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**Working Paper**

## Age, human capital and the geography of innovation

Thünen-Series of Applied Economic Theory - Working Paper, No. 71

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*Suggested Citation:* Frosch, Katharina; Tivig, Thusnelda (2007) : Age, human capital and the geography of innovation, Thünen-Series of Applied Economic Theory - Working Paper, No. 71, Universität Rostock, Institut für Volkswirtschaftslehre, Rostock

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**Thünen-Series of Applied Economic Theory**  
**Thünen-Reihe Angewandter Volkswirtschaftstheorie**

Working Paper No. 71

**Age, Human Capital and the Geography of Innovation**

by

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2007

# Age, Human Capital and the Geography of Innovation\*

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February 27, 2007

## Abstract

*An aging labor force is often associated with a decreasing innovative performance on aggregate, firm or individual level. Using a regional knowledge production function to explain patenting activity in German districts, we propose to include the effect of age in a twofold specification: First, we account indirectly for age by including the aggregate, age-heterogeneous human capital available in each district and estimating its effect on patenting performance. Second, we assume that there is an age effect that is independent of human capital and therefore include the age structure of the districts' labor force directly, too. Possible explanations for an independent age-effect are age-dependent differences in the ability to exploit innovation-relevant human capital or age-specific motivation to lead creative ideas to successful inventions. Departing from these conceptualizations provided by economics and I-O psychology, we estimate a negative binomial regression model appropriate for count data. Results on German district level indicate that engineering knowledge in the younger as well as the prime age group significantly enhances patenting performance, whereas we do not find any effect for the age group 50+. However, for older ages, the stock of experience has a positive influence. On aggregate level, we find a positive independent age effect.*

**Keywords:** knowledge production function, regional innovation analysis, human capital, aging, demographic change, patents

**JEL Classification:** O31, J24

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\*The design of this study and first results were presented in "Age and the Geography of Innovation" as contribution to the poster sessions at the Interdisciplinary Workshop on Regional Innovation, June 9, 2006, Kings College, Cambridge as well as at the World Aging & Generations Congress, September 27 - 29, 2006, University of St. Gallen. Many thanks to helpful comments provided by the discussants.

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# 1 Introduction

## 1.1 Motivation

Demographic change moving into the attention of policymakers and business leaders has lately raised the question if, how, and to what extent innovative activity depends on the age structure of the labor force. Motivated by this increased public interest, a number of studies analyzing the age-dependency of patenting output have been conducted.

So far, empirical evidence tells us that innovative activity, as measured by patenting, starts at around 30 years, rises until a period of maximum productivity, and slowly declines around age 50. Using an extensive patenting dataset for US inventors, Jones (2004) finds a hump-shaped age-patenting-profile, peaking between age 30 and 40. Jones (2005) calculates a mean age at first invention of 30.5 years in 1985, which increased by roughly one year until 1999. Henseke and Tivig (2005, 2007) as well as Hoisl (2006, 2007) use econometric methods to investigate age-patenting pattern. Using survey data for Germany these studies confirm the hump shaped age-patenting pattern but find maximum patenting productivity between 40 and 50 years. Henseke and Tivig (2005) identify the mean age at first patent with 34 years. Additionally, they show that age-productivity curves differ across industrial sectors. For agriculture and metallurgy, the mean age at invention is in the early fifties whereas for biotechnology and ITC, mean age at invention is in the early forties.

The strength of these studies is that the data used allows to determine exactly when, within a given period of time, at what age, and, as in Hoisl (2006), jointly with how many others an inventor applied for a patent. However, for several reasons, we cannot deduce from the established empirical evidence how the aging process of the labor force affects inventive performance. First of all, an identified age-invention-profile might, for example, be simply caused by experience effects with patenting application procedures or by the fact that with increasing age, inventors occupy higher hierarchical positions and act as project leaders in a number of different R+D processes (Hoisl, 2007). Second, the samples used contain only successful inventors who contributed at least one patent application during observation time; these persons are most probably positively selected as compared to the overall population of (potential) inventors. Third, as firms use patents as strategic devices, nothing can be inferred concerning the innovation capacity or activity of a firm's labor force from non-patenting at certain times. What the cited analyzes certainly are able to do, is picturing the age distribution of inventors. Given that patent data in Europe do not contain any age variables, this certainly is an advancement and results concerning, say, the industry-specificity of age-patenting profiles, provide new insights.

In this paper we advance the hypothesis that, for many reasons, to determine a broader effect of age on patenting performance, the age structure of the *total*

labor force has to be accounted for. Hereby we are inspired by Sturman (2001) who concludes from existing literature that (i) age-performance patterns are usually inversely U-shaped, (ii) other time variables like general work experience and organizational tenure influence innovative performance alongside age and (iii) non-linearity of the age-performance pattern is the outcome of simultaneous influences of these other variables that are each nonlinearly linked with age. In our analysis, the age effect would be approximated by the employees' age structure on district level, whereas the other time variables are summarized in human-capital and experience variables drawn from the employees' professional career as pictured in the dataset. An open question is how to adequately differentiate the number of employees from human capital. Finally, there is agreement among scientists that human capital – up-to-date formal knowledge as well as work experience – is an important prerequisite for innovation (Kortum, 1997; Jones, 2004; Hetze, 2004; Prskawetz et al., 2004; Hoisl, 2006). Empirically, however, existing studies include the educational level, at most, as a control variable, as they lack better data. We, to the contrary, include information on formal education as well as a whole bunch of data on professional experience. Still, no neat line between labor and (mostly embodied) human capital can be drawn empirically. This explains why we often use the terms synonymously.

The aim of our study is to provide additional evidence on the presumed age-dependency of innovation. We believe that simply including age as a variable takes too narrow a view of the process how age affects innovative performance within a firm, an industry or a region. We propose instead to distinguish two channels through which the age of employees influences innovative performance, here on a regional level. First, we account indirectly for age by including the aggregate, age-heterogeneous human capital<sup>1</sup> available in each district and estimating its effect on patenting performance. Second, we consider that apart from age-heterogeneous human capital, there is a direct (or human-capital independent) effect of age on innovative performance. We use longitudinal employment data on an individual level that is available for Germany. It allows to specify human capital variables such as formal education, general work experience and organizational tenure. We also dispose of age information, allowing us to account for age-heterogeneity of human capital. However, employment data and patenting data cannot be directly linked on individual or company level. We therefore suggest to use the Griliches-Jaffe (regional) knowledge production framework<sup>2</sup> to analyze the influence of different types of age-specific human capital on aggregate patenting activity in 343 German districts. To our knowledge, we are the first to adopt this aggregate regional perspective of the age-dependency of innovation. Also, we argue that including the indirect

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<sup>1</sup> Here and in what follows, we assume the stock of aggregate human capital to be age-heterogeneous. The underlying reason behind this is that, on individual level, human capital has an age-specific dimension.

<sup>2</sup> See Section 3.1 below.

effect helps getting rid of the 'hierarchy' effects and the selection bias mentioned above.

The rest of the paper is organized as follows. In Section 2 we review and advance some theoretical considerations about age-heterogeneous human capital and a possible human-capital independent (hence: direct) age effect on innovative performance. In Section 3, we first describe the regional knowledge production framework in its conventional form (3.1), then extend it to encompass age-specific human capital (3.2) and finally build in a direct age effect (3.3). In Section 4, we present the econometric model (4.1) as well as the data (4.2) and method (4.3) used to estimate the extended knowledge production function. Results are presented and discussed in Section 5. Section 6 concludes with a short summary and perspectives for future research.

## 2 Theoretical Framework

### 2.1 Age and innovation-relevant human capital

New technological achievements require the stock of human capital to be close to the existing technological frontier (Evenson and Kislev, 1976; Kortum, 1997). In Kortum's (1997) search model, the probability that a novel contribution emerges is negatively related to the gap between the stock of human capital and the technological frontier. Technological change shifts the technological frontier upwards and widens the technological gap, *ceteris paribus* decreasing innovative capacity. This effect becomes most obvious for knowledge acquired through formal schooling: Formal knowledge has a half-time and its value decreases over time. In the tradition of Rosen (1975), De Grip and van Loo (2002) speak of 'economic obsolescence' if the stock of human capital remains equal but its value in a certain context declines. Additionally, they mention wear and atrophy as two kinds of 'technical obsolescence', diminishing the stock of human capital itself and state that the incidence of technological obsolescence increases over age. The way out is human capital accumulation. How does it relate to age? Previous theoretical and empirical research provides evidence that the rate of human capital accumulation is lower for older workers. But if it were to compensate for technical obsolescence increasing with age, gross human capital accumulation rates should be, other things equal, higher for older than for younger workers. However, some studies suggest that learning capacity declines over age (Verhaegen and Salthouse, 1997). In this case, the same amount of formal training would lead to even less growth in human capital for older as compared to younger employees.

Human capital can be acquired through company provided and private formal learning, or through learning-by-doing. As payoff periods are shorter for older than for younger employees, motivation for the supply of or demand for formal training might be reduced. Additionally, on the part of older employees, motivation

for human capital accumulation could be weaker because of seniority wages. If accumulation rates of formal knowledge rather decline in later ages, what about learning-by-doing, then?

According to Gort et al. (1993), experience is gained by costly training-on-the-job (Mincer, 1974; Park, 1997) or by costless learning-by-doing (Arrow, 1962; Bahk and Gort, 1993; Killingsworth, 1982). For costly training, the same reasoning applies as for formal training. As for costless learning-by-doing, putting apart the learning capacity issue, older workers are less likely to be placed in domains close to the technological frontier but rather selected into less productive jobs (see e.g. Friedberg, 2001. All in all, the accumulation rate of innovation-relevant human capital is probably lower for older than for younger workers. However, human capital in its broad definition cannot be measured directly. Empirical studies usually proxy acquired formal knowledge by the level of schooling or educational attainment. Experience is measured by general work experience or, for the firm-specific part, organizational tenure. With age-specificity of human capital using variables aggregated across different ages could not suffice. We therefore propose to include schooling, organizational tenure and overall work experience for older and younger workers separately.

## 2.2 Independent age effect

Economics provides valuable models for the analysis of human capital accumulation and depreciation. Industrial and organizational psychology (I-O psychology) add some dimensions to it, in part already mentioned above. One issue is exploitability of knowledge. A person might lack the ability to exploit his human capital (i.e. to recombine knowledge). Another is motivation. If, for some reason, a person lacks motivation to use his human capital and exploitation ability to achieve innovative output (achievement motivation), performance will be reduced or virtually amount to zero. Many economic studies analyzing age-productivity profiles emphasize the influence of age-dependent psychological processes such as the decline in fluid and increase in crystalline capacity over age (e.g. Ilmakunnas et al., 2004, p. 251, Prskawetz et al., 2004, p. 36). Some additionally mention the role of the life-time development of motivation (e.g. Sturman, 2001, p. 9, Prskawetz et al., 2004, p. 28). However, none of them attempts to integrate these findings into an economic model. The decline in general mental or motivational, hence 'psychological', capacity is only indirectly considered in the econometric model by using age indicators and/or human capital indicators depending on tenure or work experience. This is a point where I-O psychology can substantially contribute. It offers some notable conceptualizations and provides extensive empirical evidence about the functional relationship between exploitation abilities, achievement motivation and performance over the life course.

*Exploitation abilities.* Simonton (1988) shows in his model based on the chance-

configuration theory that the emergence of innovative achievements does not only depend on the creative potential, but also on the capacity to exploit it. The initial creative potential, which according to the model is fixed over the life span, consists of mental elements that are available for 'chance' (i.e. random) permutations. In a first step, so called 'ideations' lead to specific chance configurations of these mental elements. But only the second step, 'elaboration', leads to the implementation of ideations and hence to concrete innovations. Simonton (1988) suggests to model innovative output as a product of the initial creative potential and two exponential processes (ideation and elaboration)<sup>3</sup>. Through the exponential functional form, this leads to the typical *hump-shaped* age-performance profile found in many creative disciplines. Economists might reject the abstract notion of a total-life span creativity and stuck to the idea of age-specific human capital. However, it is intuitive that innovative output also depends on exploitation ability. If creative performance follows the double-exponential process of ideation and elaboration, as suggested by Simonton (1988), innovative output starts to decline from a certain age onwards even if human capital was assumed to be homogeneous with respect to age. The second valuable contribution is the multiplicative linkage between exploitation ability and the stock of knowledge. Intuitively, we could define the actual innovative output as product of the potential output and a variable defined in interval [0,1] to capture age-dependent exploitation ability. Indeed, the deficit theory of aging suggests that increased age causes a deterioration in physical and cognitive abilities (for a review see Sturman, 2001). Meta-analytic results by Verhaegen and Salthouse (1997) show that reasoning, speed and episodic memory decline significantly by the age of 50. Kanfer and Ackerman (2004) state that there are abilities that decline (i.e. fluid intelligence) and abilities that increase (i.e. crystalline intelligence due to expertise) over the life span. The decline in fluid capacity could affect the ability to recombine knowledge, hence, negatively influence ideation rates.

*Motivational factors.* Kanfer and Ackerman (2004) elaborate on past and recent research and present a comprehensive framework of life-span evolution of motivation. They state that neither psychological theory nor empirical evidence can prove a general decline in work motivation caused by age. However, combined with other factors such as work environment and the prevailing incentive systems, age-related changes may very well lead to decreased work motivation. This conjecture is supported by a number of studies, economic ones included. For example, according to Gibbons and Murphy (1992), older workers show more intrinsic motivation than their younger counterparts who are driven by career concerns. A working context not adapted to motivational prerequisites of older workers might lead to decreased

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<sup>3</sup> The number of creative contributions  $p$  at career age  $t$  is specified as follows (see Simonton, 1988, p. 262):  $p(t) = c(e^{-at} - e^{-bt})$  with  $a$  being the ideation and  $b$  being the elaboration rate. Term  $c$  denotes the initial creative potential.



work motivation. Another aspect worth to note is the functional relationship between effort and utility corresponding to what Wright and Hamilton (1978) called 'grinding down': Older persons accept age-induced restrictions in resources and abilities, i.e. that the same effort leads to less utility, and lessen their expectations. On this basis, Kanfer and Ackerman (2004) infer an overall hump-shaped relationship between age and motivation. Motowidlo (2003, p. 50) considers motivation as a moderating factor influencing the effect of other variables on human performance. Two functional specifications are possible. Performance could be the product of ability – specifically, the level of human capital combined with the ability to exploit it – and motivation. In this case, actual output is potential output adjusted by a motivational effect (factor in  $[0,1]$ ). Or, motivation has an additive influence on performance. In this case, there would be a basic performance independent of a person's level of achievement motivation, and additional output would be produced according to the motivation level (for example, if career concerns still played a role as in Gibbons and Murphy, 1992).

No matter if exploitation abilities and motivational factors are multiplicatively or additively linked to human capital and provide explanatory power for innovative performance: Psychological theory and empirical findings suggest to account for an independent age effect on performance besides human capital effects.

### 3 Model

Our objective here is to estimate the effect of age on innovative performance on *aggregate* level for German districts. Referring to our theoretical considerations, in what follows, we account for age in a two-fold specification. After a general presentation of the regional production function framework, we extend the model by age-heterogeneous human capital. In a second extension, we propose to include age-dependent explanatory variables that drive innovative performance, i.e. exploitation ability and motivational factors.

As there is no direct measure for the capacity for innovation, we have to fall back on innovation output as a performance indicator. Smith (2005) suggests patenting data, bibliometric data on scientific publication and citation as well as innovation indicators based on surveys to measure innovation output. We are aware of the fact that patent applications are only an imperfect measure for innovation, but we believe that, as innovative capacity is a prerequisite for successful patenting, it is a valid proxy.

#### 3.1 The (regional) knowledge production framework

The knowledge production function framework introduced by Griliches (1979) provides the starting point for our analysis. It specifies that the production of new,

economically useful knowledge depends on R+D efforts. In its early implementations by Pakes and Griliches (1984) and Jaffe (1986) inventive activity was already operationalized by the number of corporate patents. Fritsch and Slavtchev (2005) write Jaffe’s patenting function (1986) as:

$$P_i = \alpha K_i^\beta \quad (1)$$

with  $P_i$  being the number of corporate patents counted for observation unit  $i$  (e.g. firm or region) and vector  $K_i$  incorporating the stock of different sources of knowledge for observation unit  $i$ . Vector  $\beta$  denotes production elasticities for the input factors, that is, the percentage change in patenting activity resulting from a one percentage change in the input factor considered. Term  $\alpha$  is a constant, capturing, as in any production function, the overall efficiency of the invention process. Special features in the estimation of knowledge production functions suggested by Griliches (1979) are lagged effects of input factors, spill-over effects between industries and the obsolescence of the stock of knowledge; they are generally accounted for in empirical studies.

More recent studies (Anselin et al., 2000; Fischer and Varga, 2003; Coupé, 2003; Fritsch and Slavtchev, 2005), still using the same approach, draw attention to the spatial dimension of knowledge, e.g. on knowledge spill-overs between regions or externalities of university research. There are two reasons for this focus. As the transfer of tacit knowledge requires direct interaction, proximity between the actors matter such that a (then so called) regional knowledge production function accounting for regional spill-over effects is appropriate. The number of patents in a geographical region is then modeled to depend on the stock of knowledge available in this and adjacent regions. Jaffe (1989) already used geographical units, i.e. US states as observation unit. In Germany, data availability additionally recommends using the regional knowledge production framework. As it is not yet possible to link employment information and patenting data on the firm level, the district level is the smallest observation unit available for empirical analysis. Niebuhr (2006), for example, uses it to analyze the influence of ethnic diversity on inventive activity in Germany.

### 3.2 Extension 1: Age-specific human capital

Previous studies like Crépon et al. (2003) suggest using a Cobb- Douglas production function allowing for age-heterogeneous human capital input to model the relationship between age and productivity. As they mostly explore the age-productivity pattern on an aggregate level, they include age indicators such as mean age or shares of different age groups to account for age-heterogeneous human capital. Ilmakunnas et al. (2004) use additional variables such as tenure, but assume experience to be homogeneous with respect to age. In contrast do these studies, we incorporate age effects indirectly by accounting for the stock of different types of human capital

differentiated by age. If we distinguish two age groups, young (below 50 years) and old (aged 50 and over), we can rewrite Equation 1 as:

$$P_i = \alpha K_i^y \beta^y K_i^o \beta^o \quad (2)$$

with  $P_i$  being again the number of corporate patents in region  $i$  that can be produced with the stock of human capital available in this region. Vectors  $K_i^y$  and  $K_i^o$  indicate the amount of available human capital from the share of younger and older workers in the labor force, respectively. Parameter vectors  $\beta^y$  and  $\beta^o$  contain the now *age-specific* effects of different types of human capital on patenting output. We can imagine this proceeding as 'labeling' the different types of human capital with age information, as capital is labeled in vintage models by its production year.

### 3.3 Extension 2: Independent age effect

As described in our theoretical framework (Section 2), we consider that there is an additional effect of age on innovative performance that operates directly, at any given level of human capital; it is caused by exploitation abilities or motivational factors. The decomposition of innovative performance into these direct or indirect effects is not straightforwardly possible, as there are no psychological measures available on the aggregate level of firms, regions or sectors. However, already in the 1960ties, the economist David McClelland performed what (Brown, 1965, p.450) called 'one of the more audacious investigations in the history of social science': He incorporated aggregate achievement motivation into a conventional aggregate production function.

McClelland (1961) argued that an economy's output also depends on the level of achievement motivation in its society that he called 'nAchievement'. He approximated the variable by the amount of 'achievement ideas' or 'achievement motives' contained in school books of different countries and lagged the variable by 25 years. He found that the level of achievement is positively related to economic growth. A number of studies fiercely criticized McClelland's model and econometric approach, but still found the model interesting enough to suggest improved econometric models to explore the relationship between achievement motivation and economic growth. Surely, even if psychologists argue that motivation, being a hidden construct, is difficult to measure, a serious shortcoming of his analysis was the way motivation was operationalized. We opt for keeping motivation as well as exploitation abilities hidden as they are but account for its known variability by weighting human capital. The number of patents  $P_i$  in region  $i$  then issues from human capital input adjusted by a factor in interval  $[0, 1]$ . This factor reflects the age structure of the labor force in a region and is built in to capture exploitation ability and motivational effects. These psychological factors are thus not considered a separate production input, but a possibly human-capital reducing factor. To facilitate estimation, we specify this factor as  $e^{\gamma a}$ , whereby  $a$  varies with age. This is similar to an technology index

sometimes included in aggregate production functions (e.g. Freeman, 1976). The knowledge production function then is:

$$P_i = \alpha e^{\gamma a} K_i^y \beta_y K_i^o \beta_o \quad (3)$$

Estimates for the age and production elasticities are calculated by taking natural logarithms and applying standard regression techniques. Writing out the single components of vectors  $K_i^y$  and  $K_i^o$  and taking logarithms in Equation 3 yields

$$\ln P_i = \ln \alpha + \gamma \ln a + \beta_1^y \ln K_1^y + \dots + \beta_n^y \ln K_n^y + \beta_1^o \ln K_1^o + \dots + \beta_n^o \ln K_n^o \quad (4)$$

## 4 Econometric Model

### 4.1 Model specification

We now transform the theoretical model of Equation 4 into a concrete econometric model. Thereby we distinguish between three age groups instead of young and old, as in the theoretical model: 'younger than 35 years' ( $a_1$ ), '35-49 years' ( $a_2$ ) and '50+ years' ( $a_3$ ). Also, we differentiate between two types of human capital, whether it is rather knowledge (*KNOW*) or experience (*EXP*). The absolute number of corporate patents  $P_i$  per district  $i$  hence depends (see Equation 5 below):

- on the number of employees  $EMP_i$ ,
- directly on the vector  $AGE_i$ , measured either as mean age or the share of different age groups to capture the independent age effect,
- on the stock of  $k = 1, \dots, p$  different types of knowledge  $KNOW_{k,i}^{a_q}$  in district  $i$  specified for three age groups ( $q = 1, 2, 3$ ) separately,
- analogously, on the stock of  $m = 1, \dots, s$  different types of (age-heterogeneous) experience  $EXP_{m,i}^{a_q}$ , experience available in the districts,
- vector  $X_{j,i}$  containing  $j = 1, \dots, t$  control variables such as an East-West dummy variable, the degree of urbanization, proxies for academic research and controls for districts' sectoral composition, as well as
- a stochastic error term  $\epsilon$ .

$$\begin{aligned}
\ln P_i &= \ln \alpha + \eta \ln EMP_i \\
&+ \gamma \ln AGE_i \\
&+ \beta_1^{<35} \ln KNOW_{k,i}^{<35} + \beta_2^{<35} \ln EXP_{m,i}^{<35} \\
&+ \beta_1^{35-49} \ln KNOW_{k,i}^{35-49} + \beta_2^{35-49} \ln EXP_{m,i}^{35-49} \\
&+ \beta_1^{50+} \ln KNOW_{k,i}^{50+} + \beta_2^{50+} \ln EXP_{m,i}^{50+} \\
&+ \ln \sum_{j=1}^{j=n} X_{j,i}^{\delta_j} + \epsilon
\end{aligned} \tag{5}$$

To account for the stock of regional knowledge, we use aggregate indicators for formal education ( $KNOW_{edu,i}^{ap}$ ) and engineering knowledge ( $KNOW_{eng,i}^{ap}$ ). Furthermore, three types of experience will be accounted for: general work experience ( $EXP_{gen,i}^{ap}$ ), organizational tenure (firm-specific experience,  $EXP_{firm,i}^{ap}$ ) and sector-specific experience ( $EXP_{sec,i}^{ap}$ ). Organizational tenure encompasses firm-specific parts of training (both company provided and private), learning-on-the job and learning-by doing, whereas overall work experience incorporates the general part of these human capital components. As experience variables are correlated, we estimate separate models and include only one type of experience in each specification. The same is true for engineering and academic knowledge, therefore we do not include both variables into the same estimation.

## 4.2 Data

The district level provides appropriate opportunities to analyze the age-dependency of patenting activity in Germany. The reason is disparity in the geography of patenting<sup>4</sup> on the one side and in the geography relevant age-specific human capital on the other side<sup>5</sup>,

Patenting information on district level is taken from the German Brand and Patent Office. The 'Patentatlas' prepared by Greif (2002) provides the number of corporate patent applications by districts from 1995 to 2000. All employment related variables are calculated based on longitudinal micro data from the IAB Employment Sample, Regional File, 1975 - 2001. We lag these variables by 3 years assuming that it takes a certain time from the first idea over implementation up to successful patenting application. The same is true for spill-overs from academic

<sup>4</sup> See absolute number of patent applications in Figure 1 and patenting intensity per 100,000 employees in Figure 2, Appendix A.

<sup>5</sup> See share of engineers by district in Figure 4, Appendix B and mean age of labor force by district in Figure 3, Appendix A.

research within a district or between adjacent districts, hence we apply the same time lag for these variables. Thereby, we measure spatially relevant academic research as academic patenting intensity in the district plus the average academic patenting intensity in all adjacent districts. To account for agglomeration and other spill-over effects, we control for the districts' degree of urbanization (metropolitan, urbanized, medium-densely populated, rural) according to a detailed classification provided by the Federal Office for Building and Regional Planning. Finally, as the propensity to patent varies across industries, we include controls for the industrial sector, i.e. shares of employees working in seven different non-service sectors. For a detailed overview of the variables used, their source and their exact specification we refer to Table 2 in Appendix C.

### 4.3 Estimation: Negative-binomial regression model

A typical way to estimate patent counts  $P_i$  would be the linear model or logit models. However, since patent applications are counts, least square estimation is inefficient and leads to inconsistent standard errors (Wooldridge, 2002). A count variable like the number of patents always takes nonnegative (integer) values. A natural log transformation does not help as in some districts, there are no patent applications. We use a count data model with a linear exponential regression function:

$$E(P_i|X_i) = e^{X_i\beta} \quad (6)$$

Let  $E(P_i|X_i)$  be the expected number of patents in district  $i$  conditional on the vector of explanatory variables  $X_i$ . The parameter vector  $\beta$  captures the effect of the explanatory variables on the number of patents. This specification leads to nonnegative conditional expectations of the number of patents (see Hausman et al., 1984; Cameron and Trivedi, 1986). Wooldridge (2002) shows that assuming Equation 6 as the model for  $E(P_i|X_i)$  is equivalent to using  $\log(P)$  as the dependent variable in linear regression analysis. Then the statistical model corresponds to the knowledge production function presented in Subsection 3.1 and we can interpret  $\beta$  as the elasticity of  $E(P_i|X_i)$  with respect to  $X_i$ .

In order to apply maximum likelihood methods to obtain estimator for  $\beta$ , we have to specify the distribution of  $P_i$ . Recent research on inventive activity (e.g. Coupé, 2003, Fritsch and Slavtchev, 2005 or Niebuhr, 2006) apply Poisson or Negative Binomial regression models on cross sectional patent count data. In their study about the effect of academic and public R+D on patenting output in German districts Fritsch and Slavtchev (2005) found that a Negbin II model fits the data best. As we use the same main data set, patenting statistics by Greif (2002), we choose this model in a first step. In a second step, we will fit alternative models (in particular Poisson and Negbin I) and conduct specification tests as suggested by Cameron and Trivedi (1986) in order to find the most appropriate model.

## 5 Results and discussion

Results presented here refer to measurement of inventive activity using different model specifications and the following data. The number of corporate patents for the year 2000 in the 343 German districts measure inventive activity  $P_i$ , is let to depend on the number of employees  $EMP_i$  in 1997. In Model *I*, the independent or direct age effect is represented by the mean age of employees in the respective district. As mean age does not capture the age structure of districts' labor force completely, we estimate the effect of age shares for <35 years, 35-49 years and 50+ years in Models *II* - *IV*. Simultaneously encompassing all three age groups as well as the respective age-specific human capital indicators, as we do in Model *II*, can lead to multicollinearity bias. We therefore follow the approach of Prskawetz et al. (2004) in their study about age-productivity profiles on regional level in Sweden and include only information for the youngest and the oldest age group (Model *III*) and for the prime age and the oldest age group (Model *IV*) in the same model. Table 3 in Appendix E gives an overview of the models and variables included.

		Model <i>Ib</i>	Model <i>Ie</i>
<i>Intercept</i>	Intercept	-2.5525	-1.6217
$EMP_i$	Number of employees	0.000004***	0.000004***
$AGE_i$	mean age	0.1243**	0.0956*
Share of engineers and technicians, by age group			
$KNOW_{eng}^{<35}$	<35 years		2.1055
$KNOW_{eng}^{35-49}$	35-49 years		8.8749***
$KNOW_{eng}^{50+}$	50 + years		-1.2846
Share of academic workers, by age group			
$KNOW_{edu}^{<35}$	<35 years	2.0559	
$KNOW_{edu}^{35-49}$	35-49 years	3.9700***	
$KNOW_{edu}^{50+}$	50+ years	1.5226	
Average sector specific experience, by age group			
$EXP_{sec}^{<35}$	<35 years	-0.0010	-0.0016**
$EXP_{sec}^{35-49}$	35-49 years	-0.0022***	-0.0016*
$EXP_{sec}^{50+}$	50+years	0.0021***	0.0033***
Significance levels : * : 10% ** : 5% *** : 1%			

Table 1: Estimates for human capital and age indicators, Models *Ib*, *Ie*

To account for age-heterogeneous human capital, we include average firm-specific ( $EXP_{firm,i}^{a_q}$ ), sector-specific ( $EXP_{sec,i}^{a_q}$ ) and overall working experience ( $EXP_{gen,i}^{a_q}$ ) per district  $i$ . Additionally, we incorporate the share of engineers and technicians

( $KNOW_{eng,i}^{a_q}$ ) and the share of academic workers ( $KNOW_{edu,i}^{a_q}$ ), all calculated separately for the three age groups. Control variables are the degree of urbanization, the sectoral composition, a regional dummy variable (East and West Germany) as well as the amount of academic research.

As the share of engineers and technicians is correlated with the share of academic workers, we choose different separate specifications within Models *I-IV*: Models *a*, *b*, *c* include the academic workers, Models *d,e,f* include the share of engineers and technicians. The same is true for general, firm-specific and sector-specific experience. Therefore, Models *a* and *d* account for firm-specific, Models *b* and *e* for sector-specific and Models *c* and *f* for general work experience. The models are identical with respect to all other variables included.

Conducting a negative binomial regression as described in Section 4.1 leads to the parameter estimates for mean age and different types of age-specific human capital. For illustration, we chose Models *Ib* and *Ie* as examples and present the parameter estimates for the corresponding knowledge and experience variables, namely sectors specific experience and the age-specific share of engineers, in Table 1 (for detailed results refer to Table 4, Model *Ib* and *Ie*).

In Model *Ib* and *Id* (see Table 1), mean age and patenting activity are positively related on district level. The positive age effect is significant on 5%- and 10%-level respectively. One might argue that mean age does not fully capture the age structure of a district's workforce, but the results found are robust if we include the age structure directly by age shares per district instead of mean age: In Models *IIIa-f* as well as, to a smaller extent, in Models *IVa-d*, the share of older workers per district has a positive effect on patenting output. In Models *IId-f*, we even identify a negative effect of the share of prime age workers, which is, however, only significant at 10% level. Model *IIIa*, the extreme case where we include the youngest and oldest age group, we identify a positive influence of both, the share of younger and older workers, with higher and more significant effects for older workers. This double-positive impact of older and younger workers is particularly interesting as we could think of spill-over effects between age groups: if there is enough up-to-date formal knowledge in the youngest age group, a high share of experienced older labor might enhance patenting activity.

Our findings suggest that, at least on regional level, an older workforce does not reduce patenting performance by itself. However, we are careful to interpret our results in the sense of a virtually positive independent age effect. With the available data, we were not able to control for the composition of firm size in the districts. If larger establishments produce, on average, more patent applications per inventor and, at the same time, employ a higher number of older workers, the positive age-effect could be a hidden size-effect<sup>6</sup>.

<sup>6</sup> Firm size and patenting is often found to be negatively related. However, Kim et al. (2004) show that even if the number of patents relative to R+D investments is lower for larger establishments,



The effects of engineering knowledge as well as of (formal) academic education are as expected. The share of engineers and technicians has a significant positive effect, especially for the prime age group 35-49 years and less so for the youngest age group. In our two showcase models *Ib* and *Ie*, an increase in the share of engineers and technicians would, other things equal, lead to an increase in patenting performance. Engineering knowledge of age group 50+ is, to the contrary, not significant and the parameter estimate close to zero. This suggests a decreasing relevance of 'older' technology-related human capital for innovative output on district level.

Results for the age-specific share of academic workers point into a similar direction. However, the effect is less clear than as compared to the share of engineers and technicians. In Model *Ib* (as well as in Models *Ia-c*, *IIa-c*), only the share of academic workers aged 35 to 39 has a positive effect on patenting output which is significant at 5%-level. The estimates in Models *IVa-c*, encompassing the youngest and the oldest age group and omitting the prime age group, reveal most clearly the positive effect of 'young', hence recent, academic knowledge with estimates between 4.5 and 5, significant at 1% level, whereas 'older', hence outdated academic knowledge has no significant effect on patenting performance.

From the experience variables considered, only average sector-specific experience of the prime age group, has a significant influence on patenting output. The sign is, however, surprising: The higher the stock of aggregate sectoral experience in the prime age group, the lower is patenting performance. A possible explanation is the so-called 'Silicon Valley effect' (Fallick et al., 2005), claiming that high performers display high job mobility, within as well as across industrial sectors. In this context, lower flows of labor between sectors and/or companies as indicated by longer average sectoral tenure on district level, could lead to lower patenting performance because the less innovative workers stay in their jobs whereas the more innovative ones leave. We found exactly the same age-performance pattern for general work experience as well as for organizational tenure. In contrast to the pattern found for the prime age group, if there is a significant effect of experience in the oldest age group, it is positive.

Based on our estimation results, engineering and academic knowledge relevant for innovation as measured by patenting activity have a pronounced age-specific dimension. On district level, the stock of knowledge available in the young and the prime age group helps to increase patenting activity, whereas the effect for older and therefore partly outdated knowledge is insignificant or at least less strong. This is in line with the theoretical framework we established in Section 2. Firm specific, sector-specific and overall work experience do, if ever, only display a positive effect on patenting output for the oldest age group. On district, hence aggregate, level, we do not find a negative independent age effect. Patenting activity even seems to be more intense in districts with a higher share of older labor.

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the number of patents per inventor can be higher.

## 6 Conclusion

Our first objective was to propose a model for the age-dependency of innovative performance, combining elements of human capital theory and I-O psychology. Adopting a life-span perspective, we show that there are two channels through which age can affect innovative performance: On the one hand, human capital accumulation and depreciation evolves over the life span, resulting in age-specific human capital. On the other hand, an independent effect of age based on the (age-specific) level of exploitation abilities and motivation can moderate the effect of human capital on innovative performance.

In a second step, we use the Griliches-Jaffe knowledge production framework to relate patenting output to different knowledge input variables and suggest two extensions. Based on our theoretical considerations, we introduce age-heterogeneous human capital and an independent age effect.

Our third interest was to transform the theoretical into an econometric model in order to estimate the influence of age-heterogeneous human capital and determine if there is an independent age effect. We focus on an aggregate level and use a negative binomial regression model appropriate for count data to estimate the effect of age and age-heterogeneous human capital on patenting performance in 343 German districts. Recapitulating our estimation results, engineering knowledge and, to a smaller extent, formal academic knowledge lose their innovation-enhancing effect when the labor force grows older. However, we find no indication for a negative independent age effect on aggregate level, so far. The positive relationship between age of the workforce in German districts and patenting activity might result from effects due to the distribution of firm size. From an aggregate perspective, work experience, sector and firm specific experience only display significant positive effects on patenting performance for the oldest age group. The average experience level of the prime age group even seems to be negatively related with age. A possible explanation is that high performers are highly mobile, even across industrial sectors.

In a next step, the econometric model will be further improved. We will e.g. dig into the issue of a potential firm size effect by including additional variables. Furthermore, we plan to extend the model by allowing for spatial autocorrelation as well as including spill-over effects of adjacent districts, particularly with respect to academic research as suggested by Fritsch and Slavtchev (2005).

Germany is a country living from its innovation capacity fed by education and technological experience. With an aging labor force, managers as well as policy makers will increasingly wish to know how age influences the innovation performance on different aggregation levels. It might turn out, that basing decisions on current economic wisdom concerning age-specific human capital will not suffice or even lead into the wrong direction. For example, personnel managers might be tempted to ignore the independent age effect and expend investment in training of all workers, the older ones included. In fact, this is what policy and society are expecting

them to do. However, if an independent age effect applies, that lowers learning and other relevant capacities with increasing age, careful implementation of additional measures may enhance or even condition the innovation performance, e.g. incentives systems accounting for age-specific particularities in work motivation.

### **Acknowledgments**

The employment data used for this article is the anonymized IAB Employment Subsample, Regional File 1975 - 2001. Data is made available as a scientific use file, provided by the Research Data Center of the German Federal Employment Office in the Research Institute IAB.

The study was supported by the Rostock Center for the Study of Demographic Change, Research Unit I (Aging Labor Force) and the University of Rostock, Chair of Macroeconomics, Growth and Business Cycles.

Thanks also to the participants of the Interdisciplinary Workshop on Regional Innovation, June 9–10, 2006, Kings College, Cambridge and of the 2<sup>nd</sup> World Aging and Generations Congress, September 27–29, 2006, St. Gallen for their suggestions.

A Geography of patenting activity in German districts

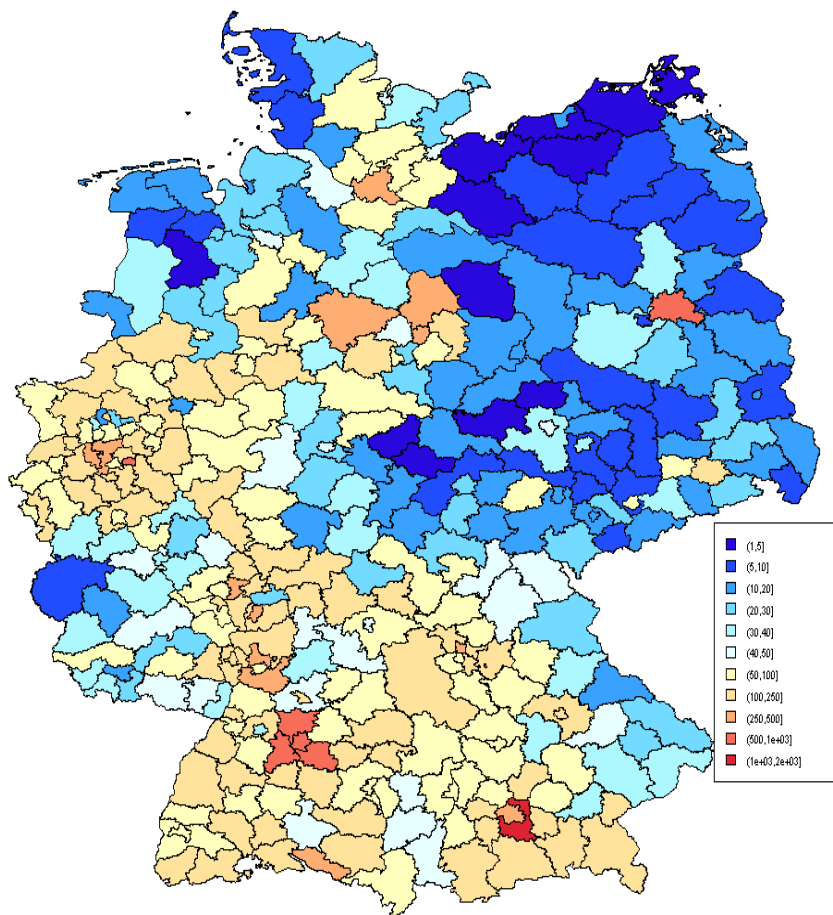


Figure 1: Corporate patent applications, by district (2000)

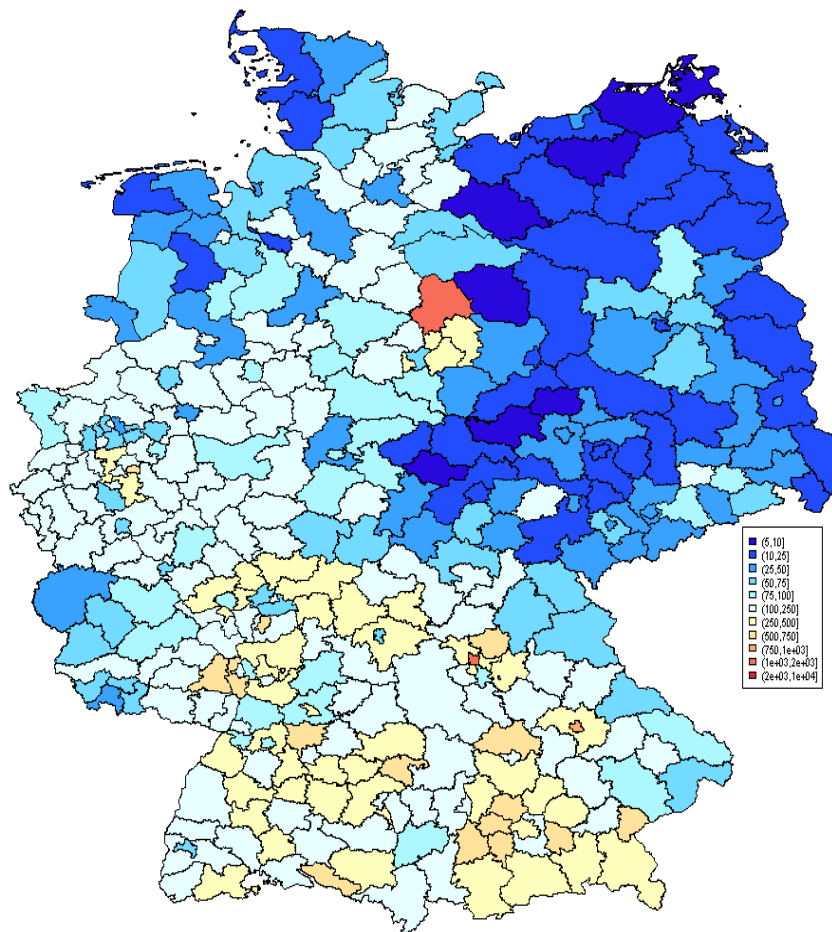


Figure 2: Corporate patents per 100000 employees, by district (2000)

### B Geography of human capital input in German districts

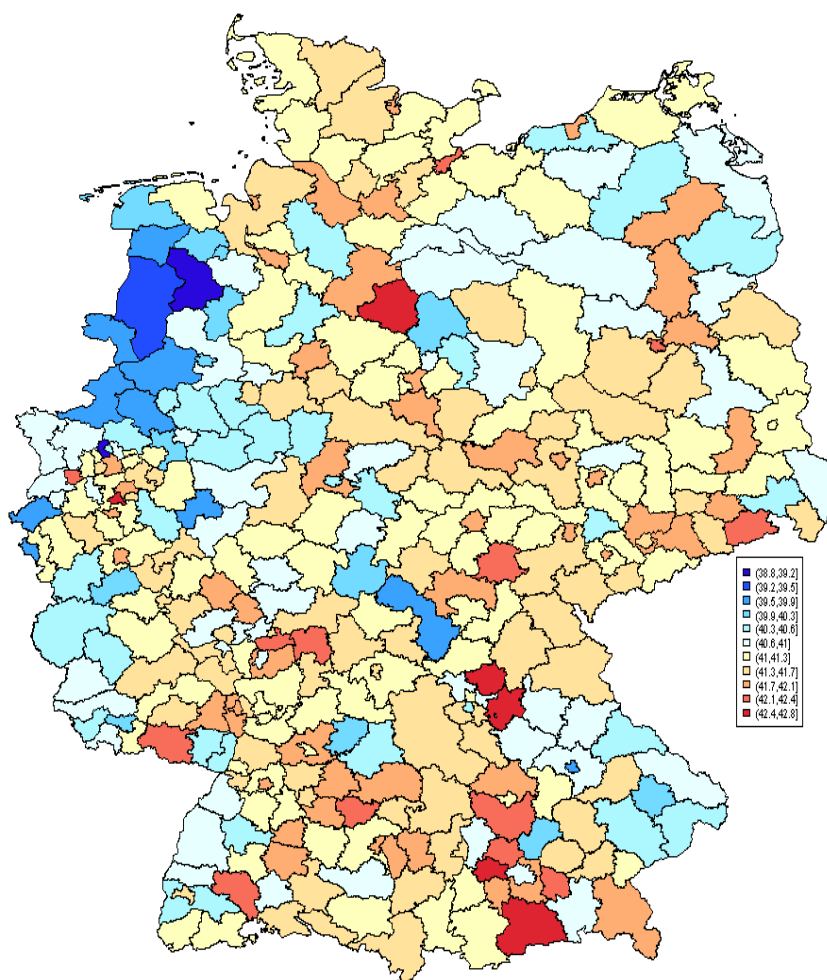


Figure 3: Mean age of labor force, by district (1997, lag=3)

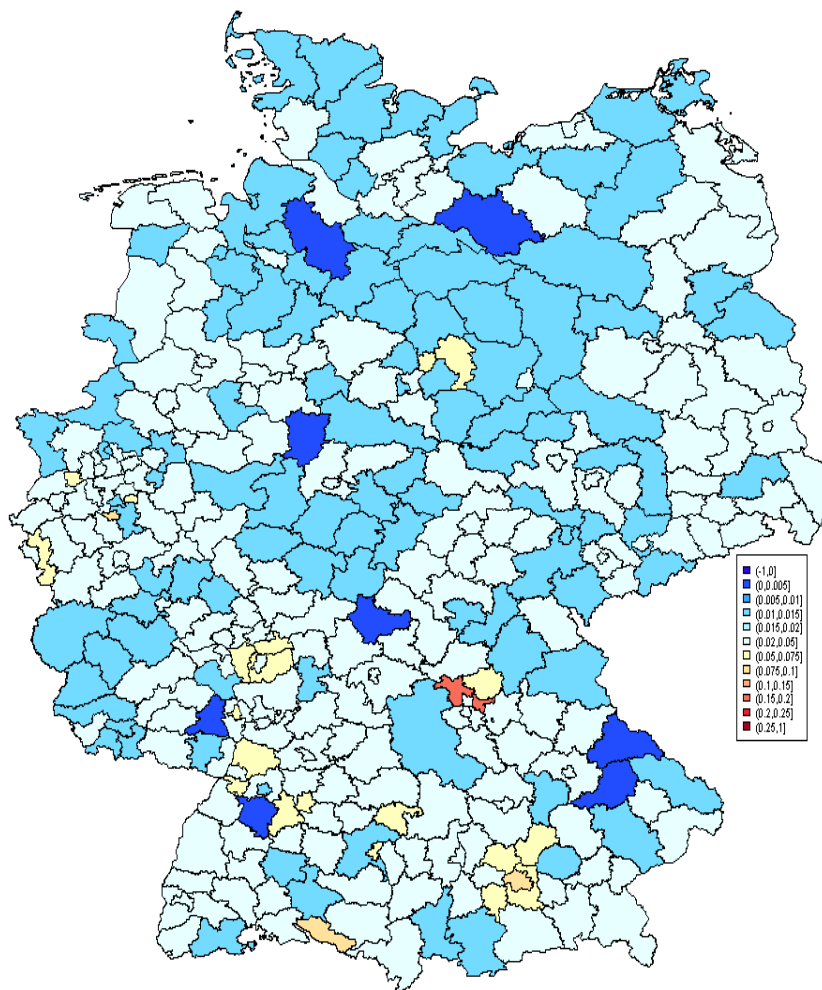


Figure 4: Share of engineers in total labor force, by district (1997, lag=3)

## C Description of data and variables

Variable	Description	Source
$P_i$	Number of corporate patent applications per district in 2000	(1)
$EMP_i$	Number of employees per district in 1997 (lag = 3, cutoff date 30.06.1997)	(2)
$AVAGE_i$	Mean age of employees per district in 1997 (lag = 3, cutoff date 30.06.1997)	(2)
$AGE_i^{a_q}$	Share of workers by age groups per district in 1997 (lag = 3, cutoff date 30.06.1997)	(2)
$KNOW_{edu,i}^{a_q}$	Share of academic workers (Uni, FH) by age group and per district in 1997 (lag = 3, cutoff date 30.06.1997)	(2)
$KNOW_{eng,i}^{a_q}$	Share of engineers and technicians by age group and per district in 1997 (lag = 3, cutoff date 30.06.1997)	(2)
$EXP_{gen,i}^{a_q}$	Average general work experience in years acquired between 1991-1997 by age group and per district	(2)
$EXP_{firm,i}^{a_q}$	Average firm specific experience in years acquired between 1991-1997 at current employer by age group and per district	(2)
$EXP_{sec,i}^{a_q}$	Average sector specific experience in current sector in years acquired between 1991-1997 by age groups per district	(2)
$wz_d$	Share of workers in sector $d = 1, \dots, 8^a$ per district (lag = 3, cutoff date 30.06.1997)	(2)
$urb$	Degree of urbanization (dummy variable <sup>b</sup> )	(4)
$patsci$	Number of scientific patent applications per 100,000 employees and district in 2000	(1)

Source 1: German Brand and Patent Office  
Source 2: IAB Employment Sample, Regional File, 1975 – 2001  
Source 3: German Research Council  
Source 4: Federal Office for Building and Regional Planning

Table 2: Description of data and variables

<sup>a</sup>Sectors are

- (1) energy, agriculture, mining
- (2) raw/basic materials and goods
- (3) manufacturing - industrial goods
- (4) manufacturing - consumption goods
- (5) construction
- (6) trade
- (7) transport and communication
- (8) services.

<sup>b</sup>Levels are rural, medium densely populated, urbanized, metropolitan and urban.



## D Overview of different model specifications

	Independent age effect			knowledge		experience			
	av.age	< 35	35-49	50+	edu	eng	firm	sec	gen
Model I	x								
a	x				x		x		
b	x				x			x	
c	x				x				x
d	x					x	x		
e	x					x		x	
f	x					x			x
Model II		x	x	x					
a		x	x	x	x		x		
b		x	x	x	x			x	
c		x	x	x	x				x
d		x	x	x		x	x		
e		x	x	x		x		x	
f		x	x	x		x			x
Model III		x		x					
a		x		x	x		x		
b		x		x	x			x	
c		x		x	x				x
d		x		x		x	x		
e		x		x		x		x	
f		x		x		x			x
Model VI			x	x					
a			x	x	x		x		
b			x	x	x			x	
c			x	x	x				x
d			x	x		x	x		
e			x	x		x		x	
f			x	x		x			x

Table 3: Different model specifications

## E Detailed result tables for Models I - IV

	Model Ib	Model Ic	Model Id	Model Ie	Model If	
<i>Intercept</i>	-2.8748	-2.5525	-4.2226	-2.3028	-1.6217	-3.6694
<i>EMP</i>	0.000004***	0.000004***	0.000004***	0.000004***	0.000004***	0.000004***
<i>AGE</i>	0.1342**	0.1243**	0.1350**	0.1115**	0.0956*	0.1072*
$EXP_{firm}^{<35}$	-0.0010			-0.0015**		
$EXP_{firm}^{35-49}$	-0.0022***			-0.0017**		
$EXP_{firm}^{50+}$	0.0021**			0.0027***		
$EXP_{sec}^{<35}$		-0.0010			-0.0016**	
$EXP_{sec}^{35-49}$		-0.0022***			-0.0016*	
$EXP_{sec}^{50+}$		0.0021***			0.0027***	
$EXP_{gen}^{<35}$			-0.0008			-0.0014**
$EXP_{gen}^{35-49}$			-0.0023**			-0.0017*
$EXP_{gen}^{50+}$			0.0027***			0.0033***
$KNOW_{edu}^{<35}$	1.9037	2.0559	2.3846			
$KNOW_{edu}^{35-49}$	3.8176**	3.9700***	3.8070**			
$KNOW_{edu}^{50+}$	1.6018	1.5226	1.3584			
$KNOW_{eng}^{<35}$				2.4370	2.1055	2.7376
$KNOW_{eng}^{35-49}$				8.2505***	8.8749***	8.9439***
$KNOW_{eng}^{50+}$				-1.2591	-1.2846	-1.8100
<i>wz<sub>1</sub></i>	1.8425	1.8162	1.6475	0.3176	0.1342	0.0773
<i>wz<sub>2</sub></i>	4.4694***	4.4538***	4.3633***	3.5873***	3.5099***	3.4012***
<i>wz<sub>3</sub></i>	5.3955***	5.4750***	5.3302***	4.2313***	4.2884***	4.1280***
<i>wz<sub>4</sub></i>	3.6896***	3.7931***	3.6690***	2.5272***	2.6166***	2.5265***
<i>wz<sub>5</sub></i>	2.7082*	2.7460*	3.2584**	0.3074	0.1730	0.7465
<i>wz<sub>6</sub></i>	2.9197**	3.0631***	3.1292***	2.4016**	2.5950**	2.6266**
<i>wz<sub>7</sub></i>	3.1471**	3.4735**	3.3931**	1.5362	1.7995	1.6561
<i>urb<sub>2</sub></i>	0.1361	0.1242	0.1190	0.1531*	0.1450	0.1392
<i>urb<sub>3</sub></i>	0.2169**	0.2017*	0.2189**	0.3219***	0.3100***	0.3231***
<i>patsci</i>	0.0142***	0.0144***	0.0140***	0.0155***	0.0158***	0.0153***
<i>east</i>	-1.5728***	-1.5725***	-1.3860***	-0.8230**	-0.8042**	-0.6173

Significance levels : \* : 10% \*\* : 5% \*\*\* : 1%

Table 4: Results Model Ia - If: Specification with mean age

		Model IIb	Model IIc	Model IId	Model IIe	Model II f
<i>Intercept</i>	10.9408	10.3275	8.8875	12.1261 *	11.4679	9.7177
<i>EMP</i>	0.000004 ***	0.000004 ***	0.000004 ***	0.000004 ***	0.000004 ***	0.000004 ***
<i>AGE</i> <sub>&lt;35</sub>	-8.1637	-7.5122	-7.2275	-9.0727	-8.1950	-7.8895
<i>AGE</i> <sub>35-49</sub>	-10.0592	-9.4001	-9.2154	-12.0384 *	-11.3228 *	-11.0173 *
<i>AGE</i> <sub>50+</sub>	-5.0929	-4.5855	-4.0872	-6.8245	-6.2643	-5.7131
<i>EXP</i> <sub>&lt;35</sub> <i>firm</i>	-0.0009			-0.0013 **		
<i>EXP</i> <sub>35-49</sub> <i>firm</i>	-0.0017 **			-0.0012		
<i>EXP</i> <sub>50+</sub> <i>firm</i>	0.0017 **			0.0022 ***		
<i>EXP</i> <sub>sec</sub> <i>sec</i> <sub>&lt;35</sub>		-0.0008			-0.0013 **	
<i>EXP</i> <sub>sec</sub> <i>sec</i> <sub>35-49</sub>		-0.0017 **			-0.0011	
<i>EXP</i> <sub>sec</sub> <i>sec</i> <sub>50+</sub>		0.0016 *			0.0020 **	
<i>EXP</i> <sub>gen</sub> <i>gen</i> <sub>&lt;35</sub>			-0.0007			-0.0013 *
<i>EXP</i> <sub>gen</sub> <i>gen</i> <sub>35-49</sub>			-0.0019 **			-0.0012
<i>EXP</i> <sub>gen</sub> <i>gen</i> <sub>50+</sub>			0.0022 **			0.0027 ***
<i>KNOW</i> <sub>edu</sub> <i>edu</i> <sub>&lt;35</sub>	1.9801	2.1241	2.3973			
<i>KNOW</i> <sub>edu</sub> <i>edu</i> <sub>35-49</sub>	3.1729 **	3.3336 **	3.1390 **			
<i>KNOW</i> <sub>edu</sub> <i>edu</i> <sub>50+</sub>	1.6239	1.5598	1.4286			
<i>KNOW</i> <sub>eng</sub> <i>eng</i> <sub>&lt;35</sub>				2.7309	2.4854	2.8594
<i>KNOW</i> <sub>eng</sub> <i>eng</i> <sub>35-49</sub>				7.2235 **	7.7566 ***	7.8263 ***
<i>KNOW</i> <sub>eng</sub> <i>eng</i> <sub>50+</sub>				-1.3670	-1.3620	-1.8242
<i>wz</i> <sub>1</sub>	1.5993	1.5725	1.4706	0.1895	0.0123	0.0344
<i>wz</i> <sub>2</sub>	4.2327 ***	4.2098 ***	4.1348 ***	3.4064 ***	3.3219 ***	3.2525 ***
<i>wz</i> <sub>3</sub>	5.3107 ***	5.3636 ***	5.2347 ***	4.2544 ***	4.2708 ***	4.1540 ***
<i>wz</i> <sub>4</sub>	3.3944 ***	3.4692 ***	3.3607 ***	2.3111 ***	2.3542 ***	2.2963 ***
<i>wz</i> <sub>5</sub>	2.2923	2.2869	2.7314 *	0.1438	-0.0143	0.4760
<i>wz</i> <sub>6</sub>	2.7492 **	2.9022 **	2.8970 **	2.2306 *	2.4167 **	2.3844 **
<i>wz</i> <sub>7</sub>	2.7878 *	3.0656 **	2.9829 *	1.2804	1.4869	1.3676
<i>urb</i> <sub>2</sub>	0.1176	0.1085	0.1021	0.1309	0.1255	0.1186
<i>urb</i> <sub>3</sub>	0.2105 **	0.1963 *	0.2099 **	0.3028 ***	0.2919 ***	0.3012 ***
<i>patsci</i>	0.0142 ***	0.0145 ***	0.0141 ***	0.0155 ***	0.0157 ***	0.0152 ***
<i>east</i>	-1.4195 ***	-1.4492 ***	-1.2527 ***	-0.6915 *	-0.6942 *	-0.5129

Significance levels : \* : 10% \*\* : 5% \*\*\* : 1%

Table 5: Results Model IIa - II f: Specification with age shares 1 - 3

	Model IIIa	Model IIIb	Model IIIc	Model IIId	Model IIIe	Model IIIf
		Model IIIb	Model IIIc	Model IIId	Model IIIe	Model IIIf
(Intercept)	-2.2027	-2.1628	-3.6250	-1.9340	-1.6267	-3.3527
<i>EMP</i>	0.000004 ***	0.000004 ***	0.000004 ***	0.000004 ***	0.000004 ***	0.000004 ***
<i>AGE</i> <sub>&lt;35</sub>	2.9592 *	3.0419 **	3.0738 **	3.1062 **	3.2838 **	3.2705 **
<i>AGE</i> <sub>50+</sub>	5.7478 ***	5.6044 ***	5.7492 ***	5.7646 ***	5.6196 ***	5.7659 ***
<i>EXP</i> <sub>firm</sub> <sup>&lt;35</sup>	-0.0011			-0.0016 **	***	
<i>EXP</i> <sub>firm</sub> <sup>50+</sup>	0.0015 *			0.0021 **	***	
<i>EXP</i> <sub>sec</sub> <sup>&lt;35</sup>		-0.0011			-0.0015 **	
<i>EXP</i> <sub>sec</sub> <sup>50+</sup>		0.0015 *			0.0019 **	
<i>EXP</i> <sub>gen</sub> <sup>&lt;35</sup>			-0.0009			-0.0014 **
<i>EXP</i> <sub>gen</sub> <sup>50+</sup>			0.0019 **			0.0025 ***
<i>KNOW</i> <sub>edu</sub> <sup>&lt;35</sup>	2.6956 **	2.8403 **	2.9543 **			
<i>KNOW</i> <sub>edu</sub> <sup>50+</sup>	2.8312 **	2.8847 **	2.6753 **			
<i>KNOW</i> <sub>eng</sub> <sup>&lt;35</sup>				4.9726 **	4.9832 **	5.3060 **
<i>KNOW</i> <sub>eng</sub> <sup>50+</sup>				0.1307	0.4501	0.0346
<i>wz</i> <sub>1</sub>	1.1445	1.0183	0.9518	0.4458	0.2106	0.2211
<i>wz</i> <sub>2</sub>	3.8241 ***	3.8350 ***	3.7080 ***	3.4901 ***	3.4605 ***	3.3446 ***
<i>wz</i> <sub>3</sub>	4.7675 ***	4.8188 ***	4.6822 ***	4.2509 ***	4.3024 ***	4.1684 ***
<i>wz</i> <sub>4</sub>	3.0094 ***	3.0567 ***	2.9362 ***	2.2793 ***	2.3033 ***	2.2141 ***
<i>wz</i> <sub>5</sub>	1.8239	1.8001	2.0651	0.3036	0.0954	0.4889
<i>wz</i> <sub>6</sub>	2.8460 **	3.0125 **	2.9489 **	2.3445 **	2.5575 **	2.4887 **
<i>wz</i> <sub>7</sub>	2.2671	2.4648	2.3347	1.6051	1.8283	1.6922
<i>urb</i> <sub>2</sub>	0.0917	0.0878	0.0786	0.1242	0.1211	0.1113
<i>urb</i> <sub>3</sub>	0.2187 **	0.2105 **	0.2135 **	0.2964 ***	0.2879 ***	0.2923 ***
<i>patsci</i>	0.0146 ***	0.0146 ***	0.0146 ***	0.0167 ***	0.0169 ***	0.0167 ***
east	-0.9990 ***	-0.9855 ***	-0.8056 **	-0.4673	-0.4773	-0.2835

Significance levels : \* : 10% \*\* : 5% \*\*\* : 1%

Table 6: Results Model IIIa - IIIf: Specification with age shares 1 + 3

	Model IVb	Model IVc	Model IVd	Model IVe	Model IVf	
(Intercept)	1.5612	1.9482	0.3811	1.7307	2.2537	0.2348
<i>EMP</i>	0.000004 ***	0.000004 ***	0.000004 ***	0.000004 ***	0.000004 ***	0.000004 ***
<i>AGE</i> <sub>35-49</sub>	-2.0020	-2.0389	-2.1654	-3.2291 **	-3.4107 **	-3.3782 **
<i>AGE</i> <sub>50+</sub>	3.5114 **	3.4229 **	3.3939 **	2.7032 *	2.5151	2.5259
<i>EXP</i> <sub>firm</sub> <sup>35-49</sup>	-0.0015 *			-0.0013		
<i>EXP</i> <sub>firm</sub> <sup>50+</sup>	0.0013			0.0018 **		
<i>EXP</i> <sub>sec</sub> <sup>35-49</sup>		-0.0015 *			-0.0012	
<i>EXP</i> <sub>sec</sub> <sup>50+</sup>		0.0011			0.0015 *	
<i>EXP</i> <sub>gen</sub> <sup>35-49</sup>			-0.0014			-0.0011
<i>EXP</i> <sub>gen</sub> <sup>50+</sup>			0.0018 *			0.0023 **
<i>KNOW</i> <sub>edu</sub> <sup>35-49</sup>	4.6943 ***	4.9006 ***	4.6946 ***			
<i>KNOW</i> <sub>edu</sub> <sup>50+</sup>	1.9856	1.9150	1.8633			
<i>KNOW</i> <sub>eng</sub> <sup>35-49</sup>				10.1032 ***	10.3673 ***	10.2771 ***
<i>KNOW</i> <sub>eng</sub> <sup>50+</sup>				-1.1285	-1.1844	-1.4620
<i>wz</i> <sub>1</sub>	0.9943	1.0245	0.8500	-0.6927	-0.7846	-0.8183
<i>wz</i> <sub>2</sub>	3.6419 ***	3.6503 ***	3.5189 ***	2.7301 ***	2.7048 ***	2.5989 ***
<i>wz</i> <sub>3</sub>	4.9952 ***	5.0814 ***	4.9191 ***	3.7226 ***	3.7850 ***	3.6505 ***
<i>wz</i> <sub>4</sub>	2.9886 ***	3.1081 ***	2.9740 ***	1.6717 **	1.7761 **	1.6937 **
<i>wz</i> <sub>5</sub>	2.0176	1.9936	2.3463	-0.3065	-0.4091	0.0436
<i>wz</i> <sub>6</sub>	2.8794 **	2.9950 **	2.9473 **	2.3549 **	2.5130 **	2.4183 **
<i>wz</i> <sub>7</sub>	2.6701 *	2.8232 *	2.6966 *	0.9775	1.0596	0.9739
<i>urb</i> <sub>2</sub>	0.1220	0.1196	0.1147	0.1151	0.1151	0.1067
<i>urb</i> <sub>3</sub>	0.1994 *	0.1906 *	0.2028 *	0.2925 ***	0.2875 ***	0.2923 ***
<i>patsci</i>	0.0160 ***	0.0163 ***	0.0161 ***	0.0170 ***	0.0173 ***	0.0170 ***
east	-1.4236 ***	-1.4969 ***	-1.2278 ***	-0.5926 *	-0.6436 *	-0.3665

Significance levels : \* : 10% \*\* : 5% \*\*\* : 1%

Table 7: Results Model IVa - IVf: Specification with age shares 1 + 3

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