The Great Divide in Scientific Productivity. Why the Average Scientist Does Not Exist*

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Abstract

We use a quantile regression approach to estimate the effects of age, gender, research funding, teaching load and other observed characteristics of academic researchers on the full distribution of research performance, both in its quantity (publications) and quality (citations) dimension. Exploiting the panel nature of our dataset, we estimate a correlated random-effects quantile regression model, accounting for unobserved heterogeneity of researchers. We employ recent advances in quantile regression that allow its application to count data. Estimation of the model for a panel of biomedical and exact scientists at the KU Leuven in the period 1992-2001 shows strong support for our quantile regression approach, revealing the differential impact of almost all regressors along the distribution. We also find that variables like funding, teaching load and cohort have a different impact on research quantity than on research quality.

JEL-classification: C14 ; C23 ; L31 ; O31 ; O32

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1 Introduction

Research performance plays an increasingly important role in funding research projects and institutions, as well as promoting individual researchers. Understanding what drives a researcher's productivity is of interest to policy makers and to governors of research organizations as it allows for more informed decisions regarding the design of science systems and career paths.

Scientific research unraveling the determinants of research productivity has not been abundant, but is gradually receiving more attention, both at the level of the individual researcher and at more aggregate levels (see for example Stephan & Levin (1992) and Stephan (1996) for a survey). Despite indications of substantial heterogeneity in the researcher population, dating back to Lotka (1926), almost all empirical studies tend to explain average productivity only.

This paper starts from the skewness of the research productivity distribution. Using a panel of individual researchers across biomedical and exact sciences at the KULeuven, we estimate the impact of a range of productivity drivers at the separate quantiles of the productivity distribution, looking at both quantity (publications) and quality (citations) of research output. Our approach allows to examine whether determinants, like the often observed 'gender' or 'access to funding' effects, operate consistently along the whole distribution versus at the lower or upper tail only. Being able to characterize the effects across the whole distribution is important for an adequate design of policy trying to affect these drivers.

To allow for the estimation of the conditional quantiles of integer counts of publications and citations, we employ recent advances in the literature that extend the quantile regression approach to count data (Machado & Santos Silva, 2005)). In addition, we control for unobserved heterogeneity of researchers by estimating a correlated random-effects quantile model (Chamberlain,1984).

We find that the effect of most regressors differs significantly at different points in the distribution, yielding strong support for our quantile regression approach. This conclusion holds for both the quantity and quality distribution. In addition, observables like funding, teaching load, gender and entry cohort have a different impact on the quantity distribution than on the quality distribution. For example, the impact of small research grants on research quality remains roughly constant across the distribution while the impact of this funding on research quantity is the highest at the bottom end of the distribution and then decreases monotonously towards the upper end. This finding would imply that an extreme selectivity in the assignment of research funds based on the argument that the researchers who were the most productive in the past 'give the most bang for the buck' may be misdirected. Although one must be cautious generalizing the results found here, the analysis makes the case for understanding the full productivity distribution, moving beyond an analysis of averages.

The remainder of this paper is organized as follows. We start by situating our research in the literature. In section 3 we discuss the data, providing details on the key aspects that we wish to address. The next section details the quantile regression approach discussing the correlated random effects model and the necessary adjustment to estimate conditional quantiles for count data. Section 5 discusses the empirical results. The final section summarizes and concludes.

2 Literature review and research design

Most existing empirical studies on academic productivity concentrate on the effects of characteristics of the individual researcher. These studies (for a review, see Stephan (1996)) have indicated the importance of characteristics like age, with publishing activity initially increasing and then declining in mid-career. Several studies have found that female scientists publish at lower rates than male scientists. They also show the importance of controlling for scientific discipline ideosyncracies. In view of the significance of team effort in science, it is also important to assess collective effects on individual productivity. Mairesse and Turner (2002) provide evidence that the quality of other researchers belonging to the laboratory is a crucial variable for explaining individual productivity.

Most of the previous studies to date aim at explaining how individual and institutional characteristics affect average productivity, ignoring the often skewed distribution of research productivity, with many researchers non-active and a few researchers accounting for the bulk of the publications. This skewed nature of the distribution of research output has nevertheless been widely documented and characterized in the bibliometric literature. A recent exception of economic research on research productivity analyzing more than just the conditional mean is the paper by Rauber & Ursprung (2006). Using data on German economists, they model a continuous measure of research output as a function of career age, cohort, gender and economic subdiscipline. As one part of their analysis, they use a cross-sectional quantile estimator to study the upper part of the productivity distribution (75^{th} - 95^{th} quantile). For each of the investigated quantiles, they find a life cycle effect.

This paper contributes to the economics of science literature on research productivity by estimating the impact of a large set of productivity determinants on both quantity and quality dimensions of research performance and this for the whole productivity distribution, using recent advances in quantile regression techniques. First, the data set allows controlling for a rich set of determining factors, such as gender, tenure, rank, hierarchical position (head of team) and seniority. Furthermore, the record of each researcher contains teaching load, administrative duties and awards of additional research funding. Second, the set covers all biomedical and exact scientists at the KU Leuven, allowing to check the influence of scientific discipline effects; Third, using publications as well as citations information, we look at both quantity and quality dimensions of research performance. We employ recent advances in quantile regression that allow its application to count data. Fourth, since the data set is a panel comprising ten years of publication data 1992-2001, we can separate age and cohort effects.

The panel nature of our dataset also allows estimating a random-effects model, which better accounts for unobserved heterogeneity of researchers. Unobserved heterogeneity among researchers makes it difficult to pin down the impact of several variables on research output. Using Chamberlain's correlated random effects model (1982, 1984), we control for unobserved heterogeneity in the quantile estimations by allowing the researcher random effect to be related to observed characteristics . For example, whether a researcher carries a high teaching load or not, is likely to be correlated with unobserved characteristics such as a high affinity for teaching. By explicitly modeling the random effect as a function of teaching load (and other variables), we are better able to identify the causal effect of teaching load on research output.

To our knowledge, this paper is the first effort to analyze research performance using quantile regressions for panel and count data. The results support our approach. First, they show the effects of determinants of research performance to differ across quantiles. Second, they indicate the differential impact of determinants across the productivity distribution to play differently for quantity versus quality dimensions of research performance. Furthermore, a formal test of the correlated random effects model clearly rejects a pure random effects approach where the random effects are assumed to be uncorrelated with the observables.

3 The data

We constructed a unique panel containing a census of the 1,036 scientists within the fields of biomedical and exact sciences, in the period 1992-2001, employed at the KU Leuven. Having only information on one institution restricts the analysis with respect to institutional characteristics. It however allows accessing detailed institutional records, generating information on a wider set of individual researcher characteristics.

The KU Leuven, the largest and oldest university in Belgium, represents the case of a research university that has the ambition to establish a top position in research in 'poles of excellence', and have a good research performance in the other areas[1]. To this end it allocates research funding to research proposals on the basis of (international) peer review of excellence in research. Recruitment and promotion decisions also carry a strong research quality requirement. In addition, research output (publications and citations) of its entire academic staff is regularly assessed since a substantial part of university public funding is allocated on the basis of these indicators.

Combining information from the personnel administration of the KU Leuven with bibliometric data, we were able to include a rich set of variables to assess research performance and its determinants. Details on the construction of the database are provided in Appendix 2. The dataset contains the following information:

- Scientific output (per researcher per year) i.e. publications and citations in ISI journals classified by scientific discipline[2];

[1]For background on institutional features of the KU Leuven, see Appendix 2.

[2]The publication and citation counts were supplied by the Centre for R&D Statistics in Leuven, using ISI-data. Citations are counted using a three-year forward citation window. There is also scientific output that does not fall under the scope of the Science Citation Index of the ISI. For instance, the ISI database does not include proceedings, which in some disciplines, like engineering, are an important publication outlet. We refer to the appendix of a companion paper (Kelchtermans & Veugelers, 2005) for details on the construction of the database.

- Organizational membership at the group (exact versus biomedical sciences), faculty (e.g. medicine) and department (e.g. microbiology and immunology) level;
- Individual and career-related variables (per researcher per year) i.e. gender, age, cohort (year of entry at KU Leuven), career age, rank (assistant professor, associate professor, professor and full professor), seniority in rank, full-time versus part time position;
- Involvement as a promoter or copromoter of research projects awarded on a competitive basis. Two major types of funding can be identified: the larger Type I (excellence) and the smaller Type II funding. See Appendix 2 for a description of the KU Leuven research strategy and the type of funding it awards.
- Other information relevant for examining scientific performance, viz. actual teaching load, other administrative duties within KU Leuven, being head of a research unit;
- Most researchers in the sample were not employed for the full 10 years: some of them retired or left the university before 2001, others joined after 1992. These entries and exits yield an unbalanced panel and allow examining cohort effects. The data set holds on average 778 researchers per year. We restricted the dataset to researchers whom we observe for at least 2 periods.

3 shows yearly averages across researchers and years of different research output measures, for all researchers as well as conditional on individual characteristics. We don't comment on the conditional means in the table here, but provide them as a reference for the interpretation of the results. On average a researcher in our dataset publishes 3.3 articles. A publication gets on average 3 citations per year and has an average impact factor of 3.2. But this average has a high standard deviation (resp 5.1 for publications and 4.2 for citations). The Lorenz curves in Figure 1 confirm the skewed distribution of research quantity (publications). For research quality (citations) the pattern is even more skewed. In the remainder of the analysis, in order to avoid overload of results, we will focus the discussion on publications, reporting results for citations only when they reveal interesting differences with publications (see section 5.3)[3].

[3] The correlation coefficient for publications and citations in our dataset is 0.77.

The propensity to publish varies greatly among disciplines. Table 4 shows the quantiles of the publication distribution by main discipline of the researcher[4]. These quantiles are obtained by comparing the yearly publication output of all researchers who share the same main discipline[5] and are then averaged across years. The characterization of the publication distribution in this table includes the output of the 814 researchers for whom we observe at least one publication in 1992-2001[6]. Although the 222 researchers with a persistently blank publication record are ignored here[7,8], note that the prevalence of (non-persistent) zeroes is still very high, as can be observed by the small (differences in) percentile values at the bottom of the distribution. For most disciplines, in each year there is at least 10% of zero inflation, so that the 10^{th} percentile equals zero. For engineering, zero inflation even amounts to 25%. All this reflects the importance of scientific discipline specific effects when examining research productivity.

Table 5 reports averages for the individual and career-related characteristics of the researchers, comparing the whole sample with the different 'percentile bands' of active researchers. Researchers are assigned to a percentile band as follows. Their publication output in a particular year is compared with the percentile values for their main discipline in that year[9] i.e. the values for which the yearly averages were reported in Table 4. Researchers are assigned to the highest percentile band they qualify for[10]. Because a researcher's output may vary across years, she may be part

[4] Table 1 and table 2 present the distribution of scientists over the respective faculties and disciplines. Within the group of Exact Sciences, the faculty of Science (192 professors) and the one of Engineering (214) are the largest. In the group of Biomedical Sciences, the faculty of Medicine (460 professors) clearly dominates in terms of size.

[5] Formally, the 100τth quantile of the publication distribution Y given x is given by $Q_Y(\tau|x) = \min\{\eta|P(Y \leq \eta|x) \geq \tau\}$.

[6] Active researchers tend to publish in several of the 10 disciplines. A researcher's main discipline is defined as the discipline in which she has published the most articles between 1992-2001. Consequently, inactive researchers i.e. for whom we don't observe any publications in 1992-2001, cannot be assigned a main discipline.

[7] All researchers, including the 'persistent zeroes', are included in the empirical analysis later on.

[8] Inspection of the data reveals that we can attribute this apparent 'inactivity' (at least partially) to the involvement of staff as practitioners in their field of expertise. In other words, some staff members may have a full-time position at the university but are nevertheless not expected to carry out research. In particular, there are four departments where more than one third of full-time staff doesn't show up in the ISI publication records. It concerns the departments of architecture, public health (where general physicians are trained), sports & motion sciences and kinesiology.

[9] Note that this procedure, by comparing researchers with their peers in the same disicpline, controls for discipline-specific publication patterns and therefore avoids that researchers from disciplines characterized by lower publication rates are all classified in the lower percentiles.

[10] For example, a researcher may publish enough articles in a given year to beat the 50^{th} percentile in her discipline but not enough to reach the 75^{th} percentile: for that year, she is classified in the 50%-75% percentile band, and in this band only. As mentioned, due to zero inflation it is possible that both the 10^{th} and 25^{th} percentile equal zero. In that case, researchers with zero publications are classified in the 10%-25% percentile band, leaving the <10% band empty.

of a different percentile band in each year, although researchers tend to be very immobile in their output levels (see Kelchtermans & Veugelers (2005), based on the same dataset).

In the whole sample about 89% of researchers are male. In line with previous studies on scientific productivity, we find that female researchers are underrepresented among the most productive researchers. No clear age pattern emerges across the percentile bands. Also the distribution over age cohorts at different points in the distribution seems roughly consistent with the distribution in the whole sample. Recent entry cohorts are overrepresented at the lower end of the distribution, while the situation is reversed at the upper end. A similar pattern emerges with respect to a rank. We distinguish between four main ranks, with rank 1 the entry level ("assistant professor") and rank 4 the highest possible rank ("full professor"). The junior ranks are more prevalent in the lower half of the distribution. For the upper half of conditional productivity distribution the proportion of full-time researchers rises to higher than average. The average teaching load for a professor increases monotonously with rank. But the averages by percentile band do not suggest that teaching substitutes for research output, on the contrary. Finally, on average 9% of the sample is involved in a type I project as a promoter or copromoter, while 11% (co-)promotes a type II project. Involvement in these research projects varies strongly by percentile band.

4 Quantile regression framework

Section 4.1 specifies the correlated random-effects model (Chamberlain, 1984) allowing to control for individual effects in a quantile model. Section 4.2 discusses the smoothing approach that allows quantile regression for count data (Machado and Santos Silva, 2005).

4.1 Conditional quantiles of productivity with panel data

It has been argued before in the literature (e.g. Fox, 1983) that the reason why some scientists are very prolific while others are not, may lie in the possession of a unique talent for research such as motivation and creativity. These idiosyncratic but unobserved characteristics are captured by an individual-specific, time-independent effect. Different assumptions for the unobserved individual effect lead to different flavors of panel-data models. While the random effects model assumes that this effect is uncorrelated with the vector of observed characteristics, an assumption which is usually hard to maintain in empirical applications, the fixed effects model allows for correlation but in an unspecified way. In a least squares framework, consistent estimates can be obtained by transforming the variables in deviations from individual means. This differencing approach is however not available for quantile regressions since quantiles are not linear operators, a critical requirement for this strategy to work (Koenker & Hallock, 2001; Koenker, 2004).

To account for unobserved individual effects in our quantile regression we use Chamberlain's correlated random-effects model (1984)[11]. In line with other research (e.g. Levin and Stephan, 1991) we expect that the unobserved individual-specific effect is correlated with some of the determinants of research productivity. Chamberlain's correlated random-effects model (1984) employs a random effects specification that allows for such correlation.

A standard linear panel-data model for our data may be written as:

$$Y_{it} = X_{it}'\beta + Z_{it}'\gamma + \alpha_i + \varepsilon_{it}$$

where $X_{it} = \left(x_{it}^1, \ldots, x_{it}^K\right)$ and $Z_{it} = \left(z_{it}^1, \ldots, z_{it}^G\right)$ are the vectors of observed characteristics with their associated parameter vectors $\beta = \left(\beta^1, \ldots, \beta^K\right)$ and $\gamma = \left(\gamma^1, \ldots, \gamma^G\right)$. The unobserved individual effect is denoted by α_i and ε_{it} is the error term. X_{it} denotes the variables that are expected to correlate with the individual effect as opposed to those included in Z_{it}.

The correlated random effects estimator uses a linear specification for the unobservable α_i consisting of the observables X_{it} plus an additional error term ν_i:

$$\alpha_i = \phi + \sum_{t=1}^{T} X_{it}'\lambda^t + \nu_i$$

[11] An alternative approach for estimating conditional quantiles accounting for individual effects is proposed by Koenker (2004). It consists of adding a penalty term to the quantile objective function as a way to impose structure on the fixed effects. While offering the advantage of leaving the relation between the fixed effect and the observables unspecified, the choice of the 'tuning parameter' that controls the degree of structure is an open research issue. Recently, Lamarche (2006) has made progress in developing a selection mechanism for the value of this tuning parameter that minimizes the estimated asymptotic variance, provided an additional assumption for the individual effects distribution is made. In this paper, we adopt a different approach.

where ϕ is a constant and ν_i is uncorrelated with X_{it} and $T \leq 10$[12].

Note that the correlated random-effects model can not take into account potential correlation between time-invariant variables and the individual effect. Based on this correlated random-effects model, the conditional quantile functions are written as linear functions of the observables. We assume that the direct effects of the variables X_i and the effects of the variables Z_i on the conditional quantiles is constant across time.

For $t = 1$ the function for quantile τ can then be written as:

$$Q_\tau \left(Y_{i1}|X_i, Z_{i1}\right) = \phi_\tau + X'_{i1}\beta_\tau + \sum_{t=1}^{T} X'_{it}\lambda^t_\tau + Z'_{i1}\gamma_\tau. \tag{1}$$

The conditional quantile functions for $t \neq 1$ are analogous to (1).Note that the linear specification (1) is in fact a reduced form model of the true, but unknown, conditional quantile functions $Q_\tau \left(Y|X, Z\right)$. In section 4.2 we will come back to this issue and comment on the functional form of the conditional quantile function we use for estimation.

A simple estimation strategy for (1) is by a pooled quantile regression on the stacked data, written as (for the τ-th quantile):

$$\begin{bmatrix} Y_{11} \\ \vdots \\ Y_{1T} \\ \vdots \\ Y_{N1} \\ \vdots \\ Y_{NT} \end{bmatrix} = \begin{bmatrix} 1 & X_{11} & X_{11} & \cdots & X_{1T} & Z_{11} \\ \vdots & & & & & \\ 1 & X_{1T} & X_{11} & \cdots & X_{1T} & Z_{1T} \\ \vdots & & & & & \\ 1 & X_{NT} & X_{N1} & \cdots & X_{NT} & Z_{N1} \\ \vdots & & & & & \\ 1 & X_{NT} & X_{N1} & \cdots & X_{NT} & Z_{NT} \end{bmatrix} \cdot \begin{bmatrix} \varphi_\tau \\ \beta_\tau \\ \lambda^1_\tau \\ \vdots \\ \lambda^T_\tau \\ \gamma_\tau \end{bmatrix}$$

The computation of the standard errors should account for the dependence between the repeated observations of a single researcher. This means that the standard formula to calculate the asymptotic variance of the quantile estimators (Koenker & Bassett, 1978) cannot be applied. Following Abrevaya & Dahl (2005), we adopt a clustered bootstrapping procedure where the bootstrap

[12] Since we have an unbalanced panel, the number of observation periods varies by individual i (we observe an individual on average 7.5 years). To simplify notation, we write $T_i = T$. The estimates reported in section 5 use $T = 2$. Higher values of T do not alter the results.

sample contains all observations of a researcher if that researcher is drawn to be included in the bootstrap sample.

We test whether our approach of modeling the individual effect in terms of observables is valid. The testing framework (following Buchinsky, 1998) is discussed in Appendix 1. The test results are reported in section 5.1.

4.2 Quantile regression for count data

The main problem when estimating conditional quantiles for a count variable Y is that, because it has a discrete distribution, $Q_\tau\left(Y|X,Z\right)$ is not a continuous function of the parameters. To be able to apply quantile regression to count data, artificial smoothness must be imposed. Machado and Santos Silva (2005) suggest a 'jittering approach' where the needed smoothness is achieved by adding to the count variable Y a random variable U, leading to a new variable $V = Y + U$. U is independent of Y, X and Z and uniformly distributed in the interval $[0,1)$. The authors show that it is possible to perform inferences about $Q_\tau\left(V|X,Z\right)$, the conditional quantile function of the smoothed data. Further, they relate the quantiles of the random variables V and Y, which is crucial since the ultimate interest lies in the quantile function of the original count data:

$$Q_\tau\left(V|X,Z\right) = Q_\tau\left(Y|X,Z\right) + \frac{\tau - \sum\limits_{y=0}^{Q_\tau(Y|X,Z)-1} P\left(Y=y|X,Z\right)}{P\left(Y = Q_\tau\left(Y|X,Z\right)|X,Z\right)} \tag{2}$$

Thus, a continuous distribution is achieved by interpolating the discrete jumps in the conditional quantile function of the counts. $Q_\tau\left(V|X,Z\right)$ can be estimated using standard quantile regression techniques[13]. In our estimation strategy, we follow Machado & Santos Silva (2005) who use an exponential specification as an approximation to the unknown conditional quantile function. By applying a monotonic transformation to the 'jittered' count variable V, the conditional quantile function of the transformed V' can be written as a linear function[14]. For $t = 1$ we have:

[13]In particular, several jittered samples are generated and used for estimation, after wich the estimates are averaged to yield the final parameters

[14]Stata's *qcount* estimation command, which we use for our analysis, implements the transformation of the 'jittered' count variable V, proposed by Machado & Santos Silva (2005). It allows estimation of the quantile parameters using linear quantile regression on the transformed V'.

$$Q_\tau\left(V_{i1}'|X_i,Z_{i1}\right)=\widetilde{\phi}_\tau+X_{i1}'\widetilde{\beta}_\tau+\sum_{t=1}^{T}X_{it}'\widetilde{\lambda}_\tau^t+Z_{i1}'\widetilde{\gamma}_\tau \tag{3}$$

with the conditional quantile functions for $t \neq 1$ analogous.

It is important to point out that this approach is particularly useful to analyze the lower end of the research output distribution, given that it is characterized by zero inflation. To see this, let x_{it}^k denote the k-th element from X_{it} and β_τ^k the k-th element from β_τ. In a dataset with $100\times\theta$ percent of zero inflation, all of the quantiles of Y up to $\tau=\theta$ will be identically zero, ruling out any effects from the observables. Expression (2) shows[15] that while it is possible for a change in x_{it}^k not to have an impact on a given quantile τ_0 of the *count* variable Y ($\beta_\tau^k=0$), it may influence the probability distribution at or below $Q_\tau\left(Y|X,Z\right)$. Therefore, it is easier to pick up dependence of the distribution of Y on X and Z by looking at $Q_\tau\left(V|X,Z\right)$ than by looking at $Q_\tau\left(Y|X,Z\right)$. Machado & Santos Silva (2005) refer to this as the "magnifying glass effect" of $Q_\tau\left(V|X,Z\right)$. As it allows studying the lower part of the distribution, this approach is particularly useful for the problem at hand, given the skewness of the productivity distribution for both publications and citations, with many zero observations.

4.3 Variables

Our empirical analysis investigates the impact of a series of variables on different quantiles of productivity. The selection of factors determining research productivity are based on the findings of previous research, as reviewed in section 2. As there is little guidance from previous research results, we hypothesize effects to hold for both quantity and quality of research output, although the size of the effects may be different for both dimensions. We close the section with a discussion of the differential impact of these variables along the productivity distribution, which is the main focus of our analysis.

The determining variables are grouped depending on whether they are part of the random effect specification or not (see section 4.1). The following characteristics are taken up as part of

[15] The same argument holds for z_{i1}^g as the g-th element from Z_{i1} and for γ_τ^g as the g-th element from γ_τ.

the X-variable, i.e. they are part of the random effect specification, assumed to correlate with the unobservable fixed effects:

- *Rank.* Researchers up for promotion are expected to have a higher motivation to provide research effort. Thus, in lower ranks, researchers should have more incentives to put in effort to get promotion. On the other hand, the higher ranks also have a strong incentive to put in effort in order to "prove their rank". In addition, having a more advanced rank may influence the way research is done. E.g. a full professor may have access to research assistants, may have a more extensive research network as well as an established reputation that allows for a more steady stream of output compared to more junior professors. Note that since past research output is taken into account when hiring and promoting, it is likely that current performance will increase the probability of getting a higher rank. To take this endogeneity (at least partly) into account, we lag the rank indicators by one period[16].

- *Seniority in rank.* The variable seniority in rank should capture increasing pressure to provide effort, the longer a researcher is in his current rank (since the more likely she is to be up for promotion). We might expect a non-linearity: once a researcher is far beyond the expected seniority (typically two years), this might reflect a structurally reduced probability to get promotion. Also, the more senior, the higher is the wage and thus the smaller is the incentive from increasing wage with rank. Especially in the end rank (full professor) seniority in rank looses its specific function and will correlate with age.

- *Head of a research unit.* Heading a research lab may boost someone's output by having access to resources for research as well as being involved in more projects with the possibility of claiming coauthorship. Conversely, a prolific researcher may find that such duties hamper

[16] For researchers who became a professor before 1992 (the first period of observation of our data, which covers 1992-2001) we observe the rank they had in 1991 so the one-period lagged rank variable can be assigned. For researchers entering in or after 1992 we do not have information on their rank in the year prior to entry. For these researchers we set the lagged rank variable in the first period of observation equal to "other rank", i.e. not one of the four main ranks. We consider this a fair assumption since these would typically be junior faculty who were active as post-docs before becoming a professor. Note that a missing value would completely remove those individuals from the dataset: due to the set-up of the correlated random-effects model, where *all* lagged rank variables enter the individual's yearly output function, a missing value for one of them would show up in every year, effectively removing the individual from the panel. An analogous comment applies to the definition of the lagged variables for funding and for "head of unit"-status.

her from spending time on doing the actual research. Given that high performers are more likely to become heads of unit, there is an issue of endogeneity, so we lag this variable by one period.

- *Project funding.* Someone's publication record is expected to benefit from having access to additional research funds since they represent additional resources. Especially the Type I funding involve serious amounts of research funding. Since research performance is typically taken up as a criterion to judge research proposals, we lag this variable by one period.

- *Number of coauthors.* We include a researcher's number of coauthors in every year in the model as a way to capture a researcher's collaborative style. Scientists that cooperate intensely with colleagues are expected to be more prolific than their peers who work in more solitary manner.

- *Teaching load.* The inclusion of actual teaching load should be able to correct for the lost time for research when having to teach students. Therefore, we expect a negative impact of teaching load on research output. Due to self-selection of professors with an unobserved preference for teaching vis-à-vis research, controlling for such unobserved individual heterogeneity may reduce the effect.

For each of the variables in the random effects specification (rank, seniority in rank, head of unit, project funding, number of coauthors and teaching load), we can separate the direct effect β on the τ-th conditional quantile of research output from the indirect effects λ working through the unobservable α_i.

The following characteristics are taken up as part of the Z-variable, representing the variables uncorrelated with α_i. Z_{it} includes both time-invariant as well as time varying variables:

- *Gender.* Previous research has repeatedly identified a productivity gap in the favor of male researchers.

- *Age and career age.* A higher (biological) age may be beneficial for performance, given that it takes time and experience to build an advantage, although we expect a decreasing effect with time. We also include seniority as professor (frequently referred to as career age). This variable might be important beyond the seniority in rank in terms of the incentive to provide effort, since wages received by professors in Belgium are not only determined by rank, but also, and strongly, by seniority as professor.

- *Entry cohort.* To disentangle age from cohort effects, we also include dummies for entry into the sample. The most important cohort effect seems to be a marked increase in hiring by the KU Leuven in 1992[17], for which we include a dummy variable.

- *Time.* Apart from entry cohort effects, we include calendar year dummies in our model to control for trends such as increased publication pressure.

- *Discipline.* All existing studies indicate the importance of controlling for scientific discipline idiosyncrasies.

- *Faculty membership.* This allows capturing the influence of organizational structure and strategy to promote and provide incentives for research, to the extent that these units are responsible for developing a good research environment. It also allows correcting for the impact of spillovers from the quality or prestige of the group to which the researcher belongs.

- *Full-time versus part-time.* Whether a professor holds a full-time position at the university has obvious implications for available research time and more generally captures whether a professor is expected to do any research at all. Part time appointments, mostly occurring at the engineering faculty in our sample, are typically for people from industry who are hired and evaluated on teaching rather than research.

With respect to the impact of the determining variables at different points in the productivity distribution, there is little existing scientific knowledge we can bring on board to formulate hypotheses. We expect for all of the observed characteristics mentioned above that they have a smaller impact at the top of the distribution than at the bottom. We hypothesize that the individual effect primarily captures the researcher's talent and that this is the predominant 'key success factor' in the upper tail of the productivity distribution, driving star performance, where it dwarfs the effect

[17] This peak in hiring corresponds mainly to a growing number of retiring faculty that needed to be replaced.

of other variables like age, gender, funding, teaching load, etc. Conversely, these observed characteristics are expected to manifest themselves more clearly at the bottom end of the distribution where the endowments and therefore the impact of research talent may be expected to be more modest, as compared to other factors. In addition, the power of incentives may decrease at the top. Variables like research funding may no longer act as high-powered incentives for researchers situated at the top of the distribution. For an established star scientist yet another research grant is unlikely to represent a major impulse to increase her output even further.

5 Empirical results

We first discuss in section 5.1 the results of various tests on model specifications, before we discuss the main results on drivers for research performance across quantiles. First the results on research quantity (publications) are reported (section 5.2). Comparisons with results for research quality (citations) are reported in section 5.3. Section 5.4 closes with a discussion on which effects differ significantly across the distribution of research performance (publications and citations), further supporting our quantile approach as compared to a typical means analysis.

5.1 Results on model tests

The panel-data results are reported[18] in table 7, following the specification as expressed in (1). Estimates for five quantiles are shown[19] together with the results of a random effects negative binomial model explaining average publication output. In the random effects negative binomial model the dispersion varies randomly across researchers such that the inverse of one plus the dispersion follows a Beta(r,s) distribution. Both r and s are significantly different from zero. A likelihood ratio test that compares the negative binomial panel estimator with the pooled estimator (i.e. the negative binomial estimator with a constant dispersion across researchers), strongly favors the panel estimator.

[18] The parameters reported here are based on 400 bootstraps and 10 jittered samples for each quantile, accounting for 400x5x10=20,000 regressions. A robustness check using 50 jittered samples for each quantile (instead of 10) shows that the point estimates are very robust.

[19] Our choice of quantiles follows the one commonly made in the field of quantile regression. Of course, choosing other quantiles would lead to different parameter estimates. However, we do not expect this to alter our conclusions.

The unobserved heterogeneity parameters λ^t are not reported. The estimates are available from the authors on request. We tested their joint significance in order to check whether our approach of modelling the individual effect in terms of observables is valid (see Appendix 1 for a discussion of the testing framework). The null hypothesis states that the λ parameters are jointly equal to zero, $H_0 : \lambda_\tau^1 = ... = \lambda_\tau^T = 0$, simultaneously for all τ with $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$. The null hypothesis is strongly rejected with a p-value very close to zero. The formal test of the correlated random effects model therefore clearly prefers this specification over the cross-sectional specification (reported in table 6 for reference). For the variables that are taken up in the random effect specification (see section 4.3), we will thus be able to distinguish between their true effect and the part that is correlated with the (unobserved) individual effect of the researcher.

5.2 Cross section and panel data results on publications

In this section we discuss the parameter estimates, emphasizing the panel data results. To allow for an easy comparison of the cross-section and panel-data results, we show the quantile estimates for a selection of parameters from Tables 6 and 7 in Figure 2. The solid line indicates the point estimates for the five quantiles of the panel-data model with the dashed lines marking the 95% confidence interval. The dotted line are the cross-sectional estimates.

- *Age.* Support for an age effect is very limited. We find a small positive effect in the 90% quantile in both the cross-sectional and panel estimates. The positive age effect at the 10% quantile for the cross-sectional model is not confirmed in the panel-data results.

- *Career age.* The models offer little or no evidence for any influence of career age: the marginally significant and negative effect in the lower quantiles of the cross-sectional model is not robust in the panel-data results.

- *Seniority in rank.* The panel estimates show a significant negative influence on publication output with a decreasing effect higher up in the distribution, which disappears at the very top in the 90% quantile. Seniority in rank has no effect in the cross-sectional specification.

- *Rank.* The three junior ranks are less productive than the most senior rank (full professor, the base category) with the productivity differential decreasing with rank. The difference between ranks is less outspoken in the panel-data model than in the cross-sectional model, especially between rank 3 (professor) and the most senior rank (full professor, the base category). Further, in both models the productivity differential between ranks becomes smaller the higher up we look in the distribution.

- *Head of a research unit.* Heading a research unit has a positive impact on publication output but in the cross-sectional model the effect disappears for the upper half of the distribution. In the panel model, the effect remains present throughout the whole distribution, although it is clearly smaller in the 75% and 90% quantiles.

- *Project funding.* Having access to project funding is positively related to research output, as expected. However, for the big type I funding it is mainly the lower quantiles that benefit. Similarly, the more modest type II research grants boost the output in the lower quantiles but this type of funding also makes the very prolific researchers even more productive. The effects of funding are comparable in both models.

- *Number of coauthors.* The number of coauthors shows up as an significant control variable in both models, with a positive effect on output, although the magnitude is small.

- *Teaching load.* The cross-sectional estimates show a small but significant negative impact on output, mainly for the lower quantiles. The panel data model shows a different picture: here we find a negative, albeit small, impact only at the top of the distribution (75% and 90% quantile). We attribute this difference to unobserved heterogeneity, with professors having an affinity for teaching likely to engage more in such activities.

- *Gender.* There is evidence of a gender effect with male researchers more productive than their female colleagues. It is interesting to see the irregularity of the gender effect along the distribution: while absent for the 10% quantile, it is strongest for the moderately active researchers (25% quantile) and then decreases gradually for the higher quantiles, but remains significant up to the very top of the distribution (90% quantile). The gender effect in the panel-data model is very robust compared to the one in the cross-sectional model, as expected, since we did not endogenize this variable.

- *Full-time versus part-time.* The control for being full-time at the university is very significant, as expected. For both models, the highest value appears in the 10% quantile, which confirms the intuition that being full-time primarily explains whether a researcher is engaged in research at all.

- *Entry cohort.* Being part of the cohort that entered professorship in or after 1992 has a negative impact on publication output but only for moderately productive researchers (25% and 50% quantile in the panel-data results). The cross-sectional model offers no support for an entry cohort effect.

- *Time (not reported in the table).* The dummies for calendar year, which may capture general trends like increased publication pressure, show a small and positive effect for the later years in the cross-sectional model. In the panel model they show a clear pattern, suggesting an increasing publication trend with the higher quantiles responding quicker than the lower quantiles: the 90% quantile shows a clearly significant positive coefficient from 1995 onwards (parameter value of 0.12 in 1995) with some of the lower quantiles joining in 1997[20].

- *Discipline and faculty membership (not reported in the table).* Controlling for discipline and organizational unit is important, with similar estimates in both models[21].

5.3 Results for citations compared to publications

Table 8 shows the panel-data results for citations for five quantiles, with the results of a random effects negative binomial model explaining average citation output[22]. Since research quantity tends to correlate with research quality, we do not expect strong differences with the results in the

[20] The magnitude of the effect tends to be greater for the lower quantiles than for the 90% quantile: we find, for example, parameter values of 0.99 and 0.66 for the 10% and 25% quantile respectively, versus 0.21 for the 90% quantile in 1999, all relative to 1992 as the base year. All these estimates are significant at the 5% level.

[21] The effect of discipline across quantiles depends on the discipline considered. For example, the productivity difference with the faculty of kinesiology & physical education (the base category) increases with quantile for the faculty of agriculture, while it decreases with quantile for the faculty of pharmacy.

[22] A likelihood ratio test that compares the negative binomial panel estimator with the pooled estimator (i.e. the negative binomial estimator with a constant dispersion across researchers), strongly favors the panel data estimator.

previous section[23]. Rather, we look for differences in the importance of productivity drivers along the distribution. The discussion first details common findings, before tackling the differences in results for quality and quantity.

The common findings for both productivity measures include:

- There is no (biological) age effect, nor a life cycle effect (career age).
- The negative effect of rank seniority decreases from lower to higher quantiles. At the top of the distribution the effect on publications or citations is no longer significant.
- The productivity difference between the three junior ranks and the full professor rank (in the favor of the latter) decreases from lower to higher rank and from lower to higher quantiles. For both the quantity and the quality model, the panel estimates are smaller than the cross-sectional estimates.
- There is a positive and decreasing effect of heading a research lab. At the top of the distribution the impact on publications or citations is no longer or only marginally significant.
- The positive effect of Type I 'excellence' funding decreases from lower to higher quantiles.
- The positive effect of the number of coauthors increases from lower to higher quantiles.
- The positive effect on productivity of gender, in favor of male researchers, is found for both the quantity and the quality model, where in both cases it remains absent for the extreme left side of the distribution (10% quantile).
- The positive effect of being employed full-time at the university decreases from lower to higher quantiles.
- There is a positive time trend.
- The effects of scientific discipline and organizational unit membership across quantiles are similar for publications and citations.

[23] When comparing quantity and quality results, we focus on signs and significance of effects.

Noteworthy differences between the quantity and quality panel data estimation results are:

- The positive effect of Type II funding remains roughly constant from lower to higher quantiles of research quality while it is decreasing with quantile for research quantity. This indicates that small chunks of additional funding represent an upward shift in quality for researchers throughout the distribution, irrespective of their research talent. The reason why this constant upward shift does not hold for Type I funding may be due to the nature of this funding: while Type II funds are more modest research grants most likely used by the researcher herself (to attend conferences, buy software, etc.), the large Type I funds are awarded to large group of researchers and the impact on the personal output of the project's (co-)promoter may be less pronounced.
- For the quality distribution, we find a negative effect of teaching load located at the lower end (10% and 25% quantile) and the top end (90% quantile), with the lower end 'suffering' more from teaching duties. For the quantity distribution there is a very small negative effect at the top end only. This may indicate that teaching duties do not prohibit research as such, but rather that unproductive (or less able) researchers may have difficulties keeping up the quality of their research when facing time constraints.
- The effect of entry cohort differs: for both quantity and quality, we find a negative effect of being part of the most recent entry cohort, but only for the 25%-50% quantile (quantity) and the 25% quantile (quality). For research quality, there is an additional point in the distribution that shows a positive effect of the most recent entry cohort, namely at the very top of the distribution. This may again point to the role of ability: while the very able and recently entered researchers are able to deliver a quality surplus relative to older cohorts, they do not publish more than their more experienced colleagues. Conversely, those recent entrants with more modest research talent endowments (in the midst or lower half of the distribution) apparently face a disadvantage relative to their more experienced colleagues, which is translated into fewer publications, usually of lesser quality. In this part of the distribution, the smaller stock of research knowledge (or perhaps the lesser experience with the research process) for the younger cohort may not be compensated for by research talent.

5.4 Results for differences across quantiles

Finally, we formally test whether a certain variable has a differential effect across quantiles, informing us whether looking at quantiles really gives us additional information compared to regressions on the mean. For example, we test whether the gender effect has an equal effect across the five estimated quantiles, with $H_0 : \beta^{male}_{\tau=0.10} = \beta^{male}_{\tau=0.25} = \beta^{male}_{\tau=0.50} = \beta^{male}_{\tau=0.75} = \beta^{male}_{\tau=0.90}$. The test results for the cross-sectional and the panel-data specification are reported in Table 9, for both quantity and quality of output. We report the χ^2-values and indicate the significance. These tests yield strong evidence that for most parameters the estimates vary over the five quantiles. The only exceptions are found in the publications model for the parameters of age (cross-section and panel), teaching load (panel) and entry cohort (cross-section). Naturally, pairwise comparisons of quantiles would show fewer significant differences than comparing the estimates of a given parameter across all quantiles[24], but overall we consider this as strong support for a quantile regression approach, compared to an analysis of mean productivity only.

6 Conclusions and further research

This paper has estimated the impact of various productivity drivers along the productivity distribution, both in terms of quantity and quality. To account for unobserved heterogeneity in the estimation of the conditional quantiles, we used a correlated random effects model, exploiting the panel nature of our dataset. We subjected the integer counts of publications and citations to a randomization approach to allow for quantile estimation.

We found strong support for our quantile regression approach vis-à-vis regressions on the conditional mean only, as indicated by the differential impact of most variables along the distribution. More specifically, we find support for the hypothesis that the top of the distribution is mainly driven by talent (or a loss of incentive power of factors like promotion or research grants), as opposed to the lower end where the impact of these characteristics is more visible. The evidence is provided by the stronger impact of several observed variables (like rank, seniority in rank, head of unit, big

[24] As noted above, we ackowledge that the choice of quantiles is somewhat arbitrary, and a different selection of quantiles may yield different results, but we do not expect this to have a substantial impact on our results.

research grants) on the lower quantiles versus a weaker (or even insignificant) effect on the higher quantiles. Also the gender effect displays different effects along the productivity distribution. While the gender effect diminishes when moving towards the top end of the distribution, it does not play any role at the extreme lower of the distribution.

As far as the comparison between the analyses for research quantity and research quality is concerned, we found several observed factors to have a very similar effect, viz. age & career age (no effect), rank & rank seniority, excellence funding, head of unit, and the control variables (co-authors, fulltime position, discipline, time, faculty membership). Given the correlation between quantity and quality of research, this strengthens our confidence in the findings. The effects of small research funds, teaching load and entry cohort show a different pattern across the quantity versus quality distribution.

Although we caution against generalizations based on this study of a single university, we believe our findings are informative with respect to the management of scientists in research organizations. In particular, the results may be informative for university governors who are implementing incentive programs or make funding decisions. For example, our estimates indicate that a reduced teaching load for not very productive researchers in an attempt to 'pull them on board' may not lead to the expected increase in publications.

With respect to funding, the results indicate that funding tends to reduce output inequality between researchers: the positive effect of funding is generally larger for the lower quantiles than is observed at the top of the distribution. One must be careful not to interpret this as meaning that the less productive researchers are more apt in converting additional funding into publications or citations than more prolific researchers[25]: the estimates are conditional on the actual distribution of research funds. As the data show, this distribution is inegalitarian with the top scientists getting most of the funding, so there likely is an issue of diminishing returns. Nevertheless, the results show that research money flowing to the lower half of the distribution may be well spent, cautioning against an extreme selectivity in awarding research funds.

[25] In addition, a full evaluation of funding decisions on productivity should take into account their impact on all researchers who belong to the funded research group, and not only on the (co-)promoters of the projects, as in the regressions presented here.

7 Appendices

7.1 Appendix 1: Hypothesis testing

We tested the correlated random effects specification as well as the difference between parameters across quantiles. This appendix discusses the minimum-distance framework of Buchinsky (1998) as well as the restriction matrices used for testing.

7.1.1 Minimum-distance testing framework

Let r denote the number of quantiles we estimate: $\tau_1, ..., \tau_r$. For a given quantile τ, the parameter vectors β_τ, λ_τ^t , and γ_τ are defined as follows: $\beta_\tau = (\beta_{\tau 1}, ..., \beta_{\tau K})$, $\lambda_\tau^t = \left(\lambda_{\tau 1}^t, ..., \lambda_{\tau K}^t\right)'$, and $\gamma_\tau = (\gamma_{\tau 1}, ..., \gamma_{\tau G})'$, with K the number of variables in X_{it}, G the number of variables in Z_{it} and $L = T \times K$. The full parameter vector for a given quantile τ is given by $\delta_\tau = \left(\phi_\tau, \beta_\tau', \lambda_\tau^{1\prime}, ..., \lambda_\tau^{T\prime}, \gamma_\tau'\right)'$. The parameter vector for all quantiles is denoted by $\delta = \left(\delta_1', \delta_2', ...\delta_r'\right)'$ where δ has dimension $r(K+L+G+1)\times 1$. Let $\widehat{\delta}$ denote the estimator of δ and $\widehat{A}$ the estimated variance-covariance matrix of $\widehat{\delta}$, obtained via bootstrapping. This matrix allow us to test hypotheses involving parameters from different quantiles.

In the minimum-distance framework, the estimator of the restricted model is defined as (Buchinsky, 1998):

$$\widehat{\delta}^R = \text{arg min} \left(\widehat{\delta} - R\delta^R\right)' \widehat{A}^{-1} \left(\widehat{\delta} - R\delta^R\right)$$

where R is the restriction matrix, the precise form of which depends on the hypothesis under consideration. The detailed specification of the restriction matrix R for the tests in the following sections is given below. Since we only consider linear restrictions, $\widehat{\delta}^R$ can be written as $\widehat{\delta}^R = \left(R'\widehat{A}^{-1}R\right)^{-1} \left(R'\widehat{A}^{-1}\widehat{\delta}\right)$ with R, $\widehat{A}^{-1}$ and $\widehat{\delta}$ known. The asymptotic variance of $\widehat{\delta}^R$ is given by $var\left(\widehat{\delta}^R\right) = \left(R'\widehat{A}^{-1}R\right)^{-1}$.

The null hypothesis is formulated as $H_0 : \delta = R\delta^R$. Under H_0, the following test statistic has a limiting chi-squared distribution:

$$\left(\widehat{\delta}-R\delta^{R}\right)'\widehat{A}^{-1}\left(\widehat{\delta}-R\widehat{\delta}^{R}\right)\underset{H_0}{\longrightarrow}\chi^2_M$$

with M the number of restrictions i.e. $M = rows(R) - columns(R)$.

7.1.2 Restriction matrices for hypothesis testing

Here we give the detailed specification of the restriction matrix R used for testing the hypotheses.

Test of correlated random effects

Test of $H_0 : \lambda^1_\tau = ... = \lambda^T_\tau = 0, \forall\tau$.

We define $R = \left[I_{r\times r} \otimes \begin{bmatrix} I_{K\times K} & O_{K\times G} & O_{(K+L+G)\times 1} \\ O_{L\times K} & O_{L\times G} & \\ O_{G\times K} & I_{G\times G} & \\ O_{1\times(K+G)} & & 1 \end{bmatrix} \right]$ with I the identity matrix, O a matrix of zeroes and $\otimes$ the Kronecker product, so that $M = rL$.

Test of equality of individual parameters across quantiles

We define $R = \begin{bmatrix} i_{r\times 1} & O_{r\times r(K+L+G)} \\ O_{r(K+L+G)\times 1} & I_{rxr} \otimes \begin{bmatrix} I_{(K+G-1)\times(K+G-1)} & O_{(K+G-1)\times L} & O_{(K+G-1)\times 1} \\ O_{L\times(K+G-1)} & I_{L\times L} & O_{L\times 1} \\ O_{1\times(K+L+G-1)} & & 1 \end{bmatrix} \end{bmatrix}$ with i a matrix of ones[26], so that $M = r - 1$.

7.2 Appendix 1. The Katholieke Universiteit Leuven

Founded in 1425, the Katholieke Universiteit Leuven (KU Leuven) is the oldest and largest university in Flanders and Belgium, encompassing all academic disciplines. About 1,400 tenured professors and more than 3,500 researchers are currently employed at KU Leuven, which has a student population of more than 30,000 students each year.

It has the legal status of a private institution, but receives most of its funding from the Belgian Government, both in a direct and in an indirect, competitive way. The basic public funding of the

[26] This definition of R requires that the r parameters to be tested (one from each quantile) are the first r elements in δ. Therefore, δ is resorted prior to calculating the test statistic.

university, that pays for the salaries of the academic personnel, has remained roughly stable in the last decade, which has resulted in a more or less stable total number of professors at KU Leuven. The funding for research on the other hand has increased continuously. Most of this funding is obtained on a competitive basis: about one quarter is private funding from industry, about half comes from project funding from national, regional and EU governments and about one quarter is from the regional government allocated to the KU Leuven based on its share of regional publications, citations and PhDs. The latter funding is redistributed within the KU Leuven on a competitive basis. We have data on two major types of projects. 'Type I' projects[27] are intended to support research groups from all disciplines with demonstrated scientific value based on international peer reviews, publications and other indicators of scientific quality. Type I projects typically receive funding of around 900,000 Euros for a total duration of five years (up to 1,625,000 Euros if several research groups are involved). 'Type II' projects[28] are somewhat more modest in set-up and are intended to stimulate potential for fundamental research. They can be awarded to individual researchers as well as research groups with a good track record in research or with the intention to start up a new line of research aiming at high quality output. Type II projects receive a maximum funding of 475,000 Euros for a total duration of four years. Both types of funding are allocated on the basis of competitive, external peer review evaluation of past team performance and project proposal. Of the pre-screened proposals that are allowed to pass the full procedure, less than 50% obtain funding.

The KU Leuven has as mission statement in the observed period to be among the top 25 European research universities in a wide number of scientific disciplines. But it aims to be among the top particularly in those disciplines in which it is already strong: biochemistry, biosciences, biomedical and several disciplines in medicine, among which are hematology, oncology and cardiology.

In terms of career structure, we distinguish between four main ranks, with rank 1 the entry level ('assistant professor') and rank 4 the highest possible rank ('full professor'). KU Leuven offers tenure to assistant professors who successfully pass the judgment of their work in the years following

[27] The actual name of these funds is 'GOA' (Geconcerteerde Onderzoeksactie). We use the generic indication 'Type I' in the paper.

[28] The actual name of these funds is 'OT' (Onderzoekstoelage). We use the generic indication 'Type II' in the paper.

their hiring. After this initial tenure decision, for which young professors are primarily evaluated on their research output as opposed to other activities, they can be promoted in successive ranks up to full professor based on their research and teaching performance, as well as duties performed within the university, with the latter typically gaining importance as one progresses through the ranks. While rank 2-4 have tenure, rank 1 are the untenured researchers. The power of the tenure decision is however limited, since in its still recent history of tenure track, the KUL has no or little records of not granting tenure.

While officially the *faculty* as organizational unit is mostly responsible for the teaching programs, and the *department* is the organizational unit for research activities, in practice both hierarchical levels are intertwined, particularly with respect to recruiting and promotion of researchers. The faculty level has a higher hierarchical position, with the *dean* being a member of the *bureau* that decides on recruitment and promotion, on the basis of *advice* from the departments.

7.3 Appendix 2. Construction of the database

The publication and citation data originate from the Science Citation Index (SCI) of the Institute of Scientific Information (ISI). As there is no one-to-one matching between authors and their affiliation address in the ISI data, publications in each of the ten yearly publication files were initially retained when at least one author was affiliated with the KU Leuven so that a number of non-University-of-Leuven related authors remained present. In a second step, we narrowed the number of publication records by means of a merge with the KU Leuven personnel files in order to only retain University of Leuven affiliated authors (see infra).

Since the ISI records do not allow distinguishing between primary- and co-authorship, we used a 'full integer' counting scheme for calculating the performance data. This means that a publication was counted as "1" for all authors of the paper. The same goes for citations: the full number of citations was added to the credits of each author of the paper, whereby an author was identified by his or her surname plus the first initial. This gives rise to homonyms: within the yearly publication files it is not possible to distinguish between authors that have the same name. As discussed below, most of these homonyms could be resolved during the merge with the university personnel file.

Because a researcher's last name plus the first initial is the only piece of information that is shared between the ISI publication records and the university personnel file, the two datasets were combined using this key. In this way, the non-University-of-Leuven affiliated researchers that were still present in the dataset but whose name did not occur in the personnel files were filtered out. Before carrying out this merge operation, 45 homonyms were dropped from the University of Leuven personnel file since we could not distinguish between these staff members. However, this does not completely rule out mistakes due to homonyms during the merge of the two files. In particular, although homonyms were removed from the personnel file, it is still possible that a homonym occurs between a University of Leuven affiliated author and an external author within the publications file. Because the name occurs in the personnel file, the publication data of both these author records will be mapped on the staff record, biasing upwards the performance of the staff member. Because the ISI records do not allow linking authors unambiguously to their affiliation, this problem cannot be resolved nor can its magnitude be estimated. We deem it to be a minor issue though, and point out that the merge key we used inherently mitigates the problem since researchers with identically spelled last names but a different initial do not yield a 'false positive'.

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9 Tables & Figures

Figure 1: Lorenz curves for yearly research output

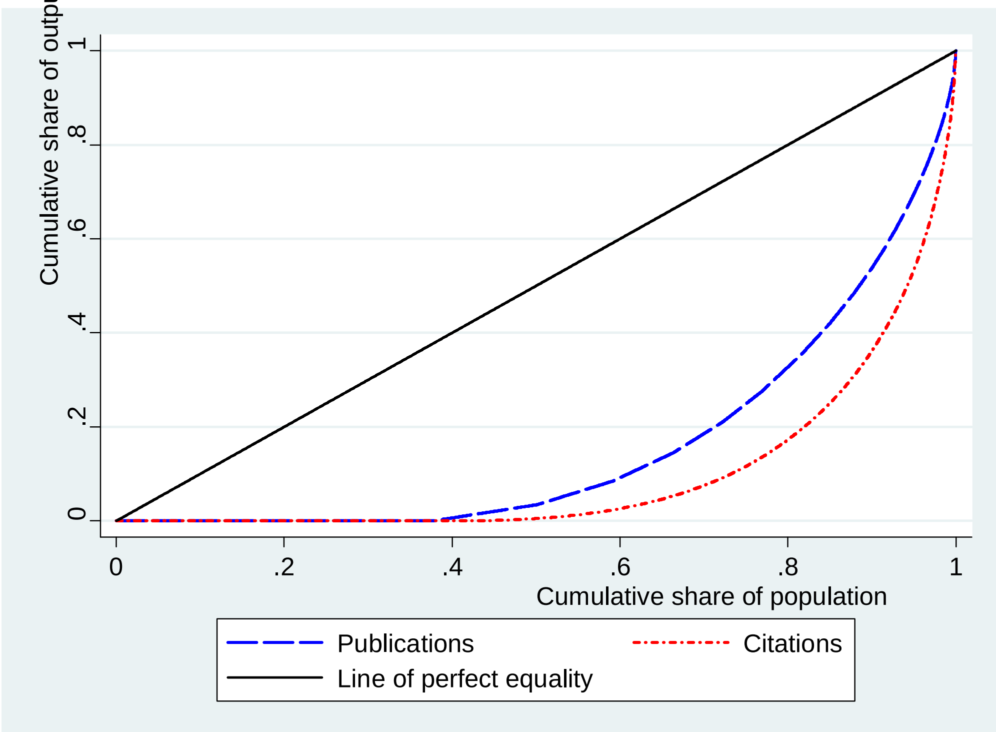

Table 1: Distribution of researchers over organizational units

Organizational Unit	Freq.	Percent
Group Exact Sciences	483	46.9
Faculty of Science	192	18.6
Faculty of Engineering	214	20.8
Faculty of Applied Bioscience and Engineering	77	7.5
Group Biomedical Sciences	547	53.1
Faculty of Medicine	460	44.7
Faculty of Pharmaceutical Sciences	36	3.5
Faculty of Physical Education & Kinesiology	51	5.0
Total	1030*	100.0

* Six people switched between groups and/or faculties in the period 1992-2001 and are not shown in this table.

Table 2: Distribution of researchers over disciplines

Main Discipline	Freq.	Percent
None (inactive researchers)	222	21.5
Clinical and Experimental Medicine II (Non-internal Medicine Specialties)	190	18.4
Clinical and Experimental Medicine I (General & Internal Medicine)	157	15.2
Biosciences (General, Cellular & Subcellular Biology; Genetics)	91	8.8
Chemistry	86	8.3
Engineering	72	7.0
Physics	65	6.3
Agriculture & environment	36	3.5
Biology (Organismic & Supraorganismic level)	31	3.0
Biomedical research	26	2.5
Mathematics	26	2.5
Geosciences & space sciences	19	1.8
Neuroscience & behavior	13	1.3
Total	1034*	100.0

* Two researchers had a tie in terms of their number of publications for two or more disciplines and are not shown.

Table 3: Research output (yearly averages)

	Observations	Publications	Co-authors per publication	Citations per publication	Impact measure per publication	(co-)pron PhD
Total	7,861	3.6 (6.0)	4.8 (5.6)	4.9 (7.2)	3.4 (3.2)	0.3 (0.
Female	797	2.0	5.1	5.6	3.8	0.1
Male	7,064	3.8	4.7	4.9	3.4	0.3
Age						
age cohort 1 (age<40)	1,620	3.2	4.5	5.5	3.7	0.2
age cohort 2 (40≤age<50)	2,590	3.9	5.1	5.3	3.5	0.4
age cohort 3 (50≤age<60)	2,789	3.8	4.5	4.3	3.2	0.4
age cohort 4 (60<age)	862	2.9	5.1	4.3	3.0	0.1
Entry cohort						
entry cohort 1 (1955-1980)	1,517	4.5	4.5	4.1	3.3	0.5
entry cohort 2 (1981-1988)	1,761	4.6	4.7	4.7	3.3	0.5
entry cohort 3 (1989-1991)	2,233	3.0	4.6	4.8	3.6	0.2
entry cohort 4 (1992-2001)	2,076	2.7	5.2	6.1	3.3	0.1
Fulltime at university	6,538	4.2	4.7	4.9	3.4	0.4
Parttime at university	1,323	0.8	5.8	6.2	3.9	0.1
Rank						
% rank 1 (junior)	1,965	1.7	5.0	5.5	3.7	0.1
% rank 2	1,967	2.7	4.9	5.2	3.6	0.2
% rank 3	1,463	3.8	4.5	4.8	3.3	0.4
% rank 4 (senior)	1,966	6.0	4.4	4.3	3.1	0.7
Rank seniority						
years in rank ≤ 3	3,928	3.2	5.0	5.2	3.5	0.2
years in rank > 3	3,933	4.0	4.5	4.7	3.4	0.4
Teaching load (year-hours)						
teaching load ≤ 3	3,986	3.3	5.1	5.8	4.0	0.2
3 teaching load ≤ 10	3,118	4.2	4.6	4.5	3.0	0.4
teaching load > 10	757	2.6	3.6	2.5	2.1	0.6
Head of unit	1,108	6.4	4.7	4.8	3.1	0.6
Not head of unit	6,753	3.1	4.8	5.0	3.5	0.3
Project funding						
type I funding	863	9.1	4.8	6.7	4.7	0.8
type II funding	918	5.6	4.6	5.2	3.2	0.6

Standard deviations in parenthesis for the total sample means.
The variables co-authors per publication, citations per publication and impact measure per publication are conditional on a publication cou
The variable (co-)promoted PhDs has missing values for 851 out of 7,861 observations.
The data source for all variables is the Policy Research Center for R&D Monitoring (ECOOM) at the University of Leuven,
except (co-) Promoted PhDs, which was supplied by the Research Coordination Service of the University of Leuven.

Table 4: Percentiles for publication output, by discipline (yearly averages)

Main discipline	Percentiles 10%	25%	50%	75%	90%
Agriculture and Environment	0.0	0.1	1.9	5.2	8.8
Biosciences	0.6	1.6	4.3	8.4	14.3
Chemistry	0.0	0.8	3.7	8.0	13.3
Engineering	0.0	0.0	1.2	3.0	5.6
Geosciences and Space Sciences	0.0	0.1	1.0	4.0	6.8
Mathematics	0.0	0.1	1.2	2.9	4.8
Clinical and Experimental Medicine I	0.0	1.4	4.0	7.1	12.1
Clinical and Experimental Medicine II	0.0	0.2	2.0	4.8	8.4
Neuroscience and Behavior	0.1	0.3	1.5	4.5	7.7
Physics	0.0	1.0	3.5	7.6	13.3
Biomedical Research	0.1	0.3	2.2	6.8	12.2
Biology	0.2	0.5	2.4	6.0	10.4
Average	0.1	0.5	2.4	5.7	9.8

Since a researcher's main discipline can only be determined if she has any output, this table only includes the researchers with at least one publication in 1992-2001 (N=814)

Table 5: Individual and career-related variables by percentile of publication output

Variable	Whole sample		Inactive researchers	Active researchers					
				Publication output percentiles					
				<10%	10%-25%	25%-50%	50%-75%	75%-90%	>90%
	mean	s.d.	mean	mean	mean	mean	mean	mean	mean
Male	0.89	0.32	0.86	0.79	0.84	0.88	0.91	0.93	0.95
Age	47.74	8.98	50.95	46.52	48.67	46.48	46.41	46.09	47.10
% age cohort 1 (age<40)	0.25	0.38	0.16	0.28	0.22	0.28	0.28	0.29	0.23
% age cohort 2 (40<=age<50)	0.32	0.36	0.26	0.28	0.28	0.33	0.33	0.35	0.37
% age cohort 3 (50<=age<60)	0.31	0.37	0.35	0.41	0.35	0.29	0.31	0.28	0.32
% age cohort 4 (60<age)	0.13	0.29	0.24	0.04	0.15	0.09	0.08	0.09	0.08
Entry cohort*									
% entry cohort 1 (1955-1980)	0.19	0.39	0.18	0.04	0.18	0.17	0.18	0.19	0.24
% entry cohort 2 (1981-1988)	0.19	0.39	0.14	0.07	0.15	0.18	0.22	0.25	0.31
% entry cohort 3 (1989-1991)	0.24	0.43	0.23	0.44	0.28	0.27	0.26	0.27	0.20
% entry cohort 4 (1992-...)	0.38	0.49	0.45	0.44	0.38	0.37	0.34	0.30	0.24
Years of employment in 1992-2001	7.51	2.88	6.48	8.45	8.07	7.89	8.19	8.42	8.61
Fulltime at university	0.80	0.38	0.47	0.90	0.81	0.87	0.92	0.96	0.98
Rank**									
% rank 1 (junior)	0.24	0.03	0.37	0.21	0.35	0.28	0.18	0.14	0.06
% rank 2	0.22	0.02	0.28	0.23	0.24	0.25	0.20	0.17	0.08
% rank 3	0.16	0.03	0.13	0.14	0.15	0.18	0.18	0.18	0.14
% rank 4 (senior)	0.25	0.02	0.14	0.08	0.16	0.19	0.26	0.35	0.55
Rank seniority***	5.71	6.69	5.64	5.40	5.78	5.24	5.44	5.79	7.45
rank 1 (junior)	2.41	2.26	3.01	3.47	3.01	2.13	1.97	1.68	1.44
rank 2	3.10	2.68	3.75	3.53	3.59	3.30	2.59	2.12	1.75
rank 3	4.25	5.00	5.77	0.75	6.54	4.85	3.20	3.15	2.51
rank 4 (senior)	12.26	8.51	16.97	18.67	14.03	12.80	11.63	10.91	10.61
Teaching load (year-hours)	4.18	4.09	3.38	2.61	3.63	4.34	4.51	4.37	4.80
rank 1 (junior)	1.49	1.77	1.72	0.86	1.42	1.54	1.26	1.25	1.04
rank 2	3.08	3.11	2.81	2.26	2.60	3.55	3.22	2.64	2.75
rank 3	4.95	3.67	4.81	3.01	5.86	5.87	4.96	3.83	3.10
rank 4 (senior)	7.96	4.40	8.31	7.56	7.95	8.95	8.67	7.56	6.45
Project funding									
% with type I funding	0.09	0.24	0.00	0.08	0.04	0.08	0.13	0.17	0.21
as promoter	0.03	0.13	0.00	0.00	0.00	0.01	0.03	0.05	0.09
as co-promoter	0.07	0.20	0.00	0.08	0.04	0.07	0.11	0.13	0.12
% with type II funding	0.11	0.23	0.02	0.10	0.07	0.10	0.14	0.17	0.22
as promoter	0.06	0.17	0.01	0.10	0.03	0.06	0.08	0.09	0.11
as co-promoter	0.05	0.15	0.01	0.00	0.04	0.04	0.06	0.08	0.12
Number of researchers	1036		222	814					

* For 44 researchers this information is missing.

** Only the four main ranks shown. People may be in other ranks which are of lesser concern here (e.g. 'jury member PhD') or may combine one of these other ranks with one of the main ranks.

*** This is the expected rank seniority for someone in a given rank; not the total number of years scientists tend to spend in each rank.

Table 6: Cross-sectional estimation results, publication data

	Quantile regressions					Zero-inflated
	10%	25%	50%	75%	90%	negative binomial
age	0.14**	0.01	0.02	0.02	0.03*	0.01
	(2.81)	(0.11)	(0.31)	(0.79)	(1.68)	(0.17)
age squared	-0.00**	-0.00	-0.00	-0.00	-0.00**	-0.00
	(-3.30)	(-0.47)	(-0.86)	(-1.57)	(-2.51)	(-0.47)
career age	-0.03*	-0.02*	0.00	0.00	0.00	0.00
	(-1.69)	(-1.65)	(0.13)	(0.37)	(0.65)	(0.11)
seniority in rank	0.01	0.00	-0.00	0.00	0.00	-0.00
	(0.64)	(0.11)	(-0.08)	(0.31)	(1.17)	(-0.31)
rank						
rank 1 in t-1	-1.18**	-0.94**	-0.75**	-0.53**	-0.38**	-0.61**
	(-10.12)	(-14.03)	(-5.42)	(-5.31)	(-7.30)	(-5.97)
rank 2 in t-1	-0.73**	-0.68**	-0.59**	-0.36**	-0.23**	-0.38**
	(-2.94)	(-7.28)	(-5.94)	(-12.98)	(-11.06)	(-5.08)
rank 3 in t-1	-0.33*	-0.35**	-0.37**	-0.24**	-0.12**	-0.22**
	(-1.84)	(-2.77)	(-3.66)	(-6.77)	(-9.65)	(-3.30)
other rank in t-1	-0.78**	-0.87**	-0.69**	-0.44**	-0.26**	-0.42**
	(-7.19)	(-7.02)	(-11.68)	(-6.19)	(-6.99)	(-5.15)
head of unit in t-1	0.51**	0.35**	0.17**	0.07	0.04	0.10**
	(3.23)	(3.50)	(2.10)	(1.35)	(0.50)	(2.02)
project funding						
type I funding in t-1	1.14**	0.63**	0.26**	0.14**	0.03	0.17**
	(10.69)	(8.73)	(4.02)	(10.87)	(0.73)	(2.73)
type II funding in t-1	0.77**	0.56**	0.27**	0.22**	0.17**	0.12*
	(9.08)	(26.45)	(22.09)	(7.94)	(15.16)	(1.82)
nr of co-authors	0.01**	0.02**	0.02**	0.03**	0.03**	0.02**
	(3.17)	(3.97)	(9.51)	(17.55)	(23.12)	(8.03)
teaching load	-0.07**	-0.03**	-0.02**	-0.01**	-0.01**	-0.03**
	(-7.17)	(-4.46)	(-4.95)	(-3.90)	(-2.01)	(-2.49)
male	0.91	0.57**	0.37**	0.24**	0.17**	0.21
	(1.31)	(3.17)	(5.30)	(14.75)	(3.71)	(1.56)
fulltime	1.28**	0.74**	0.88**	0.70**	0.57**	0.43**
	(4.77)	(7.70)	(10.55)	(8.31)	(17.68)	(3.20)
entry $\geq$ 1992	-0.07	-0.11	-0.14*	-0.09	-0.02	-0.06
	(-0.59)	(-1.45)	(-1.72)	(-1.54)	(-0.17)	(-0.64)
year dummies			*included*			*included*
main discipline			*included*			*included*
faculty membership			*included*			*included*
Observations			7,062			7,062

t-statistics in parentheses. The parameters for the quantile regressions are based on 10 jittered samples, the standard errors are calculated using 380 clustered bootstrap samples (clustering by by individual).
* $p<0.10$, ** $p<0.05$

Table 7: Panel-data estimation results, publication data

	Quantile regressions					Random effects
	10%	25%	50%	75%	90%	negative binomial[1]
age	0.10	0.02	0.03	0.03	0.03**	0.08**
	(1.64)	(0.24)	(0.37)	(0.96)	(2.62)	(3.96)
age squared	-0.00**	-0.00	-0.00	-0.00	-0.00**	-0.00**
	(-2.16)	(-0.62)	(-0.76)	(-1.57)	(-4.06)	(-6.07)
career age	-0.02	-0.03	-0.01	0.00	0.00	0.04**
	(-0.68)	(-1.61)	(-0.39)	(0.02)	(0.88)	(5.24)
seniority in rank	-0.08**	-0.05**	-0.04**	-0.02**	-0.01	-0.01**
	(-3.26)	(-3.76)	(-3.36)	(-2.71)	(-0.90)	(-2.52)
rank						
rank 1 in t-1	-0.78**	-0.84**	-0.61**	-0.39**	-0.21**	-0.25**
	(-6.22)	(-5.46)	(-4.23)	(-3.12)	(-3.43)	(-4.35)
rank 2 in t-1	-0.28	-0.40**	-0.45**	-0.21**	-0.09**	-0.13**
	(-1.23)	(-3.64)	(-12.25)	(-3.44)	(-5.80)	(-2.81)
rank 3 in t-1	-0.02	-0.11	-0.20**	-0.10	-0.01	-0.11**
	(-0.17)	(-1.49)	(-5.45)	(-1.32)	(-1.27)	(-2.66)
other rank in t-1	-0.59**	-0.77**	-0.57**	-0.28**	-0.13**	-0.25**
	(-5.13)	(-10.91)	(-6.16)	(-2.17)	(-3.42)	(-4.55)
head of unit in t-1	0.48**	0.37**	0.21*	0.07*	0.08*	0.07**
	(4.12)	(4.12)	(1.96)	(1.93)	(1.77)	(2.15)
project funding						
type I funding in t-1	0.76**	0.54**	0.20*	0.12**	0.03	0.09**
	(6.20)	(7.83)	(1.80)	(3.42)	(0.61)	(2.63)
type II funding in t-1	0.55**	0.39**	0.24**	0.18**	0.17**	0.09**
	(11.77)	(14.60)	(8.58)	(5.25)	(7.53)	(3.29)
nr of co-authors	0.01**	0.02**	0.02**	0.03**	0.03**	0.00**
	(2.13)	(7.80)	(13.66)	(44.16)	(20.06)	(28.70)
teaching load	-0.05	-0.02	-0.01	-0.01**	-0.01**	-0.01
	(-1.36)	(-1.34)	(-1.01)	(-2.43)	(-4.33)	(-1.64)
male	0.66	0.58**	0.34**	0.25**	0.18**	0.36**
	(0.78)	(3.50)	(2.34)	(15.21)	(2.93)	(3.41)
fulltime	1.27**	0.67**	0.81**	0.68**	0.61**	0.39**
	(4.04)	(11.80)	(13.07)	(6.75)	(17.42)	(5.69)
entry $\geq$ 1992	-0.30	-0.40**	-0.21**	-0.06	0.10	-0.17*
	(-1.12)	(-3.82)	(-2.03)	(-0.74)	(0.76)	(-1.76)
year dummies			*included*			*included*
main discipline			*included*			*included*
faculty membership			*included*			*included*
N			7,062			7,062

t-statistics in parentheses. The parameters for the quantile regressions are based on 10 jittered samples, the standard errors are calculated using 380 clustered bootstrap samples (clustering by by individual).

[1]Likelihood-ratio test vs. pooled negative binomial model: χ^2= 3,019.06

* p<0.10, ** p<0.05

Figure 2: Estimates for publication data (Solid = Panel, Dashed = Panel 95% CI, Dotted=Cross-section)

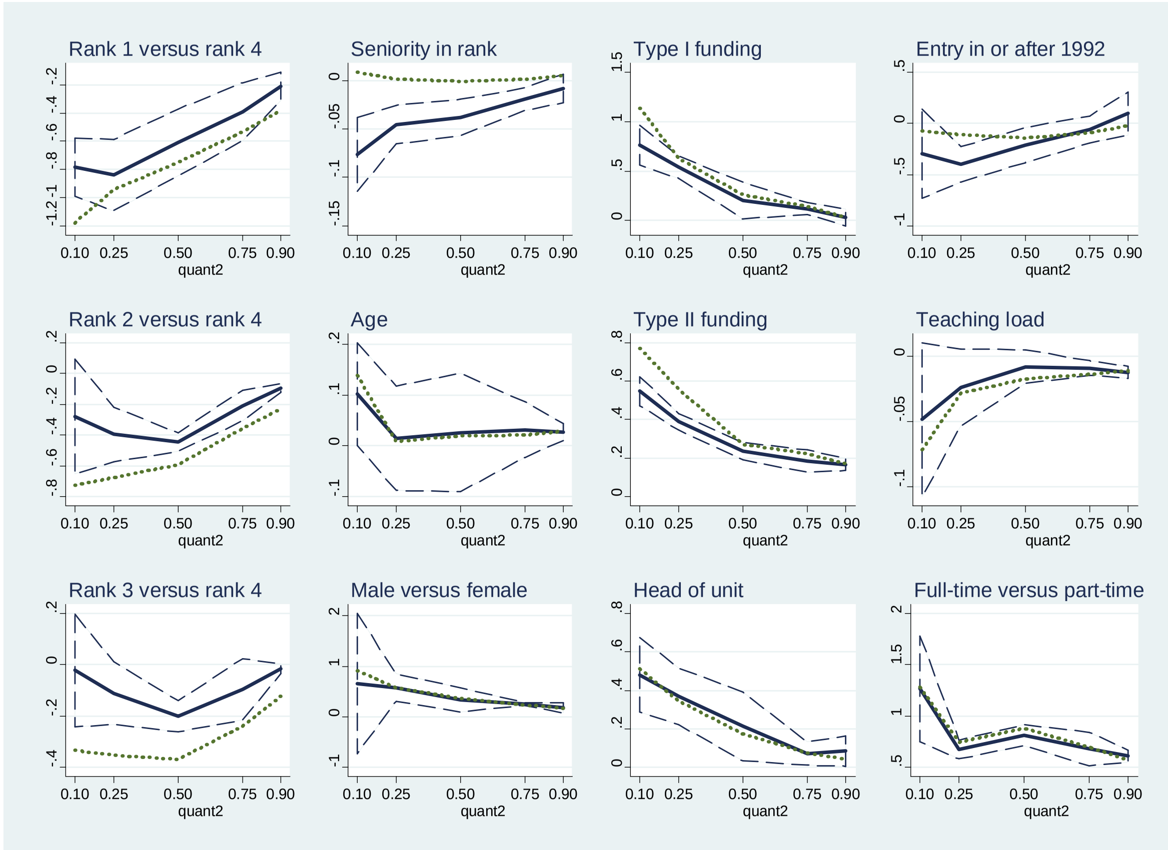

Table 8: Panel-data estimation results, citation data

	Quantile regressions					Random effects
	10%	25%	50%	75%	90%	negative binomial[1]
age	0.11	-0.08	0.01	-0.02	-0.01	0.03
	(1.57)	(-0.95)	(0.05)	(-0.23)	(-0.18)	(1.16)
age squared	-0.00**	0.00	-0.00	-0.00	-0.00	-0.00**
	(-2.05)	(0.38)	(-0.62)	(-0.30)	(-0.63)	(-2.72)
career age	-0.01	-0.04	-0.02	0.00	0.00	0.01
	(-0.24)	(-0.96)	(-1.03)	(0.03)	(0.30)	(1.45)
seniority in rank	-0.11**	-0.09**	-0.06**	-0.04**	-0.01	-0.00
	(-2.62)	(-3.74)	(-2.46)	(-20.79)	(-1.03)	(-0.10)
rank						
rank 1 in t-1	-1.28**	-1.11**	-0.76**	-0.37**	-0.31**	-0.56**
	(-4.57)	(-3.02)	(-4.45)	(-2.15)	(-3.99)	(-7.00)
rank 2 in t-1	-0.62**	-0.62**	-0.53**	-0.29**	-0.20**	-0.36**
	(-3.15)	(-2.26)	(-16.90)	(-2.88)	(-2.22)	(-5.56)
rank 3 in t-1	-0.43**	-0.06	-0.26*	-0.23**	-0.15**	-0.22**
	(-2.45)	(-0.47)	(-1.92)	(-2.68)	(-11.10)	(-3.89)
other rank in t-1	-1.34**	-1.23**	-0.77**	-0.47**	-0.34**	-0.53**
	(-4.68)	(-7.28)	(-11.44)	(-2.89)	(-5.00)	(-6.69)
head of unit in t-1	0.78**	0.67**	0.32**	0.14**	0.05	0.18**
	(3.30)	(4.22)	(2.25)	(3.51)	(0.96)	(3.98)
project funding						
type I funding in t-1	1.20**	1.06**	0.64**	0.40**	0.30**	0.41**
	(10.28)	(5.22)	(4.04)	(3.08)	(2.60)	(7.58)
type II funding in t-1	0.50**	0.76**	0.54**	0.52**	0.45**	0.26**
	(2.73)	(4.41)	(9.07)	(13.30)	(6.53)	(6.16)
nr of co-authors	0.02**	0.02**	0.03**	0.03**	0.04**	0.00**
	(2.48)	(8.31)	(9.61)	(20.90)	(27.07)	(26.39)
teaching load	-0.07**	-0.06**	-0.02	-0.01	-0.02**	-0.03**
	(-2.64)	(-2.25)	(-1.02)	(-1.22)	(-3.03)	(-4.19)
male	1.03	1.19**	0.76**	0.35**	0.18**	0.47**
	(1.19)	(4.29)	(2.94)	(2.83)	(2.31)	(5.77)
fulltime	1.20**	1.10**	1.15**	0.92**	0.55**	0.74**
	(6.14)	(9.59)	(5.95)	(13.78)	(8.35)	(9.02)
entry $\geq$ 1992	-0.36	-0.48**	-0.17	-0.10	0.16**	-0.25**
	(-0.73)	(-4.65)	(-1.12)	(-1.34)	(2.96)	(-3.55)
year dummies			*included*			*included*
main discipline			*included*			*included*
faculty membership			*included*			*included*
Observations			7,062			7,062

t-statistics in parentheses. The parameters for the quantile regressions are based on 10 jittered samples, the standard errors are calculated using 380 clustered bootstrap samples (clustering by by individual).

[1] Likelihood-ratio test vs. pooled negative binomial model: χ^2= 1,381.49

* p<0.10, ** p<0.05

Table 9: Test of equality of individual parameters across quantiles (chi-squared values)

	Publications		Citations	
	cross-section	panel data	cross-section	panel data
age	7.64	5.36	21.43**	18.34**
age squared	11.59**	7.09	30.80**	26.50**
career age	43.37**	31.24**	40.29**	65.89**
seniority in rank	7.81*	113.67**	11.92**	103.25**
rank				
rank 1 in t-1	223.19**	32.45**	233.37**	116.60**
rank 2 in t-1	80.96**	204.38**	43.59**	45.53**
rank 3 in t-1	22.76**	93.50**	21.48**	12.39**
other rank in t-1	75.82**	97.69**	419.91**	228.51**
head of unit in t-1	409.46**	115.70**	211.04**	94.35**
project funding				
type I funding in t-1	488.44**	488.54**	741.94**	250.83**
type II funding in t-1	244.39**	136.41**	43.31**	17.71**
nr of co-authors	1,267.21**	96.18**	1,742.02**	117.95**
teaching load	69.02**	4.19	31.28**	35.09**
male	24.48**	86.68**	135.72**	118.56**
fulltime	17.64**	27.20**	179.55**	390.31**
entry $\geq$ 1992	5.18	123.02**	28.57**	173.39**

The variance-covariance matrix is calculated using bootstrapping. For the publication panel-data results, 2 out of 380 bootstraps were dropped due to outliers; for the other models 1 out of 380 bootstraps was dropped.

* p<0.10, ** p<0.05