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Demographic Change and industry-specific innovation pattern in Germany

by

Golo Henseke and Thusnelda Tivig

Universität Rostock

Wirtschafts- und Sozialwissenschaftliche Fakultät
Institut für Volkswirtschaftslehre
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Golo Henseke[1,2] und Thusnelda Tivig[3]

Short Abstract

In Germany, a thread to growth is perceived from demographic change. Demographic change means that a population is aging with the perspective of shrinking. The key question is whether an aging and shrinking population has enough talents to sustain the innovation process that is at the basis of our prosperity. In this paper we deal with the age distributions of inventivity. Specifically, we confirm past conjectures that inventive productivity is age dependent and unequally distributed among inventors. Additionally, we advance the new hypothesis that any age-bias in innovation activity should show up as industry-specific. The reason is that creative productivity is depending on the rate of technological change that on its part is industry specific. We test this hypothesis with European patent data for Germany.

JEL: O31, J24, B3
Keywords: innovation, patents, age-dependent productivity, demographics, sectors

1 Motivation

Technological progress is the key determinant of economic growth in advanced economies. It consists in innovations plus the knowledge needed to use them in production (Romer 1986, 1987). Innovations issue from spontaneous or trained creativity, coupled with purposeful investment (R&D) and job-practice (learning by doing, Arrow 1962); they are thus based on knowledge and are producing new knowledge. People have different intellectual and institutional access to knowledge. The former refers to cognitive and motivational capacity; the latter encompasses access to (high-quality) schooling as well as to job practice and leading-edge technologies. Both result in heterogeneity of "human capital", defined as a worker's, firm's or nation's stock of embodied knowledge and economically useful skills. In the process of human capital accumulation, innate abilities reduce the cost of education and training in terms of own efforts, and are believed to contribute to the development of talent. In Germany, talent, or "high potentials", and, generally, "excellence", are currently considered particularly important for innovation and economic growth. This is in line with Southern et al. (1993) who note that: "When a nation feels that its standard of living is threatened, efforts to provide universal access [to education] may be traded off in favor of exploiting talent …" (p. 401).

[1] University of Rostock and Rostock Center for the Study of Demographic Change.
[2] Corresponding author: golo.henseke@uni-rostock.de
[3] University of Rostock and Rostock Center for the Study of Demographic Change.

In Germany, a thread to growth is perceived from demographic change. Demographic change means that a population is aging with the perspective of shrinking. All developed countries experience increasing life expectancy leading to aging. In some countries, altered demographic behavior ("lowest-low fertility") adds the perspective of a shrinking population. In Germany, mortality rates are higher than birth rates since the early 1970th, implying that each subsequent generation is smaller than the previous one, and the proportion of young is falling. However, public concern is not directed towards size and the age structure of population, only, but regards the quality of the labor force, too. The crucial question is whether an aging and shrinking population has enough talents to sustain the innovation process that is at the basis of our prosperity. The topic of creative productivity has thus passed the border of Psychology and Education literature into Microeconomics and finally reached Macroeconomics.

In this paper we only deal with productive creativity as manifested in innovations. Our basic interest is with age-specificity of creative productivity. We pick up a simple question, briefly dealt with in Henseke and Tivig (2005), too: What is the age-distribution of inventors and how does it vary with industry? We advance the hypothesis that creative productivity should depend on age in an industry-specific way and we test this hypothesis with European patent data for Germany. Additionally, we derive some tentative conclusions about the concentration of talent.

2 Data

In order to test our hypotheses we use cross-sectional data of inventors from an own survey of the *Rostocker Zentrum*. A questionnaire was send to 2293 German inventors whose patent application was published in 2003 at the European Patent Office in one of the following four fields: Agriculture and farm machinery, metallurgy, biotechnology, and information technology. Out of the 2293 questionnaires 381 were undeliverable while 410 returned filled in, which is a rate of return of 21 per cent. The survey took place from August till November 2004. The advantage of patent data is that it allows collecting information about inventors, i.e. about people who do R&D at the technological frontier. We asked about sex, year of birth, year of first invention and first patent, respectively, year of last invention, the area of work, and the total number of inventions over the career, so far.

The number of patents granted to a person, a firm, an industry, or an economy is an indicator of inventive capacity; at the same time the aggregate number of patents issued in an industry or economy is widely accepted as a proxy for technical change (Griliches, 1991). It is not a perfect indicator, though. Patented inventions are technical in nature; scientific discoveries and organizational innovations are not patentable. From patentable innovations roughly 80 per cent are patented (Greif, 1999). Between 1998 and 2000 around one third of German innovative companies used patents. Among bigger firms and in chemistry and machinery the share was higher (Ramer, 2002). Unfortunately we have no information about the value of the patents in our sample, or about important individual characteristics like education. A more general problem is the classification system of patents. The international patent classification is based on technical considerations. Linking it to an industry classification is not straightforward and the question arises whether a patent should be assigned to the sector where the product is produced or where the invention is used. We have not undergone the attempt to precisely match the used IPC to fitting industry sectors since our major interest is in identifying differences in the age-bias of creative productivity depending on the pace of area-specific technological progress. However, we consider our biotechnology and information technology industries to be good approximations, whereas agriculture and metallurgy are only in a broad sense comparable to the economic sectors. The lack of a time dimension also causes difficulties, because we cannot distinguish between age and cohort effects nor do we know growth rates of the population of inventors. If the population of inventors had grown with a positive rate because R&D efforts were increased, there would automatically be more young inventors. However, put apart all deficiencies, our data set still suffices to test our hypothesis.

3 Results

Before testing our hypotheses we take a quick look at some descriptive statistics. The mean age in the total sample is 45.9 years and the median is around 44 years, which is higher than the current median age in the work force and also higher than the forecasted value for 2050. The average age when the first patent was granted is 34.3 and the mean job tenure is 11 years while the median is around 7 years. As expected, the number of inventions is highly concentrated among inventors; the mean is almost 23 while the median is 10, which is a first sign of a right-skewed distribution. The variable for individual productivity that we use in this paper is the number of inventions per year as it seems more reliable than the unweighted number of inventions. The mean number of inventions per year is 2.13, and the median is 1.14. That is, more than half of the inventors in our sample are able to create more than one invention per year. The share of women in the data set is strikingly low (7.5 per cent) but consistent with the low proportion of women in technical study lines and occupations in Germany. If it wasn't for biotechnology, were women hold roughly 20 per cent of inventions in our data set, their overall contribution would be negligible. Similar results are obtained by Giuri at al. (2005).

Hypotheses 1: Age-Dependency of Inventive Productivity

Newton was 24 when he started to work at the theory of gravitation, Darwin was 29 when he developed his theory of natural selection, Einstein was 26 years old when he developed the special theory of relativity, and Marie Curie was not older than 30 when she made her milestone discoveries in radioactivity. The general belief is that Sciences and also Engineering are a young people's game. If this was true, older societies would be less creative than younger ones. The same is largely believed about individual creativity over the life cycle. Over 100 years ago Beard described the inverse u-shaped distribution of scientific productivity over the lifespan for a set of "nearly all the greatest names in history". He concluded that aging of a population could explain its "enormous stupidity and backwardness". (Cited after van Dalen, 1999.) Empirical findings are quite robust over time. Cole (1979) found a slight age-affect for a cross-sectional data of academic scientists; research output and research quality peak on average at age 40 to 44. Levin and Stephan (1991) report similar results, but for a panel dataset of scientists. Van Dalen (1999) reaches comparable results for the Nobel Prize winners in Economics. He finds that 80 per cent of the award-winning work has been completed before the age of 45. Stephan and Levin (1993) provide further empirical evidence for Nobel Prize winners, in general. Jones (2005) demonstrates a similar age effect for outstanding inventors. Already Lehman (1966) reported a productivity peak between 35 and 39 for historical inventors in a variety of technological fields as well as those still alive in the 1950s. Even before, Oberg (1960) tested the hypotheses of age-biased productivity on a sample of engineering employees. His results are ambiguous and support the importance of the particular field and task on the pattern of individual productivity: while R&D personnel's productivity peaks between 31 and 35 years, engineering employees are most valuable to the company between 51 and 60 years. Further empirical evidence for an age effect on innovative productivity is presented by Dalton and Thompson (1971) for a dataset of around 2,500 engineers in the aerospace industry and technology-based commercial industries. Their measure of productivity is based on management's assessment. They report as well a fairly early age at which productivity peaks, namely between 31 to 35 years and conjecture that with an increase in the importance of new knowledge, the age-dependency of inventive productivity sharpened. Finally, using the new PatVal dataset (a large-scale cross-national survey for the EU), Hoisl (2005) also demonstrates that inventive productivity changes over the life-cycle in terms of patent output.

In line with this literature, we expect to find an age effect, too. Additionally, we expect inventive productivity as measured by patenting to be linked to active work-age, be it only for overall costs associated with a patent application. Therefore, and given the ever longer education periods in Germany as well as the fact that some working experience could enhance inventive abilities, we expect to find patent to be rewarded at age 30-60/65. Our results are as follows. Kernel density estimates of the inventors' age distribution yield a right-skewed distribution. The modal age is around 40, the median 44 and the mean at almost 46 years. These are definitely higher values than for the overall German workforce where the median was 40.2 years in 2005, but comparable to Hoisl

(2005) who uses a much larger data set. Probably, successful innovators have an especially long educational period and/or need some kind of experience or job tenure for successful R&D. This is also stressed by the relatively high mean age of 34.6 years at which the first own patent was granted. But while the initial mean age does not significantly differ over sectors, it changes with age groups. In the group of young inventors (≤ 35) the average age of the first patent is at around 29 years, whereas for older (50-65) and old (65+) inventors the measure is 37.3 and 39.7 years, respectively. The average number of patents per year in the total sample is 2.12. The measure is higher for young inventors (2.9). Thereafter it decreases slightly, peaks again for the age group 55-65 (2.36) and drops to 1.3 for retired inventors. The values are significantly different at the 10 per cent level.

Hypotheses 2: Concentration of Genius

Apart from life-cycle variations in creative productivity, the question was raised how productivity varies within a cohort. In a seminal paper Lotka (1926) describes that the vast amount of research is performed by a small minority of scientists. He describes the frequency distribution of scientific productivity by the equation: $y = x / n^2$, with x being the number of inventors with 1 invention, n the number of inventions and y the resulting number of inventors with n inventions. This equation is called Lotka's Law and it was extensively proved in the literature. Even though the exponent of n had been different in detail, the basic conclusion, that scientific productivity is highly concentrated, was generally confirmed. The conjecture is that, for various reasons, scientific productivity is path depend and determined by early success in research. Allison and Stewart (1974), Allison at al. (1982) and Cole (1979) formulate the Accumulative Advantage Hypotheses to further explain path-dependency by relating to productivity as well as recognition.

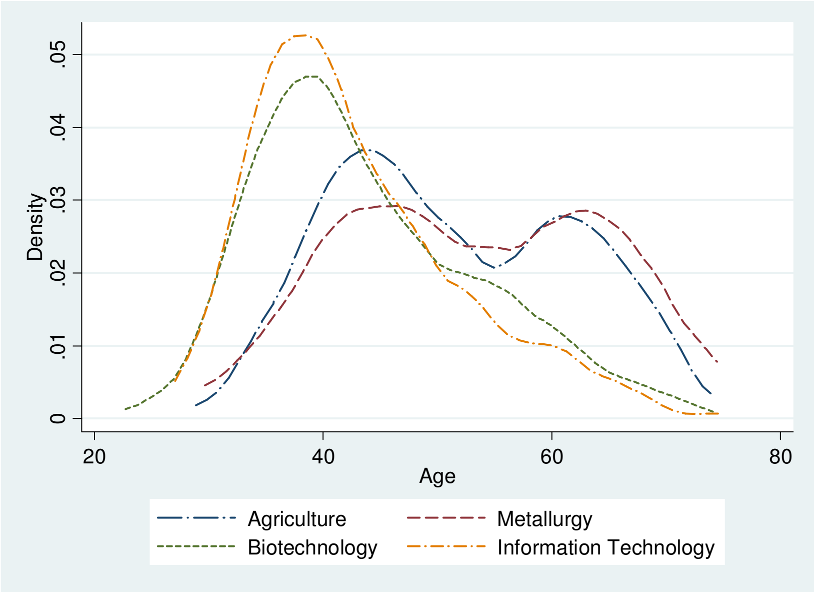
In our data set there is a huge variation in the individual number of inventions, too, ranging from 1 to around 600. In order to control for job tenure and also to be able to select occasional inventors we have weighted the number of inventions by job tenure. The resulting variable still varies impressively between individuals from almost zero to around 23 innovations per year. The median inventor in the data set is able to generate 1.2 average inventions per year, while the top 10 per cent of inventors produce at least 4 times as many and the top 1 per cent even around 12 times more inventions per year than the average. Hence, inventors are not a homogenous group. Testing Lotka's Law and hence our hypotheses we confirm that many inventors contribute only occasionally to the creation of patents, while a small minority is highly productive. Hence, if the distribution of talent in the population remains stable, the number of highly creative and inventive individuals will decrease with demographic change.

Hypotheses 3: Sector-Specific Age-Dependency of Innovations

The driving force behind collecting our survey data was to test the industry specificity of the age distribution of inventors. Our intuition was fed by an analogy with science, where successful researchers are rather young in fields in which processing and recombining information is crucial, as is the case in mathematics, and older in experience and reflection-based fields like philosophy. After a while we put that thought into economic terms and formulated the hypothesis that the age pattern of inventive productivity changes with the rate of technological change and hence, with the weights of experience versus new knowledge. Since new knowledge is almost exclusively acquired while young, we expect younger, recently trained inventors to be more productive in sectors where the importance of new knowledge exceeds that of experience. On the other hand, in experience-based sectors in which technological change is slower and more incremental in nature, older, more experienced inventors would have a comparative advantage over younger ones.

In order to test our hypotheses three empirically based regimes of technological change have been defined according to the R&D intensity: low-tech, high-tech and advanced-tech with an increasing pace of technological development over the categories. The classification of our sectors was done with help of the *Fraunhofer Institut für System und Innovationsforschung*. Agriculture is mainly low-tech, though some areas belong to high-tech industries. The same applies for metallurgy. On the other side there are biotechnology and especially information technology that are dominated by advanced-tech and high-tech products. In other words, the rate of technological change is higher in biotech and ICT compared to agriculture and metallurgy and therefore the age of inventors should be lower in the first group of industries. A quick lock at sector-specific average ages already shows that sectors should be grouped according to our hypotheses. In agriculture, the mean age is 51.4 which is very close to the value in metallurgy of 53.2 years. Contrary to that, in biotechnology and ICT, the mean ages are 43.9 and 42.9 years, respectively. As age is not normally distributed in some of the industries, we performed several non-parametric tests to verify that age distributions differ significantly between industries. The results obtained confirm that agriculture and metallurgy are different form biotechnology and information technology, whereas there are no significant differences within the low-tech group and the high-tech group. In Figure 1, kernel density estimates of the sector-specific age distributions are plotted to underline the statistical results graphically.

Figure 1 - Kernel Density Estimates of sector-specific Age Distributions



4 Econometric results[4]

Some results reported above can also be found in Henseke and Tivig (2005). To get deeper insights into the industry-specificity of the age-innovation profiles, we additionally performed an econometric analysis. The general finding in the literature is that productivity follows an inverse u-shaped pattern over the professional career, with a sharp increase in the beginning followed by a peak and thereafter a gradual decline that might also stabilise at higher ages. This pattern can be described by a polynomial function of third degree. Age is the independent variable in the estimation. The dependent variable should ideally be individual productivity, but since we cannot measure it directly, we use the relative frequency of one year age-groups instead. The estimating equation is:

$$p_i = \alpha + \beta_1 age_i + \beta_2 age_i^2 + \beta_3 age_i^3 + e_i \qquad (1)$$

with age_i as the ith age-group and p_i as the corresponding relative frequency. If inventive productivity is inverse U-shaped and the model fits the data we expect that β_1 and β_3 have positive sign while β_2 is expected to have a negative sign. The model is estimated with OLS, first for the whole sample and then for each of the four sectors separately. White correction of standard errors is used, if necessary. Results are presented in Table 1.

[4] We would like to thank Carsten Ochsen for his very helpful suggestions concerning the econometric modelling strategy. All errors are our own.

Table 1: Estimation Results Model 1

Variable	Agriculture	Metallurgy⁺	Biotechnology	Information technology⁺	Total⁺
C	-.661608	.808968***	-.589990***	-.6383***	-.447869***
	(.445788)	(.174771)	(.103077)	(.1307)	(.051310)
Age	.040557	-.049236***	.042054***	.0447***	.031071***
	(.026439)	(.010755)	(.006755)	(.0084)	(.003337)
Age^2	-.000754	.001023***	-.000881***	-.0009***	-.000631***
	(.000515)	(.000214)	(.000144)	(.00002)	(7.09E-05)
Age^3	4.56E-06	-6.84E-06***	5.78E-06***	5.87E-06***	4.02E-06***
	(3.29E-06)	(1.38E-06)	(1.00E-06)	(1.22E-06)	(4.91E-07)
R^2	.061746	.276353	.505581	.424458	.628052
Adj. R^2	.003105	.237586	.493220	.413173	.625183
F-statistics	1.052948	7.128608	40.90297	37.61217	218.9480

⁺ white standard errors to correct for the influence of heteroskedasticity
*** coefficient is significant at the 1% level

The model is able to explain quite a big part of the variability of data in the total sample, adjusted R^2 is 62.5% and all coefficients are significant at the 1% level and have the expected signs (column 5). From the estimation output it is clear, however, that the age distribution varies across industries. The estimated coefficients are different and also the overall fit of the model changes. For agriculture (column 1) the model is not able to explain the variation in the data, all coefficients are highly insignificant even though they have the expected sign; the R^2 is very low and consequently the F-statistic is insignificant. Metallurgy (column 2), that appeared comparable to agriculture from the previous test, show a different pattern. The coefficients are all highly significant but have the wrong signs. No more than one quarter of the whole variation in the data can be explained by the model used. The estimation results for biotechnology and information technology are firstly, similar to each other, confirming results of previous tests. In both cases coefficients are all significant, have the expected signs and are in both sub-samples very close to each other. The model fit is thus much better than in the other group of industries.

From the estimated coefficients it is possible to calculate the peak of each age distribution. As expected, the peak ages in biotechnology and information technology are very close to each other, 38.3 and 39 years, respectively. In agriculture the calculated peak is at 46.6 years, but the value is unreliable because of the highly insignificant coefficients. For metallurgy, the calculated peak age is very high, at 59 years, which is caused by the estimated pattern. So, estimation results generally confirm our previous findings: Biotechnology and information technology are comparable in their age distribution to each other but are different to metallurgy and agriculture. However, for agriculture and metallurgy, model (1) is not appropriate, since the variation in the age distribution cannot be explained and coefficients do not show the expected signs, respectively.

Therefore, in a next step we formulated an empirical model that allows estimating all sector-specific age distributions jointly in order to test differences between the estimated frequency distribution of age. The following specification was used:

$$p_{ji} = \alpha + \beta_{1j} age_{ji} + \beta_{2j} age_{ji}^{\ 2} + \beta_{3j} age_{ji}^{\ 3} + e_{ji} \qquad (2)$$

with age_{ji} as the *i*th one-year age group in sector *j* and p_{ji} as the corresponding sector-specific relative frequency. Sector dummies are used to model varying response parameters. Model (2) is estimated by OLS with White heteroskedasticity-consistent standard errors. As before, the expected sign of β_1 and β_3 is negative and of β_2 positive. Results can be found in Table 2 below. In the first two columns the sector-specific frequency distribution of age calculated from the sample is used as dependent variable. To eliminate part of the randomness in the data and to check the robustness of results in column 1 and 2, five-years moving averages of the age density are used in column 3 and 4. According to our hypothesis 3 we divide sectors into a low-tech and a high-tech group (column 1 and 3). Results are compared with the estimation with the full set of sector dummies (column 2 and 4). If our hypothesis is true, the coefficients and the overall quality of the estimations will not differ between the two specifications. Furthermore, the specification allows using the Wald-Test to test for significant differences between the estimated age-density patterns. Therefore, we impose restrictions on the coefficients, namely that there are equal. If the restrictions are true, then the unrestricted estimates will be similar to the restricted ones and the Wald-test statistic does not reject the Null Hypotheses of equal age patterns.

The reference sector is information technology (the high-tech group), because here the number of observations is highest. Generally, the model fits the data fairly well. All coefficients have the expected signs and the adjusted R^2 ranges from 24.7 per cent for sample data to 58.8 per cent when the age-distribution data is smoothed. For an interpretation of results remember that the estimated coefficients in the upper rows are valid for the reference group. To calculate the values for another sector or group, simple add the coefficients of the interaction variables. Insignificant coefficients of the interaction variables indicate that the age distribution of the specific sector is not statistically different from the reference category. In column 1 all estimated values are significant: The basic model itself as well as the interaction variables. Thus, there are significant differences in the sample between the age distributions in high-tech and low-tech industries. As before, we calculate the peak age which is 39.4 and 46.9 years for high-tech and low-tech industries, respectively. The adjusted R^2 is with 26.6 per cent relative low, which might be caused by the high randomness in the data and the small sample size. In column 2, the whole set of sectors is used. Compared to

Model 1, the adjusted R^2 declines. The newly added sector-variables have no further explanatory power, which is in accordance to the hypotheses. With the exception of biotechnology interaction-variables, all coefficients are significant at least at the 10% level. The estimation of the reference model is very close to results in column 1. Biotechnology does not differ significantly from the reference category while agriculture and metallurgy do. The resulting peak age for information technology is 38.6 years, for biotechnology 40.1 years, for metallurgy 48.1 years and for agriculture 47.4 years. We again use the Wald-Test to confirm that estimated age distributions are different from each other. Results again strongly confirm our hypotheses: Biotechnology and information technology, on one side, and agriculture and metallurgy, on the other side, differ from each other, while no such differences can be found within the groups. Finally, in the last two columns of Table 2 we report results with the moving average of relative age-frequencies as dependent variable. Smoothing and reduction of randomness clearly have a positive impact on the estimates and support our previous findings further. The adjusted R^2 is in both columns around 60 per cent. Again, the use of the whole set of sector dummies adds only marginal explanatory power as compared to the low-tech dummy estimation. In column 3 all coefficients are significant and have the expected signs. As before, the estimated age density distributions in low- and high-tech industries differ significantly from each other. Findings in the last column are generally in line with our hypothesis. First, the adjusted R^2 changes only slightly as compared to the previous column. Second, agriculture and metallurgy do not differ from each. But even though single estimates of biotechnology are not significant, the age-density distribution of biotechnology as a whole is now significantly different from the one in information technology at the 1 per cent level. The linear part is still equal, but the quadratic and cubic terms differ. However, differences between high and low tech industries regarding calculated peak-ages last. In ICT the peak age is 38.1 years, in biotechnology it is 39.8 years while in metallurgy and agriculture it is 48.4 and 45.9 years, respectively. A summary of the calculated maxima and minimum ages based on the estimates of model (1) and (2) can be found in Table 3. Interestingly, the calculated minimum age is sector-independent and varies around the onset of retirement; this can be seen as a further prove of the reliability of our results. Furthermore, it allows to conclude that there is a non-negligible amount of inventors who (re)start patenting after retirement.

Table 2: Estimation Results for Model 2

Variable	Sample Age Density 2 groups	Sample Age Density All sectors	MA Age Density 2 groups	MA Age Density All sectors
C	-.446610***	-.424128***	-.527597***	-.494007***
	(.084959)	(.098758)	(.071038)	(.071413)
AGE	.030763***	.030097***	.036190***	.035151***
	(.005399)	(.005947)	(.004437)	(.004312)
AGE^2	-.000618***	-.000614***	-.000734***	-.000728***
	(.000108)	(.000116)	(8.94E-05)	(8.53E-05)
AGE^3	3.85E-06***	3.87E-06***	4.65E-06***	4.67E-06***
	(6.96E-07)	(7.30E-07)	(5.83E-07)	(5.50E-07)
$(age \cdot lti)$	-.004542***		-.004889***	
	(.001298)		(.000873)	
$(age^2 \cdot lti)$	.000152***		.000162***	
	(4.74E-05)		(3.32E-05)	
$(age^3 \cdot lti)$	-1.20E-06***		-1.26E-06***	
	(4.19E-07)		(3.07E-07)	
$(age \cdot b1)$		-.005397***		-.005574***
		(.001566)		(.001337)
$(age \cdot b2)$		-.005154**		-.006318***
		(.002243)		(.001142)
$(age \cdot b3)$		-.001140		-0.001521
		(.001353)		(.000939)
$(age^2 \cdot b1)$		.000185***		.000189***
		(5.78E-05)		(5.14E-05)
$(age^2 \cdot b2)$		.000170**		.000208***
		(8.13E-05)		(4.30E-05)
$(age^2 \cdot b3)$		3.70E-05		4.96E-05
		(4.86E-05)		(3.40E-05)
$(age^3 \cdot b1)$		-1.50E-06***		-1.52E-06***
		(5.17E-07)		(4.81E-07)
$(age^3 \cdot b2)$		-1.31E-06*		-1.61E-06***
		(7.11E-07)		(3.91E-07)
$(age^3 \cdot b3)$		-2.82E-07		-3.82E-07
		(4.27E-07)		(3.02E-07)
R^2	0.291822	0.299748	0.593326	0.619532
Adj. R^2	0.266225	0.247229	0.577059	0.587826

*** coefficient is significant at 1% level
** coefficient is significant at the 5% level
* coefficient is significant at the 10% level

lti – dummy for low tech industries (agriculture, metallurgy)
b1 – dummy variable for agriculture
b2 – dummy variable for metallurgy
b3 – dummy variable for biotechnology

Table 3: Maxima and Minima of the Estimated Age Density Functions

Model (1) Separate estimation		Total	Agricult.	Metallurgy	Biotech.	ICT
Maximum at age		39.63	46.56	59.13	38.31	38.95
Minimum at age		65.02	63.67	40.58	63.3	65.19
Model (2) Joint Estimation Original Data	**High-tech ind.**	**Low-tech ind.**	**Agricult.**	**Metallurgy**	**Biotech.**	**ICT**
Maximum at age	39.38	46.88	47.43	48.09	40.07	38.58
Minimum at age	67.63	70.35	73.25	67.53	67.14	67.19
Model (2) Joint Estimation Smoothed Data	**High-tech ind.**	**Low-tech ind.**	**Agricult.**	**Metallurgy**	**Biotech.**	**ICT**
Maximum at age	39.42	46.99	45.93	48.41	39.82	38.14
Minimum at age	65.82	65.5	68.14	64.88	65.65	65.79

5 Summary and conclusion

In this paper we briefly review why aging is believed to diminish creative productivity on all levels, thus threatening welfare in advanced industrial countries. Then we picture and analyze in great detail the age structures of German inventors as identified by patents granted by the European Patent Office in the year 2003. As no age variables are contained in patent descriptions, we conducted an own survey. Its size was limited by available means. We were not aware at the time of parallel efforts conducted on a much lager scale with the PatVal survey for the EU. However, our main question was not dealt with, so far, with PatVat data.

We test three hypotheses concerning: Age dependency of productive creativity (hypothesis 1), concentration of talent (hypothesis 2), and industry-specificity of age-dependency of innovations. As far as the first two hypotheses are concerned, we essentially confirm results of other studies based on very different data sets. Yet, by interpreting results under the perspective of demographic change, we draw attention to some aspects not considered before. For example, the median age of our inventors is much higher than for the overall German workforce. Possible reasons were named before: long education periods, some other institutional factors as well as the need to gain some experience before contributing to own patents. On the side of consequences of this finding, aging in Germany doesn't seem, at least at present and for a while, that detrimental to creative productivity as currently assumed. However, under hypothesis 2 we tested Lotka's Law and found that many inventors contribute only occasionally to the creation of patents, while a small minority is highly productive. Assuming that the distribution of talent in the population remains stable, the number of highly creative and inventive individuals will decrease with demographic change.

Our original hypothesis, inspired, of course, by a whole bunch of literature in fields ranging from Psychology and Education to the Economics of Innovation and Growth theory, is hypothesis 3. Beside some descriptive statistics we run several econometric regression to test our conjecture that creative productivity is industry specific because it depends on technological change that differ, itself, across industries. We look at four fields: Agriculture and farm machinery, metallurgy, biotechnology, and information technology, which we group into "low-tech" (the former two) and "high-tech" industries (the latter two). Our result support the conclusion that in innovative and hence fast growing sectors with high rate of technological change younger inventors perform better while older ones have a comparative advantage in fields with slower technological change, in which knowledge has a lower half-time and hence experience higher value.

Currently the baby boomer cohorts are aged 35 to 44 and contribute almost one third to the labour force. There is a large supply of educated and talented individuals from which the German economy benefits in terms of innovations, technological progress and productivity. Additionally, the German economy currently draws substantial power from the export of goods that are to a large extent experience-based, too, like automobiles. In 2050 the size of the age group 35-44 will have declined by 4 million persons compared to 2003 according to a rough projection of the *Rostocker Zentrum* (2005). Their share in the labour force will be around 25 per cent or even lower if labour force participation rates of older workers increase. The question then seems just, if talents will suffice to keep the German economy at the technological frontier that might more and more be knowledge-intensive and hence in need of younger inventors. Fortunately, there are ways out of any scarcity once it is recognized.

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