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DISCUSSION PAPER

// THERESA MICHLBAUER AND THOMAS ZWICK

Precocious Inventors: Early Patenting Success and Lifetime Inventive Performance

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Precocious Inventors: Early Patenting Success and Lifetime Inventive Performance

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Theresa Michlbauer and Thomas Zwick[1]

Abstract

This paper shows that inventors with an early patenting success have a higher inventive productivity during their remaining career. We use European patent data for a period of 32 years for 1240 German inventors. The patent data are linked with survey data that provide information on an extensive list of individual inventor characteristics and time variant information on work environment characteristics for the same period. We define an early success as being in the fastest quartile of inventors applying for the first patent after completing education or being in the highest quartile of citations received for the first patent. The higher career productivity seems to be a consequence of higher individual ability rather than cumulative advantage. Inventors with high productivity early in their career cannot increase their productivity further but instead experience a regression to the mean. Inventors with a fast or high-quality first patent also experience this regression, albeit at a lower rate. In addition, these inventors do not obtain better resources, such as a higher share of research and development time, larger employers, more voluntary job moves, or more co-inventors, during their remaining career than inventors without early success.

Key Words Inventive Productivity, Early Patenting Success, Ability, Cumulative Advantage

JEL-Codes J24, M54, O31, O32

[1] Theresa Michlbauer, Chair for Human Resource Management and Organisation, University of Wuerzburg, Sanderring 2, 97070 Wuerzburg, theresa.michlbauer@uni-wuerzburg.de.
Thomas Zwick, Chair for Human Resource Management and Organisation, University of Wuerzburg, Sanderring 2, 97070 Wuerzburg, thomas.zwick@uni-wuerzburg.de; ZEW – Leibniz Centre for European Economic Research, Mannheim; Research Centre for Education and the Labour Market (ROA), Maastricht.

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1 Introduction

It is hard to observe or predict inventor ability directly (Merton, 1973b; Dasgupta & David, 1994). Therefore, individual characteristics formed before the start of the career of an inventor, such as education level, family background, or personality traits, are usually used as predictors of future inventive productivity (Dietz & Bozeman, 2005; Lawson & Sterzi, 2014). However, potential employers cannot easily observe all of these individual characteristics and the predictive value of several indicators may be limited for employers. For example, job applicants can manipulate personality tests and information about their job motivation during their job interview (Robie et al., 2007). Consequently, transparent and trustable achievements obtained before or during the first career years may be more reliable indicators to assess individual ability and future productivity for potential employers (Lazear, 1986). Identifying, attracting, and retaining young talents especially can be a decisive advantage for enterprises that rely on innovations given that few inventors achieve a high inventive productivity during their career (Lotka, 1926).

This paper proposes the time span between education and the first patent as well as the quality of the first patent as indicators of inventive career productivity. The image of the young, great mind making critical inventions is iconic (Simonton, 1988; Jones, 2010; Jones and Weinberg, 2011). In addition, patented inventions are a carefully scrutinized and publicly observable form of creativity (Audia & Goncalo, 2007) and a good indicator for inventive activity in those sectors that use patents (Griliches, 1990). Nevertheless, the informational value of the timing and quality of the first patent on lifetime inventions has hardly been assessed.

In this paper, we establish that inventors whose time between completing their education and the first patent application is in the first quartile of all inventors have a patent productivity per work year about 50% higher during their remaining career compared with other inventors. The inventive career output after the first patent is about 20% higher for inventors whose first patent is in the top citations quartile. We find a similarly large career productivity difference between inventors with and without early patenting successes for the quality (measured by number of citations) of all patents after the first patent. We finally show that the speed and quality of the first patent are independent predictors of inventive productivity.

We also explore whether the speed and quality of the first patent are a sign of inventive ability or whether the higher lifetime productivity of precocious inventors (Dietz & Bozeman, 2005, p. 354) is a consequence of cumulative advantage (DiPrete & Eirich, 2008). Merton (1973a) proposed that early patenting success may be an exogenous chance event that has positive long-term effects on inventive productivity because it leads to the attribution of additional resources or rewards. Some observers argue that the right-skewed distribution of inventive success is the consequence of cumulative advantage processes instead of ability differences between inventors (see, for example, the literature review in Allison et al., 1982). However, the distributional shape of inventive success alone is not proof of the presence of a cumulative advantage process. A right-skewed patent distribution also may evolve when all inventors produce patents with a given production rate and do not obtain resources related to previous successes. In other words, there may be a “skewed distribution of talent and tenacity” instead of cumulative advantage (Huber, 1998, 2002).

We find that high productivity during the first career years does not lead to a stronger increase in productivity in later career years; the productivity change actually is negative. This regression to the mean effect in a random distribution (Stigler, 1997) is lower for precocious inventors. Nevertheless, for these inventors, there is no indication of cumulative advantage. We also find no evidence for concrete cumulative advantage mechanisms. Precocious inventors do not have a higher share of working time devoted to research and development (R&D) activities, nor do they have a higher number of co-inventors in later career years compared with the first career years. However, we find a good match between the first employer and the precocious inventor. Fewer inventors with early success voluntarily move to another employer later in their career.

We exploit the richness of a dataset that combines survey data for 1240 German academic and industry inventors on their career between 1978 and 2010 with their complete patent history drawn from the official PATSTAT patent data provided by the European Patent Office. The survey data comprise typical *curriculum vitae* (CV) information and data on family background and personality. A unique calendar function in the survey data allows us to observe the work environment and its changes during careers. Thus, we can differentiate between the work environment during the first career years and later career years and include many potential individual drivers of inventive career success beyond age, gender, and education.

Our paper is structured as follows. Section 2 proposes individual ability and cumulative advantage as explanations for the positive correlation between early patenting success and inventive career productivity. Section 3 presents our data and the estimation strategy. Section 4 establishes that early patenting success is significantly positively correlated with lifetime patenting productivity. Section 5 shows that cumulative advantage seems not to be a driver of the correlation between early success and lifetime productivity. Our results and their potential implications are discussed in Section 6.

2 Theoretical Framework

Early Patenting Success as Indicator for Ability

There is information asymmetry about ingenuity between inventors and other labour market participants (Greenwald, 1986). According to Spence (1976), a patent may be a signal for inventive ability that reduces the information disadvantage of potential employers (Hoisl, 2007a, Melero et al., 2020). First, a patent is easily observable for everybody. For a patent to be issued, the invention must be new, useful, and not obvious to persons reasonably skilled in the specific technology. This minimum requirement is applied uniformly to all patents, and thus each patent has a minimum information value on the inventive ability necessary to obtain it (Griliches, 1990; Huber, 1998). In addition, a substantive conceptual contribution by the inventor is a legal requirement for an attribution on a patent and violating this requirement may invalidate the patent (Häussler & Sauermann, 2013). Consequently, the signalling value can be transferred to all inventors listed on a patent. Second, it is costly and time-consuming to reach the frontier of knowledge in a field, a necessary component of innovative activity (Jones, 2009; 2010). There is also a negative relationship between the human capital investments necessary to obtain a patent and the inventor's ability (Melero et al., 2020). Finally, there is a strong incentive to apply for a patent for a suitable inventive idea because a fixed amount of financial income from patents is typically shared among all listed inventors (Häussler & Sauermann, 2013).

Inventive activity is frequently a contest of priority of discovery. Speed in patenting is rewarded because usually only the first scientist gets the reputation and rewards for an inventive idea (Merton, 1973a; Dasgupta & David, 1994). Early patenting success is costlier for less able inventors because it is harder for them to speed up the invention. Young inventors in particular need time to acquire the necessary background knowledge and cannot spend the time needed for training or education on their inventive project (Jones, 2010). Higher innate talent and the mindset required for further inventions allow inventors to complete the patenting process faster than their peers (Dietz & Bozeman, 2005). Therefore, we assume that:

Hypothesis A1: *Inventors who apply for their first patent faster than their peers have a higher inventive performance for the remainder of their career.*

Reputation and economic value of a patent increase with the number of references made to it, typically calculated by forward citations in other patents or scientific work (Trajtenberg, 1990; Henderson et al., 1998; Harhoff et al., 1999; Hall et al., 2005; Sapsalis et al., 2006; Gambardella et al., 2008; Czarnitzki et al., 2009; Czarnitzki et al., 2012). In addition to the age of the inventor at the application date, the technological importance of a patent can easily be measured after several years by its number of citations (Häussler et al., 2014). Thus, we assume that an inventor obtaining many citations for a first patent signals higher inventive capacity. The positive reputation effect of a highly cited patent may be especially strong for the first patent because young inventors typically are not in a high hierarchical position and have short professional experience. Attribution on patents indicating a contribution to the inventive process is positively related to seniority and hierarchical position (Lissoni & Montobbio, 2014). Our second hypothesis is:

Hypothesis A2: *Inventors whose first patent is of higher quality than their peers have a higher inventive performance for the remainder of their career.*

Speed and high quality of the first patent may be substitutes. Jones (2010) pointed out that young inventors must decide how to divide their time between education or training and inventive activity. If they spend more time working on their inventive idea, this may allow them to apply for the first patent sooner, but reduce the technological importance of the first patent. Therefore, we assume that few inventors who apply for their first patent quickly also obtain many citations for their first patent and that:

Hypothesis A3*: Fast first patent and high-quality first patent have an independent correlation with inventive performance for the remainder of the career.*

There is a rich body of literature on determinants of inventive productivity (for example, Huber, 1998; Hoisl, 2007a,b; Giuri et al., 2007; Mariani & Romanelli, 2007; Walsh & Nagaoka, 2009; Toivanen & Vaananen, 2012; Zwick et al., 2017). However, we are aware of only three papers that analyze the quality of early career achievements as predictors of inventive career productivity.[2] Audia & Goncalo (2007) showed that previous inventive success leads to a higher probability of generating further inventions. They argued that the inventions after past successes are more frequently characterized by exploitation of earlier ideas instead of exploration of new ideas. However, patents based on exploitative ideas receive fewer citations, and thus have lower economic value and inventive quality than patents based on explorative ideas (Harhoff et al., 1999; Gambardella et al., 2008). Dietz & Bozeman (2005) analyzed CV information merged with patent data of 1200 research scientists and engineers working for the US Department of Energy, Department of Defense, and National Science Foundation. They found that scientists who have many publications before obtaining their doctoral degree have a higher number of patents per career year on average. Finally, Lawson & Sterzi (2014) looked at the patenting record of more than 500 British academic inventors. Based on CV information, they showed that the number of citations the first patent receives is the most important predictor for the number of patents an academic inventor obtains during their career, although the number of citations does not affect overall patenting productivity. They concluded that a high-quality first invention signals a high overall career output for an individual inventor.

The differences in the results among these three papers may come from several sources. Audia & Goncalo (2007) did not only look at the first patent of an inventor, but also analysed the relationship between patenting success over a period of 2 years and patenting behaviour in the following years,

[2] The early literature on the impact of early success on productivity shows that more productive scientists and inventors start their career earlier (Manis, 1951; Zuckerman, 1967; Blackburn et al., 1978). Another persistent finding is that higher inventive productivity during the first career years is correlated with higher productivity in the following career years (Meltzer, 1949; Lightfield, 1971; Clemente, 1973; Reskin, 1977).

irrespective of the state of the career. Their results came from patents in the hard disk drive sector, a nascent technology sector during the period they observed. Dietz & Bozeman (2005) and Lawson & Sterzi (2014) concentrated on the small and probably specific sub-group of academic inventors. Consequently, the results of all three papers may not be easy to generalize.

Early Patenting Success as Trigger for Cumulative Advantage

We postulate that early patenting success signals individual inventive ability. However, inventors with early patenting success may also profit from cumulative advantage, as explained in Merton's famous definition of the Matthew effect: "the accruing of greater increments of recognition of particular scientific contributions to scientists of considerable repute and the withholding of such recognition from scientists who have not yet made their mark" Merton (1973b, p. 446). Cumulative advantage means that early success attracts new resources as well as rewards. Given the uncertainty about the ability and motivation of inventors, employers attribute more scarce resources to inventors with an early success. The additional resources facilitate continued higher performance given the ability of the inventor (Owen-Smith & Powell, 2001; DiPrete & Eirich, 2008). In the extreme case, cumulative advantage completely explains higher career productivity instead of ability. In other words, lucky inventors can turn fortuitous early patents into lasting inventive productivity advantages (Cole & Cole, 1967; Allison et al., 1982).

Cumulative advantage can be shown empirically if high inventive productivity during the first career years positively correlates with inventive productivity during the remainder of the career. Our first cumulative advantage hypothesis is:

Hypothesis CA1: Inventive productivity during the first career years is positively correlated with the increase in inventive productivity in the remainder of the career.

DiPrete & Eirich (2008) posited that a small advantage during the early stage of the inventive process means that inventors have a long-term positive productivity effect in a cumulative advantage process. Thus, we assume that precocious inventors have an even steeper productivity trajectory between first career years and their remaining career. In other words, high early productivity leads to stronger cumulative advantage if the first patent is fast and high quality. We also assume that a fast patent and a high-quality first patent have an independent additional effect on cumulative advantage as posited in hypothesis A3:

Hypothesis CA2: The positive correlation between inventive productivity during the first career years and inventive productivity during the remainder of the career is stronger for inventors with a fast first patent.

Hypothesis CA3: The positive correlation between inventive productivity during the first career years and inventive productivity during the remainder of the career is stronger for inventors with a high-quality first patent.

Hypothesis CA4: The higher positive correlation between inventive productivity during the first career years and inventive productivity during the remainder of the career is independent for inventors with a fast patent and for inventors with a high-quality patent.

Cumulative advantage can not only be tested by the correlation between early career productivity and the inventive productivity during the remaining career, but it also can be shown when the employer attributes additional resources to inventors with high early productivity (Owen-Smith & Powell, 2001; Toivanen & Väänänen, 2012). Precocious inventors may have a better chance of working on R&D projects later in their career, and they are encouraged to invest time in research instead of management or organisation tasks (Merton, 1973a). This cumulative advantage mechanism assumes that employers put their best researchers on the most promising inventive projects and grant them enough time and resources to complete these projects (Zucker et al., 1998, 2002). Therefore, we assume:

Hypothesis CA5: Early patenting success is positively correlated with the share of the working time an inventor can spend on R&D tasks in later career years.

According to the signalling theory described above, outside employers can also observe precocious inventors easily (Melero et al., 2020). Their visibility increases the likelihood of being poached or moving voluntarily to another employer to improve job matching (Lazear, 1986). Job mobility may increase individual productivity because it allows employees to increase the quality of their job match, exchange their knowledge, build more experience, and enlarge their research network (Song et al., 2003; Dietz & Bozeman, 2005; Hoisl, 2007a). Especially if the new employer offers a better research environment, an employer move increases individual career productivity (Crane, 1965; Cole and Cole, 1967; Long, 1978). The quality of the research environment may be measured by the number of patents an employer has applied for (Czarnitzki et al., 2012; Mariani & Romanelli, 2007; Chabchoub & Niosi, 2005; Harhoff & Hoisl, 2010; Mansfield, 1986; Scherer, 1999; Lawson & Sterzi, 2014). Our next two hypotheses are:

Hypothesis CA6: Early patenting success is positively correlated with the probability of moving voluntarily to another employer in later career years.

Hypothesis CA7: Early patenting success is positively correlated with the probability of moving to an employer with a stronger research orientation in later career years.

Inventors with an early patent success may also benefit from better research co-operation options with other inventors (Baldini et al., 2007). There is empirical evidence that high-impact scientists enjoy more extensive exchange and better co-operation options with other inventors. Owen-Smith & Powell (2001) suggested that academic inventors with high-quality patents attract more consulting jobs and research contracts that allow them to improve their research network. Thus, we assume that early patenting success allows inventors to increase the number of co-operators. However, a larger research network results in higher inventive productivity because inventors can share or recombine their knowledge (Crane, 1972; Allen, 1979; Simonton, 1992, 2003; Dunbar, 1995; Breschi & Lissoni, 2009; Dietz & Bozeman, 2005; Jones, 2009). Our last cumulative advantage hypothesis is:

Hypothesis CA8: Early patenting success is positively correlated with the number of co-inventors in later career years.

The empirical literature on the role of cumulative advantage for the productivity of inventors is tenuous and equivocal, see for example the literature reviews by Allison et al., (1982) and DiPrete & Eirich (2008). Sociological papers mainly show an increase in inequality in publications and citations over the life cycle of the entire population or certain birth cohorts of scientists, compare Crane (1965, 1972), Cole & Cole (1967), and Allison and Stewart (1974). These papers do not show concrete cumulative advantage mechanisms, such as the attribution of resources to scientists with previous successes (DiPrete & Eirich, 2008). These works may also suffer from the compositional fallacy (Simonton, 1997). The compositional fallacy describes aggregation errors if inferences about individual experience–productivity patterns are derived from average statistics across many individuals. The resulting patterns may, for example, be biased if more productive inventors are active longer in R&D than less productive inventors (Huber, 2002). Hence, the scientometrics literature proposes testing directly whether inventors with early successes have a higher productivity rate during the rest of their career (Lotka, 1926; Levine, 1986). The only paper with a direct cumulative advantage test based on individual inventor productivity measures does not find evidence for a cumulative productivity advantage during the career (Huber, 1998).

3 Methodology and Data

Methodology

We measure the correlation of the speed and the quality of the first patent with inventive output during the remaining career and additionally control for the relevant individual and work environment characteristics when the first patent is applied for. Our empirical model is

$$Y_{ic} = \beta_1 fast_{ip1} + \beta_2 highquality_{ip1} + \delta` X_{ip1} + \epsilon_{ic}. \quad (1)$$

To avoid heterogeneity, career output Y_{itc} is measured for the entire career (*c*) excluding the first patent (*p*1). Early patenting success is denoted by the dummy variables *fast* and *highquality* based on the speed and quality of the first patent. Variable X_{ip1} denotes a vector of control variables for individual characteristics and the inventor's work environment when the first patent was applied for. Variable ε is the idiosyncratic error term. Our identification strategy assumes that there are no unobserved factors that are correlated with early patenting success and overall inventive career productivity after the first patent. Therefore, we include a broad range of individual and work environment factors.

In our next estimation step, we check whether there is a positive correlation between inventive productivity during the first career years, *t*1, and inventive productivity during the remainder of the career, *t*2, that can be explained by cumulative advantage. We use a differential equation of exponential growth (Yule process) as a formal empirical test of the presence of cumulative advantage[3],

$$Y_{it2} - Y_{it1} = \beta Y_{it1} + \delta' Z_{\mathrm{it1}} + \epsilon_{\mathrm{it1}}, \tag{2}$$

with Z_{it1}, which is a vector of resources available for the inventor during the first career years. Cumulative advantage means that a high productivity during *t*1 (Y_{it1}) increases the difference in productivity between *t*1 and the remainder of the career, *t*2 (Y_{it2} - Y_{it1}). Hence, cumulative advantage implies a positive slope parameter, β. If, according to hypotheses CA2–CA4, precocious inventors enjoy a stronger cumulative advantage, this can be measured by higher β values for inventors with early patenting success.

In a final estimation step, we analyse actual cumulative advantage mechanisms according to our hypotheses. We use difference-in-differences estimations that show whether inventors with early patenting success enjoy a better attribution of resources during the remainder of their career. Specifically, we check whether the share of R&D activities during working time, the size of the patent applicant, the probability of a voluntary job match, and the number of co-inventors increase more strongly from *t*1 to *t*2 for inventors with an early success. The changes in resources are calculated separately for the four dimensions of indicator *Z*. We include indicators for resources available for the two periods *t* = *t*1, *t*2 for each inventor and control for individual fixed effects γ_{i} besides the interaction terms between the early success indicators and *t*2 as well as a dummy for *t*2.

$$Z_{it} = \beta_1 fast_i * t2 + \beta_2 highquality_i * t2 + \beta_3 t2 + \gamma_i + \epsilon_{it}. \tag{3}$$

Cumulative advantage for inventors with an early success predicts positive coefficients β_1 and β_2.

[3] This test was proposed by Allison et al. (1982), also compare equation (3) in DiPrete & Eirich (2008).

Data

Our dataset combines patent data and individual survey data. The patenting activity of the inventors is measured using PATSTAT data for patents of German inventors filed between 1978 and 2010 at the European Patent Office. The patent data include the first filing date of a patent on a daily basis, the status of the patent application, number of co-inventors, number of forward citations per patent received during a specific time period, type of patent applicant, and technology sector. The application date of the first patent[4] determines individual age at first patent and the number of years since obtaining the highest educational degree (derived from the inventor survey).

The patent data are merged with survey data that contain the highest educational grade, social demographics, and personality traits.[5] We use a calendar function in the survey to describe changes in the work environment during the career. The calendar captures key career characteristics during five-year spells between 1965 and 2014. As our patent information ranges from 1978 to 2010, seven spells from the calendar can be used.[6] According to our estimation strategy, we differentiate between the first career years in which the first patent was applied for ($t1$) and all following active periods ($t2$). We define as the last (observable) career period the period in which the inventor reaches age 65, the period with the last observable patent for those 41 inventors who applied for patents when they were older than 65 years, or the period 2005–2010. Thus, the number of periods included in $t2$ depends on the application date of the first patent. On average, inventors report for 2.3 calendar periods (11.5 years) after $t1$. In other words, we can observe the work environment for on average 3.3 periods or 16.5 years. The distribution of the observed number of calendar periods is shown in Table A1.

We calculate career productivity in equation (1) by dividing the number of patents and their citations by the number of career years c (last career year minus year after the first patent application). In the cumulative advantage equations (2) and (3), we compare average inventive productivity and resources for $t1$ and $t2$. The periodicity of $t1$ and $t2$ comes from the mainly 5-year periods given in our calendar. Five-year brackets are useful for measuring inventive productivity to examine differences in inventive productivity over time because patents tend to be applied for in waves (Huber, 1998; Hoisl, 2007b). There is a high risk of measurement errors incurred by attrition bias with shorter productivity measurement brackets, for example, single years. Accordingly, most papers measure inventive productivity and its changes in time brackets of between 4 and 10 years (see the literature survey in Zwick & Frosch, 2017).

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[4] No inventor had applied for more than one patent on the day of the first patent application. Therefore, we can determine the first patent with certainty.

[5] For details of the data collection and matching process, see Frosch et al. (2014) and Zwick et al. (2017).

[6] The seven spells are 1978–1979; 1980–1984; 1985–1989; 1990–1994; 1995–1999; 2000–2004; and 2005–2010.

The patent data are from an administrative source. Thus, we have robust, non-biased information on patent quantity and quality.[7] We use the patent data as the source for the dependent variable in equations (1) and (2) as well as for estimating the number of co-inventors and the applicant size in equation (3). Early inventive success is measured by aggregating the patent information over all inventors. Almost all additional information used as dependent variables comes from the survey data. Therefore, we can rule out a common method bias. Information on the educational and family background can be assumed plausibly to pre-date the start of the career, even though the information was collected at the end of the observation period. However, some survey information on personality traits, such as self-assessment on risk taking, might not reflect the situation at the time of the first patent.[8]

There are 1851 inventors in the data set. For the 298 inventors who started their career before 1978, the first patent cannot be identified with certainty in the dataset and these inventors are excluded from the dataset. In addition, we only know the year in which the highest educational degree was obtained for 1492 inventors. From this group, 252 inventors only applied for one patent in their recorded PATSTAT patenting activity. They are excluded from our estimations to allow the effect of the first patent on later career productivity to be identified.[9] Consequently, our basic sample consists of 1240 inventors (67% of the original sample).[10]

Inventive Productivity

In line with the literature (Trajtenberg, 1990; Albert et al., 1991; Harhoff et al., 1999; Bakker et al., 2016; Hoisl, 2007b), quantitative and qualitative measures of patent productivity are used. To account for differences in the career length between more and less prolific inventors (Huber, 2002), the productivity measures are standardized by years of job experience, and thus are independent of total career length (Huber, 1998; Dietz & Bozeman, 2005).

Patent quantity: Patent quantity is measured by the total number of patents applied for per inventor minus the first patent divided by the number of career years, c, after the first patent in the productivity equation. In the cumulative advantage regressions, patent quantity is measured by the total number

[7] In contrast to other studies, we cannot exclude potential self-citations at inventor level. This might imply that some results for patent quality are overestimated.
[8] There remains, as in any survey data, the risk of measurement errors.
[9] We also have to exclude one inventor who applied for all (two) patents within one 5-year period. All remaining inventors have at least one patent in at least one period after the first application period.
[10] According to our hypothesis that early patenting success is a good predictor of future inventive productivity, inventors with only one patent less frequently had an early success with it (the share with a fast dummy is 19% and the share with a high-quality dummy is 21%).

of patents applied for per inventor in *t*1 and in *t*2, respectively, divided by the period lengths of *t*1 and *t*2.

***Patent quality**:* We use forward citations of patents within 5 years of its filing to measure the quality of a patent (Trajtenberg, 1990; Albert et al., 1991; Harhoff et al., 1999; Lawson & Sterzi, 2014; Bakker et al., 2016). Our measure for patent quality is the total sum of citations without the citations of the first patent divided by *c* in the productivity estimations. In the cumulative advantage regressions, the sum of the citations of all patents applied for during *t*1 and *t*2 is divided by the period lengths of both periods.

Early Patenting Success

High-quality first patent: We define a high-quality first patent as a dummy that is 1 if the first patent is among the best 25% first patents of our sample, ranked by the total number of forward citations (within 5 years of filing).

Fast first patent: We define a first patent as being filed fast if an inventor belongs to the 25% fastest inventors in our sample to file the first patent after obtaining the highest degree of education. We use the time span between the end of education and first patent instead of age to include the trade-off between education and inventive effort as well as differences in educational attainment (Jones, 2010).

Control Variables

We control for gender differences because career strategies and inventive productivity may differ between men and women (Jung & Ejermo, 2014; Hunt et al., 2012; Ding et al., 2006; Whittington, 2011; Whittington & Smith-Doerr, 2005; Frietsch et al., 2009; Naldi et al., 2005). We also use controls for birth cohorts because patenting behaviour may have changed over the years, given the patent explosion (Hall, 2004; Lawson & Sterzi, 2014) and the increase in average age at first patent (Jones, 2009). The strong increase in the number of patent applications during the last decades and the increasing burden of knowledge in many technology areas may imply a difference in the chance of patenting an inventive idea within 5 years of obtaining the highest education in the year 1980 or in the year 2000 (Levin & Stephan, 1991; Jones, 2009; Jones, 2010; Allen & Katz, 1992; Simonton, 1988; Harhoff & Wagner, 2005; Dietz & Bozeman, 2005). We also control for education level because a higher education, particularly a PhD degree, increases inventive productivity (Hoisl, 2007a; Mariani & Romanelli, 2007; Onishi & Nagaoka, 2012; Toivanen & Väänänen, 2016; Giuri et al., 2007; Akcigit et al., 2017). An engineering specialisation during schooling may be a boon for inventive output (Gruber et al., 2013). Therefore, we include a dummy variable for inventors who have an engineering specialisation in their academic education or a technical occupation for those without academic training. In addition, family background may influence inventive productivity; academically educated parents may foster an inventor's achievement (Caldas & Bankston, 1997). Hence, we include dummy variables that have a value of 1 if an inventor has a father or a mother with academic education, respectively.

Previous studies on inventive output find a relationship between personality traits and inventive performance (Dodds et al., 2002). Particularly the personality dimension openness to new experiences is positively related to innovative output (McCrae, 1987; King et al., 1996; Furnham & Bachtiar, 2008; Sung & Choi, 2009; Silvia et al., 2009; Furnham et al., 2011; Furnham et al., 2013; Lin et al., 2013; Grosul & Feist, 2014; Batey et al., 2010; Zwick et al., 2017). We include the big 5 personality inventory (openness to experience (ideas, aesthetics), agreeableness (compliance, straightforwardness), conscientiousness (order, dutifulness, competence), extraversion (warmth, sociability, activity), and neuroticism (anxiety, depression), compare McCrae and Costa, 2006) as explanatory variables. Willingness to take risks also is a personality characteristic often related to inventive performance, and thus is controlled for in this paper (Dewett, 2007; Audia & Goncalo, 2007; Zwick et al., 2017).

Although individual characteristics are key for inventive productivity, the employer is also an important determinant of patenting success (Gambardella et al., 2008; Lawson & Sterzi, 2014). Therefore, we control for the share of working time the inventor can devote to R&D activities, the number of co-inventors, the size of the employer, and a voluntary job move. In addition, we control for the employer type because it may make a difference whether the inventor works for a private firm, a university, or a public research institute (Dietz & Bozeman, 2005; Van Looy et al., 2006; Zucker et al., 2007; Crescenzi et al., 2017).

The literature is unclear whether basic or applied research activities have a stronger positive relationship with inventive productivity (Mansfield, 1980; Griliches, 1986; Lichtenberg & Siegel, 1991). Specific knowledge contributes to innovation and generalist knowledge facilitates recombination of ideas. Previous research also shows ambiguous results on whether working as a specialist or as a generalist is related to a higher inventive productivity (Jones, 2009; Melero & Palomeras, 2015). We control for the type of research activities an inventor pursues. Technology fields have different R&D and patenting activity levels (Klevorick et al., 1995; Gruber et al., 2013; Mansfield, 1986; Levin et al., 1987). Therefore, we control for the main technology sector in which an inventor is active. Following Griliches (1990) and Hoisl (2007a, 2009), we also control for the status of the patent application, which may be pending, refused, withdrawn, or granted.

4 Early Patent Success and Inventive Performance

Descriptive Statistics

Table 1 shows that during the career, an inventor in our sample files 0.61 patent applications per working year and obtains 0.55 citations per working year. The share of male inventors is 97.7%[11]. Around 92% of inventors in the dataset hold an academic degree including a PhD. More than two thirds of the inventors are engineers. About 10% of the inventors' mothers and 24% of the inventors' fathers have an academic degree. When filing their first patent, inventors are on average nearly 40 years old[12] (not shown in the descriptive statistics).

[11] The small share of 2.3% females is in line with other studies (Jung & Ejermo, 2014; Hunt et al., 2012).

[12] This value is close to the 41.4 years reported for the first patent of Swedish inventors (Jung & Ejermo, 2014).

Variables	Mean	SD	Median	Description
Inventive output				
Patent quantity	0.606	0.841	0.353	Total numbers of patents per inventor (1978–2010), divided by number of working years
Patent quality	0.547	1.126	0.160	Total numbers of citations per inventor (1978–2010), divided by number of working years
Early inventive success				
High-quality first patent	0.289	0.453	0	Dummy = 1 if the first patent is cited at least twice within 5 years of filing
Fast first patent	0.321	0.467	0	Dummy = 1 if the first patent is filed within 4 years of obtaining the highest educational degree
Individual background				
Male	0.977	0.150	1	Dummy = 1 if inventor is male
Vocational education	0.080	0.271	0	Dummy = 1 if highest level of education is vocational education
Academic education	0.544	0.498	1	Dummy = 1 if highest level of education is academic education
PhD	0.376	0.485	0	Dummy = 1 if highest level of education is PhD
Education with engineering specialisation	0.690	0.463	1	Dummy = 1 if the inventor has an educational background in engineering
Mother academic	0.100	0.300	0	Dummy = 1 if mother is academic
Father academic	0.235	0.424	0	Dummy = 1 if father is academic
Personality				
Positive risk attitude	0.392	0.488	0	Dummy = 1 if self-assessed risk attitude 7 or higher on scale between 0 and 10
Big 5 extraversion	49.60	15.43	49.37	Factor from factor analysis on 15 questions on personality traits
Big 5 neuroticism	49.51	11.11	48.80	Factor from factor analysis on 15 questions on personality traits
Big 5 openness to new ideas	49.56	18.58	50.41	Factor from factor analysis on 15 questions on personality traits
Big 5 agreeableness	50.36	12.08	49.88	Factor from factor analysis on 15 questions on personality traits
Big 5 conscientiousness	50.35	11.83	50.93	Factor from factor analysis on 15 questions on personality traits
Work environment first patent				
Generalist work experience	0.667	0.472	1	Dummy = 1 if inventor worked as a generalist
Applied R&D	0.831	0.375	1	Dummy = 1 if inventor worked in applied R&D
Basic R&D	0.131	0.338	0	Dummy = 1 if inventor worked in basic R&D
Intensive R&D work	0.637	0.481	1	Dummy = 1 if share of R&D work is more than half of the working time
Applicant size 1–24	0.285	0.451	0	Dummy = 1 if applicant with 1–24 patents
Applicant size 25–249	0.283	0.451	0	Dummy = 1 if applicant with 25–249 patents
Applicant size 250–999	0.136	0.343	0	Dummy = 1 if applicant with 250–999 patents
Applicant size 1000+	0.125	0.331	0	Dummy = 1 if applicant with 1000+ patents
Applicant firm	0.947	0.225	1	Dummy = 1 if applicant private company
Applicant university or public research institute	0.040	0.197	0	Dummy = 1 if applicant university/research institute
Applicant individual	0.013	0.113	0	Dummy = 1 if individual applicant
Number of co-inventors 0	0.121	0.326	0	Dummy = 1 if number of co-inventors is 0
Number of co-inventors 1	0.206	0.404	0	Dummy = 1 if number of co-inventors is 1
Number of co-inventors 2–3	0.402	0.491	0	Dummy = 1 if number of co-inventors is 2–3
Number of co-inventors 4+	0.271	0.445	0	Dummy = 1 if number of co-inventors is 4+
First patent is refused	0.173	0.378	0	Dummy = 1 if patent application of first patent is refused
First patent is granted	0.601	0.490	1	Dummy = 1 if patent application of first patent is granted
First patent is pending	0.212	0.409	0	Dummy = 1 if patent application of first patent is pending
First patent is withdrawn	0.015	0.120	0	Dummy = 1 if patent application of first patent is withdrawn
Birth cohorts				
Birth year after 1970	0.208	0.406	0	Dummy = 1 if inventor was born after 1970
Birth year 1966–1970	0.234	0.423	0	Dummy = 1 if inventor was born between 1966 and 1970
Birth year 1961–1965	0.248	0.432	0	Dummy = 1 if inventor was born between 1961 and 1965
Birth year 1956–1960	0.174	0.379	0	Dummy = 1 if inventor was born between 1956 and 1960
Birth year before 1956	0.135	0.342	0	Dummy = 1 if inventor was born before 1956
Technology fields first patent				
Electrical engineering	0.088	0.284	0	Dummy = 1 if main field of technology is electrical engineering
ICT	0.015	0.122	0	Dummy = 1 if main field of technology is ICT
Semiconductors	0.027	0.161	0	Dummy = 1 if main field of technology is semiconductors
Instruments	0.018	0.134	0	Dummy = 1 if main field of technology is instruments
Chemical industry	0.058	0.234	0	Dummy = 1 if main field of technology is chemical industry
Pharma/biotechnology	0.021	0.143	0	Dummy = 1 if main field of technology is pharma/biotechnology
Chemical and process engineering	0.063	0.243	0	Dummy = 1 if main field of technology is chemical and process engineering
Transportation/engines	0.255	0.436	0	Dummy = 1 if main field of technology is transportation/engines
Consumption	0.021	0.143	0	Dummy = 1 if main field of technology is consumption
Mechanical engineering/machinery	0.101	0.301	0	Dummy = 1 if main field of technology is mechanical engineering/machinery
Mechanical elements	0.086	0.280	0	Dummy = 1 if main field of technology is mechanical elements
Nanotechnology	0.047	0.211	0	Dummy = 1 if main field of technology is nanotechnology
Clean technology	0.098	0.298	0	Dummy = 1 if main field of technology is clean technology
Other technology fields	0.103	0.304	0	Dummy = 1 if main field of technology is other technology fields

Table 1: Variable descriptions and descriptive results (n = 1240). SD: standard deviation; ICT: information and communications technology.

Less than 30% of the inventors have a first patent that was cited more than twice within 5 years, and thus qualify for our first indicator of early success. More than 30% of the inventors are in the fastest quartile of inventors who applied for their first patent within 4 years of obtaining their highest education degree.

The Big Five personality dimensions of an inventor are measured on a 15-item short version of the Big Five inventory (7-point Likert scale; compare Schupp & Gerlitz, 2014). The five personality dimensions are aggregated by a principal components factor analysis with varimax rotation (negatively defined items are rescaled; compare Zwick et al., 2017). About 40% of the inventors opt for a score of 7 or higher on a Likert scale that ranges from 0 (highly risk averse) to 10 (highly risk seeking) (compare Dohmen et al., 2011).

The first patent of an inventor is filed on average with about three co-inventors (the maximum is 24 co-inventors). For first patents, 60% are granted, around 21% are pending, fewer than 18% are refused, and the rest are withdrawn by the applicant. The first patent applicant is almost always a private firm (95%). Most of the inventors in our sample work in applied R&D instead of basic R&D when they apply for their first patent (83%). About 64% of the inventors report an R&D working time share of more than half. The ratio of inventors who are specialists to those who are generalists is about 1:2 when they file their first patent

Figure A1 shows that the number of patents and their citations per inventor are right-skewed. These results are consistent with findings in other studies on patenting success (Huber, 1998; Toivanen & Väänänen, 2012, 2016; Azoulay et al., 2010). Consequently, the individual shares of the total number of patents and citations closely match Lotka's law.[13] The skewed distribution of the dependent variables requires a negative binomial model (count model) (Allison et al., 1982; Huber, 2002). Therefore, we use a Poisson regression model[14] with parameter λ (Baruffaldi et al., 2016; Sapsalis et al., 2006) and our estimation equation (1) is written as

$$Y_{it2} \sim \text{Poisson}(\mu^*_i)$$

$$\mu^*_I = \exp(\gamma' Y_i + u_i)$$

$$\exp(u_i) \sim \text{Gamma}(1/\alpha, 1/\alpha),$$

[13] Lotka's law can be expressed as $p_n = p_1/n^k$, where p_n is the proportion of inventors with n patents in all inventors, p_1 is the number of inventors with one patent, and k is a constant (Huber, 2002). The goodness of fit values, R^2, for all regressions on the distributional form of our sample are higher than 0.94. Thus, the empirical distributions closely match the theoretical distributions for the number of patents and their citations.

[14] Our dependent variables fit a Poisson distribution according to a Chi^2 goodness of fit test (Table A2). A Jacques-Bera and a Shapiro-Wilk-test for normal distribution indicate significant deviations of our dependent variables from a normal distribution.

where γ is the vector of parameters associated with the vector of explanatory variables Y_i (X_{ip1}, *fast* and *highquality*) and α is the overdispersion parameter. The econometric model of the inventive productivity estimation is

$$\widehat{\lambda_i} = \exp(\beta_1 fast_{ip1} + \beta_2 highquality_{ip1} + \delta` X_{ip1} + \epsilon_{itc}), \quad (4)$$

where $\widehat{\lambda_i}$ is the estimator of the Poisson parameter.

Tables A3a and A3b summarize the correlations between the most important variables. Our two indicators for early inventive success are strongly positively correlated with the two inventive productivity measures. The inventive productivity measures have a high positive correlation with each other. According to hypothesis A3, the two early success measures hardly correlate with each other.

Finally, we show that precocious inventors have more patents and more citations per career year than inventors without early success. Average patent number increases slightly for inventors with early success but decreases for inventors without early success from *t*1 to *t*2. Average patent quality is higher in *t*1 than in *t*2 for all four groups (Figure 1). The decrease in patent quality from *t*1 to *t*2 supports the idea of a decrease in inventive capability with age (Jones, 2010), in contrast to the slight increase in the number of patents for precocious inventors. Besides a decrease in inventive capability, a decrease in patenting success over the career may also be a consequence of industrial inventors being promoted to managerial tasks (Hoisl, 2007b).

Figure 1: Average productivity in t1 and t2 of inventors with and without early success (n = 1240).

The higher productivity of precocious inventors is matched by the better resource endowment of this group of inventors during $t1$ (Table A4). Inventors with a fast and/or a high-quality first patent have more co-inventors, larger employers, and a higher share of R&D time in their early career years than their peers without an early success. We also find that a higher number of precocious inventors voluntarily move to another employer in $t1$, although we do not know whether this move occurs before or after the first patent application.

Correlations Between Early Success and Career Inventive Performance

We assess the relationship between early patenting success and inventive career output in a multivariate Poisson regression according to equation (4) for patent quantity (Table 2) and patent quality (Table 3). In models 1 and 2 of each regression table, only one of the two indicators for early patenting success is used as an explanatory variable. In model 3, both variables are included. Controls are added in a stepwise manner in models 4 to 6; first individual characteristics are added, and then the work environment during the first patent application.

Without any further controls, inventors with a high-quality first patent file 25.9% more patents per working year during their career, c (Table 2, column 1; $p < 0.01$).[15] A fast first patent results in more than twice as many patents compared with the reference group (Table 2, column 2; $p < 0.01$). If we include all control variables, there still is a sizeable effect of 59.4% more patents ($p < 0.01$) for fast inventors, and of 19.4% more patents for inventors with a high-quality first patent. The effects of early patenting success on patenting quality during the career are similar: a highly cited first patent increases the average number of citations received per work year by 66% after including all controls (Table 3, model 6, $p < 0.01$). Likewise, a fast first patent results in an increase in patent citations of 81% ($p < 0.01$). The coefficients of the early success indicators do not change if the other indicator is added. Hence, both early success indicators are independently positively correlated with inventive success.[16] These empirical results support our hypotheses A1–A3.

The covariates in our regressions in Table 2 give us results previously found in the inventor productivity literature. Male inventors and inventors with a PhD have significantly higher career productivity. A specialisation in engineering and parents with an academic degree do not additionally drive productivity. Inventors with a positive risk attitude and with a high openness to new ideas have a

[15] We can interpret the coefficients in terms of incidence rate ratios (IRRs). The coefficients of a Poisson regression represent the log changes of the dependent variables after a change of the independent variable. The interpretation of these coefficients is not always straightforward. IRRs are an alternative representation. These ratios show the expected change in the incidence of the outcome variable after increasing the dependent variable by one unit. For dummy and categorical variables, the IRR represents the relative incidence relative to the reference category. The IRRs are obtained by using the exponential form of the coefficients, that is, the IRR of coefficient β is calculated as e^{β}. IRRs are interpreted as multiplicative. An IRR above 1 represents an increase and an IRR below 1 represents a decrease of the dependent variable after a change in the independent variable.
[16] An interaction term between both variables is insignificant.

higher productivity, whereas extrovert and conscientious inventors have a lower productivity. Generalist work experience and a high R&D share when the first patent is applied for increase career productivity. Mid-sized patent applicants for the first patent have a stronger positive correlation with career productivity than small and very large applicants. An industrial applicant for the first patent leads to higher career productivity than a university, public research institution, or an individual applicant. The number of co-inventors and mainly working in basic or applied research activities when applying for the first patent do not have a productivity effect. Including individual and work environment characteristics more than doubles R^2 from 5% to 11%.

Variables	(1) **Patent quantity**	(2) **Patent quantity**	(3) **Patent quantity**	(4) **Patent quantity**	(5) **Patent quantity**	(6) **Patent quantity**
High-quality first patent	1.259**		1.274***	1.238***	1.248***	1.194**
Fast first patent		2.190***	2.197***	1.895***	1.859***	1.594***
Individual background						
Male				1.787**	1.567**	1.638**
Academic education				1.053	1.095	1.077
PhD				1.439*	1.478**	1.423**
Education with engineering specialisation				0.884	0.896	0.919
Mother academic				1.062	1.065	1.075
Father academic				0.932	0.911	0.908
Personality						
Positive risk attitude					1.167*	1.179**
Big 5 extraversion					0.994*	0.994**
Big 5 neuroticism					0.996	0.995
Big 5 openness to new ideas					1.011***	1.012***
Big 5 agreeableness					0.996	0.996
Big 5 conscientiousness					0.993**	0.993**
Work environment first patent						
Generalist work experience						1.189*
Applied R&D						0.924
Basic R&D						1.055
Intensive R&D work						1.552***
Applicant size 25–249						1.231**
Applicant size 250–999						1.401***
Applicant size 1000+						1.199
Applicant university or public research institute						0.634***
Applicant individual						0.422***
Number of co-inventors 1						1.008
Number of co-inventors 2–3						0.952
Number of co-inventors 4+						0.989
Observations	997	997	997	997	997	997
Pseudo R^2	0.004	0.045	0.049	0.077	0.088	0.113
Log-Likelihood	-974.9	-933.9	-930.1	-903.4	-892.6	-868.2
Birth year periods - 5 categories	Yes	Yes	Yes	Yes	Yes	Yes
Main technology field - 14 categories	Yes	Yes	Yes	Yes	Yes	Yes
First patent status - 4 categories	No	No	No	No	No	Yes

*Table 2: Career productivity estimation, quantity. Poisson regression. Table shows incidence rate ratios. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.*

Variables	(1) Patent quality	(2) Patent quality	(3) Patent quality	(4) Patent quality	(5) Patent quality	(6) Patent quality
High-quality first patent	1.895***		1.919***	1.764***	1.758***	1.660***
Fast first patent		2.376***	2.398***	2.443***	2.342***	1.811***
Individual background						
Male				1.919**	1.734*	1.723*
Academic education				1.490	1.607*	1.625**
PhD				1.751**	1.901**	1.989***
Education with engineering specialisation				0.733**	0.740**	0.791*
Mother academic				1.000	0.978	0.971
Father academic				0.912	0.890	0.888
Personality						
Positive risk attitude					1.428***	1.453***
Big 5 extraversion					0.995	0.995
Big 5 neuroticism					1.006	1.006
Big 5 openness to new ideas					1.008**	1.009**
Big 5 agreeableness					0.996	0.997
Big 5 conscientiousness					0.990**	0.988**
Work environment first patent						
Generalist work experience						1.555***
Applied R&D						0.667*
Basic R&D						1.014
Intensive R&D work						1.557***
Applicant size 25–249						1.254*
Applicant size 250–999						1.343**
Applicant size 1000+						1.305
Applicant university or public research institute						0.485**
Applicant individual						0.337***
Number of co-inventors 1						1.055
Number of co-inventors 2–3						0.830
Number of co-inventors 4+						1.064
Observations	997	997	997	997	997	997
Pseudo R^2	0.0244	0.0457	0.0710	0.130	0.146	0.202
Log-Likelihood	-1030	-1008	-981.2	-918.7	-901.5	-842.7
Birth year periods - 5 categories	Yes	Yes	Yes	Yes	Yes	Yes
Main technology field - 14 categories	Yes	Yes	Yes	Yes	Yes	Yes
First patent status - 4 categories	No	No	No	No	No	Yes

*Table 3: Career productivity estimation, quality. Poisson regression. Table shows incidence rate ratios. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.*

Robustness Checks

In our robustness checks, we first vary the dependent variables. We use fractional counts or, in other words, we also divide inventive output by the number of co-inventors (Table A5, columns 1 and 2). In addition, we extend the time period for citations from 5 to 10 years for our quality measure (Table A5, column 3). Finally, we divide the number of citations by patents instead of work years (Table A5, column 4). The results remain robust.

We then use alternative indicators for early patenting success. First, we extend the period in which citations are counted from 5 to 10 years (Table A6, columns 1 and 2). Second, we use a dummy for inventors who applied for their first patent before the start of their career instead of within 4 years of the end of their education (Table A6, columns 3 and 4).[17] Again, the alternative indicators show robust results.

Lawson & Sterzi (2014) argue that birth cohort effects may drive the results given differences in the share of inventive ideas patented for inventors born later. Therefore, we re-run our regression separately for inventors born before and after 1964 and the results are still robust (Table A7).

Jones (2009; 2010) and Jones & Weinberg (2011) argue that young inventors may have to reduce the time they can devote to their inventive activity to obtain the education and training needed to reach the frontier of knowledge in their technology field, which is a necessary ingredient for inventive activities. Therefore, the maturity of a technology field may be a decisive factor in the speed and quality of the first patent. Inventors in technology fields with less accumulated knowledge may have a smaller burden of knowledge. In addition, inventions in technology fields in which experimentation is more important take more time than inventions in mainly conceptual technology fields. Therefore, having a fast or high-quality first patent[18] in a field in which experimentation is important or the burden of knowledge is high may be a stronger indicator of inventive ability compared with other technology fields. Our data give us little information about the importance of experimentation versus theory or the amount of accumulated knowledge in the technology field in which the first patent was applied for.

If we assume that factors that allow quick inventive progress also allow early completion of the education period, age at education completion may be a good indicator of the burden of knowledge and the importance of experimentation. For example, Figure 5 in Jones and Weinberg (2011) shows a positive correlation between age at highest education degree and age at great achievements for Nobel prize laureates. Based on this hypothesis, we calculate the median age at which the highest education grade was obtained for each of the 14 technology fields in which the first patent was applied for. We find substantial variation between mechanical elements (25 years) and pharmaceuticals (31 years). Next, we determine the correlation between a fast or a high-quality first patent separately for inventors in technology fields below and above the median age of 28. We do not find indicators for differences between inventors in both of the age at the end of education groups (Table A8).

We reproduce all productivity estimations using ordinary least squares (OLS) instead of the Poisson regressions presented (not shown). The coefficients are similar: for example, a fast (high-quality) first

[17] We also find robust results if we use the application of the first patent before the end of the PhD period as an indicator for a fast first patent in a subsample of PhDs, compare Dietz & Bozeman (2005).
[18] Jones (2009) explicitly mentioned that the burden of knowledge may either decrease the number of ideas and/or their quality (i.e., the "size of ideas").

patent is correlated with a 51% (16%) higher career productivity in an estimation according to the specification in Table 2, column 6.

5 Cumulative Advantage Induced by Early Career Success

We use estimation equation (2) to test whether high early patenting productivity leads to a stronger increase in productivity during period $t2$ compared with productivity in period $t1$. There is a significant negative correlation between the inventive productivity in $t1$ and the change between the productivity in $t1$ and $t2$ (Table 4, column 1). Instead of a positive correlation predicted by the cumulative advantage hypothesis, we find a regression to the mean in a random process. In other words, inventors with a high productivity during their first patenting period cannot increase their productivity further compared with this high level. A high-quality first patent is positively correlated with the difference between $t1$ and $t2$ (Table 4, columns 2 and 3). However, a fast first patent and both early success indicators together are not correlated with the productivity difference in most estimation specifications. The sum of the difference effect is negative for all inventor groups. We obtain the same results qualitatively for inventive productivity changes measured by the number of citations (Table 5).

In a robustness test, we explain the level of productivity in $t2$ (instead of the difference between $t1$ and $t2$) by the level of productivity in $t1$ (compare equation (7) in DiPrete & Eirich (2008)),

$$Y_{it2} = \gamma Y_{it1} + \epsilon_{it1}, \qquad (6)$$

with $\gamma = 1 + \beta$.

Cumulative advantage predicts a coefficient, γ, that is higher than 1. Our estimated γ is significantly below 1 and does not indicate cumulative advantage. Precocious inventors experience a lower regression to the mean (compare Tables A9 and A10).

Finally, we test whether precocious inventors are offered more resources in $t2$. Our estimations of equation (3) show whether inventors with early patenting success increase the share of R&D activities, the number of co-inventors, the size of the employer (measured by number of patents applied for by applicant), and the chance to move to another employer voluntarily. For three resource dimensions, precocious inventors cannot improve their situation between $t1$ and $t2$ compared with inventors without early success (Table 6). Only the increase in the size of the employer is moderately stronger from $t1$ to $t2$ for precocious inventors, although this increase is not a consequence of successful inventors changing to larger employers; the increase in employer size is slightly larger for precocious inventors who do not change their employer (Table A11, columns 1–3). We conclude that precocious inventors frequently stay with their employers and that these employers can increase the number of patent applications more than the employers of inventors without an early success.

Variables	(1) **Quantity difference**	(2) **Quantity difference**	(3) **Quantity difference**
Quantity in $t1$	-0.487***	-0.580***	-0.590***
	(0.0265)	(0.0393)	(0.0422)
Quantity in $t1$*fast		0.0679	0.0925
		(0.0540)	(0.0654)
Quantity in $t1$*high quality		0.200***	0.229***
		(0.0563)	(0.0716)
Quantity in $t1$*fast and high quality			-0.0777
			(0.116)
High R&D in $t2$			
Voluntary job move in $t2$			
Applicant size in $t2$			
Number of co-inventors in $t2$			
Observations	1191	1191	1191
Adjusted R^2	0.220	0.227	0.227

*Table 4: Test of cumulative advantage in productivity. Dependent variable: difference in patent quantity between t1 and t2. OLS regression. Standard errors are shown in parentheses. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.*

Variables	**Quality difference**	**Quality difference**	**Quality difference**
Quality in $t1$	-0.735***	-0.717***	-0.769***
	(0.0136)	(0.0260)	(0.0315)
Quality in $t1$*fast		-0.00590	0.0878**
		(0.0274)	(0.0420)
Quality in $t1$*high quality		-0.0268	0.0641
		(0.0275)	(0.0414)
Quality in $t1$*fast and high quality			-0.162***
			(0.0552)
High R&D in $t2$			
Voluntary job move in $t2$			
Applicant size in $t2$			
Number of co-inventors in $t2$			
Observations	1191	1191	1191
Adjusted R^2	0.712	0.711	0.713

*Table 5: Test of cumulative advantage in productivity. Dependent variable: difference in patent quality between t1 and t2. OLS regressions. Standard errors are shown in parentheses. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.*

Variables	**High R&D**	**High R&D**	**High R&D**	**Applicant size**	**Applicant size**	**Applicant size**	**Voluntary job move**	**Voluntary job move**	**Voluntary job move**	**Co-inventors**	**Co-inventors**	**Co-inventors**
Fast first patent∗$t2$	-0.179***		-0.179***	40.00**		39.78**	-0.080**		-0.080**	0.004		0.000
High-quality first patent∗$t2$		-0.018	-0.019		29.73	29.42		-0.011	-0.011		-0.276*	-0.276*
Observations	2250	2250	2250	2384	2384	2384	2384	2384	2384	1981	1981	1981
R^2	0.126	0.089	0.126	0.116	0.114	0.118	0.069	0.063	0.069	0.006	0.010	0.010
$t2$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*Table 6: Test of cumulative advantage in resources. Dependent variables: four resources dimensions. OLS regressions. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.*

6 Discussion and Conclusion

Our results reveal that precocious inventors, who are either are extraordinarily fast in applying for their first patent or who have a first patent with many citations, have a persistently higher quantitative and qualitative patent productivity over their career. These findings are consistent with the results reported for academic inventors by Lawson & Sterzi (2014) and Dietz & Bozeman (2005), whereas they are different from those of Audio & Gonzalo (2007) that a previous patenting success increases the number of patents but not the quality of patents.

Our results include industrial inventors from a broad range of technology fields and inventors who at least for parts of their careers worked in public research institutions or universities. Besides speed and quality of the first patent, we also control for the work environment during the period in which the first patent is applied for, individual education, family background, personality traits, and willingness to take risks. Furthermore, we establish that the speed and quality of the first patent are independent predictors of career productivity.

The literature proposes two interpretations for the positive correlation between early patenting success and career productivity: the higher innate ability of inventors with early success and cumulative advantage. Our results do not indicate cumulative advantage. First, high productivity during the first career years does not lead to a stronger increase in productivity during the remaining career. Instead of a productivity boost for successful inventors, we observe a regression to the mean. The regression to the mean effect is weaker for precocious inventors. However, there also is no cumulative advantage for precocious inventors. Second, inventors with an early patenting success cannot attract more resources, such as a voluntary move to possibly larger employers, more time for R&D, or more co-inventors.

Inventors with early success have enjoyed favourable working conditions during their first career years. This advantage makes it harder for them to improve their resources later in their career. Precocious inventors also profit from an increase in employer size when they do not move to another employer. The early patent may be used by the first employer after labour market entry to restrict the transfer of knowledge and thereby appropriate the inventor's idea (Kim & Marschke, 2005; Melero et al., 2020). Although the precocious inventor can signal higher inventive productivity to potential alternative employers, the poaching risk remains low because the inventor is not allowed to use previous knowledge after moving to another employer. Compared with inventors without an early success, precocious inventors also enjoy a stronger wage increase during their remaining career than during the period in which they applied for their first patent (Table A9).[19] This wage increase is comparable

[19] Annual gross income is measured in six income brackets in our survey calendar: below €10,000; €10,000–€29,999; €30,000–49,999; €50,000–69,999; 70,000–99,999; and €100,000 or more.

for inventors who stay with the employer that applied for the first patent and inventors who change their employer. Our interpretation of these patterns is that employers share their monopoly rents derived from the early invention with their precocious inventors (Toivanen & Väänänen, 2012). Thus, precocious inventors stay with their employers because they experience a good resource situation early on and participate financially in their early success. A final consequence of the good fit between the first employer and the precocious inventor is their lower unemployment risk during *t*2 than during *t*1 compared with inventors without early success (Table A11).

Our study has valuable implications for management and inventors. First, our results support the interpretation of inventive productivity being characterised by a variation-selection process (Simonton, 2003). Useful and useless variations seem to be randomly distributed within individual careers and there is no indication of cumulative advantage. Thus, productivity differences between inventors are independent of age and experience. The most prolific inventors at the beginning of their career continue to show higher productivity for the rest of their career (Huber, 1998). Second, information about early patenting success can reduce uncertainty about future inventor productivity for employers (Long, 2002; Spence, 1976). Third, employers that have hired precocious inventors before their early patenting success have a fair chance of retaining them, albeit at the cost of wage increases.

Identifying, attracting, and retaining precocious inventors can be a decisive advantage for employers that rely on innovations. According to Lotka (1926), only a tiny share of inventors achieves a high inventive productivity during the career; therefore, the distribution of inventive success is highly unequal (Price, 1965; Levine, 1986; Huber, 2002; Narin & Breitzman, 1995; Sapsalis et al., 2006; Toivanen & Väänänen, 2012, 2016; Lawson & Sterzi, 2014). The few truly prolific inventors not only contribute to corporate success by producing more patents, but also the average economic value of their patents is higher (Almeida & Kogut, 1997; Gay et al., 2010). In addition, prolific inventors are a source of ideas and inspiration for their peers, colleagues, and network members, and they can act as knowledge integrators between communities and institutional contexts (Subramaniana et al., 2013). Their knowledge-enabling function has a positive external effect on the overall innovativeness of their employers (Zucker et al., 1998, 2002; Gambardella et al., 2008; Bercovitz & Feldman, 2008; Azoulay et al., 2010).

Information about patent data is traditionally public and easily accessible (Hoisl, 2007a; Toivanen & Väänänen, 2012). Employers interested in prolific and precocious inventors in their technical field of interest can consult the European Patent Register provided by the European Patent Office or the Patent Full-Text and Image Database provided by the United States Patent and Trademark Office. Therefore, we can assume that inventors of high-quality patents do not need web-based social networks to gain visibility, and the visibility of inventors should have hardly increased recently, although social networks have generally reduced search costs and increased the job chances for able employees (Dato et al., 2020).

Further research is needed to investigate the potential productivity channels of inventors with an early patenting success. This paper establishes the outstanding importance of a fast and high-quality first patent. However, we do not examine the predictive quality of the characteristics of the second and further patents for future inventive productivity. We focus on the first patent because our sample size is decreased dramatically if we restrict it to inventors with more than two, or three, or even more patents. Future studies with access to a larger pool of prolific inventors may analyse the additional information value of including the characteristics of more than the first patent. In tentative regressions, we find evidence for a decrease in the predictive value for future productivity when we include more than the first patent. If we include not only the first patent but all patents in the year the first patent was applied for and the year after, the coefficient of the highest quality quartile on patent quality during the remaining career decreases from 66% in Table 3, column 6 to 51%. When we increase $t1$ to 3, 4, and 5 years, the coefficients for patent quality in $t2$ decrease to 47%, 39%, and 30%, respectively (all coefficients are significant at the 5% level).

Although we include more explanatory variables on individual and employer characteristics than most previous papers on inventive productivity, potential employers may have additional ability indicators when they assess job applicants or try to poach inventors from their competitors. Potential information sources are education marks in addition to education grades or the prestige of the educational institution (DiPrete & Eirich, 2008). This additional information may also contribute to the open questions of why precocious inventors enjoy a productivity-enhancing work environment before their first success and why the matching quality between precocious inventors and their first employers is so high that few of them voluntarily change their employer during their later career compared with their first career years. Thus, future work may focus on the labour market entry of inventors and the question of what the drivers of employee selection are and the match between inventors and their first employer.

Appendix

Number of periods after the first patent period	Frequency	Percent	Cumulative
1	349	29.78	29.78
2	411	35.07	64.85
3	249	21.25	86.09
4	117	9.98	96.08
5	40	3.41	99.49
6	6	0.51	100.00
Total	1240	100.00	

Table A1: Number of periods observed after the first patent.

	Patent quantity	Patent quality
Deviance goodness of fit	443.8	750.5
Prob > chi (950)	1.0	1.0
Pearson goodness of fit	561.7	1078.6
Prob > chi (950)	1.0	1.0

Table A2: Poisson distribution goodness of fit tests for inventive productivity (n = 1240).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Patent quantity	1.000															
(2) Patent quality	0.660***	1.000														
(3) High-quality first patent	0.085***	0.136***	1.000													
(4) Fast first patent	0.288***	0.229***	-0.003	1.000												
(5) Male	0.038	0.029	-0.018	-0.034	1.000											
(6) Academic education	-0.133***	-0.122***	-0.058**	-0.071**	0.074**	1.000										
(7) PhD	0.169***	0.152***	0.064**	0.169***	-0.050*	-0.848***	1.000									
(8) Education with engineering specialization	-0.068**	-0.140***	-0.039	-0.014	0.128***	0.396***	-0.399***	1.000								
(9) Academic mother	0.052*	-0.008	-0.032	0.143***	-0.028	-0.080***	0.129***	-0.005	1.000							
(10) Academic father	-0.000	-0.016	0.024	0.118***	-0.054*	0.014	0.039	0.038	0.274***	1.000						
(11) Positive risk attitude	0.064**	0.093***	0.010	-0.020	0.050*	-0.025	0.006	-0.038	-0.042	-0.013	1.000					
(12) Big 5 extraversion	0.013	0.023	0.000	-0.001	-0.003	-0.057*	0.024	-0.002	-0.008	-0.002	0.197***	1.000				
(13) Big 5 neuroticism	-0.062**	-0.019	-0.011	-0.065**	-0.039	0.033	-0.033	0.019	0.059*	0.014	-0.099***	-0.070**	1.000			
(14) Big 5 openness to new ideas	0.063**	0.056*	-0.019	-0.037	0.064**	-0.065**	0.033	-0.012	0.019	0.058*	0.266***	0.623***	0.107***	1.000		
(15) Big 5 agreeableness	-0.003	0.005	-0.017	0.006	0.032	0.048	-0.051*	0.053*	0.020	0.056*	0.149***	0.500***	-0.027	0.429***	1.000	
(16) Big 5 conscientiousness	-0.058*	-0.065**	0.032	-0.040	-0.003	-0.011	0.011	0.012	0.000	0.009	0.023	0.278***	0.064**	0.298***	0.315***	1.000

Table A3a: Correlation table (n = 1240).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) Patent quantity	1.000																	
(2) Patent quality	0.660***	1.000																
(3) High-quality first patent	0.085***	0.136***	1.000															
(4) Fast first patent	0.288***	0.229***	-0.003	1.000														
(5) Generalist work experience	0.070**	0.101***	0.071**	0.050*	1.000													
(6) Applied R&D	-0.053*	-0.085***	0.063**	-0.124***	0.028	1.000												
(7) Basic R&D	0.122***	0.130***	0.005	0.162***	0.074**	-0.418***	1.000											
(8) Intensive R&D work	0.170***	0.129***	0.074***	0.156***	0.175***	0.207***	0.120***	1.000										
(9) Applicant size 25–249	0.010	-0.012	-0.013	-0.018	0.003	-0.018	-0.006	0.016	1.000									
(10) Applicant size 250–999	0.086***	0.067**	0.027	0.029	0.036	-0.022	-0.008	0.070**	-0.250***	1.000								
(11) Applicant size 1000+	0.046	0.010	0.082***	0.069**	-0.006	0.033	-0.003	0.032	-0.237***	-0.150***	1.000							
(12) Applicant university/public research institute	-0.037	-0.050*	-0.067**	0.052*	-0.000	0.016	0.029	0.044	0.081***	0.062**	-0.053*	1.000						
(13) Applicant individual	-0.050*	-0.037	-0.010	0.029	-0.012	-0.025	0.019	-0.062**	-0.056**	-0.045	-0.043	-0.023	1.000					
(14) Number of co-inventors 1	-0.006	0.012	-0.078***	-0.004	0.008	0.005	-0.009	-0.052*	-0.005	-0.045	-0.048*	-0.023	-0.040	1.000				
(15) Number of co-inventors 2–3	-0.010	-0.040	0.011	-0.008	-0.032	0.027	-0.061**	0.041	0.017	0.034	0.008	0.032	-0.050*	-0.418***	1.000			
(16) Number of co-inventors 4+	0.044	0.063**	0.096***	0.063**	0.036	-0.036	0.096***	0.053*	0.048*	0.006	0.066**	0.004	-0.005	-0.310***	-0.500***	1.000		
(17) First patent is granted	0.026	0.044	0.091***	0.035	0.003	0.055*	-0.053*	0.046	-0.011	0.050*	-0.095***	-0.009	-0.024	0.028	0.024	-0.051*	1.000	
(18) First patent is pending	-0.069**	-0.119***	-0.056**	-0.116***	-0.014	-0.009	0.026	-0.088***	0.016	0.012	0.048*	0.064**	-0.007	-0.025	-0.015	0.057**	-0.637***	1.000
(19) First patent is withdrawn	-0.015	-0.010	-0.018	0.003	0.021	-0.071**	0.013	0.021	-0.001	-0.009	0.015	-0.025	-0.014	-0.028	0.065**	-0.013	-0.149***	-0.063**

Table A3b: Correlation table (n = 1240).

	No early success	Fast first patent	High-quality first patent	Fast and high-quality first patent
High R&D	0.59	0.83	0.72	0.83
Applicant size	244.42	376.00	399.48	461.78
Voluntary job move	0.18	0.32	0.22	0.35
Number of co-inventors	3.52	3.77	3.94	4.07
Observations	583	368	350	110

*Table A4: Average resources in t1 of inventors with and without early success. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1*

Variables	(1) **Patent quantity (fractional counts)**	(2) **Patent quality (fractional counts)**	(3) **Patent quality (10 years)**	(4) **Patent quality (by patent)**
High-quality first patent	1.719***	1.676***	1.693***	2.414***
	(0.145)	(0.201)	(0.189)	(0.142)
Fast first patent	1.614***	1.710***	1.791***	1.152**
	(0.161)	(0.229)	(0.227)	(0.0811)
Observations	997	997	997	997
Pseudo R^2	0.131	0.147	0.218	0.103
Likelihood	-755.9	-387.9	-985.6	-1058
Control individual background	Yes	Yes	Yes	Yes
Control personality	Yes	Yes	Yes	Yes
Control work environment first patent	Yes	Yes	Yes	Yes
Birth year periods - 5 categories	Yes	Yes	Yes	Yes
First patent status - 4 categories	Yes	Yes	Yes	Yes
Main technology field - 14 categories	Yes	Yes	Yes	Yes

*Table A5: Productivity estimations with alternative dependent variables. Poisson regressions. Table shows incidence rate ratios. Heteroscedasticity robust standard errors are shown in parentheses. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.*

VARIABLES	(1) **Patent quantity**	(2) **Patent quality**	(3) **Patent quantity**	(4) **Patent quality**
High-quality first patent (5 years)			1.161**	1.585***
			(0.0844)	(0.182)
High-quality first patent (10 years)	1.340***	1.844***		
	(0.102)	(0.220)		
Fast first patent	1.580***	1.759***		
	(0.125)	(0.231)		
First patent applied for before first job			2.724***	2.345***
			(0.706)	(0.688)
Observations	997	997	997	997
Pseudeo R^2	0.115	0.207	0.113	0.193
Likelihood	-865.6	-837.9	-867.4	-852
Control individual background	Yes	Yes	Yes	Yes
Control personality	Yes	Yes	Yes	Yes
Control environment first patent	Yes	Yes	Yes	Yes
First patent status - 4 categories	Yes	Yes	Yes	Yes
Birth year periods - 5 categories	Yes	Yes	Yes	Yes
Main technology field - 14 categories	Yes	Yes	Yes	Yes

*Table A6: Productivity estimations with alternative early patenting success measures. Poisson regressions. Table shows incidence rate ratios. Robust standard errors are shown in parentheses. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.*

	(1)	(2)	(3)	(4)
	Born in 1964 and after		**Born before 1964**	
Variables	**Patent quantity**	**Patent quality**	**Patent quantity**	**Patent quality**
High-quality first patent	1.140	1.585***	1.285**	1.812***
	(0.106)	(0.230)	(0.133)	(0.265)
Fast first patent	1.474***	1.663***	1.838***	2.357***
	(0.155)	(0.327)	(0.203)	(0.351)
Observations	542	542	455	455
Pseudo R^2	0.136	0.268	0.103	0.209
Loglikelihood	-510	-447.7	-340	-351.1
Control individual background	Yes	Yes	Yes	Yes
Control personality	Yes	Yes	Yes	Yes
Control environment first patent	Yes	Yes	Yes	Yes
First patent status - 4 categories	Yes	Yes	Yes	Yes
Birth year periods - 5 categories	Yes	Yes	Yes	Yes
Main technology field - 14 categories	Yes	Yes	Yes	Yes

*Table A7: Productivity estimations, results for inventors born before and after 1964. Poisson regressions. Table shows incidence rate ratios. Robust standard errors are shown in parentheses. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.*

	(1)	(2)	(3)	(4)
	Below median age of highest education in technology field		**Above median age of highest education in technology field**	
Variables	**Patent quantity**	**Patent quality**	**Patent quantity**	**Patent quality**
High-quality first patent	1.135	1.661***	1.207*	1.680***
	(0.114)	(0.232)	(0.124)	(0.280)
Fast first patent	1.696***	1.946***	1.562***	1.740***
	(0.196)	(0.326)	(0.163)	(0.323)
Observations	554	554	443	443
Pseudo R^2	0.118	0.211	0.135	0.250
Loglikelihood	-483.8	-406.9	-371.6	-401.3
Control individual background	Yes	Yes	Yes	Yes
Control personality	Yes	Yes	Yes	Yes
Control environment first patent	Yes	Yes	Yes	Yes
First patent status - 4 categories	Yes	Yes	Yes	Yes
Birth year periods - 5 categories	Yes	Yes	Yes	Yes
Main technology field - 14 categories	Yes	Yes	Yes	Yes

*Table A8: Productivity estimations, results for inventors by the median age at the highest educational degree in technology field of first patent. Poisson regressions. Table shows incidence rate ratios. Robust standard errors are shown in parentheses. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.*

Variables	**Quantity**	**Quantity**	**Quantity**
Quantity in *t*1	0.513***	0.420***	0.410***
	(0.0265)	(0.0393)	(0.0422)
Quantity in *t*1*fast first patent		0.0679	0.0925
		(0.0540)	(0.0654)
Quantity in *t*1*high-quality first patent		0.200***	0.229***
		(0.0563)	(0.0716)
Quantity in *t*1*fast/high-quality first patent			-0.0777
			(0.116)
Observations	1191	1191	1191
Adjusted R^2	0.238	0.246	0.245

*Table A9: Test of cumulative advantage in productivity. Dependent variable: number of patents in t2. OLS regression. Standard errors are shown in parentheses. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.*

Variables	**Quality**	**Quality**	**Quality**
Quality in *t*1	0.265***	0.283***	0.231***
	(0.0136)	(0.0260)	(0.0315)
Quality in *t*1*fast first patent		-0.00590	0.0878**
		(0.0274)	(0.0420)
Quality in *t*1*high-quality first patent		-0.0268	0.0641
		(0.0275)	(0.0414)
Quality in *t*1*fast/high-quality first patent			-0.162***
			(0.0552)
Observations	1191	1191	1191
Adjusted R^2	0.242	0.241	0.246

*Table A10: Test of cumulative advantage in productivity. Dependent variable: number of citations in t2. OLS regression. Standard errors are shown in parentheses. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.*

Variables	(1) Applicant size for stayers	(2) Applicant size for stayers	(3) Applicant size for stayers	(4) Salary for stayers	(5) Salary for stayers	(6) Salary for stayers
Fast*$t2$	**47.29***		**47.40***	**0.303*****		**0.303*****
High quality*$t2$		30.16	30.33		-0.00791	0.00550
Observations	1572	1572	1572	1182	1182	1182
R^2	0.103	0.101	0.105	0.644	0.624	0.644
Panel	FE	FE	FE	FE	FE	FE

Variables	(7) Salary	(8) Salary	(9) Salary	(10) Unemployed	(11) Unemployed	(12) Unemployed
Fast*$t2$	**0.295*****		**0.295*****	**-0.0356*****		**-0.036*****
High quality*$t2$		-0.016	-0.013		-0.008	-0.008
Observations	1856	1856	1856	2308	2308	2308
R^2	0.656	0.637	0.656	0.019	0.004	0.020
Panel	FE	FE	FE	FE	FE	FE

*Table A11: Test of cumulative advantage in resource changes between t1 and t2. Difference-in-differences. Observations vary because not all survey questions were answered by all inventors. Robust standard errors are shown in parentheses. FE = individual fixed effects. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.*

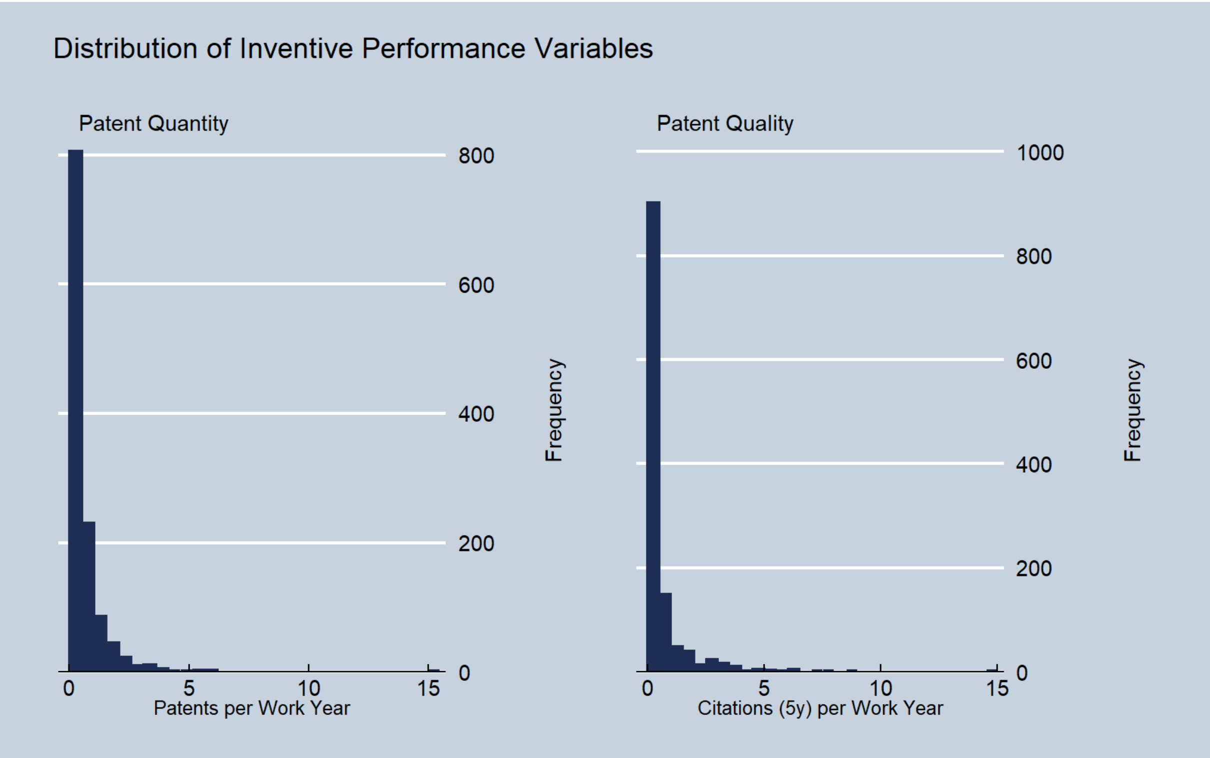

Figure A1: Distribution of dependent variables (sample of inventors with at least two patents, n = 1240).

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ZEW – Leibniz-Zentrum für Europäische Wirtschaftsforschung GmbH Mannheim

ZEW – Leibniz Centre for European Economic Research

L 7,1 · 68161 Mannheim · Germany
Phone +49 621 1235-01
info@zew.de · zew.de