Discussion Paper No. 15-001

# Individual Determinants of Inventor Productivity: Report and Preliminary Results with Evidence from Linked Human Capital and Patent Data

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## Abstract

This report offers new insights into the drivers of inventor productivity at the individual level. It includes well-known drivers, such as inventor age and education, and controls for inventor team size, and firm/applicant information, as well as period and technology field effects derived from patent data. In addition, it adds inventor characteristics that have been largely neglected in existing studies on inventor productivity, such as the breadth of work experience, divergent thinking skills, cognitive problem-solving skills, the use of knowledge sourced from networks within and outside of the inventors' field of expertise, and personality traits. The empirical model draws on a new dataset that matches information about inventors' human capital, such as creative skills, personality traits, networks, and career biographies (collected with a self-administered survey) with patenting histories for 1932 German inventors between the years 1978 and 2012 for clean technology, nanotechnology, and mechanical elements. Our results indicate that the additional inventor characteristics double the proportion of total variation of productivity explained by individual characteristics. Furthermore, we find differences in the importance of individual characteristics across industries and along the productivity distribution, between more and less productive inventors.

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# 1 Introduction and motivation

The past two decades of empirical research on the driving forces of invention have highlighted the role of knowledge stocks in scientific and technological fields, and the importance of knowledge spillover from firms or universities, resulting from mobility of R&D workers within regional industrial clusters and company networks (Anselin et al., 1997; Feldman, 1999; Murray, 2002). Furthermore, the internal resources of firms are of major importance for successful knowledge absorption (Cohen and Levinthal, 1990; Nooteboom et al., 2007).

The focus of empirical research on invention mirrors the trend that collective invention processes in private firms and large inventor teams are taking the place of independent work of a "lone genius" (Schmookler, 1957, as cited in Ejermo and Jung, 2011, p.5). This is a result of the emergence of corporate R&D in private firms and collective invention supplied by large R&D teams in the early 20$^{th}$ century (Mowery and Rosenberg, 1998, as cited in Ejermo and Jung, 2011, p. 4). Important topics in previous research on the determinants of inventor productivity at the individual level have been the patenting activities of European (Mariani and Romanelli, 2007; Gambardella et al., 2012), Italian (Lissoni et al., 2008), and Swedish (Ejermo and Jung, 2011) inventors, and the effect of age (Jones, 2010, Hoisl, 2007) and job mobility (Hoisl, 2007, 2009) on inventive performance.

However, mainly because of limitations in data availability, the inventor characteristics included are in most cases very general; usually age, gender, and educational level. Potentially important information on individual drivers of inventor productivity, such as professional experience, knowledge, skills, abilities, and personality traits are typically missing.

In this report, we explore the importance for productivity of additional individual characteristics, such as breadth of work experience, divergent thinking skills, cognitive problem-solving skills, and the use of knowledge sourced from networks, and personality traits. Based on the neoclassical economic theory of human capital (Becker, 1971; Mincer, 1974), we argue that although technological progress has become the business of private or public corporations and large teams of inventors over the past few decades, the talent, motivation, personality, and human capital endowments of the individual inventor are important for the development of technological inventions. Without human capital to make use of corporate R&D infrastructure, there would be no invention.

In particular, we investigate the effect of an extensive list of additional individual inventor characteristics on inventor productivity. We use a new dataset that matches information on inventors' human capital (skills, personality traits, networks, and career biographies) collected from a self-administered survey with patenting histories for 1932 German inventors between 1978 and 2012. To compare the inventor characteristics, we focus on inventors from the technology fields of clean technology (CT), nanotechnology (NT), and mechanical elements (ME). We compare the drivers of inventions for our three technological sectors and investigate whether these drivers differ for more and less productive inventors.

Please note that this report intends to inform the reader about the basic results of our project. It focuses on technical and data aspects and will be used as the basis for further publications and discussion papers.

The report is organized as follows. Section 2 describes the research design, Section 3 presents the results of multivariate regression models, and Section 4 offers a discussion of the results and our conclusions.

# 2 Research design

## *2.1 Data source and sample*

The data for this report were collected by means of a self-administered survey of German inventors active in CT, NT, and ME. CT and NT patents were extracted from the Worldwide Patent Statistical Database (PATSTAT) as of April 2012. Additionally, we received a list of CT patents from the Organisation for Economic Co-operation and Development (OECD) based on the taxonomy developed by the Environment Directorate of the OECD (ENV-TECH)[1]. To identify patents in ME, the ISI-OST-INPI classification was used (Schmoch, 2008).

Based on a list of all European (EP) patent applications in the three fields, with priority dates between 2004 and 2008, we identified all patent applications assigned to the three fields that listed at least one inventor with a home address in Germany. This resulted in 16,593 EP patent applications. Applications with missing address information, incomplete inventor names, and applications that listed deceased inventors were removed from the dataset. This resulted in a sample of 16,485 EP patent applications: 11,108 from CT, 2170 from NT, 3953 from ME, and 373 patent applications were assigned to more than one of the three technological areas[2]. In a second step, we identified unique inventors listed on the patent documents who had an address in Germany at the time of the patent filing. We removed 458 inventors from the sample (305 inventors mentioned on CT patents and 153 inventors mentioned on ME patents) because we wanted to question them in another survey (Frosch et al., 2014). In addition, 150 inventors were used to pretest our survey instrument (100 inventors mentioned on CT patents and 25 inventors each mentioned on NT and ME patents). We kept all inventors listed on CT or NT patents and, for budgetary reasons, selected 35% of the inventors listed on patents assigned to ME at random (2402 inventors). This resulted in 9586 inventors in our basic sample (see Table 1 for the distribution across technological areas).

We developed the survey instrument and pretested it with 150 pretest inventors between February and March 2013. In April 2013, we sent out invitation letters containing a link to our online questionnaire to the remaining 9586 inventors. A reminder letter was sent out in July 2013. Up to the end of August 2013, we received 1932 responses, yielding a corrected[3] response rate of 29.5%. Table 1 presents details of the sample sizes and the response rates.

**Table 1:** Sample sizes and number of responses by technology field.

| **Technology field** | **Sample size** (# inventors) | **Responses (N)** | **Response rate [%]** | **Corrected response rate [%]** |
|---|---|---|---|---|
| Clean technology (CT) | 5911 (all) | 1174 | 19.9 | |
| Nanotechnology (NT) | 1273 (all) | 232 | 18.2 | |
| Mechanical elements (ME) | 2402 (random sample [A)]) | 526 | 21.9 | |
| **Total** | **9586** | **1932** | **20.2** | **29.5** |

Notes:
[A)] Random sample drawn from a total of 6856 ME inventors.

To trace the productivity of the inventors over time, we searched for all patent applications of the responding inventors between the years 1978 and 2012 using PATSTAT as of April 2012, provided by the European Patent Office (EPO). The name matching was conducted using the standard identification number (ID) provided by PATSTAT. In a second step, we corrected the matches manually. This resulted in a total number of 13,190 EP patent applications. As the data are truncated in the most recent years (publication lag, grant lag, citation lag, etc.), we base our empirical analysis on EP patents filed between the years 1978 and 2010.

[1] See http://www.oecd.org/env/consumption-innovation/ENV-tech%20search%20strategies%20for%20OECDstat%20%282013%29.pdf, accessed on July 24, 2014.
[2] Patents can belong to more than one technology field. Possible combinations are: ME + CT, ME + NT, CT + NT, ME + CT + NT.
[3] Inventors who could not be reached because they had wrong addresses (2395) or were unknown (626), as well as 23 inventors who had already passed away were excluded from the original sample. To identify wrong addresses, we used a service provided by the German Post Office that identifies undeliverable letters based on their database of German addresses.

The data were supplemented[4] with bibliographic and procedural information on the respective patent, obtained from PATSTAT as of April 2012 and the European Patents Administration System (EPASYS) database as of 2012. Added data include technology classes, forward and backward citations, the number of co-inventors, and the type of applicant organization.

The matched data set allows us to add inventors' career paths, use of knowledge and networks, and stable inventor characteristics, such as personality traits, cognitive skills, and professional/career interests, to well-known individual patent applicant and patent characteristic determinants of inventive productivity, such as age or educational level. To our knowledge, no other dataset combining linked independent data sources contains all this information. This report provides an overview of selected variables from this extensive dataset, with a focus on human capital that is potentially relevant for inventive activity.

### *2.2 Variables and measurement*

#### *2.2.1 Dependent variable*

To test the robustness of our results, we measure inventive productivity, *P*, using the following four alternative indicators.

(1) The average yearly number of patent applications for inventor *i*, corrected for the size of the inventor team, $n_j$, is the **average fractional patent count**, $P_{av,i}$. This is computed as the sum of all fractional patent applications, *J*, filed between 1978 and 2010 listing inventor *i*, divided by the years of (potential) professional experience[5] accumulated until 2010, $EXP_i = 2010 - t_{0i}$, where $t_{0i}$ is the year of labour market entry provided by the inventor survey.

$$P_{av,i} = \frac{\sum_{j=1}^{J} \frac{1}{n_j}}{EXP_i}.$$

(2) The average yearly quality of patent applications for inventor *i* corrected for the size of the inventor team, $n_j$, is the **average fractional citation count**, $C_{av,i}$. This is computed as the sum of fractional patent citations (Narin and Breitzman, 1995, p. 510), $C_j/n_j$, received within five years following the publication of the patent search report (i.e. the report drafted by the patent examiners containing prior art that might impede patentability of the invention)[6] for applications, *J*, filed between 1978 and 2010, divided by the years of (potential) professional experience accumulated until the year 2010, $EXP_i$.

$$C_{av,i} = \frac{\sum_{j=1}^{J} \frac{C_j}{n_j}}{EXP_i}$$

[4] Examples of other studies that combine inventor survey data with patent data are Giuri et al. (2007), Nagoaka and Walsh (2009), and Heibel (2012).

[5] Potential professional experience provides a good proxy for actual professional experience. In particular, answers to our questionnaire indicate that 88% of the inventors in our sample have been continuously employed or self-employed since they entered the labour market. Only 3% have experienced periods of unemployment amounting to one quarter of their work life or more.

[6] For very recent years, the citation data are truncated. To avoid biased results in our regressions, we control for filing years and only use patents filed until the year 2010.

(3) The binary variable, $C_{bin,j}$, indicates whether patent *J* receives at least as many ($C_{bin,fract,j} = 1$) or fewer ($C_{bin,fract,j} = 0$) fractional citations than the average patent in the same priority year, *t*, and technology field, *k*.

$$C_{bin,fract,j} = \begin{cases} 1 \; if \; \dfrac{C_j}{n_j} \geq \overline{C}_{k_j t_j, fract} \\ 0 \; if \; \dfrac{C_j}{n_j} < \overline{C}_{k_j t_j, fract} \end{cases}$$

Average standardized citation counts for inventor *i* can then be computed as sum of the binary indicators for all patents *J* of inventor *i*, divided by the number of work years to give the **average above-average citation count** as

$$C_{av,i} = \frac{\sum_{j=1}^{J} C_{bin,fract,j}}{EXP_i}$$

To allow productivity comparisons between our three technology fields CT, NT, and ME, we additionally compute technology-specific average yearly inventor productivity, then only taking into account the citations for patents filed in the respective technology field, *f (f = ME, CT, NT)* as

$$C_{av,i,f} = \frac{\sum_{j=1}^{J} C_{bin,j} \cdot D_{f,j}}{EXP_i} \quad \text{with} \quad D_{f,i} = \begin{cases} 1 \; if \;\; patent \;\; was \;\; filed \;\; in \; techn. \;\; field \;\; f \\ 0 \; otherwise \end{cases}$$

Note that **average patent counts, average citation counts**, and **average above-average citation counts** based on whole instead of fractional counts can be obtained by simply omitting the term $1/n_j$ in the formulas given in points (1)–(3), respectively.

For technology-specific analyses, we take into account patents exclusively in a field and restrict our sample to inventors who have at least one patent in that field.

### (4) Binary indicator to identify key inventors

Finally, we define a binary variable that takes the value 1 if inventor *i* is among the 10% top performers, termed "key inventors", in the sample, and zero otherwise. For technology-specific analyses, we again restrict our sample to inventors active in the respective fields. The binary indicator takes the value 1 if inventor *i* is among the 10% top performers with respect to the average quality of their patents in ME (CT or NT) compared with all inventors in our sample who are listed on at least one patent in our three technology fields.

**Table 2:** Overview of alternative productivity measures.

| | Quantitative vs. qualitative productivity [patent vs. citation counts] | Correction for the size of the inventor team [fractional vs. whole counts] | Standardization method (at the patent level) |
|---|---|---|---|
| (1) average fractional patent count<br>**avpatno_fract** | patents | fractional | no standardization |
| (2) average fractional citation count<br>**avcitno_fract** | citations | fractional | no standardization |
| (3) average above-average citation count<br><br>**<u>overall indicator:</u>**<br>**avcitno_fract_corrD**<br><br>**<u>technology-specific indicators:</u>**<br>**MEavcitno_fract_corrD**<br>**CTavcitno_fract_corrD**<br>**NTavcitno_fract_corrD** | citations | fractional | binary indicator: comparing (fractional) citation counts with the average (fractional) citation counts per year per field<br><br>technology-specific indicators only comprise patents in the respective technology field (ME, CT or NT). |
| (4a) binary indicator to identify key inventors<br>**ALLhigh_p90_v2D** | indicator is based on the average above-average citation count as described above. It takes the value 1 if an inventor is among the 10% top performers of the sample based on all patents per inventor. | | |
| (4b) binary indicator to identify key inventors within the respective technology field<br>**MEhigh_p90_v2D**<br>**CThigh_p90_v2D**<br>**NThigh_p90_v2D** | indicator is based on the average technology-specific above-average citation counts as described above. It takes the value 1 if an inventor is among the 10% top performers of the sample with respect to all patents in ME, CT or NT and compared with all other inventors with at least one patent in ME, CT or NT. | | |

### *2.2.2 Inventor characteristics*

We use explanatory variables controlling for characteristics of the inventor (inventor age and educational level), the inventor team, the applicant, and the technology as determinants of inventive productivity (Mariani and Romanelli, 2007; Hoisl, 2007; Hoisl, 2009; Gambardella et al., 2012; Schettino et al., 2013; Gruber et al., 2013). We use additional information about inventors' human capital endowments: accumulated work experience, cognitive and creative skills, and risk attitude, in addition to personality traits not previously included in regressions on inventive productivity. An overview of all the human capital variables used in this report is presented in the Figure 1.

**Inventor age** is measured by six dummy variables taking the value of one if the inventor was younger than 40 years, 40–44 years, 45–49 years, 50–54 years, 55–59 years, or older than 60 years in the year 2010, and zero otherwise.

**Inventor's human capital**

- **Education**

The inventor's highest formal **educational level** is measured by three dummy variables taking the value one if the inventor obtained a vocational education, conducted academic studies, or received a PhD, and zero otherwise.

- **Experience, skills and attitudes**

In addition to the general knowledge captured by the socio-demographic characteristics of the inventor, we also account for the personal characteristics of the inventor that may be related to inventive output. These are work experience, cognitive style of problem solving, divergent thinking, risk taking behaviour, personality, and knowledge sourcing behaviour.

We measure inventors' **breadth of work experience** based on the proportion of time they worked mainly as a generalist rather than a specialist during their professional career. The information is derived from a biographical calendar that was part of the inventor survey. For 5-year periods between 1965 and 2009, we asked for a self-assessment of whether the inventors worked mainly as a specialist or as a generalist. The proportion of time was calculated by dividing the number of periods assessed as generalist periods by the total number of 5-year employment periods.

**Systematic thinking style (cognitive problem-solving skills)** is assessed based on the Cognitive Reflection Test (CRT) proposed by Frederick (2005). The three-item short scale provides a simple measure for the cognitive thinking style of a person[7]. The respondents were presented three puzzles that are designed so that an intuitive answer springs quickly to mind, but the correct answer is only obtained if respondents reflect more systematically on the puzzle. The more correct answers are obtained, the more systematically the respondent reflects on problems. Wrong answers can be classified as either "wrong but intuitive" and "plainly wrong". To capture a tendency for systematic thinking, we create a variable that takes the value of the number of correct CRT answers; for example, the value is 3 if all three questions were answered correctly, and zero if all answers were wrong (whether intuitive or not).

**Divergent thinking skills** are assessed based on the Alternative Uses Task method suggested by Guilford (Guilford, 1967; Christensen et al., 1970; Guilford et al., 1978). The inventors were asked to list as many original and creative uses for a brick as possible within three minutes. Inventors named between zero and 38 ideas, with an average of eight ideas per respondent. The originality and creativity of each idea was independently assessed by three reviewers based on a scale ranging from 1 (not very creative) to 5 (very creative). The total score for each idea was computed as an average of the three individual scores. As an indicator for divergent thinking, we use the median score across all ideas named by an inventor if the inventor named any ideas.

The **risk attitude** is measured based on self-assessment. The variable is between 0 (highly risk adverse) and 10 (highly risk seeking).

- **Personality traits**

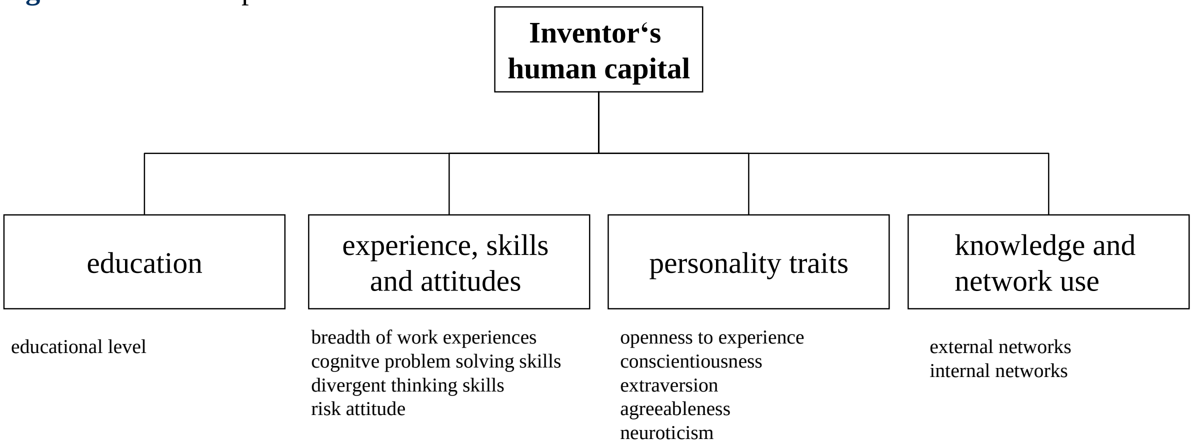
Inventor **personality** traits are assessed based on a 15-item short version of the BIG-5 personality inventory that is also used in the German Socio-Economic Panel GSOEP (Schupp and Gerlitz, 2008). The five personality dimensions were aggregated by averaging the three items corresponding to the respective dimension (negatively defined items were rescaled). According to the literature (McCrae, 1987; George and Zhou, 2001), the information on the personality trait "openness to experience" may have the strongest predictive power for inventive productivity.

- **Knowledge and network use**

We account for two different types of **knowledge sourced from networks:** knowledge obtained from networking with experts from the same field and from other fields of expertise. For each of the two knowledge sources, we use the importance, from 1 (very low importance) to 5 (very high importance), that the surveyed inventors assigned to the source.

[7] Cognitive style is based on two cognitive processes (Epstein, 1994; Sloman, 1996; Chaiken and Trope, 1999; Kahnemann and Frederick, 2002). If so-called system 1 processes are used, they produce spontaneous decisions and are "unaffected by intellect, alertness […] or difficulty of the […] problem" (Frederick, 2005, p. 26). However, system 2 processes lead to cognitive activation and concentration.

**Figure 1:** Human capital variables




Because this paper is intended to provide an overview of the dataset and the possibilities for analysis, we have deliberately chosen indicators that are close to the raw data when the indicators are used. For example, we use linear scores of the systematic problem-solving test, the divergent thinking tests scores, and the self-evaluation of risk attitude. We are aware that the relationship between these variables and inventive productivity may be nonlinear. In this case, using dummy variables for different levels of the variable might be a more appropriate approach. Similarly, instead of more sophisticated factor analysis, simple averages of the evaluations of the items belonging to each of the BIG-5 personality dimensions are used to process the information on personality. These indicators can provide initial insights into the interplay between human capital and inventive productivity. In order to obtain a causal empirical model of drivers of inventive productivity, a more sophisticated approach is required beyond the purely explorative analysis presented in this paper.

### *2.2.4 Additional control variables: applicant and patent characteristics*

We compute **applicant type shares** $s_{i,atype}$ as the number of patents $P_{i,atype}$ produced by inventor $i$ while the inventor was associated with an applicant institution of type *atype* (*atype* = research institution or university, private company, independent inventor) divided by the total number of patents, $P_i$, filed by inventor $i$: $s_{i,atype} = P_{i,atype} / P_i$[8]. On the one hand, the **applicant type shares** control for differences in the patent propensity of firms compared with research organizations or universities. The latter often prefer publication of research results to patenting (Van Looy et al. 2006). On the other hand, the applicant shares help to control for different citation patterns of patents protecting applied versus basic research. For instance, basic research often receives more citations, which occur at a later stage (Fabrizio, 2007; Martin and Irvine, 1983; Gittelman and Kogut, 2003).

Similarly, the size of the applicants' institution throughout the inventors' careers is calculated based on the size of the patent portfolio of the applicant institutions between 1978 and 2010. The data were obtained from PATSTAT. **Applicant size shares**, $s_{i,asize}$, at the inventor level are calculated as the number of patents, $P_{i,asize}$, produced while inventor $i$ is associated with applicant institutions that have filed a total number of patents within the size category *asize* divided by the total number of patents, $P_i$,

[8] To give an example: Take inventor $i$, who is named on 10 different patents between 1978 and 2010. Two of the patents were filed by a research institution, which corresponds to 20% of their overall patent portfolio ($s_{i,res} = 0.2$). Throughout the inventor's career, the majority of patents the inventor is named on (7 or 70% of the patent portfolio) were filed by private companies ($s_{i,priv} = 0.7$). Finally, the inventor filed one patent as an individual, without being affiliated with a research institution or a private company ($s_{i,ind} = 0.1$).

filed by inventor $i$: $s_{i,asize} = P_{i,asize} / P_i$.[9] The applicant size categories are: 1 patent, 2–24 patents, 25–249 patents, 250–999 patents, and 1000 patents or more.

**Period shares** capture the temporal distribution of an inventor's activity and help us to differentiate between age and cohort effects. The period shares account for the fact that differences in inventive productivity between age groups might stem from systematic increases in patenting activity over time (the so-called patent explosion (Hall, 2004)). The patent explosion could lead to biased productivity estimates in favour of younger inventors to the detriment of older inventors if the overall development of patenting activities is not controlled for by period dummies (Göbel and Zwick, 2012; Göbel and Zwick, 2013). The period share, $s_{ik}$, for inventor $i$ in period $t$ ($t$ = 1, …., 8) is calculated as the number of patents, $P_{it}$, filed by inventor $i$ in period $t$, divided by the total number of patents, $P_i$, filed by inventor $i$: $s_{it} = P_{it} / P_i$. These time periods refer to 5-year-episodes between 1978 and 2010[10].

Following Hoisl (2007, 2009), we also include **status shares** representing the shares of inventor $i$'s applications that were either granted, still pending, refused by the examiner, or withdrawn by the applicant. Patent applications are refused by the patent examiners when the underlying inventions do not meet the requirements for patentability, such as novelty, inventive step, and commercial applicability. Applications may be withdrawn by the applicants themselves during the examination process when the applicant encounters similar technological solutions (i.e. state-of-the-art), which might impede patentability. The status variables are an additional control to avoid biased results in our dependent variables. In particular, granted patents may be more likely to be cited, for example, in the search reports of patent examiners, or organizations may file a large number of patents to test the waters in the respective technological field, which would inflate our patent counts. These test–patents are later withdrawn when their intention is revealed during the examination process.

Finally, we include **technology shares** to account for the distribution of inventors' activity across technology areas throughout their careers. The technology share, $s_{ik}$, for inventor $i$ in technology area $k$ ($k$ = 1, …, K) is calculated as the number of patent applications, $P_{ik}$, assigned to technological area $k$ divided by the total number of patent applications, $P_i$, per inventor $i$: $s_{ik} = P_{ik} / P_i$. To calculate the shares, we draw on the 34 technological areas suggested by Schmoch (2008). However, we aggregate the areas into 11 distinct technological areas as the patenting activity of the inventors in our sample because the three technological fields used in this report do not cover all technologies[11].

### *2.3 Estimation strategy*

We start with the following multivariate regression model to determine the productivity of innovators,

[9] We make the assumption that the inventors are employed with the applicant organization mentioned on the patent document. Research based on the PatVal1 survey showed that this is true for 92% of the responding inventors (Hoisl, 2007). If there are several applicant institutions, which are not necessarily mentioned in the same order on the patent document as the inventors, we cannot be sure that the inventor is associated with the first applicant institution. However, a detailed analysis of inventor institutions for a random subsample of 100 inventors reveals that more than one applicant institution is mentioned on only 4% of their patents. Of these, many constitute the same applicant with another name, research institute, or single inventor. In these cases, we can assume that the first applicant, which is usually a private company, has the strongest influence on the invention process, e.g., in terms of funding or R&D infrastructure. In the end, only 2.6% of the patents in our test subsample mention several private companies as applicant institutions. In these cases, we cannot be sure that the association of our inventors with the first applicant institution is correct. However, this applies to a negligibly small share of patents.

[10] Note that the first period (1978–1979) and the last period (2010) are shorter than 5 years.

[11] 1) Electrical machinery, apparatus, energy. 2) Electrical engineering, other. 3) Semiconductors. 4) Instruments. 5) Chemistry, organic (comprises the organic subsections of chemistry, such as organic chemistry, biotechnology, pharmaceuticals, polymers, food Chemistry. 6) Chemistry, technological (consists of the engineering subsections of chemistry, such as material chemistry, materials/metallurgy, surface technology, chemical engineering, and environmental technology). 7) Engines/pumps/turbines. 8) Mechanical engineering, general areas. 9) ME. 10) Transportation. 11) Other fields.

$$\ln(I_i + 1) = \alpha + \sum_r \beta_r ageedu_r + \sum_u \beta_u addchar_u + \sum_v \beta_v appl_v + \sum_w \beta_w contr_w + \varepsilon_i$$

where $I_i$ is one of our productivity measures of inventor *i* shown in Table 2. A log transformation of the productivity variable that appears to be a suitable distribution of inventor productivity has been found to be strongly right-skewed in previous studies (Lotka, 1926; Narin and Breitzman, 1995). We also observe this in our data. As some of our inventors have not received citations for all their patents, we add 1 to the productivity count before taking logarithms[12].

The variable vectors comprise a set of *R* different socio-demographic inventor characteristics (age and educational level, *ageedu*), *U* different additional inventor characteristics (*addchar*), *V* different characteristics of the applicant (*appl*), and *W* additional control variables (*contr*), as described in Section 2.2. Vectors $\beta$ contain the parameters that measure the effect of the corresponding variables on inventive productivity, and ε is an ordinary error term. All independent variables are determined before the dependent variable and most of them are derived from another data source (survey data). Therefore, we avoid reverse causality and common source bias.

Because some of our inventors work for the same applicant organization, errors are not independent. We account for this fact by computing robust standard errors based on applicant clusters. For each inventor, the main applicant is determined as the mode of the applicants for all their patents.

## 3. Results

### *3.1 Descriptive results*

Tables 2a and b summarize the descriptive results and the correlations between the main variables.

**Table 2a:** Descriptive statistics (N = 1312).

| | mean | sd | median | Min | max |
|---|---|---|---|---|---|
| ***Productivity indicators*** | | | | | |
| av. no. of patents per work year, whole counts | 0.50 | 0.66 | 0.28 | 0.02 | 5.8 |
| av. no. of patents per work year, fractional counts | 0.20 | 0.29 | 0.11 | 0.001 | 4.77 |
| av. no. of citations per work year, whole counts | 0.50 | 1.01 | 0.16 | 0 | 14.87 |
| av. no. of citations per work year, fract. counts | 0.17 | 0.35 | 0.06 | 0 | 5.4 |
| av. above-average citations per work year, whole counts | 0.18 | 0.28 | 0.08 | 0 | 3 |
| av. above-average citations per work year, fract. counts | 0.07 | 0.13 | 0.03 | 0 | 2.32 |
| av. above-average citations per work year, fract. counts, ME | 0.02 | 0.06 | 0 | 0 | 1.53 |
| av. above-average citations per work year, fract. counts, CT | 0.02 | 0.07 | 0 | 0 | 1.6 |
| av. above-average citations per work year, fract. counts, NT | 0 | 0.01 | 0 | 0 | 0.11 |
| binary indicator for key inventor (yes=1) | 0.10 | | | 0 | 1 |
| binary indicator for key inventor (yes=1), ME | 0.04 | | | 0 | 1 |
| binary indicator for key inventor (yes=1), CT | 0.07 | | | 0 | 1 |
| binary indicator for key inventor (yes=1), NT | 0.01 | | | 0 | 1 |
| ***Inventor age in 2010 (Dummy variables, yes=1)*** | | | | | |
| *- younger than 40 years* | 0.16 | | | 0 | 1 |
| *- 40 to 44 years* | 0.22 | | | 0 | 1 |
| *- 45 to 49 years* | 0.22 | | | 0 | 1 |
| *- 50 to 54 years* | 0.14 | | | 0 | 1 |
| *- 55 to 59 years* | 0.11 | | | 0 | 1 |
| *- 60+ years* | 0.14 | | | 0 | 1 |
| inventor age in 2010[*)] | 48.26 | 9.22 | 47.00 | 28 | 82 |
| | **mean** | **sd** | **median** | **min** | **max** |
| ***Educational level (Dummy variables, yes=1)*** | | | | | |
| - vocational degree | 0.09 | | | 0 | 1 |
| - academic studies | 0.55 | | | 0 | 1 |
| - PhD | 0.36 | | | 0 | 1 |

[12] The logarithmized independent variables of the indicators described in Table 2 are labelled as follows in the dataset (1) lnavpatno_fract_1, (2) lnavcitno_fract_1, (3) lnavcitno_fract_corrD_1, MElnavcitno_fract_corrD_1, CTlnavcitno_fract_corrD_1, NTlnavcitno_fract_corrD_1.

**Table 2a:** Descriptive statistics (N = 1312) *(continued)*

| | mean | sd | median | min | max |
|---|---|---|---|---|---|
| ***Applicant size (shares)*** | | | | | |
| - 1 patent | 0.03 | 0.14 | 0 | 0 | 1 |
| - 2 to 24 patents | 0.16 | 0.33 | 0 | 0 | 1 |
| - 25 to 249 patents | 0.21 | 0.37 | 0 | 0 | 1 |
| - 250 to 999 patents | 0.14 | 0.30 | 0 | 0 | 1 |
| - 1000 patents or more | 0.47 | 0.46 | 0.37 | 0 | 1 |
| modal applicant size over career (in patents)*) | 6416.78 | 11;039.11 | 905.50 | 1 | 39475 |
| ***Applicant type shares*** | | | | | |
| - private company | 0.93 | 0.23 | 1.00 | 0 | 1 |
| - university or research institute | 0.05 | 0.20 | 0 | 0 | 1 |
| - individual inventor (no applicant institution) | 0.02 | 0.12 | 0 | 0 | 1 |
| ***Patent status (shares)*** | | | | | |
| - pending | 0.39 | 0.34 | 0.33 | 0 | 1 |
| - withdrawn | 0.16 | 0.23 | 0 | 0 | 1 |
| - refused | 0.01 | 0.06 | 0 | 0 | 1 |
| - granted | 0.45 | 0.34 | 0.46 | 0 | 1 |
| ***Additional human capital-related variables*** | | | | | |
| share of periods when worked as generalist | 0.64 | 0.37 | 0.67 | 0 | 1 |
| divergent thinking | 2.17 | 0.52 | 2.00 | 1 | 4.67 |
| systematic cognitive style (CRT Score) | 2.46 | 0.74 | 3.00 | 0 | 3 |
| risk attitude | | | 6.00 | 0 | 10 |
| ***BIG-5 personality dimensions*** | | | | | |
| openness to experience | 4.98 | 1.04 | 5.00 | 1.67 | 7 |
| conscientiousness | 5.54 | 0.91 | 5.67 | 2 | 7 |
| extraversion | 4.34 | 1.15 | 4.33 | 1 | 7 |
| agreeableness | 5.07 | 0.99 | 5.00 | 1 | 7 |
| neuroticism | 3.44 | 1.15 | 3.33 | 1 | 7 |
| ***Networking*** | | | | | |
| same field | | | 3.00 | 0 | 5 |
| different field | | | 3.00 | 0 | 5 |
| ***Technology shares*** | | | | | |
| - electrical machinery, apparatus, energy | 0.12 | 0.26 | 0 | 0 | 1 |
| - electrical engineering, other | 0.02 | 0.08 | 0 | 0 | 0.92 |
| - semiconductors | 0.05 | 0.17 | 0 | 0 | 1 |
| - instruments | 0.07 | 0.18 | 0 | 0 | 1 |
| - chemistry, „organic“ | 0.06 | 0.19 | 0 | 0 | 1 |
| - chemistry, “technological” | 0.15 | 0.27 | 0 | 0 | 1 |
| - engines/Pumps/Turbines | 0.09 | 0.20 | 0 | 0 | 1 |
| - mechanical engineering, general areas | 0.13 | 0.28 | 0 | 0 | 1 |
| - mechanical Elements | 0.18 | 0.31 | 0 | 0 | 1 |
| - transport | 0.09 | 0.22 | 0 | 0 | 1 |
| - other fields | 0.04 | 0.15 | 0 | 0 | 1 |
| patent share in clean technology (add. cat.!)*) | 0.39 | 0.41 | 0 | 0 | 1 |
| ***Patent period shares*** | | | | | |
| - 1975 to 1979 | 0 | | 0 | 0 | 0.71 |
| - 1980 to 1984 | 0 | | 0 | 0 | 0.5 |
| - 1985 to 1989 | 0.01 | | 0 | 0 | 0.8 |
| - 1990 to 1994 | 0.02 | | 0 | 0 | 0.8 |
| - 1995 to 1999 | 0.08 | | 0 | 0 | 0.83 |
| - 2000 to 2004 | 0.26 | | 0.17 | 0 | 1 |
| - 2005 to 2009 | 0.61 | | 0.60 | 0 | 1 |
| - 2010 | 0.02 | | 0 | 0 | 0.67 |

Notes:
*) Only for information, not used in regression model.

**Table 2b:** Correlations (N = 1312).

| | Variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | av. no. patents | 1 | | | | | | | | | | | | | | | | | |
| 2 | av. no. pat. (frac) | 0.87* | 1 | | | | | | | | | | | | | | | | |
| 3 | av. no. cititations | 0.76* | 0.58* | 1 | | | | | | | | | | | | | | | |
| 4 | av. no. cit. (frac) | 0.76* | 0.78* | 0.87* | 1 | | | | | | | | | | | | | | |
| 5 | age | 0.15* | 0.11* | 0.13* | 0.13* | 1 | | | | | | | | | | | | | |
| 6 | educ. voc. degree | -0.20* | -0.14* | -0.07 | -0.04 | 0.05 | 1 | | | | | | | | | | | | |
| 7 | educ. acad. stud. | -0.10* | -0.08* | -0.06 | -0.07 | -0.21* | 0.05 | 1 | | | | | | | | | | | |
| 8 | educ. phd | -0.11* | -0.05 | -0.10* | -0.06 | -0.12* | -0.08* | -0.34* | 1 | | | | | | | | | | |
| 9 | applicant size (modal) | 0.17* | 0.10* | 0.14* | 0.11* | 0.25* | 0.05 | -0.23* | -0.83* | 1 | | | | | | | | | |
| 10 | applicant firm | 0.17* | 0.13* | 0.12* | 0.09* | -0.01 | -0.02 | -0.06 | 0.04 | 0.00 | 1 | | | | | | | | |
| 11 | applicant res. | -0.04 | -0.06 | -0.06 | -0.07* | 0.08* | 0.003 | -0.06 | -0.15* | 0.19* | -0.09* | 1 | | | | | | | |
| 12 | applicant indiv. | -0.07 | -0.02 | -0.05 | -0.02 | -0.13* | 0.05 | 0.11* | -0.002 | -0.06 | -0.08* | -0.03 | 1 | | | | | | |
| 13 | share generalist | 0.00 | -0.01 | 0.04 | 0.02 | 0.05 | 0.01 | 0.02 | -0.06 | 0.05 | 0.01 | 0.03 | -0.04 | 1 | | | | | |
| 14 | divergent thinking | 0.07 | 0.05 | 0.03 | 0.03 | 0.05 | -0.13* | -0.05 | -0.07 | 0.10* | 0.03 | 0.03 | -0.02 | -0.03 | 1 | | | | |
| 15 | cognitive style | 0.06 | 0.04 | 0.02 | -0.01 | 0.10* | -0.12* | -0.13* | 0.002 | 0.08* | 0.08* | 0.01 | -0.07 | 0.02 | 0.10* | 1 | | | |
| 16 | risk attitude | 0.04 | 0.05 | 0.05 | 0.06 | -0.04 | 0.13* | -0.01 | 0.01 | -0.01 | -0.06 | -0.03 | 0.13* | -0.15* | -0.03 | -0.06 | 1 | | |
| 17 | BIG-5 openness | 0.06 | 0.10* | 0.07 | 0.09* | 0.02 | 0.12* | 0.02 | -0.06 | 0.05 | -0.04 | 0.01 | 0.07* | -0.09* | 0.05 | -0.04 | 0.33* | 1 | |
| 18 | BIG-5 conscientious. | -0.04 | -0.04 | -0.05 | -0.05 | 0.00 | 0.07* | 0.03 | -0.05 | 0.03 | -0.04 | -0.01 | 0.05 | 0.05 | -0.03 | -0.02 | 0.08* | 0.00 | 1 |
| 19 | BIG-5 extraversion | 0.03 | 0.02 | 0.02 | 0.01 | -0.05 | -0.09* | 0.07 | -0.03 | -0.01 | -0.02 | 0.001 | 0.02 | -0.09* | 0.02 | -0.06 | 0.30* | 0.33* | 0.04 |
| 20 | BIG-5 agreeableness | -0.03 | -0.03 | -0.02 | -0.02 | 0.04 | -0.005 | 0.01 | -0.06 | 0.06 | -0.02 | 0.00 | -0.03 | 0.06 | 0.01 | -0.002 | -0.04 | 0.08* | 0.14* |
| 21 | BIG-5 neuroticism | -0.005 | -0.01 | 0.01 | -0.001 | -0.04 | 0.04 | -0.01 | 0.07 | -0.06 | 0.01 | -0.02 | 0.04 | 0.02 | 0.004 | 0.04 | -0.25* | -0.03 | -0.10* |
| 22 | know. same field | 0.04 | 0.02 | 0.05 | 0.05 | 0.04 | 0.07* | -0.04 | -0.16* | 0.19* | 0.08* | 0.07 | 0.001 | -0.03 | -0.01 | -0.08* | 0.11* | 0.07* | 0.02 |
| 23 | know. oth. field | 0.03 | 0.01 | 0.01 | 0.01 | 0.04 | 0.07 | -0.04 | -0.10* | 0.13* | 0.07 | 0.04 | 0.03 | -0.13* | 0.05 | -0.13* | 0.19* | 0.19* | -0.01 |

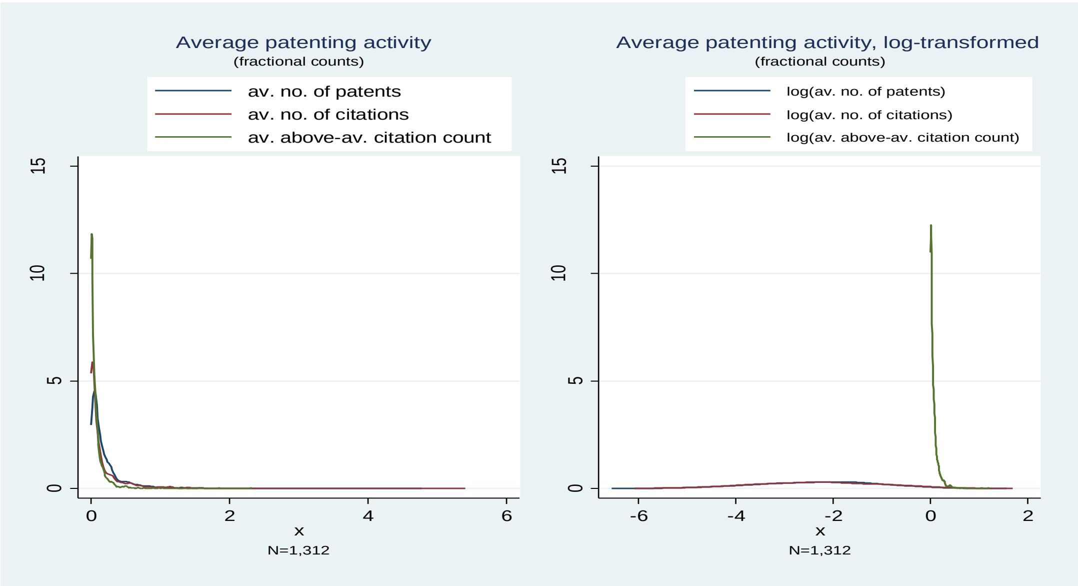
| | | 19 | 20 | 21 | 22 | 23 |
|---|---|---|---|---|---|---|
| 19 | BIG-5 extraversion | 1 | | | | |
| 20 | BIG-5 agreeableness | 0.02 | 1 | | | |
| 21 | BIG-5 neuroticism | -0.21* | -0.19* | 1 | | |
| 22 | know. same field | 0.14* | 0.03 | -0.11* | 1 | |
| 23 | know. oth. field | 0.17* | -0.02 | -0.10* | 0.67* | 1 |

Note: Pearson correlation coefficients (for two continuous variables), point biserial coefficients (for one continuous variable and one dummy variable) and phi coefficients (for two dummy variables), * $p < 0.01$.

**Average inventor productivity.** As expected, patent and citation counts follow a highly right-skewed distribution. The patents of about 25% of the inventors in our sample received no citations during the 5 years after the publication of the search report (results not reported). After log transforming our three indicators for average patent productivity, our productivity indicators still follow a highly right-skewed distribution (see Figure 2).

**Figure 2:** Distribution of average number of patents and citations (kernel density plots).

a) Inventor productivity b) Log of average inventor productivity




The inventors in our sample produced an average of 0.50 patents per year of professional experience, which received on average 0.50 citations. Accounting for team size, fractional counts amount to about one third of whole counts (0.2 patents and 0.17 citations on average), which is consistent with the fact that most of the inventions from our sample inventors are produced by teams of 3 or 4 inventors (results not reported).

**Education**. The majority of the inventors have at least an academic degree (91%), with 36% holding a PhD. Only 9% of the inventors in our sample obtained a vocational degree as their highest level of education.

**Systematic problem solving**. 58% give correct answers to all three questions of the CRT (results not reported) and thus are assumed to use a systematic instead of for example an intuitive cognitive problem-solving style. The inventors in our sample score higher than any of the groups tested by Frederick (2005, p. 29), who reported that students of the Massachusetts Institute of Technology performed highest (48% of students answered all three questions correctly).

**Divergent thinking**. On average, the inventors in our sample score 2.17 with respect to divergent thinking (minimum = 1, maximum = 4.67). The 90% decile amounts to 2.83 (results not reported). Because the creativity of the ideas was assessed on a five-point Likert scale (5 = very creative application), this result indicates that only a small share of the inventors in our sample consistently suggested very creative applications for the brick.

**Specialist vs generalist career**. The inventors in our sample on average spent more time in specialist jobs (65% of their career) than in generalist jobs.

**Risk orientation.** On average, inventors score 5.7 on the self-rating scale for risk-taking behavior that varies between 0 (low risk attitude) and 10 (high risk attitude).

**BIG-5 personality dimensions.** The median score of respondents with respect to the dimension openness to new experiences is 5.0 (possible range: 1 (low) to 7 (high). The average scores for the other four dimensions are: conscientiousness: 5.5, extraversion: 4.4, agreeableness: 5.1, neuroticism: 3.4.

**Networking, same and other fields**. The inventors in our sample assigned the same median importance to knowledge obtained from people from the same vs from other fields. The median for both variables is 3, on a scale from 1 to 5.

**Applicant size.** The inventors made the majority (61%) of their patented inventions at large and/or R&D intensive applicant organizations that patented more than 250 inventions between 1978 and 2010. Another 37% were filed by applicant institutions that were less active in patented invention over the observation time. Only 3% of the inventions patented by our sample inventors were filed by applicant institutions that did not produced any other patented inventions apart from the invention associated with the sample inventor.

**Applicant type**. Inventive activity mostly happens in private companies. Only 5% of our inventors' patent applications originate from universities or research institutes, another 2% were filed by independent inventors.

**Patent status**. 45% of the patent applications of our inventors were granted and 39% are still pending in 2013. Only 1% of the patents were refused by the patent examiners and 16% were withdrawn by the applicants themselves.

**Technology shares.** The sample inventors produce most of their patents in:

- ME (18%),
- general areas of mechanical engineering (13%),
- the engineering subsection of chemistry (material chemistry, materials/metallurgy, surface technology, chemical engineering, and environmental technology; 12%),
- a subfield of electrical engineering (electrical machinery, apparatus, energy; 12%).

On average, 39% of the patent applications of the inventors in our sample were categorized as CT patents according to the EPO.

**Period shares**. The majority of the patent applications (61%) of our sample inventors was filed between 2005 and 2009, followed by the period 2000–2004 (26%). This is unsurprising, given the fact that our sample comprises inventors who are listed on at least one patent application between 2004 and 2008.

The correlations displayed in Table 2b are low, so multicollinearity should not be a concern. The only exceptions are the different variables capturing the productivity of the inventors, which are highly correlated (correlation coefficients between 0.58 and 0.87). However, these variables depict alternative productivity measures and are never used in the same model.

### *3.2 Multivariate results*

#### *3.2.1 Fitting the basic model*

Table 3 shows multivariate results for the effects on different measures of average inventive productivity of the traditional explanatory variables, inventor age, and education, and of the characteristics of the applicant institutions (size, type) the respective inventor had been employed by during their career until 2010. The models also include controls for the technological and temporal distribution of inventors' patenting activity throughout their careers. Finally, to account for the fact that not all patents are granted, which could affect our productivity measures, the shares of patents withdrawn, refused, and pending are included as further controls.

Model 1a uses the inventors' quantitative productivity as a dependent variable, measured by the logarithmized number of patents per work year. Model 2a additionally accounts for the size of the inventor teams, as it uses the average fractional number of patents per work year (our measure 1 for productivity, described above) as a dependent variable. In Models 3a and 4a, we use the inventors' qualitative productivity as a dependent variable, measured by citation counts instead of patent counts (measure 2). Finally, Models 5a and 6a use above-average citation counts as a productivity measure (measure 3).

Model 1a explains 25% of inventors' productivity, which is highest for the youngest age group (younger than 40 years) compared with older inventors, and is higher for inventors with a PhD and an academic education compared with inventors with a vocational degree. However, the effect of a PhD is three times as large as the effect of an academic degree without a PhD. Furthermore, inventive productivity is higher for inventors who mainly worked for large, private companies and smaller for inventors who primarily worked in smaller and medium sized companies and in research institutes. Individual inventors exhibit a positive and significant effect for fractional patent or citation counts (only exception: number of citations (whole counts); Model 3a), the effect of individual inventors is also significant at the 10% level). This result is surprising, although it may be an artefact of the adaptation of our productivity measures. In particular, when large inventor teams are responsible for a patented invention, each inventor is only assigned a small fraction of the patent or value of the patent. Individual inventors profit from the fact that the patent and the patent value do not have to be shared with their co-inventors even if the absolute value of an invention might be smaller than that of an invention made by a team.

Our results are consistent with the results of earlier empirical studies on the determinants of inventor productivity. For example, Lissoni et al. (2008) found that education had a positive effect on inventive performance. Mariani and Romanelli (2007) and Hoisl (2007) found that inventor age had a negative effect and Lissoni et al. (2008) found, it had an inverted u-shaped effect.

Comparing the results across the different models shows that age and educational effects and the influence of applicant characteristics as well as the period and technology controls are lower if the quality (citations) rather than the quantity (patent numbers) of inventive output is considered. In addition, Mariani and Romanelli (2006) report that inventor characteristics primarily seem to affect the number of patents produced, and not their quality. The same pattern applies to the models using fractional counts (Models 2a, 4a, 6a) instead of whole counts (Models 1a, 3a, 5a). For example, in Model 6a, the dependent variable already accounts for team size, technology, and period effects. Age and education are still significantly related to productivity but the effects are only about one fifth of the effects obtained in Model 1a. Note that accounting for team, period, and technology effects in the dependent variable leads to a drop in the size of R-squared, but the individual and applicant-level determinants in our basic model still explain 15% of the inventors' productivity.

We base the following analyses on Model 6a. In other words, we use average above-average citation counts as a dependent variable because it most accurately captures the quality of inventive output.

**Table 3**: Regression results for the basic models.

| VARIABLES | **(Model 1a)** ln(av. no. of patents per work year + 1) whole counts | **(Model 2a)** ln(av. no. of patents per work year + 1) fract. Counts | **(Model 3a)** ln(av. no. of citations per work year + 1) whole counts | **(Model 4a)** ln(av. no. of citations per work year + 1) fract. counts | **(Model 5a)** ln(average above-average citation count + 1) whole counts | **(Model 6a)** ln(average above-average citation count + 1) fract. counts |
|---|---|---|---|---|---|---|
| academic education | 0.063*** | 0.036*** | 0.049 | 0.039** | 0.019 | 0.014* |
| | [0.022] | [0.012] | [0.033] | [0.016] | [0.016] | [0.007] |
| PhD degree | 0.182*** | 0.095*** | 0.145*** | 0.082*** | 0.079*** | 0.041*** |
| | [0.031] | [0.017] | [0.045] | [0.021] | [0.022] | [0.010] |
| age of the inventors in 2010 (reference group: younger than 40 years) | | | | | | |
| 40-44 years | -0.120*** | -0.051*** | -0.077** | -0.020 | -0.057*** | -0.018* |
| | [0.027] | [0.017] | [0.033] | [0.016] | [0.018] | [0.009] |
| 45-49 years | -0.165*** | -0.070*** | -0.115*** | -0.038* | -0.091*** | -0.035*** |
| | [0.035] | [0.020] | [0.040] | [0.020] | [0.021] | [0.011] |
| 50-54 years | -0.224*** | -0.103*** | -0.135*** | -0.051** | -0.102*** | -0.041*** |
| | [0.037] | [0.021] | [0.036] | [0.020] | [0.019] | [0.010] |
| 55-59 years | -0.272*** | -0.125*** | -0.212*** | -0.085*** | -0.134*** | -0.053*** |
| | [0.029] | [0.018] | [0.037] | [0.019] | [0.016] | [0.008] |
| 60-99 years | -0.327*** | -0.131*** | -0.249*** | -0.093*** | -0.144*** | -0.052*** |
| | [0.043] | [0.023] | [0.043] | [0.022] | [0.023] | [0.011] |
| applicant size (shares) (reference group: 1 patent) | | | | | | |
| 2-24 patents | 0.099*** | 0.058*** | 0.070*** | 0.037*** | 0.041*** | 0.023*** |
| | [0.029] | [0.019] | [0.026] | [0.014] | [0.013] | [0.008] |
| 25-249 patents | 0.200*** | 0.100*** | 0.120*** | 0.061*** | 0.067*** | 0.034*** |
| | [0.025] | [0.018] | [0.028] | [0.015] | [0.012] | [0.008] |
| 250-999 patents | 0.232*** | 0.096*** | 0.194*** | 0.072*** | 0.094*** | 0.034*** |
| | [0.031] | [0.023] | [0.039] | [0.020] | [0.017] | [0.009] |
| 1000 or more patents | 0.307*** | 0.134*** | 0.254*** | 0.102*** | 0.126*** | 0.048*** |
| | [0.028] | [0.019] | [0.031] | [0.014] | [0.014] | [0.007] |
| type of applicant (shares) (reference group: private firm) | | | | | | |
| university/research inst. | -0.130*** | -0.071*** | -0.231*** | -0.106*** | -0.106*** | -0.047*** |
| | [0.033] | [0.019] | [0.043] | [0.016] | [0.023] | [0.007] |
| individual inventor | 0.020 | 0.065*** | 0.048* | 0.053*** | 0.009 | 0.026*** |
| | [0.029] | [0.016] | [0.026] | [0.016] | [0.011] | [0.006] |
| status of the patent (shares) (reference group: granted) | | | | | | |
| patents withdrawn | 0.020 | -0.003 | -0.009 | -0.014 | -0.007 | -0.008 |
| | [0.031] | [0.016] | [0.047] | [0.021] | [0.020] | [0.009] |
| patents refused | -0.148* | -0.075** | -0.196 | -0.090* | -0.099*** | -0.042** |
| | [0.087] | [0.034] | [0.119] | [0.053] | [0.038] | [0.016] |
| patents pending | 0.031 | 0.009 | -0.003 | -0.007 | 0.006 | 0.002 |
| | [0.020] | [0.010] | [0.028] | [0.012] | [0.012] | [0.005] |
| technical areas (shares) | included | Included | included | included | included | included |
| Wald-Test | 3.00 | 3.00 | 3.87 | 3.52 | 2.49 | 2.05 |
| | p=0.0014 | p=0.0014 | p=0.0001 | p=0.0002 | p=0.0074 | p=0.0289 |
| periods (shares) | included | included | included | included | included | included |
| Wald-Test | 16.54 | 16.54 | 14.52 | 26.23 | 19.36 | 21.59 |
| | p=0.0000 | p=0.0000 | p=0.0000 | p=0.0000 | p=0.0000 | p=0.0000 |
| Constant | 0.293** | 0.187* | -0.049 | -0.038 | 0.346*** | 0.190** |
| | [0.141] | [0.109] | [0.090] | [0.044] | [0.117] | [0.086] |
| Observations | 1312 | 1312 | 1312 | 1312 | 1312 | 1312 |
| R-squared | 0.245 | 0.150 | 0.243 | 0.168 | 0.205 | 0.144 |
| F test | 34.39 | 16.07 | 17.54 | 11.29 | 26.73 | 15.72 |

Dependent variable:

- Model 1a: log of average whole patent count (patents per year in job) + 1.
- Model 2a: log of average fractional patent count (patents per year in job) + 1.
- Model 3a: log of average whole citation count (citations per year in job) + 1.
- Model 4a: log of average fractional citation count (citations per year in job) + 1.
- Model 5a: log of average above-average citation count + 1.
- Model 6a: log of average above-average citation count + 1.

A stepwise regression of Model 6a from Table 3 shows that a large share of productivity differences between inventors can be explained by time effects, technology field effects, and the characteristics of the applicants (size and type) that the inventors are affiliated with throughout their careers. Table 4 illustrates the increase in R-squared resulting from the stepwise inclusion of variables.

In more detail, 7.7%, which corresponds to about half of the explained variation in inventive productivity, results from period, technology, and status shares. This agrees with the results of Ejermo and Jung (2011) who state "the quality of patents is mainly explained by patent characteristics themselves". An additional 2.2% of productivity variation can be explained by applicant-level influences, as measured by applicant size and type. Consequently, in our case, inventive productivity measured by patent citations strongly depends on when, in which technology fields, based on which employer strategies, and in which organizations inventors are active. However, basic inventor characteristics, such as age (2.6%) and education (1.9%), still have a significant explanatory power for variations in inventor productivity in the fully specified model.

**Table 4:** Contributions to the explanation of productivity variation between inventors.

| Stepwise additional inclusion of variables: | $R^2$ of model | $\Delta R^2$ compared with previous model |
|---|---|---|
| No explanatory variables | 0.000 | |
| + Period shares | 0.068 | 0.068 |
| + Technology shares | 0.075 | 0.007 |
| + Status shares | 0.077 | 0.002 |
| + Applicant type and size | 0.099 | 0.022 |
| + Inventor age | 0.125 | 0.026 |
| + Inventor education | 0.144 | 0.019 |

### *3.2.2 Introducing an additional set of individual-level determinants of inventive productivity*

Next, we enrich our basic model (Model 6a from Table 3, displayed again as Model 1b in Table 5) with additional human capital variables, such as the type of job experience (generalist vs expert experience), the level of divergent thinking, the extent to which an inventor has a systematic approach to problem solving, inventors' risk attitudes, and personality traits according to the BIG-5 Model. Furthermore, we account for the use of knowledge from network partners in the same or in other technical areas. The results are displayed in Table 5.

**Table 5**: Regression results, extended model with additional individual-level determinants.

| | (Model 1b) | (Model 2b) | (Model 3b) | (Model 4b) |
|---|---|---|---|---|
| | ln(average above-average citation count + 1) | ln(average above-average citation count + 1) | ln(average above-average citation count + 1) | ln(average above-average citation count + 1) |
| VARIABLES | fract. counts | fract. counts | fract. counts | fract. counts |
| academic education | 0.014* | 0.014* | 0.013** | 0.013** |
| | [0.007] | [0.007] | [0.006] | [0.006] |
| PhD degree | 0.041*** | 0.040*** | 0.039*** | 0.038*** |
| | [0.010] | [0.010] | [0.010] | [0.010] |
| breadth of work experience | | 0.008 | 0.011* | 0.010* |
| | | [0.006] | [0.006] | [0.006] |
| risk attitude | | 0.003*** | 0.002** | 0.002** |
| | | [0.001] | [0.001] | [0.001] |
| divergent thinking | | 0.008* | 0.007* | 0.008* |
| | | [0.004] | [0.004] | [0.004] |
| systematic problem solving | | -0.002 | -0.002 | -0.002 |
| | | [0.004] | [0.004] | [0.004] |
| BIG-5 personality characteristics | | | | |
| openness to experience | | | 0.011*** | 0.011*** |
| | | | [0.003] | [0.003] |
| conscientiousness | | | -0.006*** | -0.006*** |
| | | | [0.002] | [0.002] |
| Extraversion | | | -0.003 | -0.003 |
| | | | [0.003] | [0.003] |
| agreeableness | | | -0.003 | -0.003 |
| | | | [0.003] | [0.003] |
| neuroticism | | | -0.0001 | -0.00004 |
| | | | [0.002] | [0.002] |
| networking, same field | | | | 0.005** |
| | | | | [0.003] |
| networking, other fields | | | | -0.005* |
| | | | | [0.003] |
| additional control variables[A] | included | included | included | included |
| technical areas (shares) | included | included | included | included |
| Wald-Test | 1.55 | 1.71 | 2.44 | 2.54 |
| | p=0.1220 | p=0.0784 | p=0.0086 | p=0.0062 |
| periods (shares) | included | included | included | included |
| Wald-Test | 19.77 | 2029 | 17.77 | 17.40 |
| | p=0.0000 | p=0.0000 | p=0.0000 | p=0.0000 |
| Constant | 0.190** | 0.150* | 0.173* | 0.169* |
| | [0.086] | [0.088] | [0.095] | [0.095] |
| Observations | 1312 | 1312 | 1312 | 1312 |
| R-squared | 0.144 | 0.151 | 0.167 | 0.170 |
| F test | 15.72 | 16.40 | 15.14 | 14.39 |

*Notes:*

All explanatory variables are calculated for the time period between job entry and the year 2010.

Dependent variable: above-average citation count.

[A]Additional controls included but not reported in the table: inventor age, applicant size shares and type shares, and status shares.

Robust standard errors based on applicant clusters in brackets.

Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.

Our results indicate that, as expected, a **positive risk attitude** and **divergent thinking skills** foster inventive productivity, whereas systematic problem solvers do not seem to exhibit a higher productivity compared with inventors using a less systematic problem-solving approach. Generalists compared with inventors with a more focused expert work experience are also not more productive (Model 2b). Furthermore, although risk attitude and divergent thinking have a statistically significant effect on inventive performance, the effect is very small. This is also mirrored in the fact that the share of explained variation in inventive productivity, as given in R-squared, hardly increases (0.7 percentage points) when we compare Model 2b with Model 1b in Table 5. However, given that only about 6% of productivity differences can be explained by individual-level inventor characteristics (3.5% by age and education, and 2.6% by other inventor characteristics, see following paragraph and Tables 4 and 5), risk attitude and divergent thinking provide about 10% of the total explanatory power to differentiate between highly productive and less productive inventors.

The picture is somewhat different if we include the BIG-5 **personality characteristics** (Model 3b). As expected, the openness to experience (often used as an indicator for creativity and innovativeness) has a significant positive effect on inventive performance. High levels of conscientiousness seem to hamper inventive performance. The other three personality traits, extraversion, agreeableness and neuroticism, do not affect inventive performance. The inclusion of the personality characteristics increases the share of explained variation in inventor productivity by 1.6 percentage points. Given that our model explains about 17% of the variation in inventor productivity, and that the lion's share of explanatory power comes from applicant-level and time effects, inventor personality has a considerable additional explanatory power. In particular, inventor personality exhibits a larger explanatory power (2.3%) with respect to productivity differences than education (1%, results not reported), and about as much as inventor age (2%, results not reported).

When controlling for inventor personality in Models 3b and 3c, the **breadth of work experience**, measured as the share of his career an inventor worked as a generalist, also has a small, but significant positive effect on inventive performance.

Finally, **knowledge** obtained from **inventor networks** in the same or other fields of expertise is also significantly related to inventor productivity. Knowledge from experts in the same field is positively related to inventive performance, whereas knowledge from experts in networks who work in other fields is negatively related to productivity. However, the sizes of the effects are small, and the inclusion of the knowledge use variables provides barely any additional explanatory power, as mirrored by an increase in R-squared of only 0.3 percentage points when moving from Model 3b to 4b.

As a conclusion, the results confirm our suggestion that inventors' talent, given by the type and breadth of work experience accumulated over the career, their personality, and their ability for divergent thinking, provide additional explanatory power as to why some inventors outperform others. More concretely, they double the explanatory power provided by previously included individual-level characteristics, such as age and education.

### *3.2.4 Technology differences in individual-level drivers of inventive productivity*

We now investigate our second suggestion; that the effect of the additional drivers of inventor productivity (inventor human capital) that are relevant at the individual level (see section 3.2.3) may differ between technical fields. In particular, we differentiated between more traditional, focused technology fields, such as ME, and emerging technology fields that draw upon a large number of different fields, such as CT. Model 1c in Table 6 shows the general results (same as Model 4b in Table 5). In Model 2c (Model 3c), only the citations of patents filed in ME (CT) are included when computing average above-average citation counts, which we use as a dependent variable. Note that in Models 1c and 4c, NT patents are included in addition to ME and CT patents. Due to the small size of the NT subsample, we refrained from restricting the sample to these patents/citations. However, in the Appendix we show the models displayed in Table 6 with a reduced number of control variables. In particular, we reduce the list of controls to age, applicant size, type of applicant, periods, and technical fields. The reduction in the number of control variables enables us to show the results for the small NT subsample. The results for the full sample and the two subsamples representing CT and ME (Table A, Appendix) are consistent with the results provided in Table 5 and repeated to facilitate the comparison between the technological fields.

**Table 6**: Technology differences in individual-level determinants of inventive productivity.

| | (Model 1c) | (Model 2c) | (Model 3c) | (Model 4c) | (Model 5c) | (Model 6c) |
|---|---|---|---|---|---|---|
| | ln (average above-average citation count) | | | binary variable = 1 if inventor in the upper 10% of performance, 0 else. | | |
| | all patents | only ME patents | only CT patents | all patents | only ME patents | only CT patents |
| | all inventors | only inventors with at least one ME patent | only inventors with at least one CT patent | all inventors | only inventors with at least one ME patent | only inventors with at least one CT patent |
| academic education | 0.013** | 0.008 | 0.001 | 0.076*** | 0.029* | 0.032 |
| | [0.006] | [0.008] | [0.005] | [0.027] | [0.017] | [0.036] |
| PhD degree | 0.038*** | 0.023 | 0.014** | 0.133*** | 0.051 | 0.063 |
| | [0.010] | [0.019] | [0.007] | [0.043] | [0.049] | [0.059] |
| breadth of work experience | 0.010* | -0.008 | 0.016*** | 0.030** | -0.008 | 0.039*** |
| | [0.006] | [0.009] | [0.004] | [0.013] | [0.014] | [0.015] |
| risk attitude | 0.002** | 0.000 | 0.001* | 0.005 | 0.006 | 0.004* |
| | [0.001] | [0.001] | [0.001] | [0.003] | [0.004] | [0.002] |
| divergent thinking | 0.008* | 0.001 | 0.007* | 0.030*** | -0.002 | 0.018*** |
| | [0.004] | [0.007] | [0.004] | [0.010] | [0.014] | [0.007] |
| systematic problem solving | -0.002 | -0.008 | 0.001 | -0.004 | -0.004 | 0.007 |
| | [0.004] | [0.008] | [0.002] | [0.010] | [0.009] | [0.006] |
| BIG-5 personality characteristics | | | | | | |
| openness | 0.011*** | 0.010** | 0.005* | 0.019*** | 0.012** | 0.010* |
| | [0.003] | [0.004] | [0.003] | [0.006] | [0.005] | [0.006] |
| conscientiousness | -0.006*** | -0.006** | -0.004* | -0.011* | -0.019** | -0.011** |
| | [0.002] | [0.003] | [0.002] | [0.006] | [0.008] | [0.005] |
| extraversion | -0.003 | -0.004 | -0.003 | -0.006 | -0.009 | -0.008* |
| | [0.003] | [0.004] | [0.002] | [0.006] | [0.006] | [0.004] |
| agreeableness | -0.003 | -0.003 | -0.001 | -0.015** | -0.005 | 0.002 |
| | [0.003] | [0.004] | [0.002] | [0.006] | [0.005] | [0.006] |
| neuroticism | -0.00004 | 0.0003 | -0.0003 | -0.003 | 0.000 | 0.000 |
| | [0.002] | [0.002] | [0.002] | [0.005] | [0.007] | [0.004] |
| networking, same field | 0.005** | 0.009* | 0.003 | 0.008 | 0.012* | 0.007 |
| | [0.003] | [0.004] | [0.002] | [0.006] | [0.007] | [0.006] |
| networking, other field | -0.005* | -0.009** | -0.001 | -0.009 | -0.017** | -0.004 |
| | [0.003] | [0.004] | [0.002] | [0.006] | [0.007] | [0.006] |
| age of the inventors in 2010 (reference group: younger than 40 years) | | | | | | |
| 40-44 years | -0.022** | -0.022** | -0.012 | -0.025* | -0.019* | -0.023*** |
| | [0.010] | [0.010] | [0.010] | [0.015] | [0.011] | [0.009] |
| 45-49 years | -0.038*** | -0.030** | -0.023** | -0.053*** | -0.015 | -0.035*** |
| | [0.010] | [0.011] | [0.011] | [0.014] | [0.013] | [0.008] |
| 50-54 years | -0.047*** | -0.041*** | -0.028*** | -0.052*** | -0.029*** | -0.036*** |
| | [0.010] | [0.014] | [0.009] | [0.009] | [0.010] | [0.009] |
| 55-59 years | -0.058*** | -0.046*** | -0.033*** | -0.058*** | -0.020 | -0.034*** |
| | [0.009] | [0.014] | [0.008] | [0.009] | [0.015] | [0.008] |
| 60-64 years | -0.057*** | -0.040** | -0.033*** | -0.053*** | -0.027** | -0.039*** |
| | [0.011] | [0.017] | [0.010] | [0.011] | [0.012] | [0.008] |

**Table 6**: Technology differences in individual-level determinants of inventive productivity *(continued).*

| | **(Model 1c)** | **(Model 2c)** | **(Model 3c)** | **(Model 4c)** | **(Model 5c)** | **(Model 6c)** |
|---|---|---|---|---|---|---|
| | ln (average above-average citation count) | | | binary variable = 1 if inventor in the upper 10% of performance, 0 else. | | |
| | all patents | only ME patents | only CT patents | all patents | only ME patents | only CT patents |
| | all inventors | only inventors with at least one ME patent | only inventors with at least one CT patent | all inventors | only inventors with at least one ME patent | only inventors with at least one CT patent |
| applicant size (shares) (reference group: 1 patent) | | | | | | |
| 2-24 patents | 0.023** | 0.039** | -0.010 | 0.305*** | 0.712** | 0.101 |
| | [0.009] | [0.018] | [0.008] | [0.101] | [0.329] | [0.122] |
| 25-249 patents | 0.035*** | 0.051*** | -0.013 | 0.341*** | 0.754** | 0.084 |
| | [0.008] | [0.016] | [0.009] | [0.104] | [0.323] | [0.119] |
| 250-999 patents | 0.039*** | 0.066*** | -0.019** | 0.357*** | 0.789** | 0.071 |
| | [0.010] | [0.018] | [0.008] | [0.101] | [0.316] | [0.123] |
| 1000 or more patents | 0.050*** | 0.052*** | 0.002 | 0.373*** | 0.760** | 0.125 |
| | [0.008] | [0.015] | [0.008] | [0.103] | [0.321] | [0.128] |
| type of applicant (shares) (reference group: private firm) | | | | | | |
| univ./research inst. ⌘ | -0.049*** | -0.023 | -0.025*** | -0.169*** | | -0.097** |
| | [0.008] | [0.022] | [0.007] | [0.043] | | [0.039] |
| individual inventions | 0.021*** | 0.062*** | -0.004 | 0.136*** | 0.123*** | -0.718*** |
| | [0.006] | [0.015] | [0.008] | [0.052] | [0.040] | [0.228] |
| status of the patent (shares) (reference group: granted) | | | | | | |
| patents withdrawn | -0.011 | -0.007 | -0.008 | -0.017 | 0.014 | -0.026 |
| | [0.009] | [0.012] | [0.007] | [0.020] | [0.019] | [0.018] |
| patents refused | -0.051*** | -0.025 | -0.056** | -0.158* | -0.160 | -0.146** |
| | [0.017] | [0.028] | [0.027] | [0.084] | [0.142] | [0.057] |
| patents pending | -0.002 | 0.001 | -0.003 | -0.009 | -0.011 | -0.012 |
| | [0.005] | [0.008] | [0.007] | [0.014] | [0.020] | [0.013] |
| technical areas (shares) | Included | included | included | included | included | included |
| Wald-Test | 2.54 | 6.16 | 1.99 | 39.73 | 79.90 | 11.96 |
| | p=0.0062 | p=0.0000 | p=0.0363 | p=0.0000 | p=0.0000 | p=0.0000 |
| periods (shares) | included | included | included | included | included | included |
| Wald-Test / chi2-test | 17.40 | 5.06 | 4.71 | 63.23 | 23.53 | 54.49 |
| | p=0.0000 | p=0.0001 | p=0.0002 | p=0.0000 | p=0.0000 | p=0.0000 |
| Constant | 0.169* | 0.003 | 0.163 | --- | --- | --- |
| | [0.095] | [0.065] | [0.118] | | | |
| Observations | 1312 | 514 | 853 | 1312 | 514 | 853 |
| R-squared | 0.170 | 0.179 | 0.162 | --- | --- | --- |
| F test | 14.39 | 7.766 | 9.587 | --- | --- | --- |
| Pseudo R-squared | --- | --- | --- | 0.160 | 0.259 | 0.217 |

*Notes:*

All explanatory variables are calculated for the time period between job entry and 2010.

Dependent variable: Average above-average citation count.

Models 1c–3c: Robust standard errors based on applicant clusters in brackets.

Models 4c–6c: Marginal effects.

Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.

⌘ Model 5c: the variable "share universities/research institutes" was excluded from the probit regression, because Univ./research inst. ! = 0 predicted failure perfectly; hence, without excluding the variable, Stata would have dropped the 7 observations for which Univ./research inst. ! = 0. This would have impeded comparability of the results between the different technology-specific models.

The estimations show that there are indeed differences in the effect of inventor characteristics on inventive productivity depending on the technological area. A scientific approach and the capacity for abstract reasoning, as indicated by the completion of a **PhD**, drives inventive performance with respect to CT inventions, but not with respect to ME.

**Broad work experience**, acquired by working mostly as a generalist rather than as an expert is conducive to the development of novelties in CT, whereas in ME, the variable does not exhibit a significant effect. In accordance with these results, **divergent thinking skills** only display a positive effect in CT. However, the personality trait **openness to experience** shows positive and significant effects in both technological areas. However, the effect in mechanical engineering is twice as large as the effect in CT.

With respect to the **source of knowledge obtained by networking** (same or different field of expertise as the inventors), a similar pattern appears as for the breadth of work experience. In ME, knowledge sourced from experts in the same fields shows a positive relationship with productivity. In contrast, a strong reliance on knowledge sourced from network partners outside the inventor's field of expertise exhibits a negative relationship with productivity. For CT, the relationship between knowledge sourced from the network and productivity is not significant.

As before, **systematic problem solving** does not affect inventive productivity.

As a last step, we run probit regressions to investigate which inventor characteristics (human capital components) affect the probability of being among the top 10% performers in our overall sample (Model 4c) and in each of the two technology fields, ME (Model 5c) and CT (Model 6c), separately. Table A in the Appendix provides probit models with a reduced number of control variables to enable us to show results for NT. The results confirm the evidence found based on the average above average citation counts. Broad work experience and divergent thinking abilities drive inventive productivity in CT only, whereas the knowledge from networks in the same field of expertise is positively correlated with productivity for inventors in ME only. Furthermore, a positive risk attitude only exhibits a significant effect in CT. As in Models 2c and 3c, openness to new experiences is positively correlated with top inventive performance in both technology fields.

The fact that the statistical significance of the above-mentioned effects increases if we look at the probability of being amongst the top 10% of most productive inventors (Models 4c-6c) compared with the models that looked at average inventive productivity (Models 1c-3c), may suggest that patenting success is a noisy indicator for inventive capacity at the lower productivity end because some people might be mentioned on patents without having contributed substantially. Consequently, if there are "true" personality traits and other individual-level characteristics for inventive capacity, these might be better identified if we look at key inventors than at average-performers. Furthermore, it turns out that experiences, skills, and attitudes of the individual inventor are determinants of top performance in CT but not in ME, whereas personality traits seem to be a more general predictor of inventive performance.

### *3.3 Robustness of the results*

In the following section, we test the robustness of our results.

#### (C1) Size effects at the applicant level

Inventors who are affiliated with very large applicant institutions for most of their career may work in very specific settings (e.g., good research infrastructure, strong networks, high relevance of strategic patenting behaviour), and are thus outliers in our analysis. The same is true for inventors who file the majority of their patents as independent inventors or who are affiliated with applicant institutions for which R&D and patenting is not a core business.

Therefore, we run Model 3a (Table 3) from Section 3.2.2 without the 10% of inventors with the largest modal applicant institution size (Model 3a, upper cut-off point: inventors with a modal size of applicant institutions of 25.921 patents) and the 10% inventors with the smallest modal applicant institution sizes (Model 3b, lower cut-off point: inventors with a modal size of applicant institutions of 0.009 patents). The outcomes remain robust. Only our control variables that capture the size of the applicant organization become insignificant.

### (C2) Fixed effects at the applicant level

We can filter out unobserved heterogeneity at the applicant level by controlling for **applicant fixed effects.** More than three quarters of the surveyed inventors are affiliated with applicant institutions that at least one other surveyed inventor is affiliated with as well. We select the modal applicant institution, which is the applicant institution listed on the majority of the inventor's patents. The applicant fixed effect is then represented by a dummy variable that takes the value of 1 if a patent corresponds to the inventor's modal applicant institution and zero if not.

Considering the applicant institution with which an inventor was associated with for the majority of their patents throughout their career, we count 448 different applicant names (results not reported). Leaving aside the 24 inventors who file most patents as individual inventors and the 254 applicant institutions that only employ one of our inventors, we obtain 170 applicant institutions where two or more of our sample inventors mainly produce their patented inventions (results not reported in Table 1). For the 1034 inventors who are associated with these applicant institutions for the majority of their patent applications, we are able to include applicant fixed effects in our multivariate analysis. The results remain robust; although the academic education and risk attitude become insignificant, the signs of the coefficients stay the same. However, R-squared increases dramatically.

### (C3) Effects of temporal or technological concentration

We added two additional control variables that describe the inventive activity of our respondents. The first variable captures the temporal concentration of the respondents' inventive activity. In particular, it controls for whether the inventors made their inventions within a short period of time or continuously during their career. The second control variable, technical concentration, accounts for whether the inventions of our respondents are concentrated in only a few technological fields or spread across many different fields. Both variables exhibit a negative relationship with productivity, which is highly significant. However, the results for the other explanatory and control variables remain unchanged. After including the two concentration measures, R-squared increases to 0.249, which is 7.9 percentage points more compared with Model 4b (Table 5). In addition, Model C1 in Table 7 demonstrates that our results are not driven by the smallest or largest employers.

**Table 7**: Robustness checks.

| | **Model C1** | **Model C2** | **Model C3** |
|---|---|---|---|
| | ln(average above-average citation count + 1) | | |
| | large/small employers excluded | applicant fixed effects | temporal and technical concentration included |
| VARIABLES | fract. counts | fract. counts | fract. counts |
| academic education | 0.018* | 0.020 | 0.015** |
| | [0.009] | [0.015] | [0.006] |
| PhD degree | 0.039** | 0.049*** | 0.037*** |
| | [0.015] | [0.015] | [0.010] |
| breadth of work experience | 0.006 | 0.013 | 0.008 |
| | [0.008] | [0.010] | [0.005] |
| risk attitude | 0.004** | 0.003 | 0.002* |
| | [0.002] | [0.002] | [0.001] |
| divergent thinking | 0.010* | 0.014** | 0.007* |
| | [0.005] | [0.007] | [0.004] |
| systematic problem solving | -0.006 | -0.006 | -0.003 |
| | [0.005] | [0.005] | [0.004] |
| BIG-5 personality characteristics | | | |
| openness | 0.010** | 0.011*** | 0.011*** |
| | [0.004] | [0.004] | [0.003] |
| conscientiousness | -0.008*** | -0.007* | -0.006*** |
| | [0.003] | [0.004] | [0.002] |
| extraversion | -0.004 | -0.005 | -0.003 |
| | [0.004] | [0.003] | [0.002] |
| agreeableness | -0.004 | -0.004 | -0.002 |
| | [0.005] | [0.004] | [0.003] |
| neuroticism | 0.002 | -0.001 | -0.000 |
| | [0.003] | [0.003] | [0.002] |
| networking, same field | 0.006* | 0.007* | 0.004* |
| | [0.003] | [0.004] | [0.002] |
| networking, other field | -0.006* | -0.007* | -0.005** |
| | [0.003] | [0.004] | [0.003] |
| age of the inventors in 2010 (reference group: younger than 40 years) | | | |
| 40-44 years | -0.024** | -0.032*** | -0.024*** |
| | [0.009] | [0.011] | [0.008] |
| 45-49 years | -0.038*** | -0.043*** | -0.043*** |
| | [0.009] | [0.011] | [0.008] |
| 50-54 years | -0.047*** | -0.044*** | -0.052*** |
| | [0.013] | [0.013] | [0.009] |
| 55-59 years | -0.064*** | -0.058*** | -0.061*** |
| | [0.011] | [0.015] | [0.008] |
| 60-64 years | -0.069*** | -0.060*** | -0.057*** |
| | [0.014] | [0.014] | [0.008] |
| applicant size (shares) (reference group: 1 patent) | | | |
| 2-24 patents | 0.215 | 0.123 | 0.006 |
| | [0.155] | [0.141] | [0.006] |
| 25-249 patents | 0.151 | 0.076 | -0.003 |
| | [0.112] | [0.139] | [0.006] |
| 250-999 patents | 0.154 | 0.068 | 0.003 |
| | [0.109] | [0.139] | [0.008] |
| 1000-9999 patents | 0.164 | 0.081 | 0.010* |
| | [0.110] | [0.135] | [0.006] |
| type of applicant (shares) (reference group: private firm) | | | |
| univ./research inst. | -0.058*** | 0.014 | -0.044*** |
| | [0.011] | [0.068] | [0.007] |
| individual inventions | 0.147 | 0.076 | 0.016** |
| | [0.103] | [0.165] | [0.006] |
| status of the patent (shares) (reference group: granted) | | | |
| patents withdrawn | -0.003 | -0.010 | -0.012 |
| | [0.012] | [0.019] | [0.007] |
| patents refused | -0.030 | -0.053 | -0.031 |
| | [0.026] | [0.055] | [0.024] |
| patents pending | 0.001 | 0.004 | -0.007 |
| | [0.008] | [0.015] | [0.005] |

**Table 7**: Robustness checks (*continued*).

| | **Model C1** | **Model C2** | **Model C3** |
|---|---|---|---|
| | ln(average above-average citation count + 1) | | |
| | large/small employers excluded | applicant fixed effects | temporal and technical concentration included |
| VARIABLES | fract. counts | fract. counts | fract. counts |
| temporal concentration | | | -0.093*** |
| | | | [0.010] |
| technical concentration | | | -0.024*** |
| | | | [0.008] |
| technical areas (shares) | included | included | included |
| Wald-Test | 1.97; p=0.0404 | 33; p=0.9716 | 3.92; p=0.0001 |
| periods (shares) | included | included | included |
| Wald-Test / chi2-test | 9.26, p=0.0000 | 12.25, p=0.0000 | 7.11; p=0.0000 |
| Constant | -0.004 | 0.268** | 0.226** |
| | [0.134] | [0.119] | [0.096] |
| Observations | 860 | 1034 | 1312 |
| R-squared | 0.150 | 0.325 | 0.249 |
| F test | 7.401 | 1.269 | 33.33 |

*Notes:*

All explanatory variables are computed for the time period between job entry and 2010.

Dependent variable: Average above-average citation count

Robust standard errors based on applicant clusters in brackets.

Significance levels: *** p<0.01, ** p<0.05, * p<0.1

### (C4) Quantile Regression

Finally, Table 8 shows the results of quantile regressions. The OLS model estimates the impact of the explanatory variables at the conditional mean of the dependent variable. Its coefficients and those of the key inventor regressions in Models 4c, 5c and 6c in Table 6 are not directly comparable. However, quantile regressions allow us to estimate the impact of explanatory variables at different points of the conditional distribution of the dependent variable.

The results show that the size of the coefficient of a PhD degree doubles between the 0.5/0.75 and the 0.9 quantile. Risk attitude is only significant at the 0.5 quantile. Networking only exhibits a significant effect at the 0.75 quantile. Finally, the size of the effects of age and firm size also increases at higher quantiles.

**Table 8**: Quantile regression (jointly estimated).

| | **(Model 1d)** | **(Model 2d)** | **(Model 3d)** |
|---|---|---|---|
| | ln(average above-average citation count + 1) | | |
| | 0.5 quantile | 0.75 quantile | 0.9 quantile |
| academic education | 0.008* | 0.003 | 0.016 |
| | [0.005] | [0.007] | [0.014] |
| PhD degree | 0.019*** | 0.022*** | 0.050*** |
| | [0.005] | [0.007] | [0.012] |
| breadth of work experience | 0.004 | 0.002 | 0.016 |
| | [0.004] | [0.007] | [0.015] |
| risk attitude | 0.002** | 0.001 | 0.003 |
| | [0.001] | [0.001] | [0.003] |
| divergent thinking | 0.005 | 0.008 | 0.012 |
| | [0.003] | [0.007] | [0.012] |
| systematic problem solving | 0.001 | -0.004 | -0.002 |
| | [0.002] | [0.003] | [0.006] |
| BIG-5 personality characteristics | | | |
| openness | 0.002 | 0.010*** | 0.021*** |
| | [0.002] | [0.003] | [0.005] |
| conscientiousness | -0.001 | -0.006* | -0.004 |
| | [0.001] | [0.003] | [0.005] |
| extraversion | -0.002 | -0.002 | -0.006 |
| | [0.002] | [0.003] | [0.005] |
| agreeableness | -0.002 | -0.002 | -0.009* |
| | [0.002] | [0.003] | [0.005] |
| neuroticism | 0.001 | -0.003 | -0.003 |
| | [0.002] | [0.003] | [0.006] |
| networking, same field | 0.002 | 0.005* | 0.003 |
| | [0.002] | [0.003] | [0.006] |
| networking, other field | -0.002 | -0.005 | -0.003 |
| | [0.003] | [0.004] | [0.006] |
| age of the inventors in 2010 (reference group: younger than 40 years) | | | |
| 40-44 years | -0.016** | -0.032*** | -0.048** |
| | [0.007] | [0.011] | [0.020] |
| 45-49 years | -0.019*** | -0.043*** | -0.078*** |
| | [0.007] | [0.010] | [0.017] |
| 50-54 years | -0.022*** | -0.057*** | -0.093*** |
| | [0.007] | [0.011] | [0.015] |
| 55-59 years | -0.032*** | -0.053*** | -0.093*** |
| | [0.006] | [0.011] | [0.019] |
| 60-64 years | -0.029*** | -0.057*** | -0.081*** |
| | [0.008] | [0.010] | [0.020] |
| Additional control variables[A] | Included | included | included |
| technical areas | | included | |
| Wald-Test | | 18.80; p=0.0000 | |
| periods | | included | |
| Wald-Test | | 315.75; p=0.0000 | |
| Constant | 0.098** | 0.312*** | 0.358 |
| | [0.046] | [0.088] | [0.234] |
| Observations | 1,312 | 1,312 | 1,312 |
| F test | 0.0946 | -36.4700 | 0.1814 |

*Notes:*

All explanatory variables are calculated for the time period between job entry and 2010.

Dependent variable: Average above-average citation count.

[A]Additional controls included (but not reported in the table): Applicant size shares and type shares, status shares.

Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.

## 4. Discussion

This paper documents selected results based on a new data set that links information about inventors' human capital (e.g., skills, abilities, attitudes, work experience, personality traits, and networks) with information from their patenting history. The main advantage of this data set is that we can control for additional information, such as personality traits, cognitive skills, or the career path of inventors (e.g., breadth of previous work experience), in regressions that explain innovative productivity. The data set includes answers and patent histories from German inventors listed on EP patent applicants in the fields ME, CT, and NT filed in the years between 1978 and 2010. Concentrating on three homogeneous yet different technology sectors allows us to analyse whether there are differences in innovative productivity drivers between technology fields and to obtain results for specific important technology fields.

Our results confirm prior findings in the literature regarding the determinants of inventor productivity. In particular, patent applicant characteristics and basic human capital variables, such as age and education, turn out to be important determinants of productivity. Even after adding established productivity controls, our additional human capital variables, particularly personal traits, creativity-related variables (divergent thinking skills, breadth of experience), and a positive risk attitude, still have explanatory power with respect to inventive productivity. Furthermore, our results exhibit a first indication that the determinants of productivity differ between technical fields. Skills, attitudes and experience, such as divergent thinking, breadth of experience, and a positive risk attitude, for instance, matter more in CT than in ME. Finally, there are differences in the determinants of inventive productivity for average inventors and key inventors.

### *4.1 Implications*

Our results have important implications for theory and practice. In particular, research on the productivity of inventors and of other employees should take into account personality traits and creativity-related variables that have been neglected so far in the literature. This allows us to form a more nuanced understanding of the drivers of creativity and output quality.

For managers, our results indicate that personality traits and creativity-related characteristics should be taken into account when hiring new employees; this can be achieved by using specialized tests. Furthermore, these characteristics should also be taken into account when designing reward and incentive systems for inventors.

Furthermore, skills, attitudes, and the breadth of work experience turned out to be particularly important in CT, which is a general purpose technology. This result could mean that these inventor characteristics affect the recombination of knowledge across technological fields. In particular, divergent thinking or experience in various fields might be valuable in this respect. In addition, networks in the inventor's own technology field only have a positive impact on productivity in an established technology field, such as mechanical engineering.

We identified additional human capital components that particularly drive inventive productivity in CT but not in ME. This underlines the importance of the design of HR instruments for recruiting and motivating R&D workers that meet the demands of the technology field in which a firm operates.

### *4.2 Limitations*

There are a number of limitations to the report, which must be mentioned. Although there are clear benefits of using patent data for this report, particularly in combination with survey data, the general limitations of using patent data still apply. Specifically, not all inventions are patentable or patented (Griliches, 1990). Even if inventions are patented, we only observe EP patent applications. This may well lead to a positive selection of the inventions and inventors in our sample.

Furthermore, even though quality-adjusted patent counts are a common measure for inventor productivity (Lanjouw and Schankerman, 2004), other unobservable output measures, such as market success, may capture additional dimensions of the productivity of inventors and the value of their patents.

Because of possible reverse causality (Lee, 2010), we do not claim a causal relationship of inventor productivity with network variables and concentration variables. However, all personality traits and individual characteristics seem to be sufficiently exogenous or predetermined to allow a causal interpretation.

### *4.3 Conclusions*

This paper adds to the small but fast growing literature on determinants of individual inventor productivity that links survey data with patent history data. The focus of our report is on human capital variables that potentially drive inventive output and quality, which have not been addressed by previous research. It adds three aspects to this literature. Based on theoretical considerations, it shows that personal traits, risk attitude, creativity-related skills as measured in tests, and selected aspects of the career, such as the breadth of work experience, all have additional explanatory power in determining who files more patents and whose patents are cited more often. It also demonstrates that the drivers of inventive productivity differ between technology fields. Finally, it shows that highly productive inventors who mainly drive patent output differ from average inventors. These additions fill important gaps in the literature and will have implications for management policy.

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## Appendix

**Table A**: Technology differences in individual-level determinants of inventive productivity (reduced set of control variables; NT included).

| | **Model A1** | **Model A2** | **Model A3** | **Model A4** |
|---|---|---|---|---|
| | ln (average above-average citation count + 1) | | | |
| | all patents | only ME patents | only CT patents | only NT patents |
| | all inventors | only inventors with at least one ME patent | only inventors with at least one CT patent | only inventors with at least one NT patent |
| academic education | 0.010* | 0.002 | 0.005 | -0.003 |
| | [0.006] | [0.007] | [0.004] | [0.007] |
| PhD degree | 0.030*** | 0.010 | 0.014** | -0.003 |
| | [0.009] | [0.016] | [0.006] | [0.007] |
| breadth of work experience | 0.007 | -0.009 | 0.017*** | 0.006 |
| | [0.006] | [0.007] | [0.005] | [0.005] |
| risk attitude | 0.003** | -0.001 | 0.001 | 0.001 |
| | [0.001] | [0.001] | [0.001] | [0.001] |
| divergent thinking | 0.008* | 0.003 | 0.007* | 0.004** |
| | [0.004] | [0.008] | [0.004] | [0.002] |
| systematic problem solving | -0.001 | -0.006 | 0.002 | -0.001 |
| | [0.004] | [0.007] | [0.002] | [0.003] |
| BIG-5 personality characteristics | | | | |
| openness | 0.010*** | 0.007* | 0.005* | -0.001 |
| | [0.003] | [0.004] | [0.003] | [0.002] |
| conscientiousness | -0.005** | -0.005** | -0.004* | 0.003** |
| | [0.002] | [0.002] | [0.002] | [0.002] |
| extraversion | -0.003 | -0.006 | -0.003* | 0.001 |
| | [0.003] | [0.004] | [0.002] | [0.002] |
| agreeableness | -0.003 | -0.002 | -0.001 | -0.003* |
| | [0.003] | [0.004] | [0.003] | [0.001] |
| neuroticism | 0.00002 | -0.0001 | -0.0001 | -0.0004 |
| | [0.002] | [0.003] | [0.002] | [0.002] |
| networking, same field | 0.005** | 0.007* | 0.004* | -0.002 |
| | [0.003] | [0.004] | [0.002] | [0.002] |
| networking, other field | -0.006** | -0.007* | -0.002 | 0.002 |
| | [0.003] | [0.004] | [0.002] | [0.001] |
| age of the inventor in 2010 | -0.002*** | -0.001* | -0.001*** | -0.001*** |
| | [0.0003] | [0.001] | [0.0003] | [0.0001] |
| applicant size (modal) [1000 patents] | 0.001* | -0.001*** | 0.0001*** | 0.00005 |
| | [0.0003] | [0.0002] | [0.0003] | [0.0001] |
| type applicant: private firm | 0.036*** | -0.009 | 0.017*** | 0.005 |
| | [0.008] | [0.020] | [0.004] | [0.004] |
| status patent: granted | 0.014** | 0.023*** | 0.010 | 0.002 |
| | [0.006] | [0.006] | [0.008] | [0.005] |
| share period post 1999 | -0.065*** | -0.027 | -0.0001 | 0.004 |
| | [0.015] | [0.025] | [0.005] | [0.008] |
| share chemical/pharma | -0.004 | -0.039** | -0.005 | 0.004 |
| | [0.008] | [0.017] | [0.004] | [0.006] |
| Constant | 0.114*** | 0.149*** | 0.025 | 0.029 |
| | [0.027] | [0.042] | [0.025] | [0.019] |
| Observations | 1312 | 514 | 853 | 175 |
| R-squared | 0.077 | 0.062 | 0.091 | 0.174 |
| F test | 9.174 | 4.380 | 16.22 | 4.543 |
| Pseudo R-squared | --- | --- | --- | |

*Notes:*

All explanatory variables are calculated for the time between job entry and 2010.

Models A1–A4: Robust standard errors based on applicant clusters in brackets.

Models A5–A8: Marginal effects.

Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.

**Table A**: Technology differences in individual-level determinants of inventive productivity (reduced set of control variables; NT included) *(continued)*.

| | **Model A5** | **Model A6** | **Model A7** | **Model A8** |
|---|---|---|---|---|
| | binary variable = 1 if inventor in the upper 10% of performance, 0 else. | | | |
| | all patents | only ME patents | only CT patents | only NT patents |
| | all inventors | only inventors with at least one ME patent | only inventors with at least one CT patent | only inventors with at least one NT patent |
| academic education | 0.089** | 0.038 | 0.074 | -0.008 |
| | [0.037] | [0.038] | [0.064] | [0.021] |
| PhD degree | 0.129*** | 0.020 | 0.113 | 0.014 |
| | [0.050] | [0.053] | [0.085] | [0.018] |
| breadth of work experience | 0.030* | -0.014 | 0.077*** | 0.018 |
| | [0.018] | [0.028] | [0.030] | [0.025] |
| risk attitude | 0.007* | 0.006 | 0.006 | -0.002 |
| | [0.004] | [0.006] | [0.004] | [0.004] |
| divergent thinking | 0.034*** | 0.005 | 0.033*** | 0.020 |
| | [0.013] | [0.029] | [0.013] | [0.016] |
| systematic problem solving | -0.006 | -0.006 | 0.011 | 0.001 |
| | [0.012] | [0.018] | [0.011] | [0.017] |
| BIG-5 personality characteristics | | | | |
| openness | 0.022** | 0.021* | 0.016* | -0.003 |
| | [0.009] | [0.013] | [0.010] | [0.012] |
| conscientiousness | -0.010 | -0.025** | -0.019** | 0.006 |
| | [0.008] | [0.011] | [0.008] | [0.014] |
| extraversion | -0.006 | -0.027*** | -0.013** | 0.009 |
| | [0.007] | [0.010] | [0.006] | [0.014] |
| agreeableness | -0.014* | -0.005 | 0.004 | -0.009 |
| | [0.008] | [0.010] | [0.009] | [0.010] |
| neuroticism | -0.00002 | 0.001 | 0.002 | 0.009 |
| | [0.007] | [0.013] | [0.007] | [0.010] |
| networking, same field | 0.008 | 0.018 | 0.013 | -0.005 |
| | [0.007] | [0.012] | [0.010] | [0.009] |
| networking, other field | -0.011 | -0.024** | -0.007 | 0.002 |
| | [0.008] | [0.010] | [0.010] | [0.010] |
| age of the inventor in 2010 | -0.003*** | -0.001 | -0.005*** | -0.003*** |
| | [0.001] | [0.002] | [0.001] | [0.001] |
| applicant size (modal) | 0.0002 | -0.003** | 0.002*** | 0.0001 |
| [1000 patents] | [0.001] | [0.001] | [0.001] | [0.001] |
| type applicant: private firm | 0.109*** | -0.005 | 0.156*** | 0.023 |
| | [0.032] | [0.069] | [0.059] | [0.042] |
| status patent: granted | 0.033** | 0.084*** | 0.060** | 0.000 |
| | [0.014] | [0.026] | [0.028] | [0.037] |
| share period post 1999 | -0.141*** | -0.084 | -0.041 | 0.195** |
| | [0.032] | [0.055] | [0.034] | [0.083] |
| share chemical/pharma | 0.020 | -0.138 | -0.012 | 0.002 |
| | [0.021] | [0.109] | [0.021] | [0.028] |
| Constant | --- | --- | --- | |
| Observations | 1312 | 514 | 853 | 175 |
| R-squared | --- | --- | --- | --- |
| F test | --- | --- | --- | --- |
| Pseudo R-squared | 0.0698 | 0.0865 | 0.150 | 0.196 |

*Notes:*
All explanatory variables are calculated for the time between job entry and 2010.

Models A1–A4: Robust standard errors based on applicant clusters in brackets.

Models A5–A8: Marginal effects.

Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.