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Age effects in scientific productivity

The case of the Italian National Research Council (CNR)

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Age effects in scientific production are a consolidated stylised fact in the literature. At the level of scientist productivity declines with age following a predictable pattern. The problem of the impact of age structure on scientific productivity at the level of institutes is much less explored. The paper examines evidence from the Italian National Research Council. The path of hiring of junior researchers along the history of the institution is reconstructed. We find that age structure has a depressing effect on productivity and derive policy implications. The dynamics of growth of research institutes is introduced as a promising research field.

Age effects in scientific production

The existence of age effects in scientific production is one of the few consolidated stylised facts in the economics and sociology of science.

The decline of scientific productivity with age may depend on a variety of factors.

On one hand, as time goes by the initial differences among scientists in individual productivity get larger. Most theories of scientific productivity postulate a stochastic and cumulative mechanism[1] or a Matthew effect,[2] whereby those that gain recognition initially in their careers receive reward and resources, which will be used to carry out further research. If this is true, initial differences in individual productivity will tend to be larger over time. Allison and Stewart[3] found that the Gini index for publications and citations of scientists monotonically increases over time in a series of cohorts from the date of the PhD, with the exception of biologists. This evidence is interpreted as strongly supporting the notion of reinforcement or positive feedback.

Another way of looking at the problem of age is to model productivity as the outcome of a number of features that interact multiplicatively, rather than additively. For example a model may assume that several elements or mental factors play a role (e.g., technical ability, finding important problems, and persistence). As it happens in any multiplicative model, the distribution of productivity is more skewed than the

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distribution of any of its determinants. As a result, a cohort of scientists starting with a given distribution will end up with a more dispersed distribution and the variance will increase over time.

On the other hand, it is plausible that scientists work on research not only for the sake of intrinsic pleasure of scientific puzzle solving, but also in the expectation of receiving future income. If this investment motivation is correct, it will inevitably happen, as in any theory of human capital accumulation with finite horizon, that the level of investment will decrease when scientist approach the date of retirement. Models of human capital are central in the theory of life cycle of scientists. This life cycle effect was found by Levin and Stephan[4] for most scientific areas with the exception of particle physics.

The impact of age at the level of research organisations is less clear, however. Within an institute, for example, experienced scientists might compensate their individual decline with a well organised activity of training of junior researchers, so that productivity at the level of institute is not depressed. Being less creative at the individual level, they might be still prolific in supporting young researchers and identifying promising research avenues that they do not pursue personally. Furthermore, aged scientists may have acquired capabilities in managing and coordinating research teams and laboratories.

More generally, little is known on the pattern with which people of different age are mixed within research institutes and the resulting impact on scientific productivity.

These problems are becoming critical in science policy given the alarming evidence on the increasing average age of researchers in most European countries. For example, in Italy the proportion of professors and researchers in the age class 24-44 was 60% in 1984 and only 29% in 2001. Those that entered the academic system in the age class 24-34 were 19% of the total in 1984 and only 5% in 2001.[5] The problem of ageing of researchers has attracted the attention of the European Commission, that issued a number of research projects on the topics.[6]

Faced with this problem, there are also suggestions that a massive effort should be made by hiring waves of new researchers in a concentrated period of time, in order to reduce drastically the average age. While by definition the problem of ageing worsens over time in the absence of recruitment of many young researchers, it is not at all clear what should be the time path of recruitment.

We contribute to this debate by examining a large public research organisation. The paper analyses thoroughly the effects of the age structure of researchers and the age of institutes on scientific productivity, and introduces the theme of dynamics of growth of institutes as a new research field.

Data and methodology

Data description

This paper contains a detailed analysis of the effect of the age structure of researchers on scientific productivity of the Italian National Research Council (Consiglio Nazionale delle Ricerche, CNR). Spanning many scientific and technological areas, CNR is one of the largest public research institutions in Europe. The history of CNR is a major part of the history of scientific communities and of the emergence of whole new areas in the Post War Italian science.

We constructed an original dataset by integrating three official documents produced by CNR in recent years:

- Report on the CNR scientific activity in 1997 (published in 1998);
- Report on the CNR personnel in 1997 (unpublished internal documentation);
- Report on the CNR European research funding.

The integration of these data was not a trivial task. The documentation on personnel gives biographical data on individual researchers, technicians and administrators, together with the CNR affiliation in 1997. We assigned all reported individuals to institutes and integrated these data (input data) with those reported in the official Report, which include both input data and output data. Input data include, for example, research funds, funds from external sources or total costs while output data include total number of publications and number of international publications. Interestingly, the Report did *not* include data on personnel by institute. In practice, until now there was no official document that gave the opportunity to merge the information on scientific production with information on the structure of research units, so that productivity measures could be derived.

The research areas considered in the analysis are listed in Table 1.

In order to conduct the analysis by areas with a sufficient number of observations we carried out the following consolidation, keeping into account the similarity of scientific fields (Table 2):

- Environment and habitat with Geology and mineral science;
- Biotechnologies and molecular biology with Medicine and biology;
- Engineering and architecture with Innovation and technology.

Fields with a small number of institutes (e.g., Mathematics) are included in the overall analysis, but not in the analysis by research area.

The list of variables considered in the analysis is reported in Table 3. We strictly follow the definition of variables described in the CNR Report. Manipulations of variables are described explicitly.

Table 1. Research areas

Code	Research area
A1	Agriculture
A2	Environment and habitat
A3	Biotechnologies and molecular biology
A4	Chemistry
A5	Economics, sociology and statistics
A6	Physics
A7	Geology and mineral science
A8	Engineering and architecture
A9	Innovation and technology
A10	Mathematics
A11	Medicine and biology
A12	Law and politics
A13	History, philosophy and philology

Table 2. Aggregation of research areas

Aggregation	Corresponding research area	No. of obs.
MA1	Agriculture	24
MA2	Environment and habitat and Geology and mineral science	26
MA3	Biotechnologies and molecular biology and Medicine and biology	27
MA4	Chemistry	26
MA5	Physics	28
MA6	Engineering and architecture and Innovation and technology	31

Table 3. Variables in the dataset (all variables refer to CNR institutes)

a) Size indicators

Variable	Definition
T_PERS	Total number of personnel
RESFUN	Total research funds in million lira
N_RESFUN	Research funds obtained from the state in m.l.
M_RESFUN	Research funds obtained from the market m.l.
T_COS	Total costs in million lira
LABCOS	Labour costs in million lira

b) Personnel indicators

Variable	Definition
T_RES	Total number of researchers
TECH	Number of technicians
ADM	Number of administrative staff
ORD_RES	Number of researchers
SEN_RES	Number of senior researchers
DIR_RES	Number of research directors

c) Age structure indicators

Variable	Definition
TPERS_AG	Average age of personnel
TECH_AG	Average age of technicians
ADM_AG	Average age of administrative staff
ORD_AG	Average age of researchers
SENR_AG	Average age of senior researchers
DIR_AG	Average age of research directors
TRES_AG	Average age of researchers (all types)
TPERS_AS	Average age of entrance at work for all personnel
ORD_AS	Average age of entry at work for researchers
SENR_AS	Average age of entry at work for senior researchers
DIR_AS	Average age of entry at work for research directors
TRES_AS	Average age of entry at work for researchers (all types)
TPERS_OL	Average work experience for all personnel
ORD_OL	Average work experience for researchers
SENR_OL	Average work experience for senior researchers
DIR_OL	Average work experience for research directors
TRES_OL	Average work experience for researchers (all types)

d) Scientific productivity indicators

Variable	Definition
T_PUB	Total number of publications
P_INTPUB	Percent international publications
INTPUB	Number of international publications
PUB_PERS	Publications per capita
IPUPERS	International publications per capita
PUB_RES	Publications per researcher
IPURES	International publications per researcher

e) Other indicators

Variable	Definition
P_MARFUN	Percent of funds raised from the market
P_INV	Percent of total costs allocated to investment
COPUB	Cost per publication
COPUBINT	Cost per international publication
AVIM	Average impact factor
INST_AG	Institute age*
RGROW_P	Average growth (using T_PERS)**
RGROW_R	Average growth (using T_RES)***
GAI	Geographical agglomeration index

Source: *CNR Report* (1998) and our elaboration

* It is computed from the date of earliest hiring of personnel.

** The indicator is computed dividing the Total number of Personnel by the Institute age, i.e. T_PERS/INST_AG.

*** The indicator is computed dividing the Total number of Researchers by the Institute age, i.e. T_RES/INST_AG.

Limitations of data

The dataset is one of the richest available on scientific production of public institutions in terms of data on both inputs and outputs. However, limitations should not be underestimated.

First of all, data refer to just one year. In the literature on bibliometrics and the economics of science is well known that data on scientific publications should be averaged over several years, in order to take into account the inherent variability of the phenomenon over time. All in all, the size of the sample is so large and the aggregation by institute so fine that a picture over one year can still be considered reliable, at least with regards to broad patterns.

Second, we take as a definition of scientific production the *number* of total and international publications. At this stage of the research, we have no access to data on individual publication nor we can control for quotations of CNR publications. In addition, we recognise that the output of activity of CNR is not limited to scientific publications but also includes patents, consulting, technology transfer to industry and public administration, and, to a limited extent, teaching and the creation of spin-off companies. We do not have data on these joint output and are forced to stick to a view of output as represented by publications. We are planning further research on individual career patterns, using bibliometrics indicators, but this will require a lot of work.

However, we believe that the view that the *main* institutional output of CNR should be scientific publications is fundamentally correct.

Finally, we have data on 1997. We can trace back the biography of personnel since their date of birth and date of entry at CNR. This will allow, for example, to reconstruct the evolution of entry waves over time. It must be clear that we can observe only those that are still at the CNR in 1997, while we know nothing about those who entered (at any date) but left CNR before 1997. This means that our measures are sui generis. We will provide, therefore, estimates that work as upper or lower bounds to dynamic phenomena. With all these limitations, the dataset is still rich of information and (hopefully) some surprise.

We carried out all analyses at two levels: aggregate level (CNR) and by scientific area. Differences in scientific practices is so large that a pure aggregate view might be criticised on the ground of unobserved heterogeneity.

Scientific productivity

Definition and measures

By scientific productivity we mean a measure of the ratio between the output of scientific research and its inputs.

Although there are several outputs from scientific research, the notion that scientific publications capture the essence of its productive output is widely accepted. Within scientific publications two main measures are normally used: count of publications, and citations of publications. The former is a gross indicator of quantity, the latter is an approximated measure of quality, as reflected in the use that the scientific community does of the results of research. There is a huge amount of work in scientometrics, bibliometrics and research evaluation about these indicators, their limitations and their meaning*.

For the purpose of this paper we will not enter into this literature and will assume a simple position. The output of research will be considered the self-reported count of

* On general bibliometric theory and methodology useful references are Refs 7–10. Count data have characteristics discussed at length in the bibliometric literature: see Refs 11–15. Citation data are examined in Refs 16–19. Refs 20–22 examine the quality of national scientific production.

publications. The CNR Report also includes an impact factor, but since we do not have access to the procedure through which it has been computed we will stick to a more reliable measure of quantity*.

Of course, the quantity of publications tell us nothing about their quality. In future research we plan to use systematically data at the level of individual scientist (of which we know the name from CNR files) in order to build data on the quality of publications and the scientific profile and reputation of scientists at each institute. This will require a large effort.

Summing up, we will use two measure of output at the level of institute:

- number of international publications (INTPUB);
- total number of publications (T_PUB).

For the sake of completeness we will also report the percentage of total publications which is made internationally (P_INTPUB). This is 60.89% on the average, although there are institutes with much lower incidence, so that the standard deviation is fairly high (21.82) with respect to the mean.

Coming to productivity, one should introduce the distinction between multi-factor productivity and single-factor productivity. The former captures the notion that the production of scientific papers require the use of intellectual inputs from researchers, but also the use of equipment and experimental infrastructure, and the collaboration of technicians and administrative staff.

We cannot account for the former effect, since we do not have data on capital equipment at the level of institute. We have one-year data on the percentage of funds allocated to investment, but from this isolated number it is not possible to derive any meaningful approximation of capital endowment or utilization. On the contrary, we can take on board the contribution of non-researcher personnel to scientific output.

Based on the aggregate measures of output we have built four measures of productivity:

- number of international publications per researcher (IPURES);
- number of international publications per unit of personnel (IPUPERS);
- total number of publications per researcher (PUB_RES);
- total number of publications per unit of personnel (PUB_PERS).

Indicators based on international publications, in our view, should be privileged, since CNR operates in fields that naturally have international communities (with the

* In addition, there are some methodological problems with impact factors (see Refs 23–24).

partial exception of law and history, A12 and A13, that anyway have been excluded from the analysis by research area).

Available data would allow the construction of another series of indicators of publications per unit of research funding or per unit of total costs (e.g. per million lira). We believe, however, that these measures are partially endogenous. In fact, we do not know which is the exact mechanism of allocation of CNR research funds to institutes, nor we know whether total costs carefully reflect the use of resources or include some form of organizational slack. In other words, we do not know whether costs and funds actually reflect the use of productive inputs. Given this situation, we prefer to stick to more crude but easily interpretable measures of physical productivity, i.e. quantity of output per person actually employed into the productive process.

Distribution of scientific productivity

Descriptive statistics at the level of the whole CNR are reported in Table 4.

Table 4. Scientific productivity indicators – Descriptive statistics

Variables	No. Obs.	Minimum	Maximum	Mean	Std. Deviation
T_PUB	187	2.00	382.00	62.89	52.54
INTPUB	187	0.00	209.42	38.94	34.45
P_INTPUB	187	0.00	100.00	60.89	21.82
IPURES	187	0.00	19.67	3.50	2.80
IPUPERS	187	0.00	19.00	2.04	2.15
PUB_RES	187	0.40	27.67	5.75	3.84
PUB_PERS	187	0.17	26.00	3.29	3.06

The average institute has an annual output of 63 papers of which 39 are published internationally. There are institutes with as few as 2 total publications. The distributions of total output have the familiar skewed shape, with a long right-hand tail. There is more than that, however. The interesting question is whether production is more skewed than size of institutes.

In terms of productivity, the average institute has an output of 5.75 publications per researcher and 3.5 international publications per researcher.

The first striking evidence is that scientific productivity has a large variability across institutes. The standard deviation of all productivity measures is almost as high as the average value, with high variation coefficients.

The total number of publications per researcher (PUB_RES) varies from an average of less than 1 to 27.67, while the number of international publications per researcher (IPURES) varies within the interval 0- 19.67.

The distribution of productivity indicators is highly skewed, with a very long right-hand tail and some outliers. Almost 50% of institutes have an average of less than 3 international publications per researcher per year, while the remaining 50% has up to 19 international publications, an extremely high level.

These findings raise several interesting questions.

First of all, is this variability just the outcome of heterogeneity of scientific disciplines? It is well known that publication practices are widely different across disciplines, both in terms of co-authorship practices, the typical number of publications per year, and the very definition of what accounts for a scientific article. In some areas researchers are expected to produce one or a few papers per year, while in others the typical output is in the range 10-20. Scientometrics literature offers several evidence on such differences.

We therefore replicated the analysis of variability of scientific productivity at the level of scientific disciplines. A careful inspection of data shows that roughly the same level of variability is reproduced within scientific areas (see Table 6 and Appendix A).

Second, the notion that scientific productivity at the individual level has a skewed distribution is familiar to scholars of science and science policy.* As it is well known in the economics of science, the productivity of scientists is well represented by the Lotka's law,[34] according to which, if the most productive scientist produces k papers, the second most productive produces $k/2^2$, the third produces $k/3^2$ and so on, with a sharply decreasing function. If scientists of different individual productivity are mixed together in institutes, then the distribution of average productivity per institute should be less asymmetric. If, on the other hand, the distribution of average productivity reproduces such asymmetries, then there must be systematic factors at work. In principle, one could think of institutes as mixing individuals with different productivities, so that the variance of the distribution across institutes becomes lower than the variance across individuals. In this line one could think of institutes as sampling young researchers from a distribution. If institutes sample from the same pool of talents, the resulting variance of productivity at the level of institutes must be low.

* Refs 25–27 examine the specialized literature on individual scientist's productivity. The appropriate level of analysis of the economics of science is an object of debate. The new economics of science assumes the individual scientist as the appropriate level (see Refs 28–31), while other contributions stress the intrinsic collective nature of modern science (see Refs 32, 33).

On the other hand, there may be phenomena of cumulativeness and self-selection. If high productivity scientists are free to choose, they will probably join institutions with a high prestige. If good quality institutes are free to choose candidates, will attract and hire highly productive junior scientists. Low quality institutes will attract only low quality candidates. If this process is cumulated over time large differences across institutes may be created and maintained.

According to our data, the latter effect seems to be predominant. Within the same scientific area, hence within a community with roughly similar publication practices, one can observe variation coefficients of large magnitude.

It is not only that individual scientists differ in their productivity. It is true, in addition, that there are extremely good institutes and extremely poor institutes within the same area. It is not only individual talent that matters, it is also the way in which science is organized at the microlevel.

The variability in productivity is even higher if we examine other indicators (see Table 5).

Table 5. Other indicators of scientific activity – Descriptive statistics

Variables	No. Obs.	Minimum	Maximum	Mean	Std. Deviation
P_MARFUN	187	0.00	66.00	14.36	11.38
P_INV	187	1.00	53.00	8.28	6.80
COPUB	187	7.58	426.00	57.29	46.29
COPUBINT	187	10.38	1475.96	113.63	138.00
AVIM	157	0.21	6.50	1.93	1.25

The Cost per publication, COPUB (Total costs/Total number of publications), may be as low as 7.58 million lira on average in the "least expensive" institute or as high as 426 million lira in the "most expensive" one, with an average cost of 57.29 million.

An international publication may cost an institute from 10.38 to 1475.96 million lira (see COPUBINT descriptive statistics in Table 5). Eliminating the outliers in the distribution, we still get an extremely skewed distribution. As we explained before, we are reluctant to interpret these data as reflecting actual productivity, since we do not exactly know how costs are computed. Anyway, differences of this magnitude should create some concern in administrators and policy makers.

For a subsample of institutes (n=157) we also have data on the average impact factor (AVIM). The average value is 1.93, the maximum 6.5.

How large is the distance between best and worse performers?

In order to control for the variability introduced by sectoral heterogeneity, we computed productivity indicators across scientific areas and constructed two measures of the asymmetry of the distribution. The former is a measure of the range between the highest and the lowest institute in terms of performance (RES_HL= IPURES for the best institute (HIGH)/ IPURES for the worst institute (LOW); PERS_HL= same transformation on IPUPERS). The latter is a measure of the distance between the best and the second best (RES_FS= IPURES for the best institute/IPURES for the second best institute; PERS_FS= same transformation on IPUPERS). The results are displayed in Table 6.

The data clearly show that variability is reproduced within scientific areas to a great extent.

On the average the best institute is 40-50% better than the second best institute for both indicators. In most scientific areas, however, this ratio is in the range 10-20%, implying that scientific excellence is not the territory of individual outliers.

On the average, in terms of productivity of researchers, the best institute is 13 times more productive than the worst institute.

Table 6. Indicators of scientific productivity asymmetry by scientific area

Area	RES_HL	RES_FS	PERS_HL	PERS_FS
A10	3.49	1.12	3.16	1.07
A12	3.80	1.44	2.64	1.56
A13	5.75	2.38	8.63	3.15
A5	3.99	1.14	2.99	1.56
MA1	6.07	1.11	7.55	1.05
MA2	10.68	1.24	24.41	1.24
MA3	28.47	2.36	20.45	1.70
MA4	8.30	1.13	16.09	1.10
MA5	4.27	1.11	6.08	1.27
MA6	56.73	1.04	219.23	1.61
		Descriptive statistics		
Mean	13.15	1.41	31.12	1.53
Std. Deviation	16.16	0.49	63.12	0.59
Minimum	3.49	1.04	2.64	1.05
Maximum	56.73	2.38	219.23	3.15

Within the six large scientific areas, the top institute is between 4 and 57 times more productive than the worst one.

Scientific areas in which the ratio HIGH/LOW are extremely high should take action to investigate the reasons of such gap. Inspection of distribution of individual institutes in each scientific area may help administrators and policy-makers to identify the explanation.

As a matter of fact, this analysis seems to show that institutes largely differ in their productivity and that differences do not depend on sectoral specificities. Should funding policies at CNR level reflect these differences? From an economic point of view, resources would be utilized more efficiently if they were shifted away from inefficient institutes and reallocated to good performers.

We are therefore left with a puzzling question: what does account for large differences in scientific productivity across institutes in the same area? This question requires an effort of data collection and analysis which goes beyond the scope of this paper. However, we have detailed data to investigate in depth the effect of age structure on institutes' average productivity.

Rather than addressing the question "what is the impact of age on individual productivity" we explore the problem of "how age structure of scientists affect scientific productivity at the level of institutes".

Age effects

Age structure

The age structure of personnel shows an interesting pattern. Remember that we are not examining data on individuals, but on institutes. Data are therefore computed as average values for each institute.

The entry level for research personnel (i.e. researchers, ORDRES) has an average age of almost 40. The minimum average age for researchers is 30.4, the maximum average is as high as 48.6.[*] The average age was quite high at 45.7 years for all personnel in 1997. Part of it is due to technical people and administrative staff, whose average age was 43. However, researchers too were, on average, 44 years old, and younger researchers were almost 40 years old.

The distribution of the average age of researchers and of the personnel are very far from normal. From the nonparametric density estimation it emerges clearly that the distributions of the age of researchers and of total personnel are bimodal (see Figure 1).

[*] Recall that these are averages at the level of institute. There may be individual researchers who are younger but the minimum average age across all researchers of an institute is 30.4.

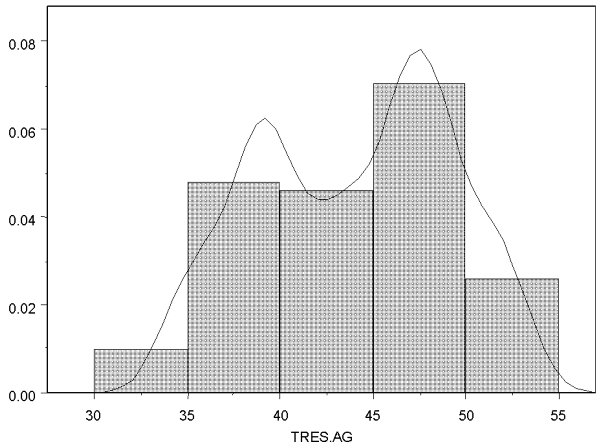

Figure 1. Nonparametric estimation of the TRES_AG density distribution

This shows the presence of two populations. This result has been confirmed by the analysis of the age of entrance at work. It suggests that the entry of individuals does not follow a smooth pattern over time, but rather a waveform dynamics.

Senior researchers are much older, with an average of 53.6, a minimum of 40.5. Research directors are only slightly older, with an average of 54.2. The typical career path seems to be approximately the following: entry as researcher at the age of 31-35, stay as researcher until an age comprised between 40 and 50. Within this interval, several researchers become senior researchers – there are not many researchers over 42. Among senior researchers, a subgroup with basically the same age structure become research directors. These are rough approximations, of course: a careful career analysis should be based on panel data and follow a cohort of individuals over time.

Age of entry

We have data on the age of birth and age of entry of all scientists that are still at the CNR in 1997. Clearly, all individuals that entered but left before 1997 are not included in the observations. These are cases of death, retirement, and exit towards other positions. So we have data on entry that do not permit to calculate entry rates correctly, but rather entry rates sui generis. This limitation of data must be clearly understood and kept in mind.

Interestingly, the average entry age is the same for all personnel categories, at around 30 years. Those that are now senior researchers or directors entered in their 30s; those that are now researchers slightly afterward. Although the typical career pattern seems reasonable, there are some important problems behind the age structure.

First, the average age of entry is computed across all individuals who are currently employed. They entered the CNR, on the average, in their 30s, that is, in the ‘60s, ‘70s, or ‘80s. If we compute the average age of entry across time, by building cohorts of age of entry of researchers, an interesting pattern emerges. As it is clear from Figure 2 and Figure 3 the age of entry witnessed a slow but steady increase over the period. In the '60s people entered on average at the age of 25, while in the '90s the average age was ten years larger. This is striking.

In part, it reflects the longer duration of university curricula and of de facto university studies in Italy. But it also reflects the difficulty of CNR in hiring researchers immediately after their Ph.D., that is, around 30. Therefore the average age of entry of 31.45 for researchers (and similar values for senior and directors) must be interpreted as the mean between the past and the present. And the present situation is less pleasant.

Of course, the probability that a scientist would exit decreases over time in the sample (scientists that were 35 years old in the ‘60s are now retired). This may underestimate the average age of scientists that entered earlier. Nothing can be said on the extent of the distortion. Nevertheless, the pattern is very strong. It seems that the threshold for entering CNR has been progressively increased. Young scientists are now much older than when they received their Ph.D.

What did they do meanwhile? In most cases they accepted various forms of non permanent jobs, ranging from post doc grants to research contracts, for many years in line. Is this long waiting line necessary to evaluate research capabilities? The answer is most probably no. The only plausible reason is that shortage of funds makes the supply of research positions largely inferior to availability of skills, producing a rationing effect. Rationing does not necessarily favor the best talents. The reason is that most talented people have higher opportunity costs and may receive interesting offers to work abroad or, less likely, to work in other institutions.

Second, inspection of Figure 2 clearly shows that the dynamics of hiring junior researchers is waveform. There have been periods of expansion around the years 1970, 1985 and 1995, and several periods of contraction. In addition, one can identify quite long periods of complete stop (e.g. around 1980), whose political, financial or institutional origins should be investigated carefully.

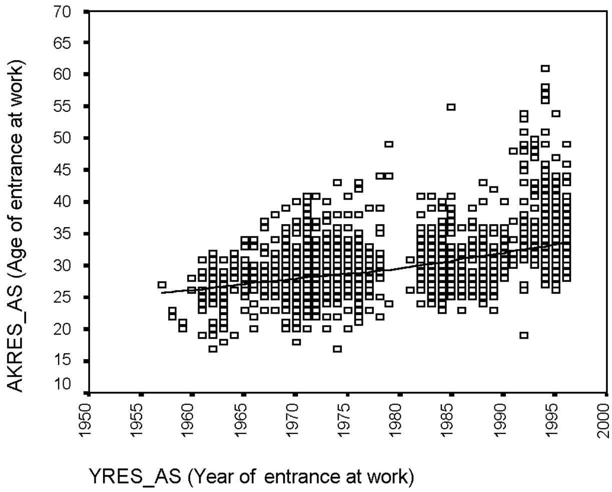

Figure 2. Evolution of the age of entry at work (1957-1997)
Note: The solid line represents the *loess* (locally weighted least square) curve.

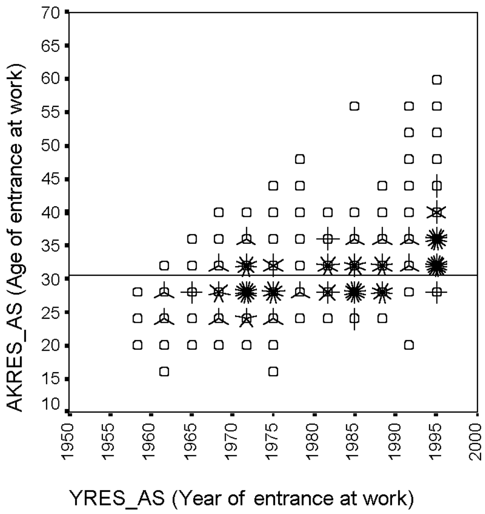

Figure 3. Evolution of the age of entry at work (1957-1997) – Sunflower
Note 1: Each petal represents 10 researchers.
Note 2: The reference line (the solid line) is the mean of the age of entrance at work of the whole CNR researchers (2386 observations considered).

It seems that hiring policies follow the upturn and downturn of political cycles, rather than the intrinsic needs of scientific evolution. In fact, the flow of talented graduate and post-graduate students can be considered steady over time around a trend, apart from sectoral shifts due to the rise of interest for particular scientific areas (e.g. computer science in the '70s, or biotechnology in the '90s). If this is true, hiring policies should follow the supply of talented people by opening opportunities at a steady rate. If not, there are several unpleasant consequences. Talented people may be discouraged from engaging into scientific career and go to the industry or other jobs. Uncertainty over the timing and volume of hiring may induce biases in the planned investment in human capital. Finally, when hiring is massive and concentrated in a few years, the rate of hiring may be larger than the rate of supply of talented people, so that hiring takes place among people ranked low in terms of research quality. If high quality people did not "queue-up" but decided to leave research, low quality people have better opportunities to enter.

In economic terms, those that have higher opportunity costs may leave while those that do not have better external opportunities may have the incentive to stay for long periods with CNR on the expectation to enter during an expansion wave.

This conjecture is confirmed by a third finding. The variance around the mean increases steadily, particularly in the '90s. In this period people who entered the CNR might have been as old as 50 years or even more. They probably were "queing up" since long time.[*] If this is the situation, hiring policies do not open new opportunities, but rationalize the existing structure of personnel. These trends can be found across all scientific areas (see figures in Appendix B).

This interpretation is supported by an inspection of the distribution of the age of researchers. A nonparametric estimation of the density distribution[**] (Figure 1) shows a bimodal pattern, suggesting the presence of two populations of researchers. The same pattern can be seen in the density distribution of institute age (see Figure 4).

[*] This conjecture was confirmed by a small number of interviews with directors of institutes, who confirmed that the complete stop of recruitment in the years before led to offer short term contracts to young scientists for many years in line. According to many interviewees, however, the quality of these scientists was in general high. Although they received job positions abroad they often preferred to pursue experiments in their labs.

[**] We use a Gaussian kernel estimator. The choice of the bandwidth has been done applying the rule of thumb by Silverman.[35]

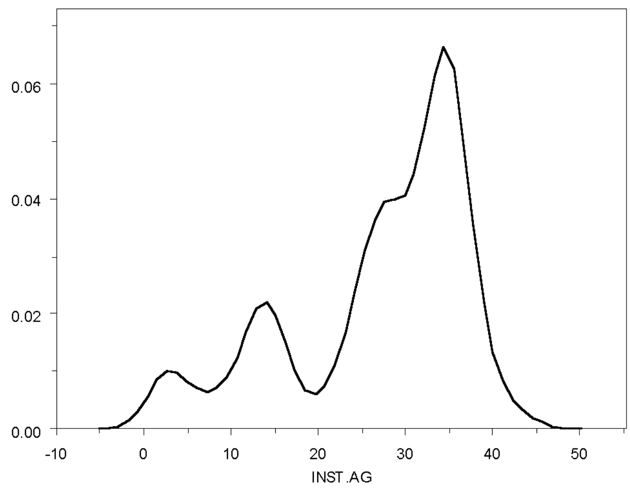

Figure 4. Density distribution of institute age (INST_AG)

Effects of age structure on scientific productivity

With respect to age, our interest is in evaluating the impact of age distribution on productivity. This effect is different from the one assumed in the life cycle hypothesis. We do not have longitudinal data on scientists' production and do not assume that younger scientists are monotonically more productive than older ones. Rather, we assume that institutes with higher average age have a lower turnover. They are presumably less able to attract young scientists and are more likely to be isolated from the latest developments in science.

As a first approximation we consider the average age of scientists and of all personnel within institutes. Institutes with higher average age of scientists are old institutes in which the entry of young scientists has not compensated the effect of ageing of incumbents.

Correlation analysis shows a systematic negative association between productivity indicators and the average age of researchers. The relation is statistically significant for the indicators of productivity of all personnel (IPUPERS) and of researchers (IPURES) in three cases: average age of ordinary researchers, of all researchers, and of all personnel (see Table 7).

Table 7. Correlation between average age and indicators of scientific output and productivity

Variable	T_PUB	P_INTPUB	INTPUB	IPURES	IPUPERS	PUBRES
TRES_AG	0.348**	–0.072	0.331**	–0.158*	–0.278**	–0.141
TPERS_AG	0.377*	–0.81	0.353**	–0.203*	–0.325**	–0.197**
ADM_AG	0.168*	–0.06	0.170*	–0.62	–0.105	–0.067
TECH_AG	0.266**	–0.54	0.254**	–0.144	–0.223**	–0.162
ORD_AG	0.267**	–0.30	0.277**	–0.216**	–0.301**	–0.287**
SENR_AG	0.008	0.118	0.026	–0.114	–0.103	–0.159
DIR_AG	0.104	0.157	0.109	0.023	–0.102	–0.076

* Pearson Correlation is significant at the 0.05 level (2-tailed).
** Pearson Correlation is significant at the 0.01 level (2-tailed).

This negative association has an interesting pattern at the level of scientific areas (Appendix C). In geology, chemistry and physics we observe a negative and significant relation between average age of personnel and researchers and productivity, with coefficients in the range 0.30-0.50, while in engineering, medicine and agriculture the relation is still negative but the coefficient is very small and never significant. This pattern, interestingly, still holds for correlations between institute age and productivity, with negative significant coefficients in the range 0.40-0.80, for geology, chemistry and physics (Appendix D).

It seems that in disciplines that have a more applied nature, an external orientation (e.g. patients, industry) and a more important role for practical experience as opposed to discovery, institutes with a higher average age still manage to keep productivity high.

The general negative relation does not necessarily mean that older scientists are less productive in absolute terms. Rather, institute with higher average age of researchers might have a lower proportion of younger scientists, that they wouldn't or couldn't attract. The average age of an institute reflects its attractiveness and scientific vitality. In fact, the average age of existing personnel is lowered each time a young researcher enters the institute. The higher the scientific prestige of the institute, the resources available for job positions and the prospects for career, the higher the number of young candidates wishing to enter. The average age may be considered a summary statistics for turnover and attractiveness.

Our data show that the higher the average age of researchers, the lower the scientific productivity (see Table 7). It is interesting to note that the average age of senior researchers and of directors of research is not significantly related to productivity (in the latter case, the coefficient is even positive). This confirms that what is in place is not a life-cycle effect. Institutes with old directors or a group of old senior researchers may well be highly productive.

There is also an effect of age structure on the cost of publications and on the ability to raise market funds (see Table 8).

Table 8. Correlation between average age and indicators of cost, impact factor, and market funds

Variable	COPUB	COPUBINT	AVIM	P_MARFUN
TRES_AG	0.196**	0.119	0.067	–0.239**
T_PERSAG	0.155*	0.086	0.057	–0.246**
ADM_AG	0.071	0.083	0.119	–0.101
TECH_AG	0.044	0.011	–0.033	–0.135
ORD_AG	0.345**	0.205**	0.175*	–0.158
SENR_AG	0.131	0.078	0.146	0.073
DIR_AG	0.126	–0.136	0.028	–0.029

* Pearson Correlation is significant at the 0.05 level (2-tailed).
** Pearson Correlation is significant at the 0.01 level (2-tailed).

Not surprisingly, the higher the average age of researchers, the higher the total cost of publications and of international publications. The increased weight of wage structure is not compensated by increases in productivity.

A very interesting result, moreover, is that the percentage of funds raised from the market is negatively correlated with average age. It is not true that institutes with more experienced researchers are more able to attract the interest of external founders of research. Quite the opposite could be true.

Age of institutes and the dynamics of growth

We computed the age of institutes, by considering the earliest date of entry of personnel.* Several interesting results emerge from the analysis. The nonparametric density estimation of the distribution** of institute age (Figure 4) shows a remarkable waveform pattern. It seems that new scientific institutions follow some sort of political discrete process, rather than an attempt to follow scientific developments over time.

First, the age of institutes is strongly correlated to size. The size of institutes has grown almost linearly with age. Plotting size against age, both in terms of researchers and total personnel, one gets the clear view that no institute is allowed to grow rapidly in its early stages. Large institutes are also old institutes. No large institute (more than 25 researchers and 50 total employees, say) is younger than 25-30 years.

* Again, this is a sui generis measure. A control on administrative data is still under way.
** We recall that we use a Gaussian kernel estimator. The choice of the bandwidth has been done applying the rule of thumb by Silverman.[35]

The pattern of growth is made clear by Figures 5 and 6. The variable on the X axis is the ratio between size at the final year and the age. It measures how many employees any institute has received, on the average, each year of its life. The variable is measured for total personnel (T_PERS) and researchers (T_RES), respectively.

Several points are worth attention.

First, the large majority of institutes grew at a rate of less than one researcher per year and less than two employees per year over their life. This means that the size of institutes grows linearly (in absolute differences) over time with this fixed rule.

Second, it is also visible an accelerated growth pattern for a few institutes. However, among the few institutes that have grown more rapidly (more than one researcher and two employees per year of life) we find predominantly those that are old and hence large at the final year. Only a few small and young institutes grew at an accelerated rate. This means that rapid growth is not achievable in an early stage of the life of an institute, but rather during its life.

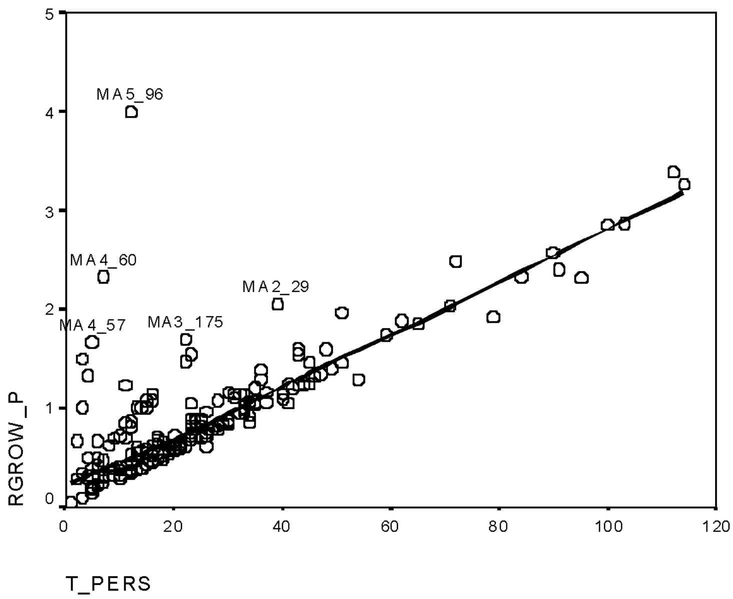

Figure 5. Plot of average growth (average number of personnel per each year of life, T_PERS/INSTAG) against size (number of personnel, T_PERS)
Note: The black line is the lowess line that interpolates 85% of points.

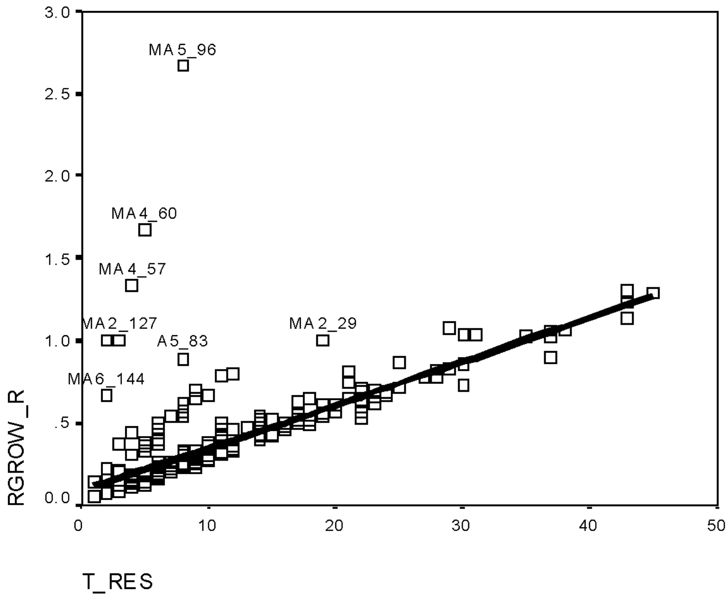

Figure 6. Plot of average growth (average number of personnel per each year of life, T_RES/INSTAG) against size (number of researchers, T_RES)
Note: The black line is the lowess line that interpolates 85% of points.

A suggested industrial dynamics interpretation

The analysis of Figures 5 and 6 shows that there are three identifiable clusters. The first is the largest one and is composed by all institutes that grew roughly at the same average rate, identified by the black line in both Figures. This group is formed by 152 institutes, or 81.29% of the total.

A second group enjoyed a slightly larger average growth and lies along a higher imaginary path (28 institutes, 14.97%).

Finally, a small group lies clearly outside the previous paths (7 institutes, 3.74%), having benefited from a much larger average rate of growth.

In order to interpret these different patterns, we plotted the average growth against the age of institute. Figures 7 and 8 show an illuminating pattern.

Institutes in their childhood (less then 5 years of life) receive strong support and grow at a rate of 1.33 researchers and 1.83 employees per year.

This high growth dynamics has short life, however. As soon as institutes become older (around 10 years of life), the average growth is greatly reduced. The average growth reaches the minimum for institutes at age 25.

Surprisingly enough, older institutes grew with a larger average growth: institutes aged 35 or 40 years lie on an increasing section of the curve. It may be that they received more resources when they where young (possibly because CNR received more funds in the '60s or '70s), or it may be that older institutes continue to receive large resources in their maturity (possibly because they are larger and more powerful). Particularly in the latter case, since older institutes are less productive, this pattern amounts to a severe misallocation of resources.

To investigate which explanation holds it is necessary to examine the path of growth of individual institutes. The aggregate picture, aggregating institutes of different age with no reference to their history, only suggests a plausible pattern.

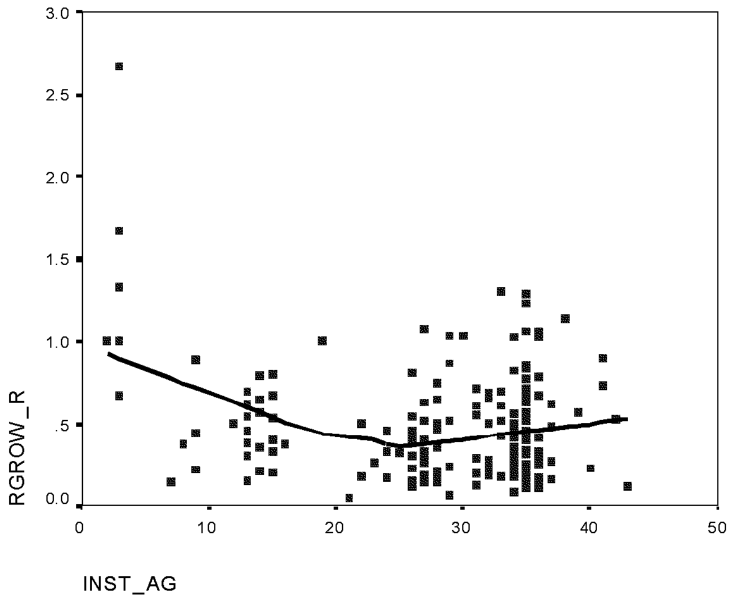

Figure 7. Plot of average growth (average number of researchers per each year of life, T_RES/INSTAG) against institute age (INST_AG)
Note: The black line is the lowest line that interpolates 85% of points.

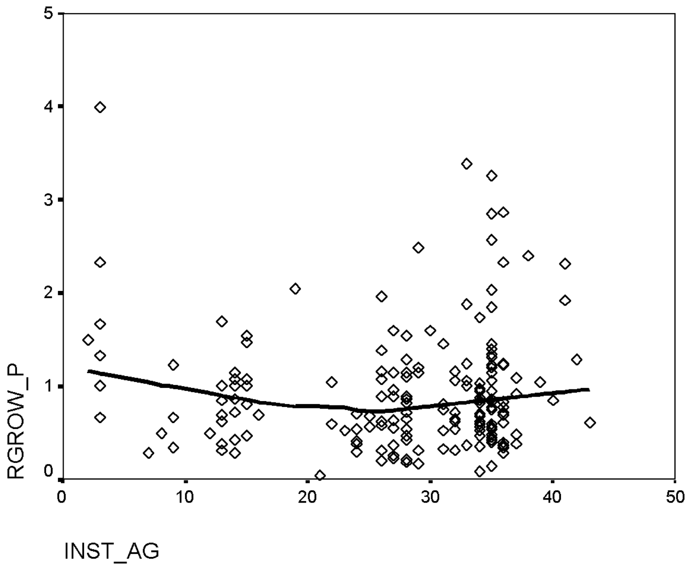

Figure 8. Plot of average growth (average number of personnel per each year of life, T_PERS/INSTAG) against institute age (INST_AG)
Note: The black line is the lowest line that interpolates 85% of points.

The notion of industrial organisation of science was introduced recently in economics (see the special issue of *Review d'Economie Industrielle* "L'économie industrielle de la science," 1997). We suggest that a promising line of research is industrial dynamics of science, i.e., the pattern of natality, survival, growth and mortality of research institutions.

It is clear that the institution does not allow any rapid growth to young but highly productive institutes. They may grow large, but not fast.

Not surprisingly, older institutes have also older population of researchers and other employees.

Table 9 confirms that these groups exhibit different features. The small group of high growth institutes is very young, very small and extremely productive (8.11 paper per researcher). On the contrary, institutes that grow by 0.46 researchers and 0.93 units per year are very large and old, have aged personnel, and are less productive.

The fact that the majority of institutes eventually collapse in the latter group is extremely insightful.

Table 9. Summary statistics – average value, standard deviation in brackets – of research institutes by growth category

Variables	High growth	Medium growth	Low growth
		Age variables	
TRES_AG	35.90	38.96	45.28
	(1.94)	(3.74)	(4.67)
TRES_OL	2.58	6.98	14.78
	(0.42)	(3.08)	(5.54)
TPERS_AG	36.70	40.04	47.17
	(2.36)	(2.98)	(3.88)
TPERS_OL	4.50	9.25	18.51
	(0.48)	(2.81)	(5.26)
INST_AG	2.86	13.29	30.65
	(0.38)	(2.26)	(7.03)
		Productivity indicators	
IPURES	8.11	3.01	3.38
	(5.53)	(1.98)	(2.58)
IPUPERS	6.79	1.93	1.83
	(5.84)	(1.44)	(1.69)
		Fund and cost indicators	
RESFUN	406.43	442.96	1,184.01
	(376.65)	(438.29)	(1,943.58)
T_COS	773.57	1,274.86	3,518.70
	(558.22)	(959.86)	(3,429.23)
COPUBINT	36.81	106.40	118.50
	(33.37)	(119.16)	(143.42)
		Rate of growth indicators	
RGROW_R	1.33	0.53	0.46
	(0.67)	(0.21)	(0.31)
RGROW_P	1.83	0.88	0.93
	(1.09)	(0.43)	(0.63)
T_RES	3.86	7.14	13.93
	(2.12)	(3.54)	(9.77)
No. Obs.	7	28	152

This finding could shed light on the mechanisms of allocation of resources. It seems that institutes receive resources in proportion to their age, not to their scientific production or productivity. Eventually you may become large, but you need to invest a lot of resources to survive, strengthen your institutional visibility, engage in lobbying and request of resources, and the like. The path of growth is extremely narrow for everybody. This means that the allocation of resources for growth takes place by distributing opportunities “in due time”, rather than by encouraging promising research areas and teams. Growth is managed as a political process, rather than a competitive one. Not only resources are distributed equally, also opportunities for growth do not follow the typical asymmetry and disruptive nature which is found in the scientific evolution.

Unfortunately, the higher the age of institutes, the lower the scientific productivity. Productivity indicators IPURES and IPUPERS are significantly and negatively correlated to the age of institutes. This effect is mainly due to a number of young and highly productive institutes. Combining the two results, the critical policy making problem becomes: should young and more productive institutes grow more rapidly than others? Evidence tells this did not happen.

Another interesting result is that older institutes are not more capable to find external sources of funding. The percentage of funds received from external sources (P_MARFUN) is negatively and significantly correlated with the age of institutes (see Table 10).

Table 10. Correlation between age of institutes and other indicators

Variable							
	Indicators of size of institutes						
	T_RES	T__PERS	ADM	TECH	ORD_RES	SEN_RES	DIR_RES
	0.496**	0.512**	0.453**	0.465**	0.323**	0.474**	0.515**
	Indicators of age structure						
	TRES_AG	TPERS_AG	ADM_AG	TECH_AG	ORD_AG	SEN_AG	DIR_AG
INST_AG	0.693**	0.798**	0.391**	0.684**	0.453**	0.246**	0.434**
	Indicators of scientific production and productivity						
	T_PUB	P_INTPUB	INTPUB	IPURES	IPUPERS	PUBRES	
	0.376**	–0.108	0.329**	–0.304**	–0.435**	–0.247**	
	Indicators of cost, impact factor, and market funds						
		COPUB	COPUBINT	AVIM	P_MARFUN		
		0.131	0.034	0.011	–0.236**		

* Pearson Correlation is significant at the 0.05 level (2-tailed).
** Pearson Correlation is significant at the 0.01 level (2-tailed).

In sum, institute age, institute size, and researchers average age are all correlated. The bad news is that they all are negatively correlated to productivity and the ability to raise money.

In sum, data show the existence of a strong age effect at the level of institutes. At the micro-level, scientific productivity of the overall system depends on the ability of institutes to satisfy regularly a certain turnover of job positions over time, in order to attract young talented scientists. In reality, CNR has experienced a steady increase in the age of entry, and managed recruitment and institutional speciation as a waveform and discrete process. In addition, CNR lacks institutional mechanisms to give a prize to young and highly productive institutes. Growth is a matter of time, not merit.

Conclusions and policy implications

Based on detailed evidence at the micro level on research institutes we demonstrated that scientific productivity declines with the average age of researchers of the institute. We also found an almost linear law of absolute growth for the size of institutes, which on the average increase their size by the same absolute amount each year. The institutional system seems to be based on a uniform rate of (absolute) growth, which depends on allocation rules that follow political processes.

Several important policy problems may be discussed in the light of this evidence.

There is increasing concern in Europe regarding the increasing average age of researchers. This concern is well grounded. The key problem is not the declining individual productivity, but rather the fact that as time goes on, it becomes increasingly difficult to create the research climate within scientific institutions that attracts young and talented scientists. The turnover of scientific personnel must be kept high on a permanent basis.

This is related to a second important policy problem. Faced with the problem of ageing of researchers, some European opinion makers propose to launch massive campaigns for recruiting many thousands of young researchers.

The process of recruitment of young researchers, which could have reduced the average age, is waveform and was subject to a significant process of increase of the entry age.

Our data suggest that the appropriate recruitment policy for scientific institutions is based on a steady flow of job opportunities, that encourage the investment of human capital and reduce the time interval between the graduate degree and a permanent position.

If recruitment is based on long periods of stasis and discrete waves of massive entry, the system of incentives of young graduate students may be severely distorted. A clear policy implication is that governments and large public research organisations should decide a steady state rate of growth and plan recruitment campaigns within short, regular and reliable time intervals.

We have shown an interesting pattern of growth of size of research institutes, whereby the rate of growth is uniform across the population of institutes and approximately constant over time. The long run size dynamics of research units is an interesting research topics in itself.* We propose that this growth pattern is dependent on structural properties of the institutional public research system.

*

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* We are not aware of studies trying to map the "industrial dynamics" of research institutes in the long run. This might give interesting insights into the structural properties of institutional systems of public research in different countries.

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Appendix A
Scientific productivity indicators per research area

Table 1.1 Scientific productivity indicators – Descriptive statistics

a) MA1 Agriculture

	N	*Minimum*	*Maximum*	*Mean*	*Std. Deviation*
T_PUB	24	10	63	34.08	13.98
INTPUB	24	5.0	41.0	21.15	10.81
P_INTPUB	24	30	90	60.83	14.28
IPURES	24	1.01	6.15	2.84	1.41
IPUPERS	24	0.59	4.42	1.45	0.98
PUB_RES	24	2.00	8.50	4.63	1.81
PUB_PERS	24	1.20	7.00	2.38	1.50

b) MA2 Environment and habitat, Geology and Mining

	N	*Minimum*	*Maximum*	*Mean*	*Std. Deviation*
T_PUB	26	8.00	158.00	54.27	35.77
INTPUB	26	2.00	80.58	25.27	17.18
P_INTPUB	26	21.00	86.00	48.81	18.52
IPURES	26	0.58	6.21	2.48	1.40
IPUPERS	26	0.25	6.21	1.57	1.55
PUB_RES	26	2.25	9.00	5.00	1.69
PUB_PERS	26	1.14	9.00	2.97	2.13

c) MA3 Biotechnologies and molecular biology, Medicine and Biology

	N	*Minimum*	*Maximum*	*Mean*	*Std. Deviation*
T_PUB	27	4.00	382.00	77.41	83.27
INTPUB	27	2.00	209.42	53.00	47.48
P_INTPUB	27	36.00	100.00	74.04	16.75
IPURES	27	0.67	18.98	4.61	3.48
IPUPERS	27	0.46	9.49	2.35	1.87
PUB_RES	27	1.33	26.00	6.26	4.79
PUB_PERS	27	0.97	13.00	3.20	2.59

d) MA4 Chemistry

	N	*Minimum*	*Maximum*	*Mean*	*Std. Deviation*
T_PUB	26	19	112	61.27	27.90
INTPUB	26	12.92	88.48	44.29	19.12
P_INTPUB	26	57	100	73.69	11.66
IPURES	26	1.29	10.73	4.20	2.64
IPUPERS	26	0.59	9.45	2.69	2.41
PUB_RES	26	1.82	16.50	5.73	3.46
PUB_PERS	26	0.86	13.20	3.62	3.05

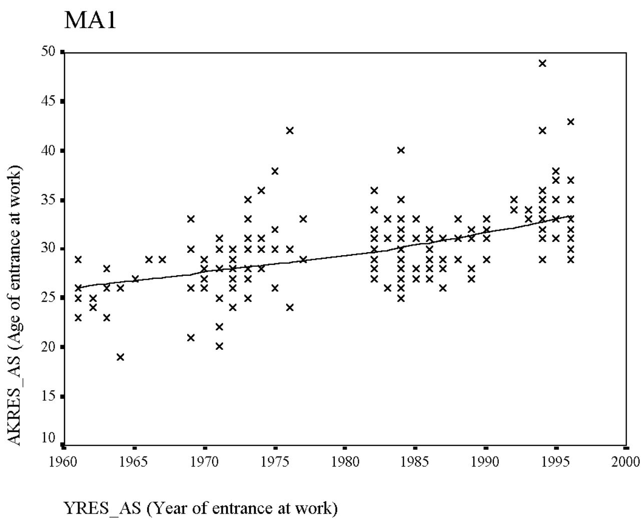
e) MA5 Physics

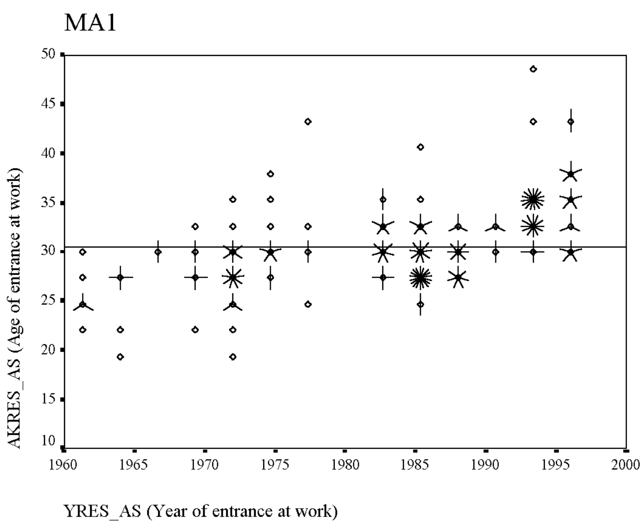
	N	*Minimum*	*Maximum*	*Mean*	*Std. Deviation*
T_PUB	28	17.00	220.00	102.39	60.87
INTPUB	28	17.00	151.94	73.77	40.35
P_INTPUB	28	54.00	100.00	75.50	11.57
IPURES	28	1.99	8.50	4.30	1.54
IPUPERS	28	0.93	5.67	2.41	1.08
PUB_RES	28	3.25	9.38	5.73	1.95
PUB_PERS	28	1.61	5.67	3.19	1.26

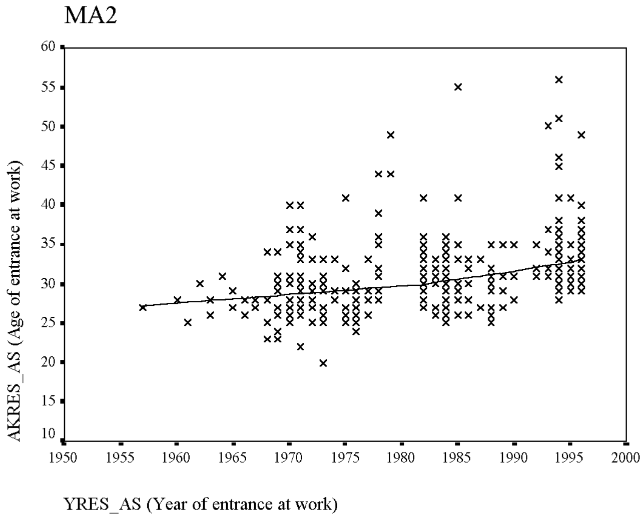
f) MA6 Engineering and architecture, Innovation and Technology

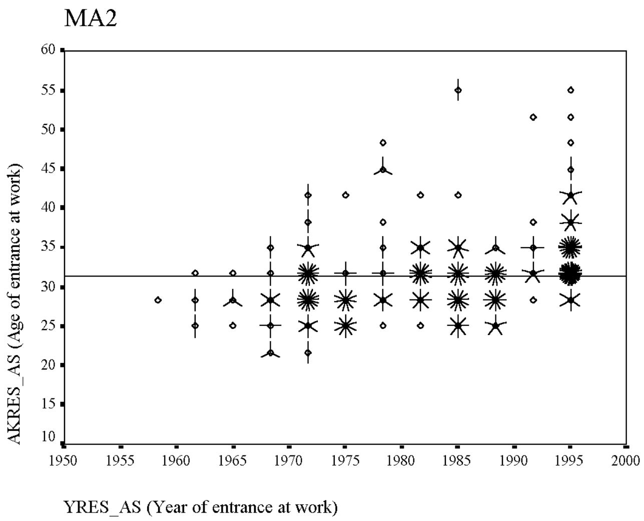
	N	*Minimum*	*Maximum*	*Mean*	*Std. Deviation*
T_PUB	31	2.00	203.00	60.90	51.28
INTPUB	31	1.04	110.50	33.04	30.80
P_INTPUB	31	8.00	100.00	54.35	22.30
IPURES	31	0.35	19.67	3.50	4.45
IPUPERS	31	0.09	19.00	2.08	3.78
PUB_RES	31	0.40	27.67	6.38	5.99
PUB_PERS	31	0.17	26.00	3.45	5.07

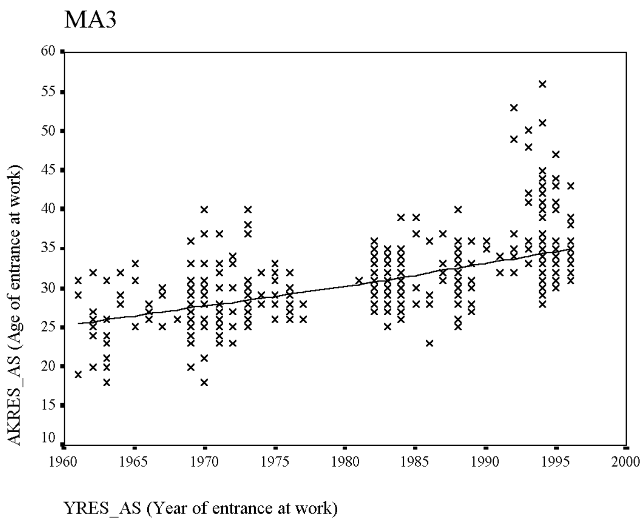
Appendix B
Trend of the age of entry at work (1957-1997) per Research Area

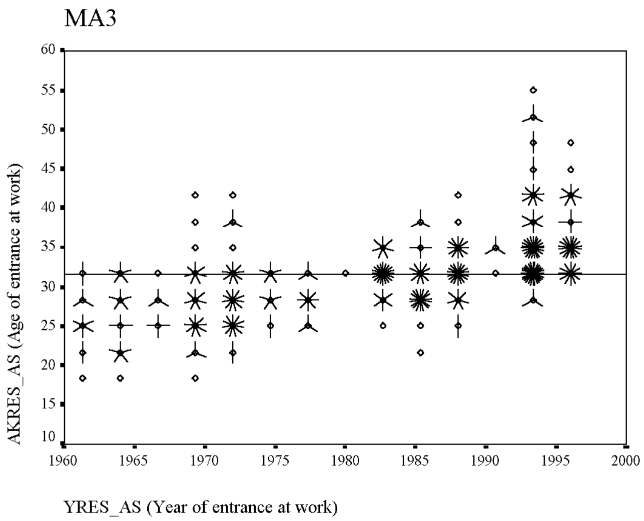


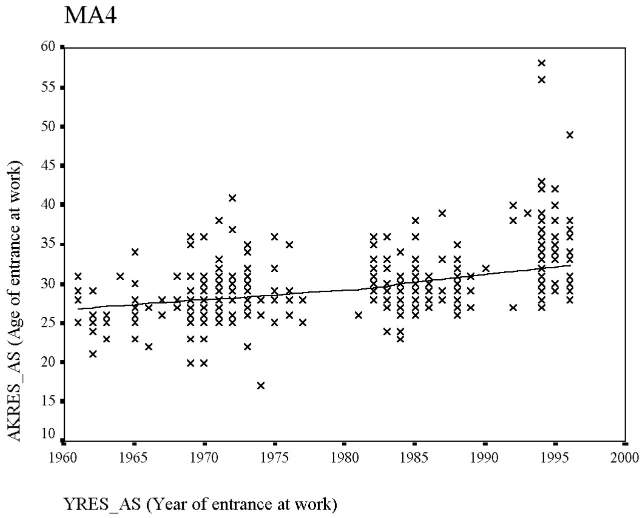


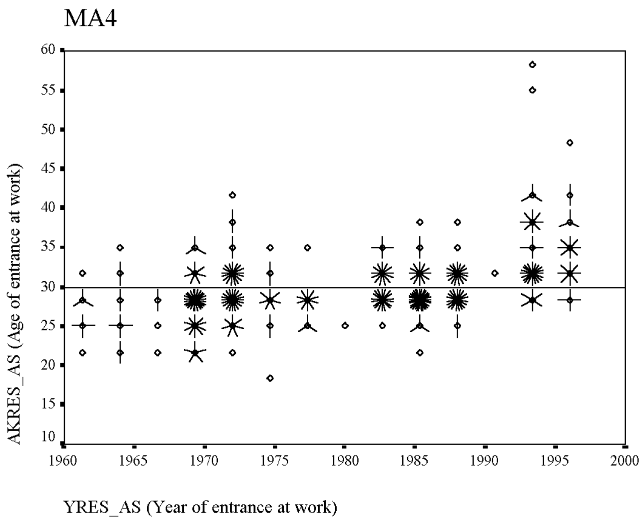

MA2
AKRES_AS (Age of entrance at work)
YRES_AS (Year of entrance at work)

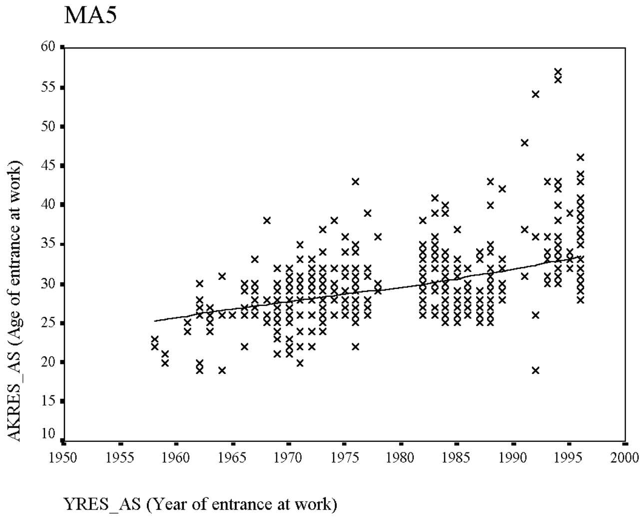

MA2
AKRES_AS (Age of entrance at work)
YRES_AS (Year of entrance at work)

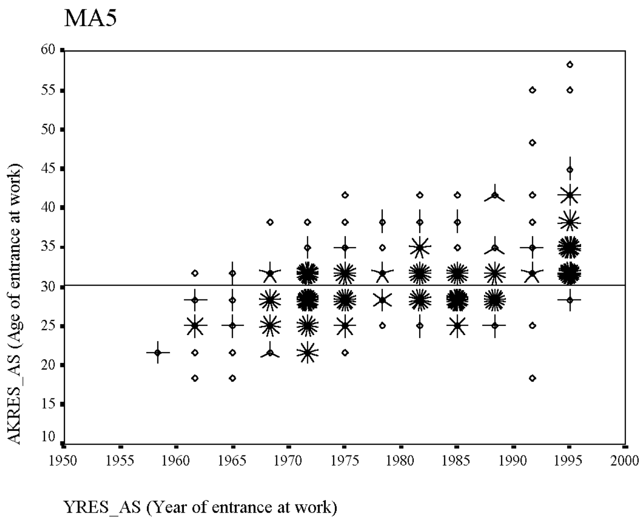

MA3
AKRES_AS (Age of entrance at work)
YRES_AS (Year of entrance at work)

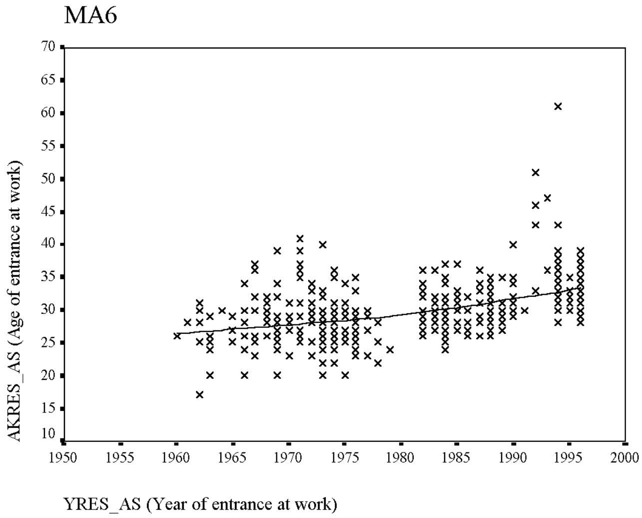

MA3
AKRES_AS (Age of entrance at work)
YRES_AS (Year of entrance at work)

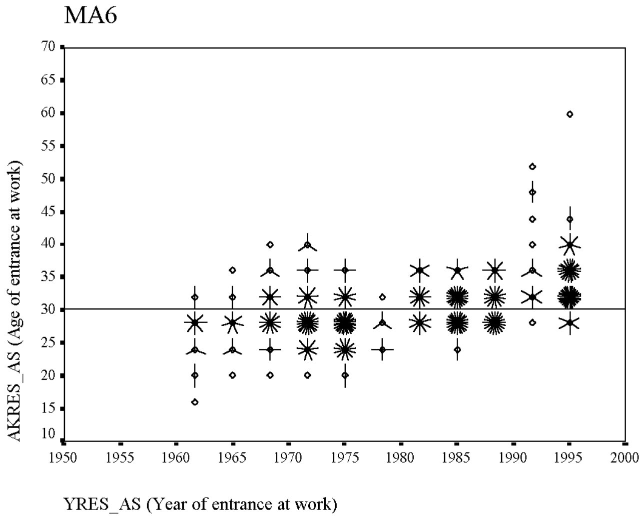

MA4
AKRES_AS (Age of entrance at work)
YRES_AS (Year of entrance at work)


MA4
AKRES_AS (Age of entrance at work)
YRES_AS (Year of entrance at work)


MA5
AKRES_AS (Age of entrance at work)
60
55
50
45
40
35
30
25
20
15
10
1950
1955
1960
1965
1970
1975
1980
1985
1990
1995
2000
YRES_AS (Year of entrance at work)


MA5
AKRES_AS (Age of entrance at work)
60
55
50
45
40
35
30
25
20
15
10
1950
1955
1960
1965
1970
1975
1980
1985
1990
1995
2000
YRES_AS (Year of entrance at work)


MA6
AKRES_AS (Age of entrance at work)
YRES_AS (Year of entrance at work)


MA6
AKRES_AS (Age of entrance at work)
YRES_AS (Year of entrance at work)

Appendix C

Correlation between average age and indicators of scientific output and productivity per research area

a) MA1 Agriculture

Variable	*T_PUB*	*P_INTPUB*	*INTPUB*	*IPURES*	*IPUPERS*	*PUBRES*
TRES_AG	0.155	0.092	0.153	–0.057	–0.401	–0.093
TPERS_AG	0.228	0.085	0.198	0.019	–0.263	0.010
ADM_AG	0.552*	0.181	0.549*	0.216	0.040	0.129
TECH_AG	0.265	0.084	0.222	0.377	0.461*	0.451*
ORD_AG	0.068	–0.135	–0.038	0.023	–0.177	0.077
SENR_AG	–0.454	–0.196	–0.447	–0.543*	–0.551*	–0.508*
DIR_AG	–0.388	–0.290	–0.475	–0.405	–0.687**	–0.247

* Pearson Correlation is significant at the 0.05 level (2-tailed).
** Pearson Correlation is significant at the 0.01 level (2-tailed).

b) MA2 Environment and habitat, Geology and Mining

Variable	*T_PUB*	*P_INTPUB*	*INTPUB*	*IPURES*	*IPUPERS*	*PUBRES*
TRES_AG	0.461*	–0.346	0.376	–0.539**	–0.579**	–0.331
TPERS_AG	0.464*	–0.529**	0.297	–0.692**	–0.687**	–0.406*
ADM_AG	0.143	–0.357	0.012	–0.466*	–0.549**	–0.283
TECH_AG	0.351	–0.448*	0.188	–0.562**	–0.596**	–0.247
ORD_AG	0.357	–0.326	0.291	–0.532**	–0.614**	–0.403*
SENR_AG	0.424	0.483*	0.525*	0.465	0.202	0.066
DIR_AG	0.380	–0.043	0.363	–0.146	–0.338	–0.077

*Pearson Correlation is significant at the 0.05 level (2-tailed).
** Pearson Correlation is significant at the 0.01 level (2-tailed).

c) MA3 Biotechnologies and molecular biology, Medicine and Biology

Variable	*T_PUB*	*P_INTPUB*	*INTPUB*	*IPURES*	*IPUPERS*	*PUBRES*
TRES_AG	0.412*	–0.034	0.493**	–0.044	–0.121	–0.037
TPERS_AG	0.374	–0.058	0.437*	–0.008	–0.109	0.005
ADM_AG	0.136	0.016	0.115	0.430	0.155	0.385
TECH_AG	0.203	–0.118	0.249	0.067	0.046	0.085
ORD_AG	0.367	–0.021	0.475*	–0.082	–0.220	–0.094
SENR_AG	–0.060	–0.280	–0.051	–0.063	0.255	0.032
DIR_AG	0.219	0.055	0.214	0.275	0.184	0.303

* Pearson Correlation is significant at the 0.05 level (2-tailed).
** Pearson Correlation is significant at the 0.01 level (2-tailed).

d) MA4 Chemistry

Variable	*T_PUB*	*P_INTPUB*	*INTPUB*	*IPURES*	*IPUPERS*	*PUBRES*
TRES_AG	0.408*	0.114	0.469*	–0.563**	–0.594**	–0.580**
TPERS_AG	0.437*	0.082	0.497**	–0.564**	–0.609**	–0.589**
ADM_AG	0.176	0.167	0.236	–0.295	–0.179	–0.368
TECH_AG	0.351	0.111	0.419*	–0.451*	–0.556**	–0.486*
ORD_AG	0.321	–0.049	0.339	–0.651**	–0.655**	–0.658**
SENR_AG	–0.413	0.070	–0.416	–0.658**	–0.541**	–0.681**
DIR_AG	0.260	–0.437	0.207	0.059	0.278	0.156

* Pearson Correlation is significant at the 0.05 level (2-tailed).
** Pearson Correlation is significant at the 0.01 level (2-tailed).

e) MA5 Physics

Variable	*T_PUB*	*P_INTPUB*	*INTPUB*	*IPURES*	*IPUPERS*	*PUBRES*
TRES_AG	0.684**	–0.540**	0.652**	–0.318	–0.451*	–0.071
TPERS_AG	0.676**	–0.542**	0.653**	–0.430*	–0.555**	–0.210
ADM_AG	0.474*	–0.328	0.442*	–0.407*	–0.372	–0.287
TECH_AG	0.541**	–0.470*	0.535**	–0.472*	–0.510**	–0.311
ORD_AG	0.565**	–0.467*	0.529**	–0.389*	–0.495**	–0.170
SENR_AG	–0.029	–0.380	–0.130	–0.187	–0.417	–0.028
DIR_AG	0.160	–0.036	0.153	0.085	0.182	0.054

* Pearson Correlation is significant at the 0.05 level (2-tailed).
** Pearson Correlation is significant at the 0.01 level (2-tailed).

f) MA6 Engineering and architecture, Innovation and Technology

Variable	*T_PUB*	*P_INTPUB*	*INTPUB*	*IPURES*	*IPUPERS*	*PUBRES*
TRES_AG	0.182	–0.247	0.102	–0.003	–0.141	0.091
TPERS_AG	0.383*	–0.261	0.297	–0.123	–0.243	–0.054
ADM_AG	0.116	–0.215	0.052	–0.271	–0.305	–0.187
TECH_AG	0.367	–0.177	0.309	–0.158	–0.204	–0.127
ORD_AG	0.038	–0.049	0.015	–0.003	–0.141	0.091
SENR_AG	–0.379	–0.254	–0.395	–0.315	–0.279	–0.245
DIR_AG	–0.202	–0.031	–0.211	0.110	0.007	0.143

* Pearson Correlation is significant at the 0.05 level (2-tailed).
** Pearson Correlation is significant at the 0.01 level (2-tailed).

Appendix D
Correlation between average age and indicators of scientific productivity per research area

a) MA1 Agriculture

Variable							
	Indicators of size of institutes						
	T_RES	T__PERS	ADM	TECH	ORD_RES	SEN_RES	DIR_RES
	0.298	0.335	0.234	0.303	–0.065	0.493*	0.449*
	Indicators of age structure						
INST_AG	TRES_AG	TPERS_AG	ADM_AG	TECH_AG	ORD_AG	SEN_AG	DIR_AG
	0.543**	0.682**	0.243	0.539**	0.119	–0.050	–0.085
	Indicators of scientific production and productivity						
	T_PUB	P_INTPUB	INTPUB	IPURES	IPUPERS	PUBPERS	
	0.290	0.227	0.331	–0.331	–0.115	–0.214	
	Indicators of cost, impact factor, and market funds						
		COPUB	COPUBINT	AVIM	P_MARFUN		
		0.365	0.189	0.140	0.075		

* Pearson Correlation is significant at the 0.05 level (2-tailed).
** Pearson Correlation is significant at the 0.01 level (2-tailed).

b) MA2 Environment and habitat, Geology and Mining

Variable							
	Indicators of size of institutes						
	T_RES	T__PERS	ADM	TECH	ORD_RES	SEN_RES	DIR_RES
	0.524**	0.586**	0.553**	0.618**	0.463*	0.452*	0.400*
	Indicators of age structure						
	TRES_AG	TPERS_AG	ADM_AG	TECH_AG	ORD_AG	SEN_AG	DIR_AG
INST_AG	0.634**	0.759**	0.556**	0.666**	0.594**	0.274	0.373
	Indicators of scientific production and productivity						
	T_PUB	P_INTPUB	INTPUB	IPURES	IPUPERS	PUBRES	
	0.502**	–0.616**	0.291	–0.738**	–0.827**	–0.406*	
	Indicators of cost, impact factor, and market funds						
		COPUB	COPUBINT	AVIM	P_MARFUN		
		0.611**	0.598**	–0.131	–0.066		

* Pearson Correlation is significant at the 0.05 level (2-tailed).
** Pearson Correlation is significant at the 0.01 level (2-tailed).

c) MA3 Biotechnologies and molecular biology, Medicine and Biology

Variable							
	Indicators of size of institutes						
	T_RES	T__PERS	ADM	TECH	ORD_RES	SEN_RES	DIR_RES
	0.620**	0.559**	0.474*	0.470*	0.456*	0.632**	0.601**
	Indicators of age structure						
	TRES_AG	TPERS_AG	ADM_AG	TECH_AG	ORD_AG	SENR_AG	DIR_AG
INST_AG	0.774**	0.740**	0.439	0.485*	0.593**	0.432	0.518*
	Indicators of scientific production and productivity						
	T_PUB	P_INTPUB	INTPUB	IPURES	IPUPERS	PUBRES	
	0.462*	–0.121	0.529**	–0.257	–0.341	–0.203	
	Indicators of cost, impact factor, and market funds						
		COPUB	COPUBINT	AVIM	P_MARFUN		
		0.228	0.120	–0.047	–0.045		

* Pearson Correlation is significant at the 0.05 level (2-tailed).
** Pearson Correlation is significant at the 0.01 level (2-tailed).

d) MA4 Chemistry

Variable							
	Indicators of size of institutes						
	T_RES	T__PERS	ADM	TECH	ORD_RES	SEN_RES	DIR_RES
	0.607**	0.682**	0.439*	0.629**	0.239	0.574**	0.660**
	Indicators of age structure						
	TRES_AG	TPERS_AG	ADM_AG	TECH_AG	ORD_AG	SENR_AG	DIR_AG
INST_AG	0.875**	0.900**	0.383	0.840**	0.805**	0.468*	0.164
	Indicators of scientific production and productivity						
	T_PUB	P_INTPUB	INTPUB	IPURES	IPUPERS	PUBRES	
	0.283	0.001	0.286	–0.708**	–0.775**	–0.691**	
	Indicators of cost, impact factor, and market funds						
		COPUB	COPUBINT	AVIM	P_MARFUN		
		0.542**	520**	0.419*	–0.565**		

* Pearson Correlation is significant at the 0.05 level (2-tailed).
** Pearson Correlation is significant at the 0.01 level (2-tailed).

e) MA5 Physics

Variable							
	Indicators of size of institutes						
	T_RES	T__PERS	ADM	TECH	ORD_RES	SEN_RES	DIR_RES
	0.683**	0.672**	0.628**	0.603**	0.554**	0.597**	0.576**
	Indicators of age structure						
	TRES_AG	TPERS_AG	ADM_AG	TECH_AG	ORD_AG	SENR_AG	DIR_AG
INST_AG	0.749**	0.829**	0.731**	0.791**	0.702**	0.281	0.237
	Indicators of scientific production and productivity						
	T_PUB	P_INTPUB	INTPUB	IPURES	IPUPERS	PUBRES	
	0.559**	–0.536**	0.512**	–0.397*	–0.495**	–0.155	
	Indicators of cost, impact factor, and market funds						
		COPUB	COPUBINT	AVIM	P_MARFUN		
		0.255	0.448*	0.195	–0.595**		

* Pearson Correlation is significant at the 0.05 level (2-tailed).
** Pearson Correlation is significant at the 0.01 level (2-tailed).

f) MA6 Engineering and architecture, Innovation and Technology

Variable							
	Indicators of size of institutes						
	T_RES	T__PERS	ADM	TECH	ORD_RES	SEN_RES	DIR_RES
	0.476**	0.473**	0.513**	0.415*	0.350	0.469**	0.539**
	Indicators of age structure						
	TRES_AG	TPERS_AG	ADM_AG	TECH_AG	ORD_AG	SEN_AG	DIR_AG
INST_AG	0.580**	0.826**	0.209	0.739**	0.237	0.180	–0.215
	Indicators of scientific production and productivity						
	T_PUB	P_INTPUB	INTPUB	IPURES	IPUPERS	PUBRES	
	0.445*	–0.272	0.320	–0.303	–0.414*	–0.207	
	Indicators of cost, impact factor, and market funds						
		COPUB	COPUBINT	AVIM	P_MARFUN		
		–0.262	–0.224	–0.024	–0.360*		

* Pearson Correlation is significant at the 0.05 level (2-tailed).
** Pearson Correlation is significant at the 0.01 level (2-tailed).