Workforce age, inventive performance and knowledge absorption: The case of European regions

Katharina Frosch[1]

Max Planck Institute for Demographic Research

Abstract:

The capacity to bring forth pioneering technological advances appears to be a young men's game. Yet there exists only scarce evidence on aggregate innovative performance of firms, regions or countries. Based on patent counts for 146 European regions between 1995 and 2003, we study how regions' inventive performance is related to the different types and qualities of knowledge as provided by young, prime age and senior workers. In this, age effects are allowed to vary for different types of knowledge, and imperfect substitutability with respect to age and knowledge fields is assumed.

First results from a pooled model indicate that both general and technological knowledge drives inventive output in European regions, with the effect of technological knowledge being four times stronger than for general academic knowledge. However, our findings suggest that technological knowledge looses its innovation-enhancing effect at older ages.

[1] Max Planck Institute for Demographic Research
Address: Konrad-Zuse-Str. 1, 18057 Rostock, Germany
Phone: (0) 49 381 2081 148, Fax: (0) 49 381 2081 448, Mail: frosch@demogr.mpg.de

1. TOPIC AND MOTIVATION

Technological progress is the linchpin of developed regions such as the European Union, Japan or the US. At the same time, they are faced with sweeping demographic changes as a result of long-term below-replacement fertility and a continuous rise in life expectancy.

In this context, policy makers and business executives have expressed their concern if and how upward shifts in the age structure of the workforce will affect an economy's capacity to generate technological advances. In a nutshell, the question is whether we can 'teach old dogs new tricks' or not. However, there is only scarce evidence on the effects of workforce ageing on aggregate innovative performance of firms, regions or countries.

The focus of this study is to investigate how inventive performance in European regions is related to the age structure of the general workforce, as well as to the age of highly educated workers, engineers as well as scientists in particular. The assumption is that these 'brains' are of crucial importance in the creation of new economically relevant knowledge.

Based on patent counts for 146 European regions between 1995 and 2003 and by means of a regional knowledge production function, we study the differential effects of knowledge as provided by young, prime age and senior workers on inventive performance.

2. WORKFORCE AGE, THE EMERGENCE OF NOVELTIES AND KNOWLEDGE ADOPTION

Previous studies at the individual level suggest an inversely-U shaped relationship between age and the number of patents produced, with highest performance shown by inventors aged between 30 and 50 years (Mariani and Romanelli, 2007; Schettino et al., 2008). A similar pattern is found for the quality of patents (Hoisl, 2007; Harhoff and Hoisl, 2007), albeit the decline at older ages has not been unanimously confirmed. However, industrial invention in knowledge intensive fields as well as pioneering technological advances seem to be a young men's game, whereas in the more experience-based fields, innovative performance peaks later and remains stable until late in the career (e.g. Jones, 2005; Simonton, 1988, 2007; Henseke and Tivig, 2007).

Explanations for these different age patterns are based on the assumption that young inventors in high-tech sectors profit from their up-to-date specialist knowledge recently acquired at university, whereas older inventors' knowledge may be prone to obsolescence caused by technological change. On the other hand, successful invention may also be driven by older inventors with year-long experience, who have holistic knowledge about customer's needs and market structure and who dispose of the skills needed to embed new ideas in the existing technological context. This is for example the case for the engineering industry.

Meanwhile, the aggregate level of firms, regions and countries provides an alternative opportunity to explore the relationship between workforce age and innovation. Even if previous studies on firm and country level do not relate innovative performance back to the single worker but rather to a group of workers at a certain age, they allow to identify effects that go beyond the direct contribution of individuals. We may think for example of older workers enabling younger workers to produce economically relevant novelties by sharing their experience (see. e.g. Hetze and Kuhn, 2007, Kuhn and Hetze, 2007).

However, previous studies at the aggregate level of firms have relied on very general measures of innovative performance such as value added high-tech sectors as compared to more traditional sectors (e.g. Daveri and Maliranta, 2007; Ilmakunnas and Maliranta, 2007). Accordingly, productivity in high-tech sectors is to a large degree driven by the share of younger or prime age workers, whereas in more traditional sectors, prime age and older workers contribute most to firms' productivity.

Other studies have used indicators such as the likelihood to bring forth a product innovation or even a market novelty (e.g. Schneider, 2008), or to adopt new technology (e.g. Meyer, 2007 for the firm level and Prskawetz and Lindh (2007) for the country level). Results indicate that the higher shares of employees around 30 years, the higher the likelihood that firms or countries adopt or bring new technologies to the market.

Though, even if these indicators are more closely related to innovation than indicators drawing upon overall productivity, they represent fairly rough binary innovation measures and are probably heavily biased towards large firms. Furthermore, with the exception of Schneider (2008), none of the aggregate-level studies of workforce age and innovative performance takes into account that the performance of groups of workers may not only differ according to their age, but also depending on the specific field in which they are employed.

This study features three novel contributions as compared to previous research:

- We focus on inventive activity as measured by patent applications, which has been found to proxy industrial innovation reasonably well (Griliches, 1990; Acs et al., 2001).
- Age effects are allowed to vary across different types of knowledge inputs (e.g. technological, managerial or general academic knowledge).
- In contrast to the previously mentioned studies on firm-level, we relax the assumption that workers of different age and employed in different knowledge fields are full substitutes.

Both, patenting activity as well as the age composition of the workforce that drives technological progress, i.e. workers in S&T occupations, display considerable variation across regions (see also Fig. 1 and 2, Appendix). This makes European regions an appropriate setting to study age effects on regional inventive performance.

3. RESEARCH METHODS AND DATA

To determine productivity differentials of the knowledge inputs relevant for regional inventive activity as provided workers of different ages, we investigate by econometric analysis how inventive performance in 146 European NUTS 2 regions of 12 countries[2] is related to the structure of their respective workforces.

The analysis is based on the well-known production function framework suggested by Griliches (1979) and first applied by Jaffe (1986, 1989). The knowledge production relates the output of new, economically useful knowledge generated in a region and measured, for example, by patenting activity, to the knowledge inputs available in a region. As a proxy for the new knowledge produced by a region, we use the number of patents successfully applied for at the European Patenting Office (EPO) with priority dates between 1997 and 2003 in each of the regions. Data source is the *OECD REGPAT Database*.

Knowledge inputs for the knowledge production function can be R&D (research and development) investments, the supply of technologists, scientists and other highly skilled workforce, a region's academic infrastructure, clustering of certain industrial activities or other agglomeration effects (see e.g. Feldman and Florida, 1994).

[2] Countries covered (number of regions per country in brackets) are: AT (9), BE (11), DE (38), DK (1), ES (17), FI (5), NL (12), FR (22), IE (2), IT (21), SE (8).

To account for variations in the productivity of different types of knowledge as provided by workers of different ages, we divide the regional workforce into mutually exclusive sub groups along age (20-34, 35-49 and 50-64 years) and three knowledge fields (science and technology occupations, other occupations requiring an academic degree as well as unskilled workers). The reasoning behind this 'quality knowledge aggregate' is twofold: First of all, it accounts for the fact that the effect of knowledge provided by younger and older workers on regional inventive performance may differ from each other. Second, these age-differentials are allowed to vary for different types of knowledge (e.g. managerial, technological, general knowledge).

A similar approach has been widely applied in studies on age effects in firm-level productivity (e.g. Hellerstein and Neumark, 1995; Hellerstein et al., 1999; Aubert and Crépon, 2004; Daveri and Maliranta, 2007). However, as a novelty and in contrast to previous modelling strategies, we assume the different types of knowledge in the 'quality knowledge aggregate' are only incomplete substitutes. More concretely, knowledge provided by unskilled workers cannot fully replace engineering knowledge, or management knowledge provided by older and younger groups of workers differs in its characteristics.

Workforce indicators for the quality knowledge aggregate across age and occupational fields are constructed on the basis of ad-hoc extractions of the *European Labour Force Survey*. The elements of quality knowledge aggregate are lagged by two years to allow them to unfold their effect on regional inventive performance (see also Fritsch and Slavtchev, 2007 or Bilbao-Osorio and Rodríguez-Pose, 2004). They hence refer to the time period 1995-2001. At the same time, using lagged variables may alleviate potential endogeneity issues.

Apart from knowledge inputs embodied in the regional workforce, a number of control variables are introduced, for example the average size of firms in the region as well as three agglomeration measures (see also Feldman and Florida, 1994): First of all, we include the density of labor force per km^2. Second, we account for the share of value added generated by the manufacturing sector to account for the density of industry. Finally, the average density of available knowledge per km^2 in adjacent regions as proxied by the number of patents produced is included. The control variables are computed based on *Eurostat Regional Indicators*, ad-hoc extrapolations of the *European Labour Force Survey* as well as the *OECD REGPAT database*.

As patenting information is count data and the distribution is overdispersed, a negative binomial regression model is the adequate choice for estimation (see Cameron and Trivedi, 1986). Exploiting the panel structure of the data, a fixed effects model including year dummies is estimated, which allows to control for unobserved, time-constant heterogeneity in regions as well as for time trends that affect patenting activity uniformly across regions.

4. PRELIMINARY RESULTS

As a starting point, we estimate a pooled model accounting for two fields of knowledge, i.e. knowledge provided by science and technology (S&T) workers and knowledge provided by other medium or highly skilled workers (see also Table 1). First results indicate that both, specialized technological knowledge as well as knowledge provided by other qualified workers drive regional inventive activity. However, the favourable effect is four times stronger and more significant for S&T knowledge than for more general knowledge.

In a second step, we ask whether there are age differentials in the productivity of these two types of knowledge. The pooled model indicates that age effects are only present for S&T workers: Positive effects on regional inventive performance result mainly from the knowledge provided by the youngest age group of workers (20-34 years). Furthermore, higher shares of 50-64-year-old S&T workers seem to considerably hamper inventive performance. A possible interpretation for these patterns is that S&T knowledge drives inventive performance, albeit only if it is up-to-date. General knowledge has a less favourable effect, however, unlike for S&T, knowledge depreciation seems not to play a role.

Table 1: Age-of-knowledge effects on patenting activity in European regions, 1997 – 2003

	Pooled estimation		Fixed effects estimation	
	Without age effects	With age effects	Without age effects	With age effects
S&T workers	2.09**		0.01	
- 20-34 years		8.51**		-0.45
- 35-49 years		4.7		1.03*
- 50-64 years		-10.38**		-0.81
Skilled workers	0.56*		0.05	
- 20-34 years		1.97		-0.02
- 35-49 years		-2.47		0.05
- 50-64 years		3.95		-0.04
LL	-4284	-4261	-2405	-2402

Notes:
Results are derived from a Negbin model (pooled and with fixed effects).

Dependent variables (in year t):
Number of EPO patents

Explanatory variables (in year t-2):
Labour force (in 1.000), quality knowledge aggregate (S&T workers and skilled workers in three age groups; unskilled workers omitted)

Control variables:
year dummies (all models); knowledge density, industry density, average firm size and country dummies (in pooled estimation, only)

Significance levels * 10% ** 5% *** 1%

Source:
Own calculations based on OECD REGPAT Database 2008; European Labour Force Survey ad-hoc extrapolations; Eurostat Regional Indicators.

Still, the results have to be interpreted with caution. In the pooled model, we cannot differentiate whether the age effects reflect variations in inventive productivity, or whether young S&T workers are preferably employed in high performance regions. In particular, unobserved structural characteristics of regions may be of crucial importance, and young S&T workforce as well as high-tech industry may simultaneously cluster in certain regions, leading to a spurious correlation between young S&T workforce and inventive performance.

Accounting for such structural, time-invariant effects by re-estimating the model including fixed effects, we find that age effects disappear with exception of S&T workers in their mid-career (35-49 years) who significantly foster inventive activity. Similar dynamics of the age effects in pooled as compared to fixed effects panel regression models have been found in firm-level studies on age and productivity (see e.g. Malmberg et al., 2008, for a clear-cut empirical illustration of similar endogeneity biases).

As a conclusion, regions with many young S&T workers have a high inventive potential, whereas regions with an older S&T workforce may be disadvantaged due to the fact that the knowledge of their S&T workforce has depreciated over time. However, introducing fixed effects into the estimation suggests that most of the inversely U-shaped age-performance pattern found in the pooled estimation results from (unobserved) structural characteristics of regions, i.e. mostly time-invariant characteristics such as the sectoral structure. This considered, results propose that it is the group of prime age S&T workers (35-49 years) who drive inventive performance. More concretely, not only up-to-date expert knowledge, but also a certain degree of work experience seems to be crucial.

The analysis will further elaborate on these aspects. Furthermore, we plan to investigate where age differentials for the knowledge inputs considered on inventive performance emerge from. In this vein, one possible anchoring point is to explore whether the age structure of the S&T and of the overall workforce hampers the absorption of knowledge as a predisposition of the generation of inventions.

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DATA SOURCES

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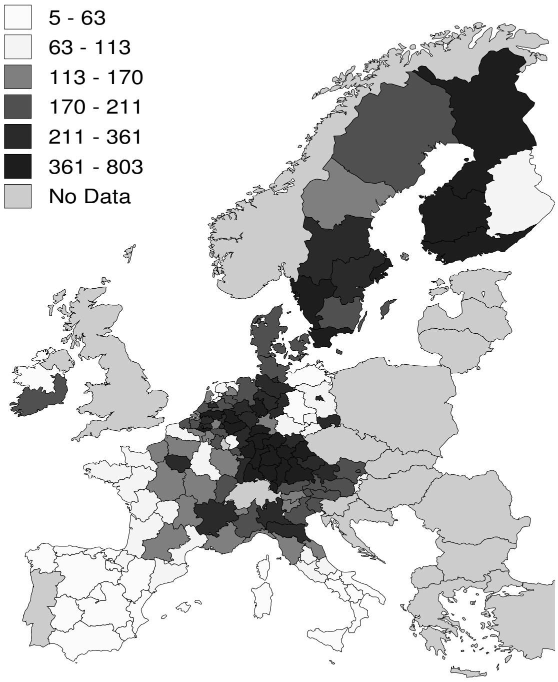
APPENDIX

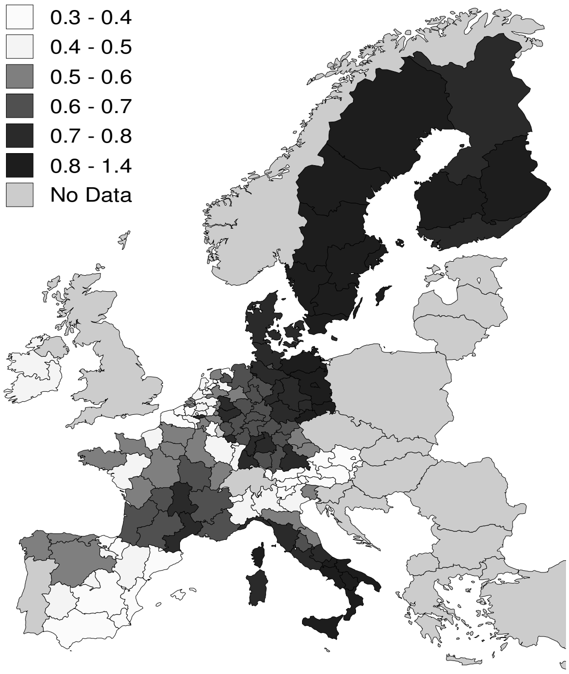
Figure 1: Regional patenting activity
Indicator: Number of EPO patent applications per 100,000 labour force, average 1997-2003.



Source:
Own calculations based on OECD RegPat Database as well as on ad-hoc extrapolations of the European Labor Force Survey.

EuroGeographics for the administrative boundaries.

Figure 2: Age ratio of S&T workers
Indicator: Ratio of 50-64-year-old S&T to 20-34-year-old S&T workers, average 1997-2003.



Source:
Own calculations based on ad-hoc extrapolations of the European Labor Force Survey.

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