Does Demographic Aging Contribute to the Innovation Divide Across German Labour Markets?*

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Abstract

In this paper we examine the causal effect of workforce age structure on the regional innovation system by estimating a regional knowledge production function for functionally delineated labour market regions. In particular, we apply a IV panel approach that accounts for time-constant unobserved regional effects and potential endogeneity. Overall, we find a hump-shaped age-innovation profile suggesting that the aggregate impact of demographic ageing may in fact be negative. Moreover, the differences in the average age between German regions are able to explain large parts of the innovation divide across German labour markets. In further extensions of the paper we explicitly aim to estimate the substitution effects between different regional age group shares in order to reveal insights into potential innovation enhancing effects of knowledge transfers in agglomerated labour markets between age-heterogenous individuals.

Keywords: regional innovation system, demographic ageing, knowledge production function, regional disparities, age diversity

JEL: R12, O31, J11

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1 Introduction

Demographic ageing is increasingly becoming one of the most pressing challenges that industrialized economies are facing in the 21st century. According to the latest Eurostat projections over the next 50 years, workforce ageing will continue in all European countries, though the magnitude, speed and timing are likely to vary. This demographic trend has raised the concern that an ageing workforce may reduce productivity, innovative capability and thus, ultimately, competitiveness in the global, knowledge-based economy. This is particularly true for Germany, which, according to the UN Population Division, has the second hightest median age behind Japan.[1] More strikingly, workforce ageing is very likely to affect labour markets in very different ways on a regional scale. Studies for Germany show, that demographic aging is increasingly aggravating a demographic polarization trend: major cities are experiencing declining average ages (relative to the national value), whereas the age distribution of rural areas is shifting upwards. (Gregory and Patuelli 2013). Since the age of workers is known to be one key determinant of innovative behaviour, this demographic divide may likely turn into an innovation divide.

The aim of this paper is to shed light on this demographic trend and identify the causal effect of demographic age structure on innovation at the regional level. The aggregate effect might thereby not simply be the sum of firm- and individual level effects. The reason is that knowledge externalities way arise at the regional level through formal and informal interactions between individuals of different age groups. Such interactions might arise, for instance, due to the fact that young workers are largely disposed with the ability to generate and recombine new knowledge (fluid intelligence), whereas older workers are largely endowed with the ability to use skills, knowledge, and experience (crystallized intelligence). The different skill endowments across age groups may complement each other and create positive spillovers. Such spillovers may thereby not only take place within a firm, but also across firms via social interactions inside and outside the workplace and may even partially balance out the disadvantages of individual ageing that has been found on the firm-level.

There are only a few studies on the link between workforce age structure and innovation on the aggregate level. Most studies focus either on the individual or firm level.[2] One disadvantage of those existing studies is that they use more general performance indicators such as economic growth and productivity (e.g. Brunow and Hirte 2006). In this paper, we are more interested in

[1] See `http://esa.un.org/unpd/wpp/Documentation/pdf/WPP2012_HIGHLIGHTS.pdf`.

[2] For an extended and well written survey see Frosch (2011).

the creation of ideas and up-to-front knowledge as a key driver of long-run economic performance. Among the few studies on the regional level that use innovation or business start-up measures are Bönte et al. (2009) and Frosch (2009). Moreover, the current literature suffers from a lack of estimation approaches that deal with the endogeneity of the workforce. A few country-level studies by Feyrer (2007), Prskawetz et al. (2007) and Lindh and Malmberg (1999) are an exception in this regard. Finally, to the authors knowledge, there is no study so far that links demographic ageing to regional disparities nor that addresses formal and informal knowledge interactions between age-heterogenous workers as an influencing factor of reginoal idea creation.

This paper makes at least four contributions. First of all, we investigate the geography of innovation and workforce age structure for labour market regions recently defined by (Kosfeld and Werner 2012) based on commenting flows. This is particularly important when investigating patent applications using the home address of inventors. To the authors knowledge, we are the first to study innovation on such labour market regions for Germany.[3] Second, we exploit the cross-sectional variation between German regions to estimate a knowledge production function using the number of patents (and citations) as a more direct measure of innovation. We thereby use the regional workforce age structure as our central input measure and control for potentially confounding factors such as public and private R&D expenditures, the number of creative professionals, agglomerations effects and the regional industry mix. Based on the estimations we calculate the regional age-innovation profile. Thirdly, we address the potential endogeneity of the regional workforce due to endogenous age-selective migration by exploiting the cross-sectional variation in the age structure of workers and by using lagged population age group shares as instrumental variables. We then contrast this approach to a panel estimation that accounts for unobserved heterogeneity, yet should be more problematic with regard to endogenous (period-wise) migration. Fourthly, in further extensions of the paper we explicitly aim to estimate the substitution effects between different age groups in order to reveal insights into potential innovation enhancing effects of knowledge transfers between age-heterogenous individuals.

Overall, we find a hump-shaped age-innovation profile suggesting that the aggregate impact of demographic ageing may in fact be negative. We further show that differences in the average age between East and West Germany are able to explain large parts of the innovation divide

[3] Fritsch and Slavtchev (2011) use German planning regions. However, these regions partly reflect political boundaries due to the different federal states.

across West German labour markets.

The paper is structured as follows. Section 2 discusses the spatial knowledge production function and gives a short literature review on relevant empirical evidence. Section 3 introduces the data and provides descriptive statistics on the key variables. In Section 4 we describe the econometric approach and present the results of the empirical analysis. Finally, Section 5 concludes.

2 The Regional Production of Knowledge

The starting point for our analysis is the knowledge production function which originally has been thought of as operating on the firm level (Griliches 1979). More generally, the knowledge production function describes the relationship between innovative inputs and outputs.

$$I_{output} = f(I_{input}). \tag{1}$$

One of the inputs that is considered to be the main driver of innovations are investments to R&D. While empirical studies at the country and industry-level confirm the link between R&D and innovations (Scherer 1983, Griliches 1987, Acs and Audretsch 1990), the link seems to be much weaker at the firm-level, thus indicating the presence of knowledge spillovers that go beyond the firm (Audretsch and Feldman 2004). At the same time, such spillovers have been argued to be locally bounded since the transfer of knowledge seems to be linked to face-to-face interactions (Von Hippel 1994, Manski 2000). Hence, the natural unit of measuring the generation of innovations appears to be the region, thus giving rise to the regional knowledge production function.

Regional knowledge production functions have been estimated with different measures of innovative outputs and inputs as well as at different spatial units. Jaffe (1989), for example, establishes a positive link between regional research activities by both private corporations and universities and regional patent activity. Using new product innovations as a measure of innovative output, spillovers from academic research and the relevance of corporate spending on R&D have also been confirmed by Acs et al. (1992). Similar findings have been found for Austrian regions by Fischer and Varga (2003).

In addition to R&D, human capital has been added as a major input to the regional knowledge production function. In particular, skilled labour has been considered to serve as a main vehicle for knowledge spillovers (Malecki 1997, Feldman 1999). Consistent with this notion, Audretsch and feldman (1996) find that industries with higher shares of skilled labour have a greater tendency to cluster spatially. Knowledge externalities thus seem to be closely linked to the skilled workforce, a notion that is also confirmed by empirical studies on patent activities in the US (Ceh 2001).

Our approach partially builds on this literature, but additionally takes account of the age of the regional knowledge base. The age structure of the regional workforce could matter for a number of reasons that have partially been laid out in the introduction. In particular, regional innovations could depend on age due to an age-dependent individual capacity to innovate and an age-dependent intra-firm and interfirm knowledge transfer. In particular, experienced, older workers may be better linked to other key actors than younger workers. On the other hand, inter-firm mobility as a vehicle of knowledge transmission may be reduced with mobility rates typically declining with age. In addition, the regional workforce may affect the localization of innovative industries as well as the regional start-up rate. In order to allow the regional innovation process to be affected by the age structure of the regional human capital base, we thus extend the regional knowledge production function to

$$\begin{aligned} P_i &= \alpha RD_i^{\beta} \times HK_i^{\gamma} \\ &= \alpha RD_i^{\beta} \times SKILL_i^{\gamma_1} \times AGE_i^{\gamma_2} \times (SKILL_i \times AGE_i)^{\gamma_3} \end{aligned}$$

where P_i is some measurement of the innovative output in region i, RD refers to R&D investments, and the regional human capital base HK is decomposed into an age and skill component and a skill-specific age effect. The interaction between skills and age allows the regional age-innovation profile to differ by skill group. We can thus test whether it is the age structure of the total workforce that matters for innovation or whether innovation is driven mainly by high-skilled workers of a particular age group.

3 Data and Descriptives

We define a region as a local labour market and use the classification of Kosfeld and Werner (2012). The classification comprises 141 functional delineated local labour markets based on a factor analysis with the criterion of reasonable commuting time (maximally 45 to 60 minutes in dependence of the attractiveness of the center) and have the size of more than 50,000 inhabitants. The defined local labour markets thus, not only just include the political boundaries of the city but also its neighboring communities, to the extent that they are part of the same local labour market as suggest by communing patterns (in the following we use the terms labour markets and regions interchangeably). For each of the 141 regions, we calculate the number of regional innovations as well as demographic and regional indicators for the time period 1995-2008.

As a measure for innovative outcomes in the regional knowledge production discussed in Section 2 we use regional patent activity. There are several advantages and disadvantages of using patenting data on the regional level (Giese and von Reinhard Stoutz 1998, Giese 2002). On the one hand, patent applications are a useful indicator of research and invention activities on the local level, as they include information on the regional origin of inventor activities, i.e. place of residence and therefore indirectly the location of the research institute. On the other hand, not every invention becomes the subject of a patent application, nor does a patent necessarily become a marketable product or process. Moreover, the reasons for a patent application may not only rest on protecting an invention against unjustified use, but may reflect strategic concerns such as securing and extending regional markets, prestige advertisement and the demonstration of innovative capacity to the economic counterparts. Despite these disadvantages, empirical evidence by Acs et al. (2002), who provide an exploratory and a regression-based comparison of the innovation count data and data on patent counts at the lowest possible levels of geographical aggregation, suggests that patents provide a fairly reliable measure of innovative activity. Also, the survey study by Griliches (1998) concludes that patents are a good indicator of differences in inventive activity across different firms.

For this reason, we use patent data that is provided by the European Patent Office (EPO) in order to measure regional innovations. The data contains patent data both at the applicant and inventor level. Whereas the applicant is the holder of the patent right, the inventors are the actual inventors cited in the document. We focus on patent inventors since we are interested in the spatial distribution of the actual inventors rather than the location of the formal holder of the patent, which is often one of the firm's headquarters. Since patents may have been developed by serval inventors located in different regions, we apply a fractional counting approach to assign to every region the respective share of the patent. For instance, an inventor who developed a patent in Mannheim with one further individual working abroad would generate 0.5 patents for this region.

For the calculation of the age structure of the regional workforce, we make use of the regional file of the Sample of Integrated Labour Market Biographies (SIAB) from the Institute of Employment Research (IAB) for the years 1995-2008. The data set is an employment subsample provided by the German Federal Employment Agency and contains information on workers that are subject to social insurance contributions by their employers, thus excluding civil servants and self-employed individuals. The data includes individual employment histories on a daily basis and contains, among others, information on the age and education of workers. We restrict the analysis to the employed workforce. Although knowledge spillovers are not entirely restricted to the employed workforce, it is nonetheless unlikely that unemployed workers will participate in the relevant social interactions. We therefore decided to exclude unemployed individuals. Furthermore, we restrict our data set to working individuals older than 18 years because the few employed workers below this age constitute a certain, particularly low-educated group or individuals who are currently undergoing a vocational training. Moreover, we have information on the labour market region of all workplaces. Hence, all regional measures that we calculate based on the SIAB refer to the regional workforce. We consider this as an advantage of our data because regional innovations should be linked to the regional workforce rather than to those living, but not necessarily working in the labour market. Since labour market units are constructed to contain most commutes within the region, the distinction should anyhow be of no major concern.

We then use annual cross sections of the SIAB data at the cut-off date 30th June and calculate the mean age of the workforce as well as the share of workers below 36, between 36 and 49 and above 49 years of age for each region. While the mean age may capture the ageing effect, the age shares will allow for interregional differences in the age composition of the regional workforce. In the empirical model we will also be interested in the interaction effects between these age group shares. In addition, we use the SIAB data for the calculation of further control variables such as the share of workers in certain industries (16 categories) and the share of workers in different skill groups (6 categories). Furthermore, we calculate the share of creative professionals and bohemians of a region. As noted before, the generation of ideas and innovation largely depends on creative professionals working in the field of education, engineering, science, and arts (Florida 2002, Wojan et al. 2007). We define the professionals as the group of technological employees characterized as improving technology in the line of business they pursue. The concentration of creative professionals again depends on local amenities that can be measured by the share of bohemians such as artists, publishers, or audio engineers. For the classification of creative professionals and bohemians we follow Wedemeier (2012). As further regional control variables we use population density and public research and development (R&D) expenditures (regular and external funding) provided by the German Statistical Office (Destatis). Moreover, we use private R&D expenditures from the German Stifterverband.

In order to get a first rough idea about the relationship between the number of patents per worker and the age structure of the regional workforce, Figure 1 shows the respective quantile maps for the average values during the period 1995 to 2008 across the 141 labour market regions. For instance, the first quintile (light blue) depicts the values for the 20 per cent least innovative regions which values range from 1 to 9 patents, whereas the fifth quintile contains the values for the most innovative regions (dark blue), with values ranging from 53 to 218. The maps show that innovations are mostly generated in West Germany around the cities Duesseldorf, Aachen, Mainz, Darmstadt, Heidelberg and particularly between Stuttgart, Freiburg, Munich and Regensburg. In contrast, only a few East German cities such as Jena, Dresden and Berlin seem halfway competitive in the production of knowledge.

The map for the average age further reveals that almost all East German regions have on old workforce indicating that plant closures and out-migration of young workers after reunification has strongly affected the age structure of the East German labour force.[4] In contrast, Bavaria constitutes the mirror image of East-Germany, where almost all regions belong to the 20 percent youngest regions in the country. The demographic landscape for the remaining regions looks mixed. Whereas few labour markets belong to are among the upper quintile (Bremershaven, Wuppertal) other regions are among the lowest (Emsland, Borken, Aschaffenburg, Trier).

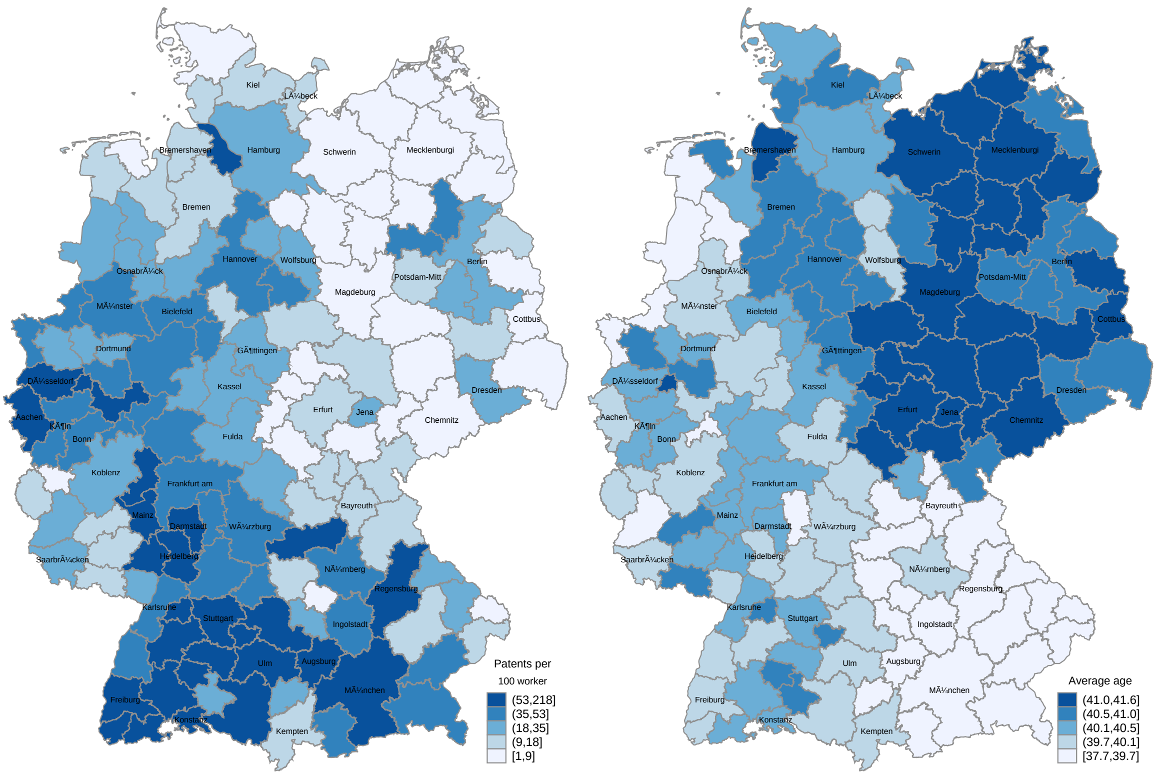
Overall, the maps show that both variables vary largely on a regional scale. The regional variation suggests systematic differences between East and West Germany, which will be taken into account in the regression analysis. Moreover, Figure 1 is already indicative for the potential endogeneity that we face. In particular, innovative regions may be attractive for individuals of certain age groups, thus suggesting the causal link between age and innovation to work in both directions. Moreover, the regional age structure is likely to be closely linked to other relevant characteristics of the regional workforce, especially the skill structure. The empirical analysis in

[4]Burda and Hunt (2001) and Hunt (2004) provide empirical evidence for age-selective migration patterns of East-West migration after reunion and discuss the corresponding reasons.

Figure 1: Quantile maps of the number of patents per 100 worker and average workforce age for 141 labour market regions (average values, 1995-2008)

(a) Number of patents per 100 worker

(b) Average workforce age



the next section, needs to address these concerns by following an Instrumental Variables (IV) approach in order to isolate the causal impact of ageing on regional innovations. For this, we later use historical population age shares as instruments for our workforce age structure.

Table 1 contains the mean summary statistics for German regions across the entire time period 1995-2008. The table includes the averages for all regions (Column 1), for the lowest innovative regions (Column 2) and for the highest innovative (Column 3) regions. For the calculation of the means for the lowest and highest innovative regions we sort all regions by their number of patents per 100 worker and define the upper and lower quintile of this distribution. We then calculate the regional characteristics for both quintiles. In order to get an impression on the divide between the lowest and highest innovative regions, Column (4) shows the differential between columns (3) and (2). Whereas the most innovative regions generated, on average, 80.81 patents per worker, the lowest innovative regions contributed only 5.2. The patent efficiency gap of 76.61 demonstrates the large innovation divide across German regions. Table 1 demonstrates that this innovation gap coincides largely with well-known drivers of innovation. For instance, innovative regions exhibit larger public and private R&D expenditures, larger workforce and population densities and larger shares of creative professionals. Interestingly, innovation hubs show larger (smaller) shares of high- and low-skilled (medium skilled) workers, which might reflect recent results from task-based approaches which speak in favour of a technology induced job polarisation on the labour market Autor, Levy, and Murnane (2003). Moreover, knowledge creators comprise higher (lower) share of younger (older and mid-aged) workers, which is also relfected in the lower average workforce age. Finally, idea-driven labour markets show a higher age diversity.

Table 1: Summary statistics for (20-percent) lowest and highest innovative labour market regions (average values, 1995-2008)

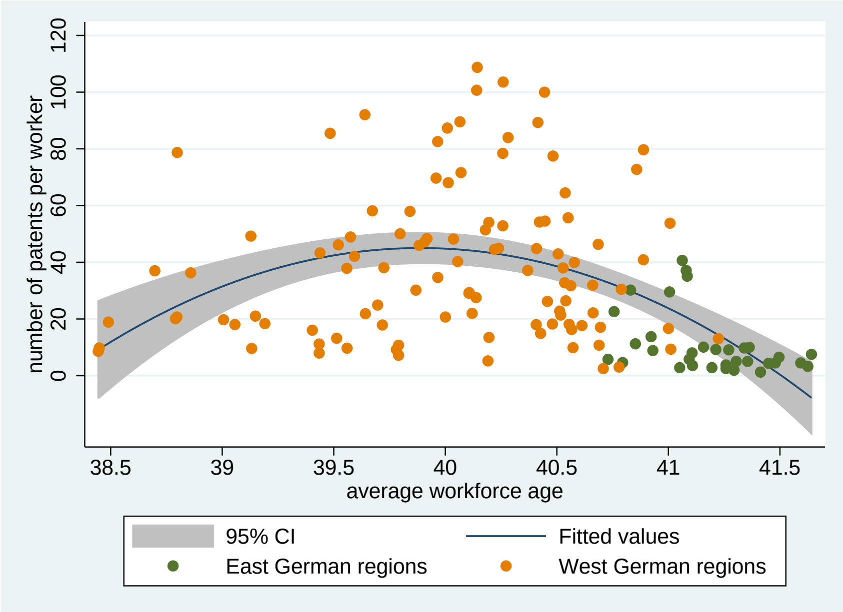
Variable	(1) All regions	(2) Lowest innovative regions	(3) Highest innovative regions	(4) Differential between (3) and (2)	Data Source*
number of patents per worker	33.87	5.20	80.81	75.61	EPO
average workforce age	40.28	40.91	40.17	-0.74	SIAB
workforce age dispersion	10.35	10.18	10.47	0.29	SIAB
workers younger than 36 (in percent)	18.08	16.08	18.54	2.46	SIAB
workers between 36 and 49 (in percent)	59.99	60.71	59.46	-1.25	SIAB
workers older than 49 (in percent)	21.92	23.21	22.01	-1.21	SIAB
creative professionals (in percent)	5.12	3.69	6.26	2.56	SIAB
bohemians (in percent)	0.68	0.63	0.83	0.19	SIAB
high-skilled workers (in percent)	5.72	6.01	6.59	0.58	SIAB
medium-skilled workers (in percent)	82.73	88.01	78.08	-9.94	SIAB
low-skilled workers (in percent)	11.55	5.97	15.33	9.36	SIAB
workforce size (in 1000)	4.10	2.61	4.96	2.35	SIAB
private R&D expenditures (in 1000 Euro)	243.92	19.97	624.78	604.81	GST
public R&D expenditures (in 1000 Euro)	135.19	38.04	217.87	179.83	DeStatis
population density (population per 100 km2)	443.11	226.30	630.83	404.53	DeStatis

* EPO: European Patent Office, SIAB: Sample of Integrated Labour Market Biographies released by German Federal Employment Agency, DeStatis: Regional database released by Federal Statistical Office, GST: German Stifterverband (Innovation Agency for the German science system)

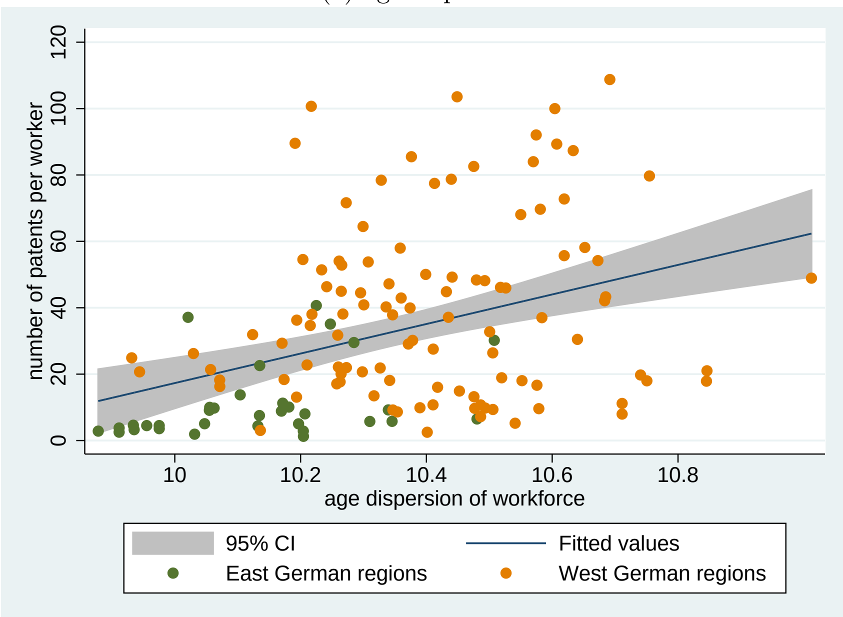
The descriptive evidence so far indicates that innovative regions have a younger and more homogenous workforce. In order to check this hypothesis more directly, Figure 2 shows scatterplot graphs for average workforce age and age diversity (both on x-axis) and patents production (y-axis). The fitted line in case of average age (quadratic prediction) hints at an inverse-U shaped age-innovation profile at the regional level. East German regions thereby agglomerate around the downward sloping part of the curve. Furthermore, the scatterplot for age diversity (fitted line is a linear prediction) hints at a positive relationship between a more age heterogenous workforce and innovation production. Again, East German regions agglomerate at the bottom left part of the scatterplot, indicating an old, homogenous and low innovative part of the country.

Figure 2: Scatterplots between average workforce age, age dispersion and patent production (average values, 1995-2008)

(a) average workforce age



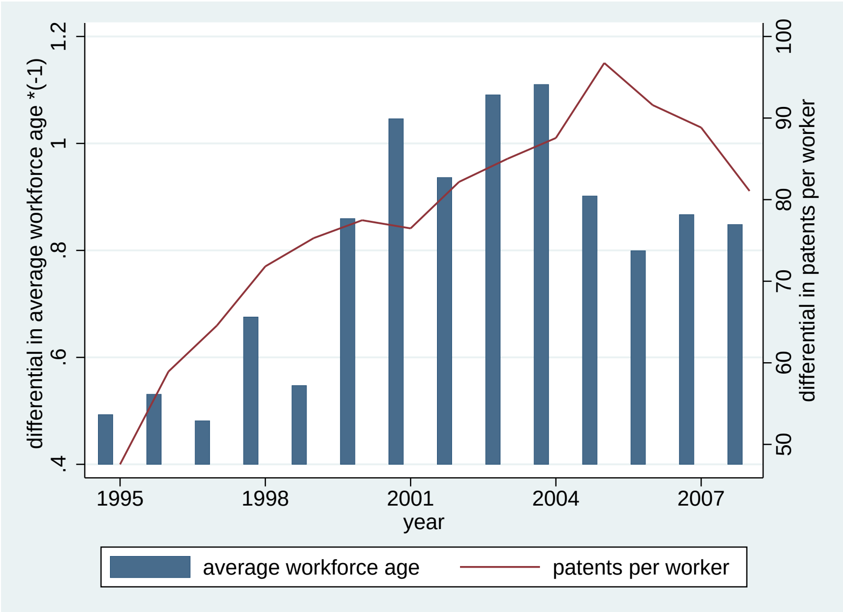
(a) age dispersion



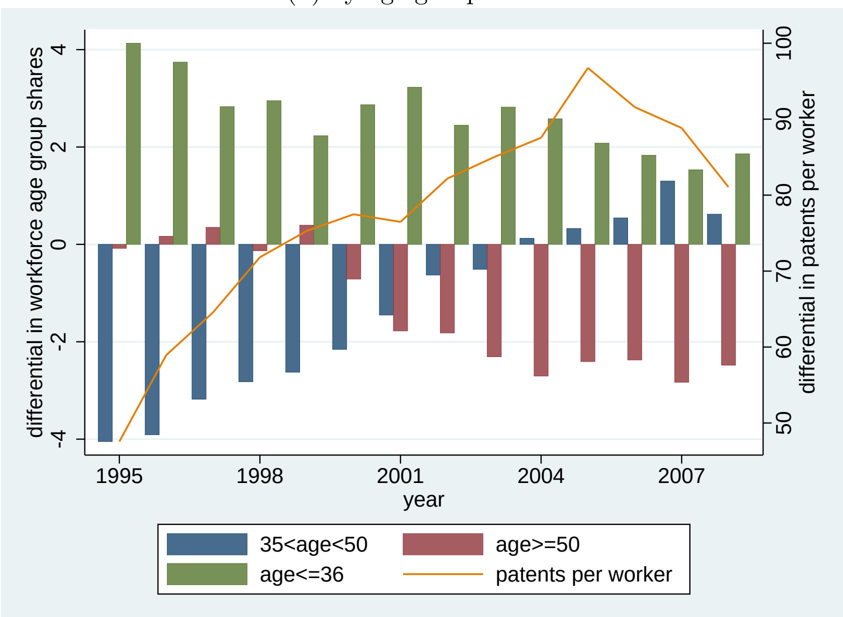
In order to get a better impression on how the innovation and demographic gap have developed over time and whether an increase in the demographic divide coincides with an increase in the innovation divide, Figure 3 depicts the differentials of patents per worker and average workforce age between the lowest and highest innovative regions over time (graph a). For a more detailed picture we also depict a similar graph for the three different age group shares (graph b). The results show that the innovation gap increased steadily until 2005, before declining slightly during the last three years. In 2008, the innovation hubs generated 80 patents per workers more compared to their weakest counterparts. Interestingly, the gap in the average workforce age increased further as well. Until 2004, a typical high innovation regions had an average workforce age that was around 1.1 years younger than low innovation regions. Interestingly, similar to the innovation gap, this gap closed somewhat during the end of the observation period.

Figure 3: Differential in patent production, average workforce age and age group shares between the highest and lowest innovative labour market regions (1995-2008)

(a) average workforce age



(b) by age-group shares



The development by age group shares (graph b) allows a more detailed view of the demographic change. In particular, the development shows that the aggregate trends discussed above are mainly driven by decreasing shares of older workers in innovation hubs, rather than increasing share of younger ones. The bar graph also shows that idea-driven labour markets are experiencing increasing shares of typically productive mid-aged workers compared to their unproductive counterparts. The results suggests that well performing regions are faced with a relatively favourable demographic development, whereas weak performing regions are confronted with a relatively unfavourable development with respect to their demographic age structure. Of course, whether there exists a causal link between workforce age structure and innovation stands to be tested by means of an regression analysis conducted in the following section.

Interestingly, the observed patterns also hint at possible substitution processes. Obviously, innovation regions seem to have relatively attracted more mid-aged workers at the expense of older and partly younger workers (compared to less productive regions). This might reflect, that innovative companies increasingly seek for high-qualified, experienced and particularly productive workers. However, it might also simply reflect out-migration trends of mid-aged workers that has increased the relative measure towards innovative regions. In the supplement versions of this paper we will therefore explicitly estimate the substitution elasticity between different age groups.

4 Empirical Analysis

4.1 Estimation approach

The objective of the empirical analysis is to estimate the knowledge production function as described in Section 2 with the regional age structure and the stock of age-specific human capital as our central input measures. To identify the model we exploit the variation that is given across the 141 labour market regions between the time period 1994-2008. For the estimation we apply two different approaches: (A) a cross-sectional estimation and (B) a panel estimation approach, both discussed in the following.

(A) Cross-sectional estimation. The advantage of the cross-sectional estimation is that it is less likely to be biased by the endogeneity of (period-wise) migration as in a panel approach. The reason is that the age structure of the workforce that we observe at any given point in time always results from two distinct forces: migration and natural population movements (new cohorts entering and exiting the labour market). To the extent that the regional age structure is inherited from the past due to past economic shocks that are not related to the contemporary innovation activity, but that still affect the contemporary age structure, the reversed causality should be less of a concern. In contrast, changes in the regional age structure over time are strongly determined by endogenous forces such as migration. Hence, as suggested by Brunow and Hirte (2006) one approach to mitigate the endogeneity of the age structure is to exploit the cross-sectional variation only since interregional differences in the age structure mainly reflect differences in the age structure of the non-migrant workforce. We thus take logs of the knowledge production function in section 2) and estimate the OLS-model for a cross-section of regions where all variables are defined as the average values between 1995 and 2008:

$$\ln P_i = \alpha + \beta \ln RD_i + \gamma_1 MAGE_i + \gamma_2 MAGE_i^2 + \gamma_4 PROF_i + \delta X_i + u_i$$

where P_{it} stands for the number of patents in region i, RD reflects public and private R&D expenditures and HK_{it} the human capital base of the regional economy. HK_{it} again comprises several human capital inputs including the share of creative professionals in a region, $PROF$, the mean age of the regional workforce, $MAGE$, and its squared term to allow for a non-linear age-innovation profile as suggested by the descriptive results in Section 3. In addition, X_i captures factors that may affect innovation outcomes and could potentially be related to the regional age structure such as population density, the structure of the regional industry base measured by the regional employment share of 16 industries, the size of the workforce as well as a dummy for East-West differences.

Although we argue in favor of this cross-sectional approach in order to mitigate the problems arising from endogenous migration, it is unlikely that the endogeneity problem has been fully resolved. For this reason, we instrument the current workforce age structure with lagged population shares. Similar to Feyrer (2007) we argue that contemporaneous population demographics will strongly covary with workforce demographics and at the same time should be orthogonal to age-specific participation rates in the innovation sector. Using lagged population demographics as an instrument then addresses migration, and, more generally, reverse causality. For the instrumentation we exploit historical population shares for the working-age population that is available from the German Statistical Office starting from 1985. The population data includes 17 population shares for the entire population. For our IV specification we use both the population shares and sizes, depending on the significance in the first stage estimates. Moreover, we add the squared term of the predicted mean age based on the first stage estimates as an additional instrument for age squared as suggested by Wooldridge (2002). Note, that at this stage, the coefficients of interest may still be biased due to unobserved regional heterogeneity. For this reason, we also exploit the panel dimension in order to mitigate this bias, but this comes at the cost of aggravating the reversed causality problem.

(B) Panel estimation. One main disadvantage of the cross-section model is that unobserved factors may still bias the estimates. If, for example, a region has institutions or a certain culture that support an ageappropriate working environment, we would not want such factors to confound our estimates. To the extent that such factors are time-constant, we can estimate the above model based on a panel and add regional fixed effects in order to eliminate such potential biases. In particular, we collapse our yearly panel to a panel of five periods, each comprising three years ($t1 : 1994 - 1996$, $t2 : 1997 - 1999$, $t3 : 2000 - 2002$, $t4 : 2003 - 2005$, $t5 : 2006 - 2008$, $t6 : 1994 - 1996$). We do so by calculating average regional values for all these periods.[5] We then estimate the following model:

$$\ln P_{it} \quad = \quad \alpha + \beta \ln RD_{it} + \gamma_1 MAGE_{it} + \gamma_2 MAGE_{it}^2 + \gamma_4 PROF_{it} + \delta X_{it} + c_i + t + \epsilon_{it}$$

where the composite error consists of the region fixed effect c_i as well as an idiosyncratic error term ϵ_{it}. The term t captures a potential time trend. Note that this model controls for all kinds of regional amenities that otherwise would confound our estimates. We apply a similar instrumental variable approach using population shares lagged 3 periods ($t - 1 : 1991 - 1993$, $t - 2 : 1988 - 1990$, $t - 3 : 1985 - 1987$).

4.2 Results

Table 2 shows the cross-section results starting with a basic OLS specification with R&D and human capital inputs only (Column 1). We then successively add controls for agglomeration (measured by population density), workforce size (Column 2) and industry dummies (Column 3). Finally, Columns (4)-(6) report the instrumental variables estimates and its results from the first stage. The IV model is estimated with the general methods of moments (GMM) estimator. The elasticity for private sector R&D expenditures range between 0.35-0.57. For public sector R&D we find a smaller elasticities between 0.02-0.07. The findings are very similar to other

[5] Some of the variables are only available for the time period after 1994. For these variables we calculate the first time period based on the years 1995 and 1996 only.

studies on the German regional innovation system such as the one by Fritsch and Slavtchev (2007). Based on a random effects panel model, the authors find a production elasticities of private sector R&D between 0.22 and 0.17. Also, similar to the latter study we find only a small impact of university funding on regional innovations. Thus, our model is able to replicate standard findings found in the literature.

Table 2: Estimation of the regional number of patents with OLS and IV (cross-section, 1995-2008)

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	IV GMM	first stages	
Dependent variable: num. of patents (log)	$\ln P_{it}$	$\ln P_{it}$	$\ln P_{it}$	$\ln P_{it}$	$MAGE_{it}$	$MAGE_{it}^2$
R&D INPUTS						
private RaD exp. (log, in 100 tsd Euro)	0.57***	0.48***	0.41***	0.35***	-0.04	-3.26
	(11.51)	(9.17)	(8.74)	(5.33)	(-0.82)	(-0.84)
public RaD exp. (log, in 100 tsd Euro)	0.05**	0.04**	0.05**	0.08**	0.02	1.87
	(2.37)	(2.07)	(2.29)	(2.42)	(0.87)	(0.90)
HUMAN CAPITAL INPUTS						
average workforce age	18.20***	20.95***	20.75***	70.20***		
	(3.08)	(3.75)	(4.20)	(2.68)		
average workforce age (squared)	-0.23***	-0.26***	-0.26***	-0.88***		
	(-3.09)	(-3.78)	(-4.23)	(-2.69)		
num. of creative professionals (in log)	0.16*	0.37	0.10	0.09	-0.42*	-33.73*
	(1.90)	(1.43)	(0.35)	(0.28)	(-1.74)	(-1.75)
REGIONAL INDICATORS						
dummy for East Germany	-0.58***	-0.19	-0.07	0.17	-0.25	-19.98
	(-3.59)	(-1.14)	(-0.34)	(0.58)	(-1.00)	(-1.01)
population density (log, in tsd)		0.40***	0.34***	0.46***	0.06	4.83
		(4.46)	(3.77)	(4.12)	(0.60)	(0.63)
workforce size (log, in tsd)		-0.28	0.08	0.09	0.32	25.26
		(-1.13)	(0.30)	(0.28)	(1.17)	(1.17)
INSTRUMENTS: POPULATION SHARES IN 1985						
lagged pop. share, 15-18 (in log)					455.3***	36404.3***
					(2.72)	(2.72)
lagged pop. share, 18-20 (in log)					-597.0***	-47691.6***
					(-2.81)	(-2.80)
lagged pop. share, 30-35 (in log)					-16.1**	-1268.8**
					(-2.24)	(-2.21)
lagged pop. share, 40-45 (in log)					43.2***	3452.5***
					(3.85)	(3.88)
constant	-360.29***	-412.45***	-416.72***	-1398.8***	45.41***	2031.3***
	(-3.05)	(-3.71)	(-4.27)	(-2.67)	(12.93)	(7.32)
With industry dummies?	no	no	yes	yes	yes	yes
N	141	141	141	141	141	141
R^2	0.910	0.926	0.946	0.894	0.800	0.804
F	229.4	232.8	131.7	89.4	19.2	19.8
F-Test of excluded instruments					16.04	16.31
Hansen (J statistic)				0.812		
Hansen (p-value)				0.666		

Note: t statistics in parentheses * p<0.10, ** p<0.05, *** p<0.01; columns (3)-(6) include industry-dummies (16 categories). The IV model is estimated with the general methods of moments (GMM) estimator.

Regarding the main variables of interest, we find a significant and strong impact of the regional age structure on knowledge production. In particular, the coefficients of the mean age and its squared term suggest a hump-shaped relationship between the average workforce age and innovations. In order to quantify the exact size of the effects, we will calculate and plot the age-innovation profile later on (see Figure 4). The estimates are robust across different specifications including IV GMM. The latter suggests that simple reverse causality from innovations to demographics is not driving the results. In fact, the orthogonality restrictions of the instruments and the estimated residuals are accepted in the model by the Hansen Test. Also, the first stages show values for the F-Test of excluded instruments above 10 which suggests that our estimates are not suffering from weak instruments.

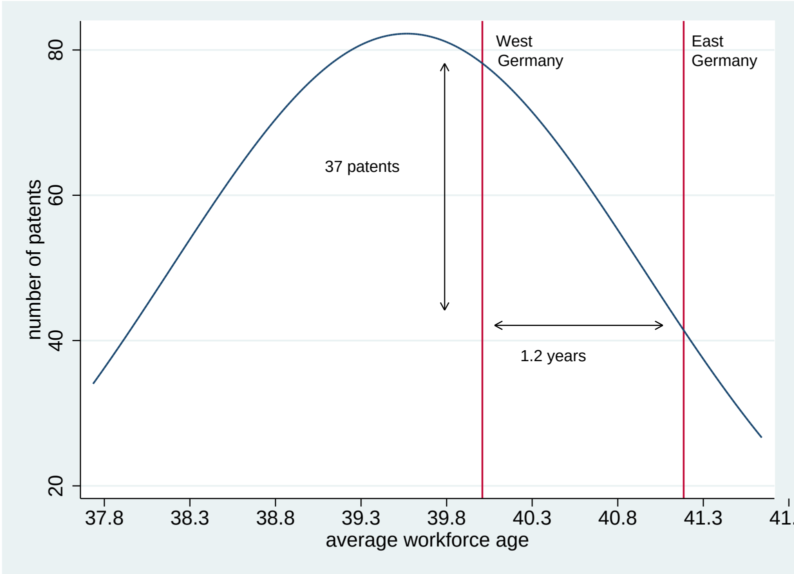
The remaining controls show plausible outcomes. For instance, the number of creative professionals has a positive and significant (at the 10 percent level) impact on innovations in the basic specification. Also, being located in East Germany significantly negatively reduces idea creation. These coefficients turn insignificant once population density is controlled for. This makes sense, since agglomeration captures most of the East-West differences due to the large rural landscape with mostly less innovative industries in East Germany. Moreover, most professionals operate in agglomerated areas. Finally, workforce size shows insignificant coefficients, which suggests that most of its variation is already captured by population density.

Despite the dummy for East Germany in our model, the results in Table 2 may still be driven by systematic East-West differences. Therefore, we run separate regressions for West German regions only. The results are shown in Table 4 in the appendix and confirm the former findings.

Figure 4 shows the estimated age-innovation profile based on the IV GMM model in Table 2. The pattern clearly reflects the hump-shaped pattern of average regional workforce age and innovation. We are now interested in how the differences in the average workforce age between East and West German regions contribute to the overall divide in patent production. According to calculations, the overall gap is 189-45=144 patents, that is an East German region exhibits, on average, about 144 patents more compared to a typical West German region. Calculating the predicted patents for an average region based on the age-innovation profile yields 118 patents for West Germany and 23 for East Germany, which makes a difference of 95 patents. Thus, 95 out of 144 patents can be explained by different average ages (about 1.2 years, on average) between East and West Germany. In other words, regional differences in the age structure between East and West Germany are able to explain almost 65 percent of the East-West knowledge production gap.

We now turn to the results for the panel estimation. In particular, Table 2 shows the

Figure 4: Regional age-innovation profile, cross-section (1995-2008)



results for pooled OLS (Column 1), pooled OLS with a time trend (Column 2), fixed effects (Column 3) and the reduced form estimates of the instrumental variables estimates (Column 4). The first stage estimates of the IV model are reported in columns (5) and (6). For the panel approach we use lagged population age-group sizes, since they turned out more significant compared to population shares. Overall, the model shows similar elasticities with respect to R&D expenditures. However, in the FE models, the size of the coefficients decreases strongly. This has also been found by other studies estimating regional knowledge production functions and reflects the fact that the impact of variables such as R&D, which do not change much over time, are included in the fixed effect (Fritsch and Slavtchev 2007). Regarding the impact of age structure on innovations, the coefficients show similar signs compared to the cross-section estimates, although only significant in the IV GMM model. The lower coefficient might hint at potential unobserved factors that are biasing the estimates from the cross-sectional approach upwards. The Hansen Test and the F-Test of excluded instruments suggest that our instruments are valid.

Again, in order to see whether the results are driven by East-West differences, Table 5 in the appendix shows the same regressions for West German regions only. The estimates turn significant in all specifications suggesting that changes in regional age structure in East Germany might have a reverse impact on innovation, thus counterbalancing the overall effects in Table 3.

Table 3: Estimation of the regional number of patents with POLS and FE IV GMM (panel, 1995-2008)

	(1)	(2)	(3)	(4)	(5)	(6)
	POLS	POLS	FE	FE IV GMM	first stages	
Dependent variable: num. of patents (log)	$\ln P_{it}$	$\ln P_{it}$	$\ln P_{it}$	$\ln P_{it}$	$MAGE_{it}$	$MAGE_{it}^2$
R&D INPUTS						
private RaD exp. (log, in 100 tsd Euro)	0.33***	0.32***	0.07***	0.05**	-0.02	-1.72
	(9.48)	(9.32)	(3.34)	(2.10)	(-0.94)	(-0.90)
public RaD exp. (log, in 100 tsd Euro)	0.06**	0.06***	-0.07**	-0.09***	-0.03	-2.28
	(2.29)	(2.66)	(-2.60)	(-3.43)	(-1.07)	(-1.15)
HUMAN CAPITAL INPUTS						
average workforce age	1.02	1.37	1.11	9.53***		
	(0.96)	(1.35)	(1.31)	(5.29)		
average workforce age (squared)	-0.01	-0.02	-0.01	-0.12***		
	(-0.96)	(-1.48)	(-1.38)	(-5.46)		
num. of creative professionals (in log)	0.21	0.28	0.17	-0.14	-0.12	-11.11
	(0.87)	(1.17)	(0.89)	(-0.63)	(-0.67)	(-0.81)
REGIONAL INDICATORS						
population density (log, in tsd)	0.20**	0.28***	2.04***	-0.10	-3.76***	-306.05***
	(2.30)	(3.12)	(2.95)	(-0.12)	(-6.30)	(-6.43)
workforce size (log, in tsd)	0.01	-0.03	-0.95*	-2.34***	0.36	13.27
	(0.04)	(-0.13)	(-1.80)	(-4.03)	(0.81)	(0.38)
time trend		0.15***	0.15***	0.37***	0.38***	31.38***
		(3.43)	(3.67)	(4.44)	(9.79)	(10.15)
INSTRUMENTS (LAGGED 3 INTERVALS=9 YEARS)						
lagged pop. group size, 10-15 (in log)					-1.17***	-84.72***
					(-3.33)	(-3.08)
lagged pop. group size, 15-18 (in log)					0.31**	28.68***
					(2.43)	(2.86)
lagged pop. group size, 20-25 (in log)					-1.14***	-89.10***
					(-5.24)	(-5.09)
lagged pop. group size, 35-40 (in log)					2.16***	162.40***
					(6.94)	(6.62)
constant	-28.76	-33.88*	-18.07			
	(-1.42)	(-1.74)	(-1.09)			
N	705	705	705	705	705	705
R^2	0.909	0.913	0.685	0.575	0.947	0.949
F	109.6	127.8	43.7	33.6	392.6	410.8
F-Test of excluded instruments					22.24	22.01
Hansen (J statistic)				1.840		
Hansen (p-value)				0.399		

Note: t statistics in parentheses * p<0.10, ** p<0.05, *** p<0.01; all estimations include industry-dummies (16 categories). The IV model is estimated with the general methods of moments (GMM) estimator. Standard errors are clustered by region.

5 Conclusion

The aim of this paper was to evaluate the causal effect of demographic age structure on innovation at the regional level. In particular, we were interested in whether regionally varying speeds of workforce ageing has increased the regional innovation divide in Germany. The study is motivated by the currently observed demographic trends across German labour markets: whereas few attractive regions are increasingly able to keep and attract young workers, other regions are suffering from out-migration of their youngest and educated workers. For this, we estimated a knowledge production function for functionally delineated labour market regions with the regional age structure as our central input measure. For the estimations we were able to address potential endogeneity of the regional workforce due to endogenous migration by exploiting the cross-sectional variation in the age structure of workers. We contrasted this approach to a panel estimation that is preferable with regard to unobserved regional heterogeneity, yet should be more problematic with regard to endogenous migration. Moreover, we use lagged population demographics as instruments to address potential endogeneity arising from age-selective migration and, more generally, to address reverse causality, mostly neglected in the current literature.

Overall, we find a hump-shaped age-innovation profile suggesting that the aggregate impact of demographic ageing may in fact be negative. The results are robust across several specifications including an OLS IV and a panel fixed effects IV model. We further show that differences in the average age between the highest and lowest innovative regions are able to explain large parts of the innovation divide across West German labour markets.

However, the results are very preliminary. In future extensions of the analysis we want to estimate interaction effects between different age group shares in order to gain insights into potential complementarities between different age groups. Moreover, based on our results, we also plan to predict the future development of regional innovation outcome, given population projections.

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Appendix

Table 4: Estimation of the regional number of patents with OLS and IV for West Germany (cross-section, 1995-2008)

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	IV GMM	first stages	
Dependent variable: num. of patents (log)	$\ln P_{it}$	$\ln P_{it}$	$\ln P_{it}$	$\ln P_{it}$	$MAGE_{it}$	$MAGE^2_{it}$
R&D INPUTS						
private RaD exp. (log, in 100 tsd Euro)	0.53***	0.46***	0.40***	0.40***	-0.02	-1.59
	(9.11)	(7.67)	(8.16)	(10.02)	(-0.40)	(-0.41)
public RaD exp. (log, in 100 tsd Euro)	0.04	0.03	0.03	0.02	0.04	3.57
	(1.47)	(1.25)	(1.21)	(1.15)	(1.59)	(1.62)
HUMAN CAPITAL INPUTS						
average workforce age	16.00**	19.66***	19.72***	27.73**		
	(2.40)	(3.24)	(3.27)	(1.98)		
average workforce age (squared)	-0.20**	-0.25***	-0.25***	-0.35**		
	(-2.40)	(-3.26)	(-3.28)	(-2.00)		
number of creative professionals (in log)	0.23**	0.45	-0.08	-0.12	-0.06	-5.32
	(2.48)	(1.55)	(-0.25)	(-0.43)	(-0.18)	(-0.19)
REGIONAL INDICATORS						
population density (log, in tsd)		0.41***	0.33***	0.38***	0.15	12.06
		(4.29)	(2.99)	(3.83)	(1.25)	(1.30)
workforce size (log, in tsd)		-0.31	0.33	0.37	-0.10	-7.57
		(-1.12)	(1.09)	(1.41)	(-0.26)	(-0.25)
INSTRUMENTS: POPULATION SHARES IN 1985						
lagged pop. share, 10-15 (in log)					-54.72**	-4253.8**
					(-2.23)	(-2.19)
lagged pop. share, 15-18 (in log)					608.77***	48672.0***
					(2.75)	(2.77)
lagged pop. share, 18-20 (in log)					-716.17**	-57386.4**
					(-2.58)	(-2.60)
lagged pop. share, 30-35 (in log)					-20.32*	-1631.4*
					(-1.94)	(-1.96)
lagged pop. share, 40-45 (in log)					46.85***	3749.6***
					(3.61)	(3.65)
constant	-317.23**	-387.32***	-395.00***	-551.6**	42.53***	1792.9***
	(-2.39)	(-3.21)	(-3.31)	(-1.98)	(8.64)	(4.60)
With industry dummies?	no	no	yes	yes	yes	yes
N	108	108	108	108	108	108
R^2	0.886	0.910	0.939	0.936	0.764	0.765
F	161.7	162.9	111.7	100.0	11.2	11.6
F-Test of excluded instruments					16.04	16.31
Hansen (J statistic)				3.011		
Hansen (p-value)				0.390		

Note: t statistics in parentheses * p<0.10, ** p<0.05, *** p<0.01; columns (3)-(6) include industry-dummies (16 categories). The IV model is estimated with the general methods of moments (GMM) estimator.

Table 5: Estimation of the regional number of patents with POLS and FE IV GMM for West Germany (panel, 1995-2008)

	(1)	(2)	(3)	(4)	(5)	(6)
	POLS	POLS	FE	FE IV GMM	first stages	
Dependent variable: num. of patents (log)	$\ln P_{it}$	$\ln P_{it}$	$\ln P_{it}$	$\ln P_{it}$	$MAGE_{it}$	$MAGE_{it}^2$
R&D INPUTS						
private RaD exp. (log, in 100 tsd Euro)	0.32***	0.32***	0.08***	0.07***	-0.00	0.02
	(8.03)	(7.87)	(3.18)	(2.74)	(-0.04)	(0.01)
public RaD exp. (log, in 100 tsd Euro)	0.03	0.04	-0.06**	-0.09***	-0.03	-2.48
	(1.16)	(1.34)	(-2.05)	(-3.63)	(-1.05)	(-1.17)
HUMAN CAPITAL INPUTS						
average workforce age	2.50**	3.06***	1.77*	7.70***		
	(2.26)	(2.97)	(1.86)	(4.42)		
average workforce age (squared)	-0.03**	-0.04***	-0.02**	-0.10***		
	(-2.29)	(-3.10)	(-1.99)	(-4.69)		
num. of creative professionals (in log)	0.05	0.12	0.04	-0.07	0.04	2.53
	(0.21)	(0.48)	(0.18)	(-0.32)	(0.19)	(0.15)
REGIONAL INDICATORS						
population density (log, in tsd)	0.19**	0.26**	-0.05	-3.48***	-4.29***	-353.81***
	(2.01)	(2.47)	(-0.06)	(-3.03)	(-4.43)	(-4.57)
workforce size (log, in tsd)	0.24	0.18	-0.32	-1.38*	0.93	56.18
	(0.92)	(0.70)	(-0.46)	(-1.81)	(1.47)	(1.12)
time trend		0.09**	0.17***	0.54***	0.47***	38.48***
		(2.00)	(3.49)	(5.15)	(7.43)	(7.73)
INSTRUMENTS (LAGGED 3 INTERVALS=9 YEARS)						
lagged pop. group size, 10-15 (in log)					-1.75***	-127.62***
					(-3.81)	(-3.53)
lagged pop. group size, 15-18 (in log)					0.52**	43.67**
					(2.29)	(2.44)
lagged pop. group size, 20-25 (in log)					-0.96***	-77.54***
					(-3.05)	(-3.12)
lagged pop. group size, 35-40 (in log)					2.05***	150.81***
					(4.47)	(4.16)
constant	-53.28**	-64.09***	-34.59*			
	(-2.47)	(-3.17)	(-1.97)			
N	540	540	540	540	540	540
R^2	0.904	0.906	0.650	0.511	0.942	0.944
F	96.9	108.0	40.6	21.4	265.7	274.1
F-Test of excluded instruments					14.95	15.11
Hansen (J statistic)				1.430		
Hansen (p-value)				0.489		

Note: t statistics in parentheses * p<0.10, ** p<0.05, *** p<0.01; all estimations include industry-dummies (16 categories). The IV model is estimated with the general methods of moments (GMM) estimator. Standard errors are clustered by region.