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Innovation and Age

The rise in innovators' age at peak productivity: reasons and policy implications

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1 Introduction

According to public opinion, famous innovators produce their groundbreaking inventions in their early ages. Einstein was just 26 when he produced his major work (Jones 2010, 1), Gauss developed least squares when he was 18 (Levin & Stephan 1991, 114) and Heisenberg invented matrix mechanics and the uncertainty principle at the ages of 23 respectively 25 (Jones et al. 2014, 6). Likewise, today, the domain of information technology features prominent examples of young innovators. Steve Jobs was 20 when he co-founded Apple and had not even reached his 30ies when he created the first Macintosh (Isaacson 2011, 130, 135ff.). However, while these cases of outstanding innovation at early age shape much of the public perception of innovation, in fact, most innovations are produced at an older age. Recent empirical findings even suggest that innovators' age at peak productivity has been rising over the past century (Jones 2010, 2011).

At first sight, innovators' age does not seem to be worth much research. After all, it should be important that an innovation gets made at all, and less how old innovators are when they produce their major innovation. At second sight, however, innovator's age at peak productivity does have important implications for science policy. First, science policy has an interest to get a good match between individuals' *innovation potential* and their *innovation productivity.* If individuals reach the peak of their innovation potential at an early age, individuals should be able to exploit this potential and not be occupied with studies. Hence, one of the objectives of science policy must be to set incentives in a way to get a close match of innovation potential and productivity. Second, given the importance of innovation for economic growth (e.g. Mowery & Rosenberg 1989; Jones 2011, 116f.) and the market's underproduction of knowledge, science policy has an interest in inducing university graduates to enter an innovative career (Jones 2011, 118f.). If the peak of innovative productivity shifts to an increasingly later point in innovators' careers, the earnings from innovative activity, e.g. wage stream and patent royalties, will likewise be delayed to the future, which makes an innovative career less attractive. To keep innovative careers attractive, science policy must respond to age trends in innovative careers.

The remainder of the paper will be structured as follows: In section 2, evidence of innovators' rising age at peak productivity will be presented. Section 3 models this trend. Jones (2011) has developed a model that considers shifts in the life cycle productivity and a general demographic trend as drivers of the rise in innovators' age at peak productivity. According to Jones (2010), it is mostly productivity shifts in the early life cycle that account for the age trend. Section 4 examines more closely possible reasons for the productivity shift in the early life cycle. In particular, extended training periods, an increase in collaboration in science and a shift from conceptual to experimental work may explain the productivity shift. Section 5 derives policy implications and section 6 concludes.

2 Evidence of the rise in innovators' age at peak productivity

The empirical relationship between age and achievement has been subject of developmental psychology since at least the 1950ies, when Lehmann (1953) published *Age and Achievement*. Developmental psychology has found that innovation productivity generally rises rapidly with age until it has reached a definite peak and declines thereafter (Simonton 1988, 252). The location of the peak can be subject to considerable variation depending on the domain of achievement. For instance, poets, pure mathematicians and theoretical physicists tend to reach the peak of their productivity already in their 20ies and 30ies whereas novelists, historians or philosophers usually produce their main work not before their late 40ies or 50ies (ibid.). Further, Weinberg & Galenson (2005) find that peaks of innovative productivity can even vary within disciplines, depending on whether researchers work deductively, i.e. apply abstract principles, or inductively, i.e. work with experiments. For instance, while an Economics Nobel laureate working deductively publishes her major work at the mean age of 25, an experimental Economics Nobel laureate publishes her major work in her 50ies on average (ibid.). Notwithstanding the inter- and intradisciplinary differences regarding the age at peak productivity, the age distribution seems to have shifted to the right across all disciplines, i.e. the age at peak productivity has increased, while the general shape of the age-productivity curve has remained unchanged. In the following I refer to Jones (2011, 2010) to establish evidence of the increasing age at peak productivity.

To produce this evidence, datasets must contain information on which innovator reached the peak of her productivity at which age and in which year. These age-year observations constitute the central element of the dataset. Innovators' peak productivity can be defined differently. Jones (2011, 108; 2010, 2) makes three suggestions. First, he considers all Nobel Prize winners in Physics, Chemistry, Medicine and Economics and defines the major research leading to the Nobel Prize as the peak of productivity (2010, 2). Second, Jones considers innovations listed in almanacs of the history of technology and defines innovators' peak productivity as the research leading to the innovation (ibid.). Finally, he takes an innovator's first patent as peak of productivity, and considers all U.S. patents since 1985 (2011, 109).

To test the hypothesis of increasing age at peak productivity, Jones regresses innovators' ages at peak productivity on the year of great achievement (2010, 2):

$$a_i = \alpha + \beta t_i + \gamma X_f + \epsilon_i \tag{1}$$

where a_i denotes the age of individual i at the time of great achievement, t_i is the year of great achievement and X_f are fixed effects for the field of achievement and country of birth. Table 1 shows that Nobel Prize winners' mean age at great achievement has increased by 5.83 years, great inventors' mean age by 4.86 years and patentees' mean age by 6.57 years over the 20$^{\text{th}}$ century if one does not control for fixed effects. The trend even strengthens if one includes fixed effects. As presented in table 2, the mean age then increases by 7.79 years, 8.18 years and 6.71

years per century respectively. The inclusion of fixed effects into the model takes account of the potentially unobserved time invariant effects that country of birth and field may have on Nobel Prize winners' and great inventors' age at peak productivity. For patentees field and patent assignee type fixed effects are included. The parentheses show robust standard errors for age trends.

Table 1: Trends in age at peak productivity, without fixed effects (Jones 2011, 109)

	Age at great achievement, Nobel Prize winners	Age at great achievement, inventors almanacs	Age at first patent
Age trend, in years per century	5.83***(1.37)	4.86** (2.31)	6.57***(.95)
Observations	544	286	6541
Time span	1873–1998	1900–1988	1985–1999
Average age over time span	38.6	39.0	31.0

** Significance at the 95 % confidence level
*** Significance at the 99 % confidence level

Table 2: Trends in age at peak productivity, with fixed effects (Jones 2011, 109)

	Age at great achievement, Nobel Prize winners	Age at great achievement, inventors almanacs	Age at first patent
Age trend, in years per century	7.79***(1.54)	8.18** (3.29)	6.71***(.99)
Observations	544	248	6541
Time span	1873–1998	1900–1991	1985–1999
Average age over time span	38.6	39.0	31.0

** Significance at the 95 % confidence level
*** Significance at the 99 % confidence level

Unfortunately, a *European* dataset on age at first patent equivalent to Jones' dataset does not exist. However, Hoisl found that European patentees patented most between the age of 41 and 45 over the period 1977 to 1999 (2005, 8). While this does not allow making any inferences on an age trend in innovators' peak productivity in Europe, it at least shows that – contrary to public belief – European innovators do not reach the peak of their productivity before their 40ies.

3 Modeling the rise in innovators' age at peak productivity

Based on these empirical findings, it is natural to ask for the reasons of the rise in innovators' age at peak productivity. To my knowledge, Jones is the only one until today who explains this age trend with a sophisticated econometric model. Others before him have observed how innovative productivity changes with age but have failed to explain these changes (e.g. Zuckerman 1977, 166ff.).

According to Jones, the age trend may be explained in two ways (2010, 3ff.). First, it may be traced back to productivity shifts in innovators' life cycles. Innovation productivity may have shifted either at the beginning of the life cycle, for instance due to extended training periods, or at the end of the life cycle, for instance due to improved health or greater importance of experience for innovation (Jones 2010, 3). Second, the rise in age may simply be due to demographics. As the entire population gets older, innovators may likewise get older (ibid.). Jones' empirical strategy to find out which of the two mechanisms is responsible for the rise in age at peak productivity is the following: He first examines how the life cycle innovative productivity has shifted over time and then decomposes the shift into demographic and productivity components.

To implement his strategy, Jones begins with defining the probability that an innovation is produced by innovators of particular ages, which depends on innovators' productivity and the population age distribution at different times. Given year-age observations of great innovations and population age distributions, Jones then applies the maximum likelihood method to estimate how innovative productivity must have shifted such as to maximize the probability of observing the year-age pairs indeed observed. This additionally requires a submodel that explains changes in the life cycle innovative productivity. Once Jones has estimated the life cycle productivity shift, he holds fixed the population age distribution to decompose the shift into demographic and productivity components. The following paragraphs explain these steps in more detail.

The probability that an innovation is produced by innovators of particular ages depends on two things, namely the innovation productivity of different cohorts and, second, the size of different cohorts (Jones 2010, 3). For instance, innovators in their 30ies will probably display a higher innovation productivity than those in their 70ies, which raises the probability that an innovation is produced by an innovator in her 30ies rather than by one in her 70ies. At the same time, if there are hardly any innovators in their 30ies but very many in their 70ies, this raises the probability that an innovation is produced by an innovator in her 70ies. Accordingly, the probability that an individual of age a produces a great innovation at time t can be written as the population age density weighted by the innovation productivity:

$$\Pr(a,t) = \frac{p_{\mathrm{a}}(t)\bar{x}_{\mathrm{a}}(t)}{\sum\limits_{a} p_{\mathrm{a}}(t)\bar{x}_{\mathrm{a}}(t)} \tag{2}$$

where $p_{\mathrm{a}}(t)$ is the population age distribution of cohort a at time t and $\bar{x}_{\mathrm{a}}(t)$ is the average innovation productivity of cohort a at time t. According to equation (2) $\Pr(a,\ t)$ can shift either due to changes in the average innovation productivity - which corresponds to life cycle productivity shifts - or due to changes in the age distribution - which corresponds to demographic effects. To estimate shifts in the life cycle productivity with the help of the maximum likelihood method, Jones models the average innovation productivity, $\bar{x}_{\mathrm{a}}(t)$ (cf. section 3.1). The population age distributions chosen are presented in section 3.2.

3.1 Life cycle productivity

The innovation productivity of an individual i, x_i, can be written as a function of her age, a_i, her education duration, e_i, and a measure of other factors affecting the innovation productivity such as talent and health, z_i (Jones 2010, 4):

$$x_{\mathrm{i}} = I(a_{\mathrm{i}} \geq e_{\mathrm{i}})g(a_{\mathrm{i}}; z_{\mathrm{i}}) \tag{3}$$

where

$$I(a_{\mathrm{i}} \geq e_{\mathrm{i}}) = \begin{cases} 1, & \text{if } a_{\mathrm{i}} \geq e_{\mathrm{i}} \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

and $g(a_{\mathrm{i}}; z_{\mathrm{i}})$ is individual i's innovation productivity if fully educated.

Hence, the individual innovation productivity, x_i, can only be positive once an individual has started her career, i.e. $a_{\mathrm{i}} \geq e_{\mathrm{i}}$. To derive an expression for the average innovation productivity of cohort a, $\bar{x}_{\mathrm{a}}$, one can apply the law of large numbers:

$$\bar{x}_{\mathrm{a}} = \frac{1}{N_{\mathrm{a}}} \sum_{i=1}^{N_{\mathrm{a}}} x_{\mathrm{i}} \quad \xrightarrow{\mathrm{p}} \quad E[x_{\mathrm{i}}] = E[I(a_{\mathrm{i}} \geq e_{\mathrm{i}})g(a_{\mathrm{i}}; z_{\mathrm{i}})] \tag{5}$$

Assuming that e_i and z_i are independent (Jones 2010, 4):

$$\bar{x}_{\mathrm{a}} = E[I(a_{\mathrm{i}} \geq e_{\mathrm{i}})g(a_{\mathrm{i}}; z_{\mathrm{i}})] = E[I(a_{\mathrm{i}} \geq e_{\mathrm{i}})]E[g(a_{\mathrm{i}}; z_{\mathrm{i}})] \tag{6}$$

Hence, the average innovation productivity of cohort a can be decomposed into two parts, namely $E[I(a_{\mathrm{i}} \geq e_{\mathrm{i}})] = L_1(a)$, and $E[g(a_{\mathrm{i}}; z_{\mathrm{i}})] = L_2(a)$ such that $\bar{x}_{\mathrm{a}} = L_1(a)L_2(a)$ (ibid.). While L_1 captures the average age at career start, L_2 represents the life cycle productivity once the career has started (Jones 2010, 4).

To be able to estimate L_1, Jones assumes that e_i is distributed logistically within cohorts, with μ as average age of career beginning and ω as variance parameter (2010, 4). The choice of a logistic distribution is reasonable given that the age-productivity curve increases until it reaches a definite peak (cf. section 2).

$$L_1 = \frac{1}{1 + e^{\frac{-(a-\mu)}{\omega}}} \tag{7}$$

To be able to estimate L_2, Jones assumes again a logistic curve, with θ denoting the life cycle innovation productivity once educated and ρ the variance parameter (2010, 4):

$$L_2 = 1 - \frac{1}{1 + e^{\frac{-(a-\theta)}{\rho}}} \tag{8}$$

If life cycle effects can explain the rise in the age at peak productivity, shifts in μ or θ or both will occur. These shifts over time can be modeled as polynomial expansion (2010, 5):

$$\mu(t) = \mu_0 + \mu_1 t + \mu_2 t^2 + ... \tag{9}$$

$$\theta(t) = \theta_0 + \theta_1 t + \theta_2 t^2 + ... \tag{10}$$

3.2 Population data

As a reminder, Jones' goal is to estimate shifts in the average innovative productivity with the help of the maximum likelihood method. His submodel of the average innovation productivity, $\bar{x}_{\mathrm{a}}$, has been derived above. To be able to perform a maximum likelihood estimation, data on the population age distribution, $p_{\mathrm{a}}(t)$, are missing.

Nobel Prize winners and great innovators as listed in the almanacs come from different countries with different age distributions (Jones 2010, 5). Since age distributions over the entire 20$^{\text{th}}$ century are available for only very few countries, with the U.S. as one of them, Jones only considers the age distributions of (subsets of) the U.S. population. He performs maximum likelihood estimations based on the age distribution of the entire U.S. population, the subset of active U.S. workers and the subset of U.S. scientists and engineers (ibid.).

3.3 Empirical results

Table 3 presents the maximum likelihood estimations for shifts in the innovation productivity over the life cycle. μ_0 denotes the mean age at career start at the beginning of the 20$^{\text{th}}$ century, while μ_1 denotes the shift in the mean age at career start over the 20$^{\text{th}}$ century. This shift is large and significant: While the mean age at career start was around 23 years ($= \mu_0$) in 1900, a century later, the mean age of career start has risen by around 8 years ($= \mu_1$) to 31 years. This holds irrespective of the age population (entire U.S. population, U.S. active workers or U.S. scientists and engineers) chosen. All shifts are significant at the 5 % level.

θ_1 denotes shifts in the life cycle innovative productivity once educated. All these shifts are close to zero ($\theta_1 \approx 0$). Hence, the shift in life cycle productivity can exclusively be traced back to the beginning of innovative careers, i.e. shifts in the mean age at career start. Standard errors are given in parentheses.

Table 3: Maximum likelihood estimation of innovative productivity over the life cycle (Jones 2010, 6)

		U.S. population	U.S. active workers	U.S. scientists and engineers
Early life cycle logistic curve	μ_0 Initial mean in years	24.0 (2.05)	23.3 (2.30)	23.4 (1.95)
	μ_1 trend in years per century	7.76 (3.22)	8.29 (3.49)	8.32 (2.71)
	p-values	.016	.018	.002
Later life cycle logistic curve	θ_0 initial mean in years	45.5 (2.36)	46.6 (2.21)	50.5 (3.90)
	θ_1 trend in years per century	-0.00e-03 (8.63e-03)	-0.00e-03 (6.70e-03)	0.14e-03 (6.88e-03)

While an increase in age at peak productivity due to increases in later life cycle productivity can be excluded, the 8-year shift in the early life cycle productivity must be decomposed into demographic and productivity components. In other words, it must be examined which part of the shift can indeed be traced back to productivity shifts and which part can be explained with an aging population. In order to decompose the 8-year increase into these two effects, Jones holds fixed the population age distribution and finds a 5-year increase in the mean age at peak productivity (Jones 2010, 6). Reversely, he holds fixed the innovation productivity and finds a 3-year increase in the mean age at peak productivity (ibid.) Hence, approximately 40 % of the age trend can be explained with an aging population while the remaining 60 % can be explained with changes in the life cycle productivity at the beginning of innovators' career.

To my knowledge, Jones' model has not yet been challenged and his findings have not been tested in other papers. However, Jones has not been the only one to hypothesize on drivers behind the shift in early life cycle productivity (cf. 4).

4 Explaining the rise in innovators' age at peak productivity

The preceding section has demonstrated that the rise in age at peak productivity can largely be attributed to changes in the early life cycle productivity. Naturally, the question arises *why* early life cycle productivity has shifted. Three possible reasons will be discussed below. First, the shift in life cycle productivity may be due to longer training periods. If students need longer to finish their undergraduate or graduate degrees and PhD students need longer to receive doctorates, then the beginning of their innovative career will be shifted towards older ages. Second, the nature of the innovation process may have changed in a way that delays peak productivity. In particular, the trend towards teamwork may have lengthened the innovation process. Third, an emphasis of experimental over conceptual work may have raised the age at peak productivity. Importantly, the following paragraphs point to *possible* drivers of the productivity shift only. Whether they are causal of the rise in age at peak productivity is not tested empirically here and is left to future research.

4.1 Extended training periods

Training periods may have lengthened at the undergraduate and graduate respectively PhD level. At the undergraduate level, Bound et al. (2010) find that the time to completion of the bachelor degree has increased over the past decades in the U.S., especially for undergraduates at less selective public universities and community colleges. Whether training at the PhD level has lengthened can best be evaluated based on the *time-to-degree* measure, i.e. the time elapsed between completion of the undergraduate degree to the doctorate. One might expect that the *time-to-degree* has increased over the past decades, given the cumulative nature of knowledge and innovation (e.g. Scotchmer 1991; Weitzmann 1998). As knowledge and innovation expand further, PhD students' educational burden increases if they want to keep up to date with the cutting edge of research (Jones 2009). Hence, PhD students may have to learn more and longer before starting an innovative career. However, the median *time-to-degree* in 1978 and the median *time-to-degree* in 2015 are very close to each other (cf. figure 1). From 1978 to 1994, the median *time-to-degree* has increased from 9 to 10.8 years (National Science Foundation 2017). Afterwards, it decreased again, reaching 8.7 years in 2015 (ibid.). This general trend can be observed across all disciplines: the median *time-to-degree* increased until the early and mid 1990's, and then decreased again until 2015 (ibid.).

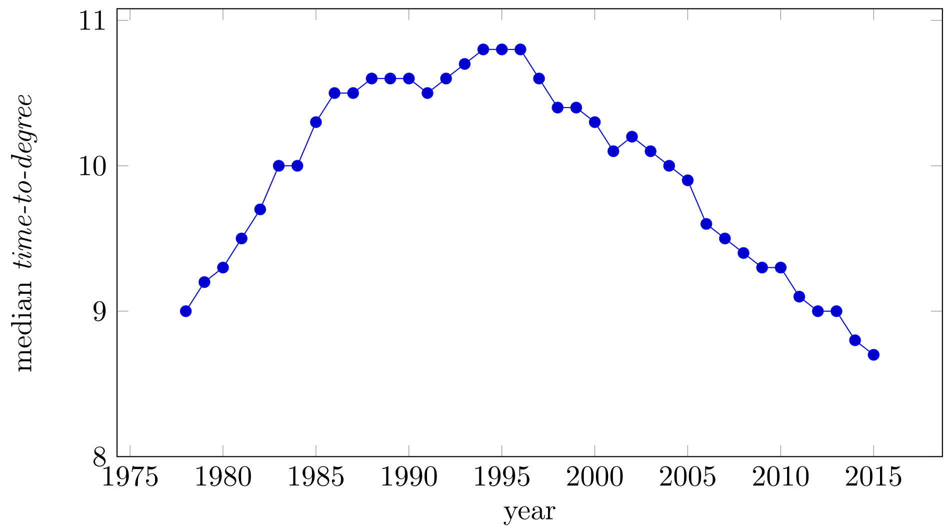

Figure 1: *Time-to-degree* for U.S. PhD students, 1978–2015 (National Science Foundation 2017)

A similar development over time can be observed for the median *age-at-doctorate* which is closely linked to the median *time-to-degree*: the higher the median *time-to-degree*, the higher the median *age-at-doctorate* ceteris paribus. The median *age-at-doctorate* was 31.7 in 1978, then increased to 34.2 in 1993 and then fell again to 31.6 in 2015 (National Science Foundation 2017). Apparently, U.S. doctorates are not older today than they were three decades ago. Finding corresponding data on the median *time-to-degree* and the median *age-at-doctorate* for Germany is difficult because German universities have not been obliged to report on PhD students and doctorate recipients until 2017 (Bundesbericht wissenschaftlicher Nachwuchs 2017, 88). Based on the scarce data available, the mean *age-at-doctorate* was 32.7 years in 2000 and 32.6 years in 2014 (ibid.), i.e. the mean *age-at-doctorate* has not significantly changed over the past fifteen years.

To conclude, these data suggest that training periods at the PhD level have not increased while training periods at the undergraduate level have extended. Notwithstanding these results, training periods at the PhD level may have increased in the first half of the 20$^{\text{th}}$ century and be responsible for changes in the early life cycle productivity (Jones 2010, 8ff.).

4.2 Increase in collaboration

Another reason for the productivity shift in the early life cycle may be the trend towards innovation in teams. The trend towards teamwork in science is well documented (Hollis 2001, Hudson 1996). From 1955 to 2005, the mean number of authors has risen from just below 2 to almost 4.5 for science and engineering papers and from roughly 1.25 to 2.5 for social science papers (Jones 2011, 113). According to Jones (2011), the reason for the trend towards teamwork lies - again - in the cumulative nature of knowledge and innovation. One possible reaction to the ever extending body of knowledge is to specialize in narrower knowledge and draw on others for complementary knowledge, which may also explain why the median *time-to-degree* in 1978 is not very different from the one in 2015: PhD students focus on a narrower field of research.

The crucial question is whether the increase in teamwork in science - whether co-authorship or team patenting - can explain the productivity shift in the early life cycle. Intuitively, teamwork should speed up the innovation process due to gains from labor division and should thus raise the age at peak productivity. However, there is evidence that teamwork in science in fact slows down the innovation process for two reasons. First, reviewing teamwork is much more time-consuming than reviewing single-authored work. According to Ellison (2002), co-authored papers tend to be more complex than single-authored papers given that the reason for researchers working jointly on a paper is that one person alone could hardly possess all the specialized expertise needed for writing the paper (966). While it took between six to nine months for a submitted Economics paper to be accepted in the 1970ies, it took approximately 2 years at the beginning of the 21$^{\text{st}}$ century (Ellison 2002, 974). Due to the lengthening of the review process, it may therefore take time until researchers have published their first paper. This in turn may induce PhD students to stay longer in graduate schools and delay the beginning of their careers because they want to submit papers before graduation and entering the job market (Liu & Park 2004, 519). Second, working on an innovation project in a team may be more time-consuming than working on an innovation project alone (Ductor 2014). Innovators will very often be involved in many teamwork projects at a time, which makes the synchronization of tasks difficult. Ductor (2014) terms this a congestion problem: some team members may have to wait for the other team members' contributions until they can continue working. This may delay the submission or publication of papers and the release of innovations.

4.3 Shift from conceptual to experimental work

As mentioned above (cf. section 2), Weinberg & Galenson (2005) explain differences in the location of the peak of productivity with a distinction between disciplines that work primarily conceptually and those that work primarily experimentally. Conceptual work does not require much accumulated knowledge but requires researchers to depart from existing paradigms, which may be easiest prior to the adoption of these paradigms (Jones et al. 2014, 19). Hence, conceptual work is likely to be done at the outset of careers. Experimental work, on the other hand, builds on accumulated knowledge and experimental innovators are therefore likely to produce their major work towards the end of their careers. Indeed, when Jones et al. distinguish between conceptual and experimental Nobel Prize winners, the mean age at peak productivity of the latter is 4.6 years higher than the one of the former (2014, 21). Accordingly, the shift in life cycle productivity may be due to a shift in emphasis from conceptual to experimental work in more recent years: as the number of experimental relative to conceptual innovators increases and experimental innovators reach the peak of productivity at a later age, early life cycle productivity decreases. In addition, as experimental work rests upon the accumulation of knowledge and the body of knowledge to be acquired expands ever further, experimental innovators may need even longer to produce major work, which additionally lowers early life cycle productivity.

To conclude, three explanations of the productivity shift in innovators' early life cycles have been examined, namely an extension of training periods, a trend towards teamwork and a shift of emphasis from conceptual to experimental work. A look at data renders an extension of training periods at the PhD level in the more recent past as driver of the productivity shift invalid. The trend towards time-consuming teamwork and experimental work, on the other hand, may be better suited to explain the productivity shift. However, it cannot be said whether teamwork and a shift towards experimental work are indeed causal of the productivity shift.

5 Policy implications

As indicated in the introduction, science policy must be worried about the rise in innovators' age at peak productivity for two reasons. First, science policy has an interest in aligning *innovation potential* with *innovation productivity*. Research in the field of neurology has shown that the number of neurons and the total myelinated fiber length in the brain white matter - which are crucial for creative innovation - begin to decline once an individual has passed her 20ies (Pakkenberg et al. 2003; Heilmann et al. 2003, 374). The better the match of *innovation potential* and *innovation productivity*, the lower will be the opportunity costs from letting university students or young graduates spend their potentially most innovative years with activities other than innovation. Hence, science policy should try to at least contain or even reverse the age trend described.

Second, science policy must be worried about the described age trend because it reduces the incentives for graduates to enter a scientific career and thus endangers one of the drivers of economic growth. A modified example by Jones (2011, 118f.) can explain how an increase in the age at peak productivity makes a scientific career less attractive. Assume that a researcher publishes an important paper or is granted a patent at the peak of her productivity and that the value of this achievement is V. V may consist of patent royalties, greater success probability when applying for grants in the future and, above all, higher wages. An increase in the age at peak productivity implies that the receipt of V is shifted towards a later point in an innovator's life. With a discount rate of 10 %, V would have to increase by 10 % to compensate the innovator for a one year delay in the receipt of V. If the receipt of V is delayed by 6–8 years as suggested above, V would have to increase by 44–54 % to keep a scientific career as attractive as it was without the age trend.

Against this background, two policy options should be considered: a shortening of training periods and a more attractive financial incentive system for researchers. Section 4 has shown that the *time-to-degree* has not increased for PhD students. Still, one idea to reverse the age trend would be to shorten the *time-to-degree* for PhD students, e.g. by reducing graduation requirements such as writing pre-theses and taking PhD classes. Similarly, high-school and undergraduate studies could be shortened, and the shift from G9 to G8 in selected German states can be seen as step into this direction.

A second policy choice would be to pay innovators better to keep science an attractive field of employment despite the age trend. Figure 2 shows the evolution of professors' basic wages between 2003 and 2016. These basic wages are set by science policy at the federal level, science policy at the state level has the possibility to slightly adjust these basic wages, and universities can pay professors bonus payments in case of extraordinary achievement in research or teaching or if they have been offered positions elsewhere (Detmer & Preißler 2003, 50ff.; Bundesbesoldungsgesetz §33 Abs.1). The focus lies on these German professors' basic wages at public universities because, for any other wages paid in science, the influence of science policy would be difficult to distil. For instance, *total* (rather than basic) wages paid at German public universities depend on royalties determined by universities themselves and in the U.S., science policy has hardly any influence on wages paid at public universities.

German law distinguishes between three ranks of professorship. *W1* corresponds to junior professorships, *W2* and *W3* correspond to full professorships, with *W3* professors ranked higher and paid better than *W2* professors. In the years 2003 to 2016, *W1* gross basic monthly wages have increased from 3338.24 € to 4460.67 €. This corresponds to an increase of 34 % in nominal wages. Over the same period, *W2* gross basic monthly wages have increased from 3813.38 € to 5541.73 €, which corresponds to an increase of 45 % in nominal wages, and *W3* gross nominal basic wages have increased by 34 % from 4630.53 € to 6193.71 €. The data on basic wages have been taken from the archives of *oeffentlicher-dienst.info*.

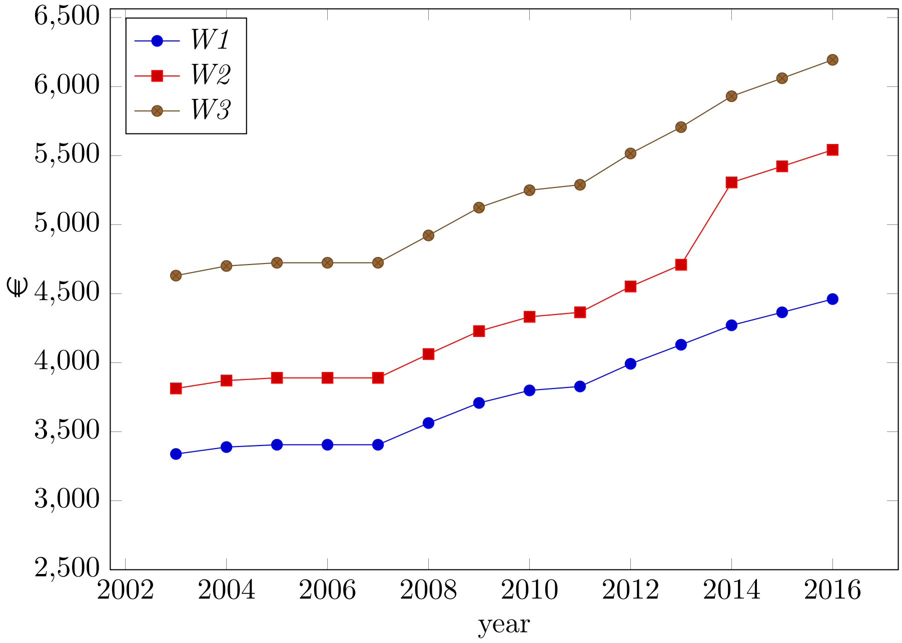

Figure 2: Basic wages for the three ranks of professorship, 2003-2016

Between 2003 and 2016, inflation has raised the price level by 21 % (Statistisches Bundesamt 2017). Hence, all gross basic wages have increased in real terms between 2003 and 2016. A particularly sharp increase can be observed for the *W2* gross basic wage: it increased by 45% and hence lies 24 percentage points above the price level rise. This extraordinary increase reflects a ruling by the Federal Constitutional Court according to which the *W2* gross basic wage did not compensate professors sufficiently and science policy had to raise basic wages (Bundesverfassungsgericht 2012). Hence, based on the analysis of professors' basic wages in Germany, science policy has - partly voluntarily and partly forced - raised the financial returns to scientific careers recently.

6 Conclusion

6.1 Summary

Contrary to public belief, innovators are often in their late 20ies or even beyond their 20ies when they produce their major work. The average age at peak innovative productivity has increased by around 8 years over the last century, from 23 to 31 years (Jones 2010, 2011). This paper has tried to identify the reasons for this age trend with reference to Jones (2009, 2010, 2011). Based on his model (2010) the rise in age at peak productivity can be largely attributed to productivity shifts at the beginning of innovators' careers. Three reasons for this productivity shift in the early life cycle have been considered, namely a lengthening of training periods, a trend towards teamwork and a shift of emphasis from conceptual to experimental work. Over the past decades, the *time-to-degree* has increased for undergraduate students and remained stable for PhD students. The trend towards teamwork may have contributed to the productivity shift as research in teams involves longer review processes associated with a deliberate postponement of entrance into the academic labor market and difficulties regarding the synchronization of tasks. Finally, the shift from experimental to conceptual work may have shifted productivity as the former requires more lead time than the latter. Importantly, no causal relationship between these three factors and the productivity shift could be established.

Science policy has an interest to reverse the described age trend. The further peak innovative *productivity* and *potential* fall apart, the greater the opportunity costs from wasting individuals' potentially most innovative years with activities other than innovation; and the older innovators are at the peak of their productivity, the less attractive an innovative career becomes for them. The shortening of training periods and raising of financial returns to innovative careers have been considered as policy options.

6.2 Outlook

If the age at peak innovative productivity continues to rise, graduates have increasingly few incentives to opt for an innovation-producing career. Private research institutions may be more flexible to compensate for the age trend in terms of financial rewards than public research institutions. Hence, unless public research institutions keep pace with the employment benefits granted elsewhere, they will have increasing difficulties to attract gifted graduates.

With the help of an econometrically sophisticated model this work has shown that the reasons for the shift in age at peak productivity are to be located at the beginning of innovators' life cycles. However, this work has failed to establish causality between the life cycle productivity shift and the factors listed above - extended training periods, the emphasis on teamwork and the shift towards experimental work. It is up to future research to examine these potentially causal relationships with the help of an econometrically more sophisticated strategy.

Literature

Bound, John, Lovenheim, Michael F. & Turner, Sarah. 2010. "Increasing time to baccalaureate degree in the United States." *National Bureau of Economic Research*, Working Paper No. 15892.

Bundesbesoldungsgesetz. § 33, Leistungsbezüge. Retrieved May 2017. https://www.gesetze-im-internet.de/bbesg/__33.html.

Bundesverfassungsgericht. 2012. "Leitsätze zum Urteil des Zweiten Senats vom 14.Februar 2012, 2 BvL 4/10." https://www.bundesverfassungsgericht.de/SharedDocs/Entscheidungen/DE/2012/02/ls20120214_2bvl000410.html.

Detmer, Hubert & Preißler, Ulrike. 2006. "Die W-Besoldung und ihre Anwendung in den Bundesländern." *Beiträge zur Hochschulforschung*, 28(2): 50-66.

Ductor, Lorenzo. 2014. "Does co-authorship lead to higher academic productivity?" *Oxford Bulletin of Economics and Statistics*, 77(3): 385-407.

Ellison, Glenn. 2002. "The slowdown of the Economics publishing process." *Journal of Political Economy*, 110(5): 947-993.

Gehaltsrechner Öffentlicher Dienst. Retrieved May 2017. http://oeffentlicher-dienst.info/c/t/rechner/beamte/bund/a/2017?id=beamte-bund-2017&matrix=1.

Heilman, Kenneth M., Nadeau, Stephen E. & Beversdorf, David O. 2003. "Creative Innovation: Possible Brain Mechanisms." *Neurocase*, 9(5): 369—379.

Hoisl, Karin. 2005. "A closer look at inventor productivity - what makes the difference?" Zentrum für Europäische Wirtschaftsforschung, http://ftp.zew.de/pub/zew-docs/veranstaltungen/inno_patenting_conf/Hoisl.pdf.

Hollis, Aidan. 2001. "Co-authorship and the output of academic economists." *Labour Economics*, 8(4): 503-530.

Hudson, John. 1996. "Trends in multi-authored papers in Economics." *The Journal of Economic Perspectives*, 10(3): 153-158.

Isaacson, Walter. 2011. *Steve Jobs. Die autorisierte Biografie des Apple-Gründers.* München: Random House.

Jones, Benjamin F. 2009. "The burden of knowledge and the 'death of the renaissance man': is innovation getting harder?" *Review of Economic Studies*, 76(1): 283-317.

Jones, Benjamin F. 2010. "Age and great invention", *The Review of Economics and Statistics*, 92(1): 1-14.

Jones, Benjamin F. 2011. "As science evolves, how can science policy?" *Innovation Policy and* *the Economy*, 11(1): 103-131.

Jones, Benjamin F., Reedy, E. J. & Weinberg, Bruce A. 2014. "Age and scientific genius." *National Bureau of Economic Research*, Working Paper No. 19866.

Konsortium Bundesbericht wissenschaftlicher Nachwuchs. 2017. *Bundesbericht wissenschaftlicher Nachwuchs. Statistische Daten und Forschungsbefunde zu Promovierenden und Promovierten in Deutschland*. `http://www.buwin.de/dateien/buwin-2017.pdf`.

Lehman, Harvey C. 1953. *Age and great achievement*. Princeton, NJ: Princeton University Press.

Levin, Sharon G. & Stephan, Paula E. 1991. "Research productivity over the life cycle: evidence for academic scientists." *The American Economic Review*, 81(1): 114-132.

Liu, Haoming & Park, Cheolsung. 2004. "The evolution of the graduation-publication process." *Economics of Education Review*, 23(5): 519-531.

Mowery, David C. & Rosenberg, Nathan. 1989. *Technology and the pursuit of economic growth*. Cambridge, MA: Cambridge University Press.

National Science Foundation. 2017. *Survey of earned doctorates*. `https://www.nsf.gov/statistics/srvydoctorates/#tabs-2`.

Pakkenberg, Bente, Pelvig, Dorte, Marner, Lisbeth, Bundgaard, Mads J., Gundersen, Hans J. G., Nyengaard, Jens R. & Regeur, Lisbeth. 2003. "Aging and the human neocortex." *Experimental Gerontology*, 38(1-2): 95-99.

Scotchmer, Suzanne. 1991. "Standing on the shoulders of giants: cumulative research and the patent." *The Journal of Economic Perspectives*, 5(1): 29-41.

Simonton, Dean K. 1988. "Age and outstanding achievement: what do we know after a century of research?" *Psychological Bulletin*, 104(2): 251-267.

Statistisches Bundesamt. *Verbraucherpreisindex*. Retrieved May 2017. `https://www-genesis.destatis.de/genesis/online/link/tabellen/611*`

Weinberg, Bruce A. & Galenson, David W. 2005. "Creative careers: the life cycles of Nobel Laureates in Economics." *National Bureau of Economic Research*, Working Paper No. 11799.

Weitzman, Martin L. 1998. "Recombinant growth." *Quarterly Journal of Economics*, 113(2): 331-360.

Zuckerman, Harriet. 1977. *Scientific Elite. Nobel Laureates in the United States*. New Brunswick, NJ: Transaction Publishers.

Statutory Declaration

I hereby declare that I wrote this seminar paper without the help of others. Any content drawn from outside sources is marked as such. This seminar paper has never been submitted to any other examination office. I am aware that any untrue declaration can have legal consequences.

Kiel, 05/30/2017