373**
	(1.24)	(0.79)	(1.19)	(0.70)	(0.38)	(2.01)
FEMALE	-0.1853***	0.0744	-0.1904***	0.0671*	-0.1306**	-0.0045
	(2.62)	(0.88)	(2.87)	(0.81)	(2.06)	(0.23)
RANK 2	0.8864***	0.5468***	0.8894***	0.5382***	1.3106***	-0.032***
	(10.75)	(5.16)	(10.77)	(5.24)	(17.40)	(2.94)
RANK 3	1.3627***	0.8683***	1.3647***	0.8858***	2.3845***	-0.024***
	(16.92)	(8.81)	(16.79)	(9.29)	(32.71)	(2.13)
RANK 4	1.8054***	1.2075***	1.5251***	1.0756***	2.9372***	0.0386***
	(21.66)	(12.17)	(13.98)	(7.96)	(32.16)	(2.41)
RANK 5	2.33***	1.9209***	1.8572***	1.8009***	4.654***	0.2407***
	(26.60)	(18.66)	(16.87)	(13.35)	(52.95)	(9.77)
CONST	-3.232***	1.9498***	-2.9718***	2.0261***	-3.0586	0.8649***
	(29.35)	(14,96)	(26.36)	(15.17)	(30.36)	(24.97)
DUMMY						-4.1135***
						(140.99)
Observations	14300	3585	14300	3585	14300	14300

(Pseudo-) R^2	0.28		0.29		0.15	0.94
Log Likelihood	-5764.2	-17616.6	-5700.4	-17605	-15079.0	
	Note: Absolute t value in parentheses, based on a clustering robust Variance-Covariance Matrix (except Tobit) Tobit : Marginal Effects on Unconditional Expected Value are reported					

*** denotes significant on the 1 percent level, ** on the 5 percent level and * on the 10 percent level.

Table IV

	Number of Articles	Av. Number of Pages Produced per Article (Contribution)	Av. Quality	Co-authorship Ln (Authors)	Av. Quality
T	0.3393***	0.0578***	0.0905***	-0.1907***	0.0706***
	(8.46)	(4.61)	(4.34)	(2.76)	(3.52)
T^2	-0.0397***	-0.0088***	-0.0108***	0.004***	-0.0084***
	(7.39)	(4.98)	(3.66)	(3.96)	(2.91)
T^3	0.0018***	0.0004***	0.0005***	-0.0002***	0.0004**
	(6.76)	(4.31)	(3.06)	(3.04)	(2.39)
T^4	$-2.53E^{-5}$***	$-5.68E^{-6}$***	$-7.23E^{-6}$***	$1.96E^{-6}$**	$-5.55E^{-6}$**
	(6.20)	(3.78)	(2.81)	(2.26)	(2.20)
C7580	0.3871***	-0.0256	0.0549	0.0157	0.055
	(2.77)	(0.48)	(0.50)	(0.51)	(0.50)
C8186	0.8220***	-0.0984*	0.2099*	0.108***	0.2024*
	(6.56)	(1.90)	(1.75)	(3.35)	(1.66)
C8792	0.8957***	-0.1467***	0.5028***	0.227***	0.4699***
	(7.39)	(2.63)	(4.32)	(7.30)	(4.00)
C9398	1.0508***	-0.1286**	0.4187***	0.2924***	0.3586***
	(10.08)	(2.46)	(3.78)	(9.14)	(3.11)
MICROECONOMICS	0.1205	-0.2618***	0.3591***	0.0946*	0.4269***
	(0.62)	(4.65)	(3.30)	(1.78)	(3.79)
MACROECONOMICS	0.2416	-0.1016*	-0.0186	0.0215	0.0146
	(1.49)	(1.82)	(0.17)	(0.42)	(0.13)
PUBLIC ECONOMICS	0.3455**	-0.16***	-0.1057	0.0273	-0.0479
	(2.10)	(3.03)	(1.13)	(0.54)	(0.49)
ECONOMETRICS	0.1958	-0.2439***	0.0373	0.139**	0.0913
	(1.12)	(3.75)	(0.28)	(2.41)	(0.65)
FEMALE	-0.3279	0.0887	0.142	-0.0476	0.1181
	(1.51)	(1.34)	(1.24)	(1.15)	(1.01)
RANK 2	0.9253	0.0289	0.8598***	-0.0205	0.8784***
	(1.26)	(0.27)	(3.98)	(0.29)	(4.01)
RANK 3	1.7832**	0.1555	1.0638***	-0.0791	1.0456***
	(2.50)	(1.51)	(5.24)	(1.14)	(5.10)
RANK 4	2.3834***	0.1761*	1.2331***	-0.0670	1.1985***
	(3.35)	(1.75)	(6.05)	(0.98)	(5.85)
RANK 5	3.0497***	0.1353	1.9051***	-0.0407	1.8608***
	(4.29)	(1.34)	(9.37)	(0.61)	(9.13)
CONST	-4.5774***	2.5126***		0.1673	
	(6.16)	(21.71)		(2.03)	
NO. OF ARTICLES		-0.0114	-0.0062		
		(1.13)	(0.37)		
LN (D_SIZE)			-0.3947***		
			(8.72)		
LN(COAUTHORS)					0.3251***
					(5.17)
Observations	3585	3585	3585	3585	3585
(Pseudo)-R^2		0.59	0.08	0.10	0.07
Log Likelihood	-3520.6		-5018.3		-5079.7

Note: Absolute t-value in parentheses, based upon a clustering robust Variance-Covariance Matrix
Estimation methods:
Number of Articles: Zero-Truncated NegBin
Av. Contribution: OLS on Logarithm of Average Contribution
Av. Quality: Ordered Probit
Co-authorship: OLS on Logarithm of author-index

*** denotes significant on the 1 percent level, ** on the 5 percent level and * on the 10 percent level.

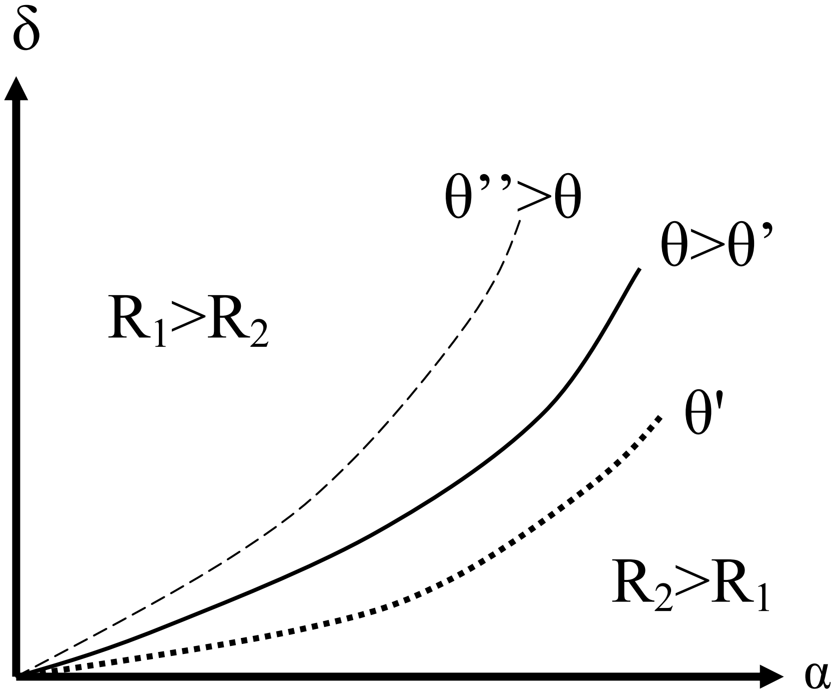


Figure 1

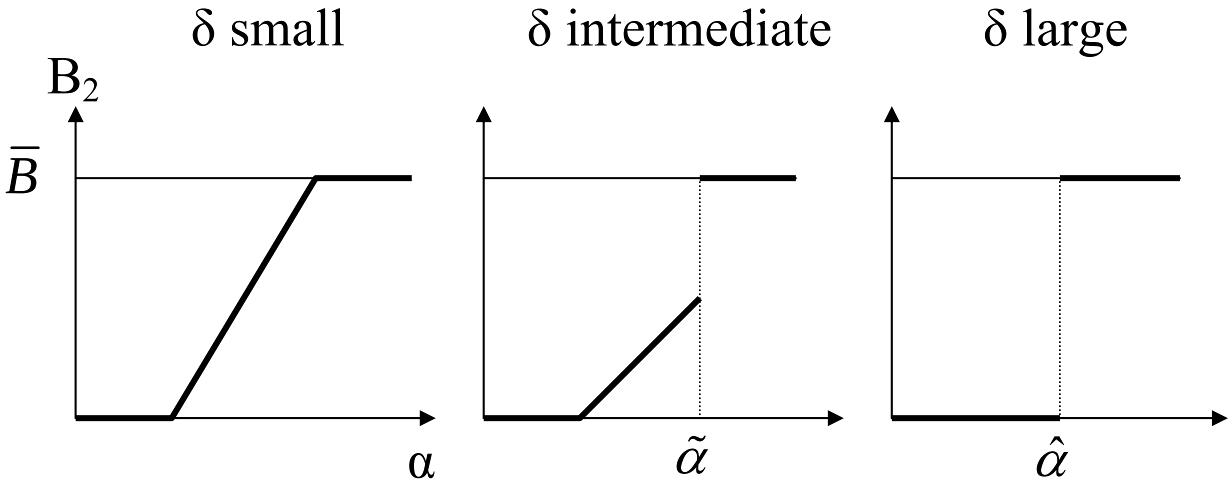
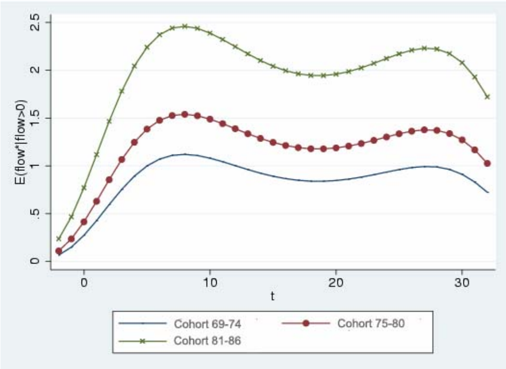


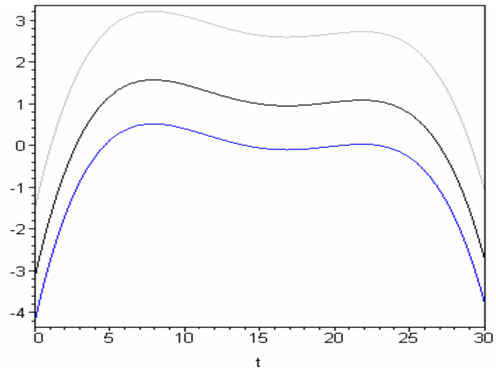
Figure 2a Figure 2b Figure 2c

Figure I/1



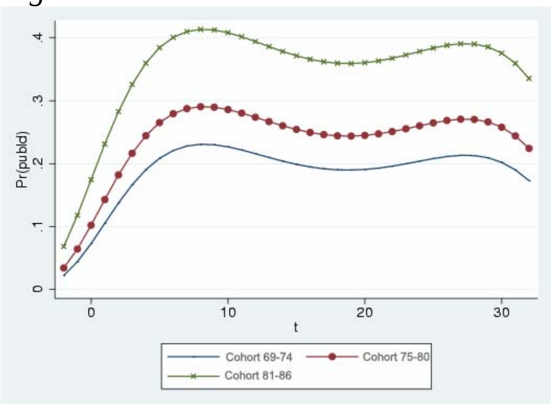
Tobit for different cohorts

Figure I/2



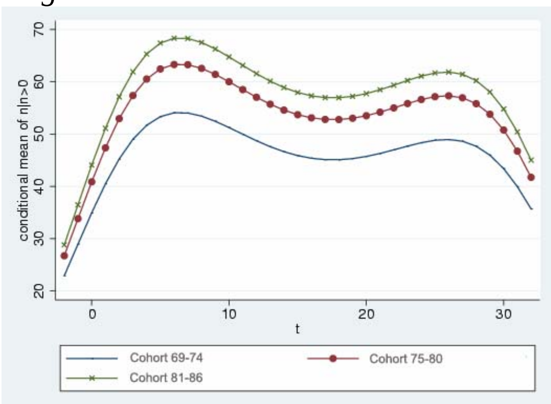
CLAD for different cohorts:
86-81, 80-76, 75-69(from top to bottom)

Figure I/3a



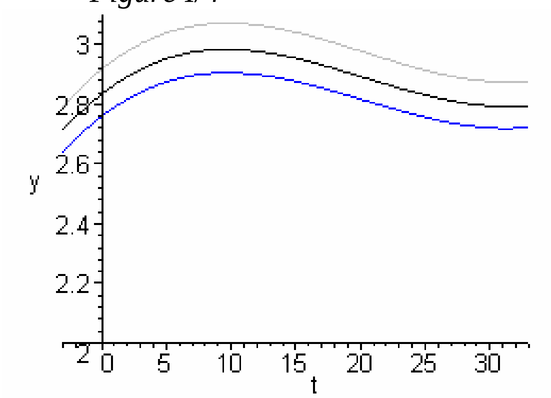
Hurdle Model: Probability of being active

Figure I/4b



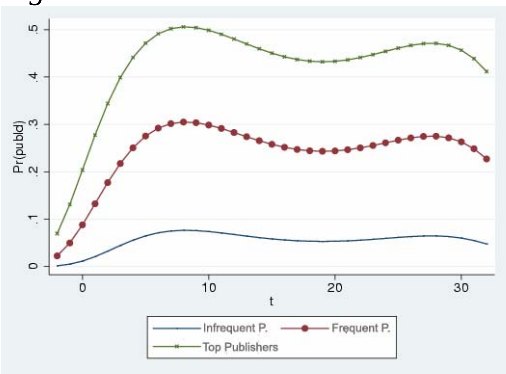
Hurdle Model: Conditional productivity

Figure I/4



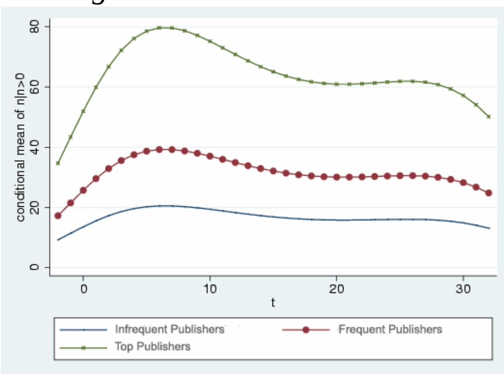
Log-Linear Model for different cohorts:
86-81, 80-76, 75-69 (from top to bottom)

Figure III/1a



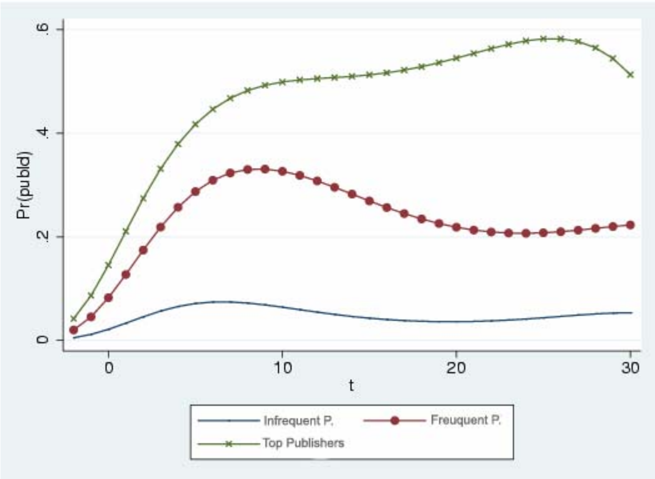
Hurdle Model: Probability of being active

Figure III/1b



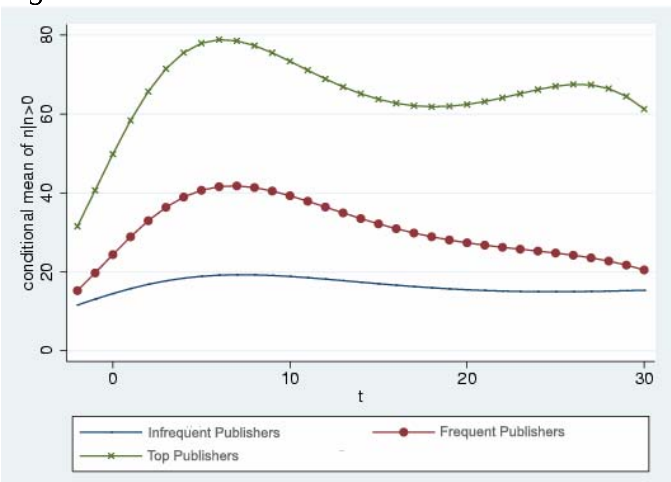
Hurdle Model: Conditional productivity

Figure III/2a



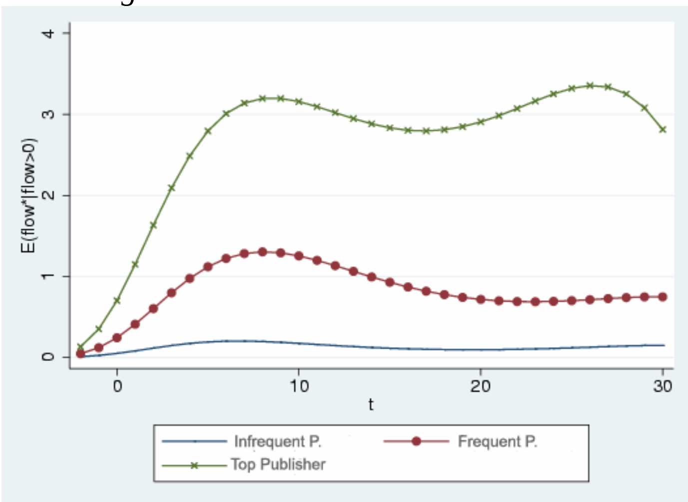
Hurdle Model: Probability of being active for different ranks

Figure III/2b



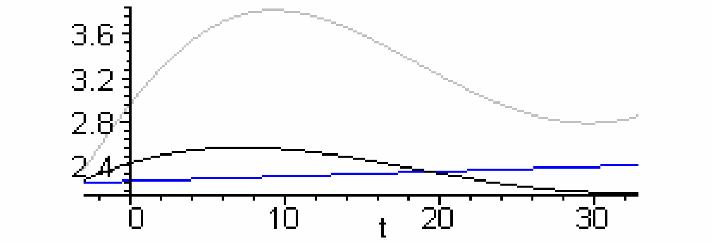
Hurdle Model: Conditional productivity

Figure III/3



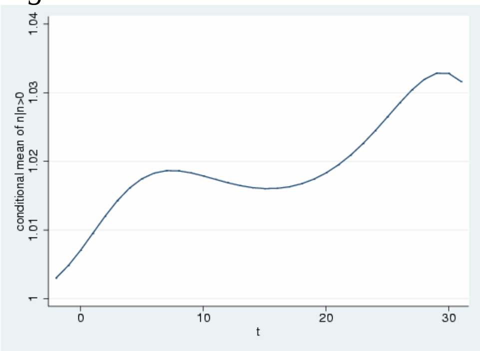
Tobit; class of 1970, different ranks

Figure III/4



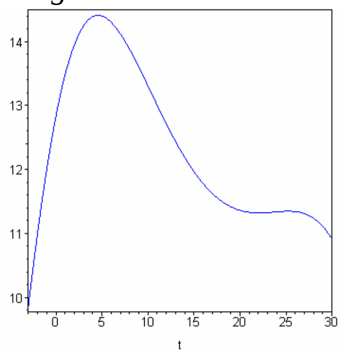
Log Linear Model for Top, Frequent and Infrequent Publishers (from Top to Bottom)

Figure IV/1



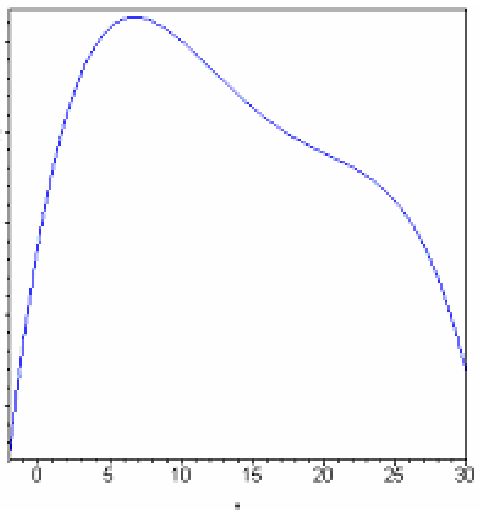
Number of Publications by Macroeconomist, Class of 1970, Rank 3

Figure IV/2



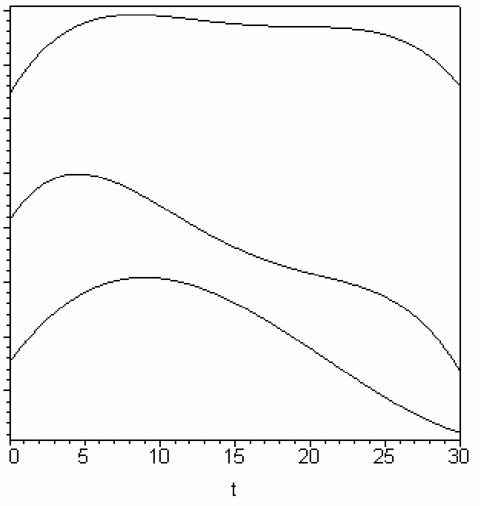
Average N. of Pages written by Macroeconomist, class of 1970, Rank 3

Figure IV/3



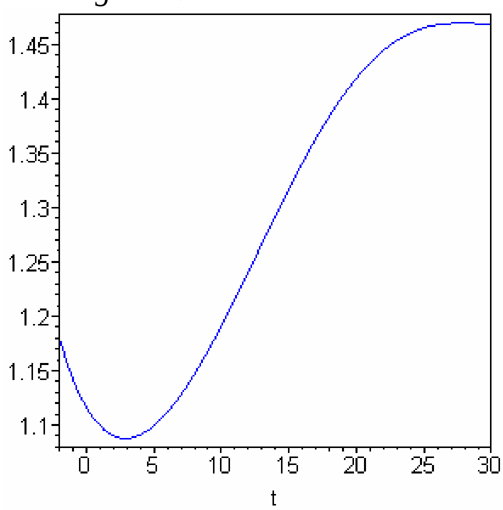
Average Quality (overall estimate)

Figure IV/4



Average Quality for top, frequent and infrequent publishers (from Top to Bottom)

Figure IV/5



Co-authorship over the Lifecycle
Year of Ph.D.: 1970, macroeconomist, Rank 3

APPENDIX

Table V Total datapoints 14300 Variable	Mean	Std. Dev.	Min.	Max.
SCORE	1.257174	3.62931	0	56.833333
LENGHT	12.99601	7.418703	0.5	71
DQUAL	0.2534889	0.2012735	0.0833333	1
NUMBER_ON	1.619805	1.065489	1	14
FEMALE	0.044965	0.2072346	0	1
MICROECONOMICS	0.1395105	0.3464906	0	1
MACROECONOMICS	0.2770629	0.4475635	0	1
PUBLIC ECON.	0.3466434	0.4759176	0	1
ECONOMETRICS	0.1462238	0.3533428	0	1
OTHER	0.0905594	0.2869916	0	1
RANK1	0.1774126	0.3820308	0	1
RANK2	0.1853846	0.3886229	0	1
RANK3	0.203986	0.4029728	0	1
RANK4	0.2074126	0.4054678	0	1
RANK5	0.2258042	0.4181254	0	1
AUTHORS	1.568133	0.6135071	1	4

Deconstruction:

Assume two papers are published in year t, one together with a coauthor (40 pages, low quality) and the other one without co-author (15 pages, quality 1/2). The score is then calculated as:

$$Score=1/2*40*0.08+1*15*0.5=9.1$$

The number of pages attributed to the author is denoted by

$$Pages=1/2*40+1*15=35$$

We then simply divide *Score* through *Pages* to arrive at the average quality for year t: $\frac{9.1}{35} = 0.26$.

To compute the average (quantitative) contribution per paper we divide *Pages* through the *number* (here 2) of articles written. This is a measure of the *average contribution* (measured in pages; here 17.5) to each paper authored or co-authored.

Further Figures: Densities

Figure A1: Density of Flow | Flow>0

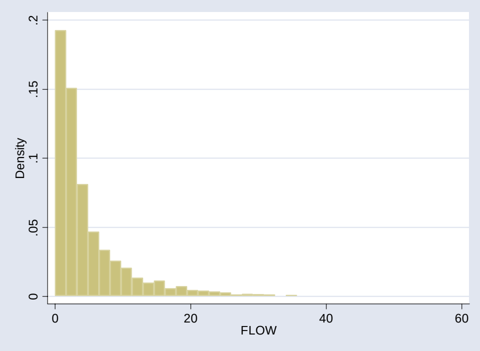


Figure A2: Density of transformed Flow

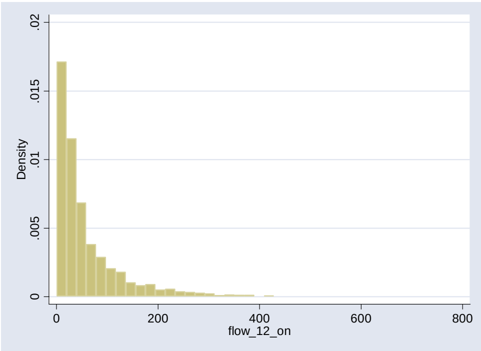


Figure A3: Density of Average Quality

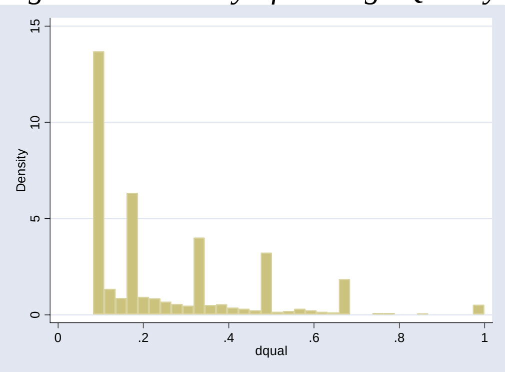


Figure A4: Density of Ln (Av. Length)