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Do only new brooms sweep clean? A review on workforce age and innovation

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Summary

The relationship between age and creative performance has been found to follow a hump-shaped profile in the arts and sciences, and in great technological achievement. Accordingly, accelerating workforce aging raises concern about whether future capacity to innovate is endangered. This paper provides a review of existing studies exploring age effects on innovative performance, both at the individual and the macro levels.

Empirical evidence confirms the hump-shaped relationship between workers' ages and innovative performance, with the highest levels of performance seen between ages 30 and 50, depending on the domain. Industrial invention in knowledge-intensive fields, and great invention in general, seem to be a young man's game. Yet in more experience-based fields, innovative performance peaks later, and remains stable until late in the career.

Moreover, the quality of invention remains rather stable at older ages. However, individual-level evidence has to be interpreted with caution due to the presence of selectivity biases and unobserved heterogeneity.

Studies at the levels of firms, regions, and countries address some of these issues. Results of these studies have indicated that young professionals drive knowledge absorption, innovation, and technological progress, whereas more experienced workers are more relevant in mature technological regimes.

Apart from integrating the existing empirical evidence on different levels of aggregation, a strong focus is on methodological issues and conceptual challenges. This review therefore provides a sound basis for further studies on the impact of workforce aging on innovative performance. In addition, promising directions for future research are proposed.

1 Introduction

Firms operating in mature economies have to keep up with low-wage countries that have ample and young labor available at low cost. Maintaining a competitive advantage and sustained growth thus has to rest upon the generation, diffusion, and adoption of innovative products, services, and production technology. For these reasons, excellence in basic and applied research, the invention of market-ready, novel products, as well as superior technological production standards are high on the agenda of business and technology policy. Today, economies like those of the European Union, Japan or the United States rank among the top nations in terms of investment in research and development (R&D), the pool of human resources in science and technology, and the number of patents issued (OECD 2007, pp. 25, 51, 55 and 89).

Increasingly, however, these nations are faced with sweeping demographic changes as a result of long-term below-replacement fertility and a continuous rise in life expectancy. What will the future bring? Policy makers and business executives have expressed concerns about whether and how upward shifts in the age structure of the workforce will affect an economy's capacity to generate technological advances. The looming shortage of young and highly-skilled workers has become a veritable bogeyman for the recruiting departments of technology firms.

An Irish proverb says, "New brooms sweep clean – but an old brush knows every corner." Young workers with up-to-date specialist knowledge are often supposed to be the only guarantors for high innovative capacity. Yet if this is the case, what then is the role in industrial innovation of more senior workers with years of work experience? The goal of this literature review is to summarize and critically discuss existing evidence on the question of how workers' ages relate to their performance in industrial innovation, both at the individual and at the aggregate levels.

It should be noted that, in the discussion that follows, we draw upon Jaffe (1986, p. 988), and understand innovation in a broad sense as "new economically useful knowledge". It is the most general definition we can choose to describe different kinds of "innovations", encompassing process and product innovations, or inventions; and embracing incremental as well as radical innovation. We therefore deliberately narrow the scope of this review to the *generation* of new knowledge that may lead to new products and services or improved production processes, and how it is related to the *age composition* of the *workforce*.

One question that should be considered in the context of changing age composition of the workforce and the capacity to innovate is how the age of individuals relates to their ability to bring forth economically relevant novelties. Addressing this issue, the following section of this paper reviews studies on age-specific inventive performance at the individual level (Section 2). However, because they suffer from major methodological and conceptual drawbacks, these studies do not conclusively answer the question of how innovative performance is related to the age of the inventor. Some of these issues are tackled in studies at the aggregate level, which address the question of how the innovative performance of countries, regions, and firms depends on the age composition of their respective workforces. A review of these studies is provided in Section 3. Section 4 concludes with a summary and a discussion of areas for future research.

2 Workers' ages and innovation

This section summarizes previous empirical research on age-specific innovative performance at the individual level. We start by looking at evidence about the most productive ages of great inventors (2.1) before focusing on conventional industrial innovation (2.2). We first sketch the results of some early studies on the performance of engineers and other workers in innovation-relevant occupations. Subsequently, the findings of a more recent stream of research on age-specific inventive performance based on patenting activity are discussed and integrated. As we will see, the latter field of study is not only concerned with the question of at what ages inventors are most productive, as measured by number of patents, but also with investigating how patenting quality evolves over inventors' careers.

2.1 Age and great invention

Empirical evidence points towards an inversely u-shaped relationship between an inventor's age and performance as measured by the number of great inventions. Lehman (1953), for example, finds a curvilinear, clearly left-skewed distribution across the ages at which 402 well-known inventors made notable contributions. Later, he confirmed these results for the emergence of pioneering advances in electrical and mechanical engineering by way of historiometric analyses based on technological almanacs (Lehman, 1966, p. 274). Accordingly, inventive productivity is low at the very start of the career, but rapidly increases until ages 30 to 40, when it reaches its maximum. More than 50% of all great technological achievements are contributed by inventors younger than 40 years old (p. 275). At older ages, creative performance gradually levels off again. Following a similar approach, Jones (2005) further substantiates Lehman's (1953, 1966) findings on great achievements in the history of technology during the 20th century. Additionally, he points out that the age-performance curve of great inventors has shifted towards older ages in recent decades. Per century, he detects an upward trend in the age of great achievement of about eight years, as estimated for 294 great inventors in the US. His explanation for this upwards shift is that innovators face an increasing educational burden, with a continuously increasing stock of knowledge, in times of technological change (see also Jones, 2005a).

The findings for great invention are in line with more than a century of research about creative performance by scientists, artists, writers, and other creative workers (see reviews by Simonton, 1988, 2007), as well as with evidence about the life course evolution of general work productivity, as measured by supervisors' ratings, production records (Warr 1993; Sturman 2003; Skirbekk 2004, 2008), or – if we agree with the assumption that productivity is mirrored by wages – age-earnings profiles (e.g., Card and Lemieux 2001).

Explanations provided for the characteristic pattern of age and creative achievement in different fields are declines in cognitive abilities for older individuals found in laboratory experiments (Jones e.g. 2005b, p. 10 or Oberg 1960, p. 246), as well as decreased motivation. According to Schaie (1958), for example, most mental abilities reach their maximum before age 35, and decline more or less steadily afterwards. Flexible thinking, which is thought to be of particular importance for creative achievements, even peaks in the mid-twenties, and declines more rapidly afterwards than most other abilities he tested. Other authors, such as Reese et al. (2001) and McCrae et al. (1987), add that divergent thinking – i.e., the ability to rapidly produce a large number of ideas or solutions to problems that tend to be different from those of most other people (Guilford 1967) – becomes more difficult after reaching a certain age. However, as Jones (2005a, p. 10) argues, the lower performance at older ages may also result from decreased effort. Indeed, age-related declines in motivation for achievement have been identified in various studies, as summarized by Kanfer and Ackerman (2000).

2.2 Age and industrial innovation

However, up to now, the reviewed studies discuss either general creative or scientific performance, or, when the focus is on technological novelties, exceptional advances. Nowadays, most inventions emerge in a business context, and the engagement of profit-seeking firms in innovation is perceived to be an important driver of technological change in endogenous growth theory (Romer 1990a; Aghion and Howitt 1992; Grossman and Helpman 1994, p. 24). The question is, then, how the age of workers affects conventional industrial innovation, as mirrored in the development of patentable and marketable products and services, or major improvements of existing products and processes. Indeed, some studies investigate whether the previous findings on age and great achievement also prove true in the context of industrial invention. However, innovative performance in a business context cannot be observed directly, and is perhaps even more difficult to judge than general work performance. Therefore, assessing the contribution of individual workers is a difficult task.

2.2.1 Age and innovative capacity measured by supervisors' and peer assessments

A number of studies explore age-specific performance of R&D workers in private corporations, based on management or peer assessments. For technological workers, such as engineers and scientists, these studies confirm that innovative performance first increases, and then decreases with age. Maximum performance is reached between the mid-thirties and mid-forties (Oberg 1960, p. 256, Dalton and Thompson 1971, and Pelz and Andrews 1966). In similar analyses for military organizations, Vincent and Mirakhor (1972), as well as Stahi (1977, p. 73), obtain negative correlations between age and innovative performance, but without including more detailed age groups or allowing for a non-linear relationship between age and performance.

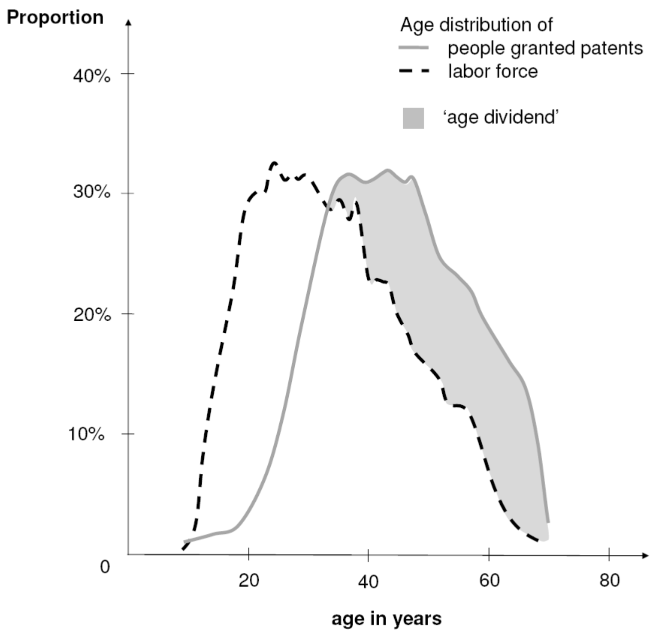
Oberg (1960, p. 249) argues that patents and publications are unsatisfactory measures for performance, as many workers substantially contribute without having the chance to be involved in patents and publications. However, supervisors' or peer rankings may be biased. For example, when compiling rankings, managers may acknowledge in their evaluations senior workers' past achievements and loyalty (Salthouse and Maurer, 1996, p. 357)1[1].

2.2.2 Age-invention profiles

Other authors therefore choose to investigate age-specific inventive performance based on the number of patents applied for by inventors' ages. In this context, Mariani and Romanelli (2007, p. 1128) as well as Giuri et al. (2007, p. 1111), point out that advances in systematic empirical evidence about the effect of inventors' characteristics on their productivity has been severely hampered, as official patenting statistics do not offer personal information about the inventors, such as age or education level. An early study based on a small sample of inventors in chemistry and chemical engineering was published by Stewart and Sparks (1966). In contrast to the results of previous studies, they do not find a decline of patenting performance at older ages.

More recently, Jones (2005b), as cited in Feyrer (2008, p. 89), overcomes the problem of a lack of age data in official patenting statistics by linking date-of-birth information to US patenting information for a large sample of inventors between 1975 and 1995. He finds that the median age of inventors is 48, and remains quite stable over the whole time period.

Figure 1: Age profile of US people granted patents and total labor force in 1990



Source: Jones (2005a), as cited in Feyrer (2008, p. 90 and 92), adapted and extended

[1] For a comprehensive discussion about the assessment of general work performance over the life course, see Skirbekk (2004) and Skirbekk (2008, p. 193) as well as Sturman (2003, p. 615).

Figure 1 shows the distribution of ages of the US inventors granted patents in 1990, as well as the age distribution of the entire US workforce identified by Jones (2005a), as cited in Feyrer (2008, p. 90 and 92). With inventive performance being independent of age, and assuming that all inventions emerge from the current labor force, both curves should be congruent. However, the age-at-patenting curve is clearly shifted towards older ages, with a comparatively long plateau of high performance in the late thirties and mid-fifties. Until the late thirties, for each single year of age, the share of workforce exceeds the share of patents produced.

If the underlying statistical population (i.e., the labor force) is controlled for, we observe an 'age dividend' in invention (grey shaded area in Figure 1) starting in the late thirties. It is therefore possible that the number of inventions per labor force in older economies may be far higher than in very young economies, where experience still has to be built. In other words, if we have to face reductions in the level of inventive activity, they will likely be caused by a declining number of workers, rather than by lower age-specific inventive performance at older ages.

Henseke and Tivig (2008) confirm Jones's (2005a) results for Germany, finding an average age of 45.9, and a median age of 44 years at invention, for an own survey of 410 German inventors whose patent application was published in 2003. Furthermore, the authors show that age-performance profiles with respect to patent applications in information technology as well as biotechnology – where up-to-date knowledge is crucial – are heavily left skewed, with most contributions being achieved before age 50, and maximum performance at around ages 35 or 40. For more experience-based fields, like agriculture and metallurgy, the authors find a first peak in the late forties, and a second, smaller one at around 60 years of age[2].

What do we learn from these somewhat diverse results? Age-invention profiles in knowledge-intensive fields follow a curvilinear, inversely u-shaped functional form, with most inventions being made by inventors between the ages of 35 and 50, depending on the domain. The fact that age-invention profiles tend to be strongly left-skewed in knowledge-intensive fields indicates that young inventors in high-tech sectors profit from their up-to-date specialist knowledge recently acquired at university, whereas older inventors' knowledge may be prone to obsolescence caused by the rapid technological change in these sectors.

Other industries are characterized by long innovation cycles, as, for example, tends to be the case in the chemical and pharmaceutical industries. In such a setting, a successful (in this case, patentable) invention may depend upon whether new ideas can be successfully embedded in the existing technological context, and in accordance with customers' needs, as, for example, tends to be the case in the engineering industry. In these sectors, younger inventors may still rely as before on up-to-date knowledge, whereas inventors at older ages produce similar successes based on their experience. The mingling of these two age-specific strategies in invention possibly explains the existence of two modes in the age distribution of inventors, as described in Henseke and Tivig

[2] Similar double-peaks had been found earlier by Pelz and Andrews (1966) and Vincent and Mirakhor (1972) regarding the performance of R&D workers as measured by management assessments, and for other creative disciplines, as described by Simonton (1988, pp. 252-253).

(2008) for the experience-based sectors; a long plateau of high performance, as outlined in Jones (2005a); or performance stabilizing at older ages, as posited in Stewart and Sparks (1966). Unexpected or no age effects at all may, therefore, be especially likely to appear when the industry in which inventions take place is not controlled for, and different age-invention profiles are confounded (see also Simonton 1991, p. 70).

Note that the previous studies plot the frequency distribution across inventors' ages for a *cross-sectional sample of patents* at a certain point in time. In such a setting, age-invention profiles do not necessarily reflect age-specific performance only, but also mirror the age distribution in the overall statistical population[3], i.e., all potential inventors as given in the labor force, as in Jones (2005a), and as given in the workforce of the respective industrial sector, as in Henseke and Tivig (2008). Ideally, to learn about how inventive performance evolves over the life course, we would compare it for the same individuals at earlier and later stages of their careers.

Another reason for interpreting age-invention profiles with caution is that they fail to disentangle the effects of age and other (cohort-specific!) factors, such as educational attainment, that are known to drive inventive performance. The average educational attainment of younger individuals still tends, for example, to be higher than for their more senior counterparts (see Lutz et al. 2007)[4]. As in the purely descriptive age-invention profiles mentioned above, the effects of age and age-specific levels of education, at least as main drivers of innovation, are confounded, given that inventive performance at older ages may be higher than the age-invention profiles suggest.

Consequently, despite these promising attempts, evidence shedding light on the question of how industrial innovation depends on workforce age at the individual level is still sparse, especially if we compare it to the abundant evidence about age and creative achievement in general (see, for example, Simonton 1988, 2007).

2.2.3 Age-specific inventive performance over the life course

Only very recently has the novel and large PatVal survey become available, providing an opportunity to link inventors' individual characteristics to the quantity and value of patents they produce. It covers the inventors of 9,017 patents filed at the European Patenting Office (EPO), with a priority date between 1993 and 1997 by inventors in France, Germany, Italy, the Netherlands, Spain, and the United Kingdom (for an overview see Giuri et al. 2007). The survey is complemented with patenting information for all patents each inventor in the sample applied for between 1988 and 1998 (Mariani and Romanelli 2007, p. 1130). The great improvement of this dataset when compared with the earlier cross-sections of patents is that it offers longitudinal information about the patenting activity of a sample of inventors, whose demographic and other characteristics we know.

[3] This is less problematic in the context of great technological achievement, assuming that the whole population consists of potential innovators, and that real 'genius' will blaze a trail to itself.

[4] The difference between the population share with a tertiary degree at ages 60-64 is up to 32 percentage points lower than for the group of 30-34-year-olds (e.g., in Korea and Japan). For France, Finland and Belgium, the difference still amounts to more than 20 percentage points. Germany and the US display a smaller educational gap between these two age groups (seven and eight percentage points).

According to Giuri et al. (2007, p. 1111), as well as Mariani and Romanelli (2007, p. 1132), the inventors are, on average, 45 years old at the time of the survey, which took place in 2003. Comparing mean ages of inventors across industries, the mean ages of inventors are significantly lower (early forties) in knowledge-intensive sectors, such as information technology, optics or biotechnology; than in more experience-based fields, such as agriculture, metallurgy, and most engineering disciplines, where mean ages range from the mid-forties to the early fifties. The results derived from the PatVal dataset therefore confirm the earlier findings that the production of patents is not necessarily a young man's game only, but that, in knowledge-intensive fields, innovation happens earlier than in more experience-based industries.

Mariani and Romanelli (2007), as well as Schettino et al. (2008), further analyze the dataset econometrically. They regress the log number of patents produced by an inventor in a certain time period spanning 10 or 14 years, respectively, on inventors' ages at a certain point in time (1995 in the case of the first study), as well as on a number of individual and organizational control variables. Both studies yield statistically significant positive parameter estimates for inventors' ages in its linear form, and negative parameter estimates for inventors' ages in its quadratic form. This econometrically confirms the inversely u-shaped relationship between age and inventive performance found in the more descriptive analyses discussed before: the marginal effect of age on creative productivity first increases, and then declines with age. However, according to the results of these two studies, the turnaround does not happen until relatively late, between the ages of 50 and 55. Moreover, older inventors lag to a much lesser extent behind the maximum performance of their prime-age counterparts than younger inventors, who produce relatively few patents at the start of their careers.

In conclusion, if other relevant determinants of individual inventor productivity besides age are controlled for, the number of patents produced at a certain age first increases with age, peaks at around 50 years, and then slowly levels off. Note, however, that the second-order polynomial of age (age and age^2) may not fully capture the functional form, and that the confidence intervals for the age effects are quite broad[5].

What, then, is the relationship between inventors' ages and the quality of the inventions they produce? Based on a recent survey of 3,350 German inventors, Harhoff and Hoisl (2007, p. 1159) find, for example, that the monetary value of patents is positively related to inventors' ages. However, as age is only included in its linear form, this does not contradict the existence of a slight decline at older ages. Furthermore, the authors themselves point out that comparatively high inventive quality at older ages may partly result from positive selection if, over time, only the most skilled inventors remain in the innovation business. This may be demonstrated by the fact that more than 75% of the inventors in the PatVal Survey have at least an academic degree, and more than a quarter have a PhD[6].

[5] Actually, monotonically decreasing, as well as monotonically increasing, the relationship between age and innovative performance still lie in the bands of confidence interval for the age polynomials.

[6] As Hoisl (2007a, p. 16) argues, as most inventors are highly educated, the variation in this variable is actually so small that its effect on patenting quality remains statistically insignificant (see also Mariani and Romanelli 2007, p. 1137).

Assuming that high-quality inventions are more likely to provide a basis for subsequent inventions, inventive quality[7] can also be assessed by the number of citations per patent received within a fixed time period after the patent has been published (e.g., five years). Based on this approach, Hoisl (2007a) studied the age-specific patenting quality of a PatVal sample of more than 3,000 German inventors who produced a total of 35,210 patent applications at the European Patent Office (EPO) over at least a part of their lives (between 1977 and 1999). She thereby differentiates inventors by the length of their involvement in patenting activity. Long-term inventors (20 years or more) are the most productive group, and patenting quality follows the well-known inversely u-shaped pattern: quality increases until about 50 years of age, and then slowly levels off. Still, inventive quality remains high and fairly stable between ages 40 and 64, not falling below 80% of maximum performance, which is reached at ages 45-54. Inventors engaging in patenting activity for less than 20 years produce, on average, inventions of lower quality than long-term inventors, but age-effects are not significant[8].

Two similar studies provide some insight into age-specific inventive quality, depending on age and other inventor characteristics, such as educational level. Mariani and Romanelli (2007, p. 1137) do not find significant age effects on the quality of patents, whereas Schettino et al. (2008, p. 18)[9] show that the marginal effect of an additional year of age on patenting activity is positive until age 50, and then slightly decreases.

How can we explain these somewhat conflicting results, which appear to provide different answers to the question of whether a decline in patenting quality occurs after age 50? First, as Hoisl (2007a) argues, inventors' career paths matter. Following this reasoning, they propose that, in samples dominated by long-term inventors, performance follows the well-known inversely u-shaped pattern, with a peak at around 50 years; whereas, when inventors are active for a shorter part of their careers, patenting quality is not age-sensitive.

Second, as mentioned earlier, Harhoff and Hoisl (2007) suspect that the increasing quality of patents with inventors' ages partly results from selection effects: over time, only the most skilled inventors remain in the innovation business, and the others drop out. Thinking even further, we suggest that, in particular, short-term inventors joining patenting activity at older ages are highly positively selected, as only the most productive ones start inventing at older ages. This again supports Hoisl (2007b)'s finding that declines in patenting quality at older ages are not present for short-term inventors.

Regarding the relationship between age and inventors' performance, we can, in conclusion, state that it increases with age, with only minor or no declines at all at older ages. Taking into account the different career paths followed by inventors, additional individual and organizational characteristics appear to be important. Furthermore,

[7] For a short overview of indicators for patent value see Harhoff and Hoisl (2007, 1145).

[8] Note that, in this study, in contrast to Mariani and Romanelli (2007) and Schettino et al. (2008), other individual characteristics of inventors are not included in the regression analysis, as individual heterogeneity is statistically controlled for through fixed effects estimation.

[9] However, their measure of patent quality is different from that of Hoisl (2007a) and Mariani and Romanelli (2007), as they use a value index based on citations, patent families, and claims. Furthermore, they refer to a very specific subsample of the PatVal comprising only 570 innovators from the Italian Marche region.

selectivity may bias the results, as, at older ages, only the most productive inventors may remain active, whereas the less productive ones drop out over time.

2.2.4 Age and the adoption of new knowledge

Finally, Giuri and Mariani (2007) go beyond the existing research on the relationship between age and the quantity or quality of patents produced. They study the effect of inventors' ages on their propensity to absorb knowledge from people external to their organization.

We include this study in this review, suggesting that such knowledge spillovers can be interpreted as an "intermediate good" for the subsequent creation of patentable inventions. Drawing upon survey results for interaction inside and outside the organization for inventors of a subsample of 6,750 patents included in the PatVal study, the authors find that being 10 years older implies, *ceteris paribus,* an estimated drop in the probability for both geographically close and distant interactions of around 3%.

Another study in this context is Weinberg (2004), who explores how the adoption of information and communication technology (ICT) is related to workers' age and experience. Using data on computer use in the US between 1984 and 1997, he finds that younger workers adopt ICT more rapidly than older workers. Similarly, Aubert et al. (2006) show for French firms that older workers face reduced hiring opportunities in innovative firms, and that organizational innovations increase their exit probabilities much more than for younger workers.

These results imply that the stock of up-to-date technological knowledge is highly relevant for the successful and rapid adoption of new technology. In this area, both knowledge freshly acquired in academic education, as well as knowledge accumulated over the course of a career through on-the-job-learning, seem to matter. We suggest that the higher capacity for technology adoption at younger ages is related to higher cognitive flexibility for new tasks, as previously mentioned.

2.3 Summary and discussion

Empirical studies on the age-dependency of great invention and industrial invention provide valuable insight into how the capacity to produce technological novelties differs across ages. Evidence suggests an inversely u-shaped relationship between age and innovative performance, with the highest levels of performance shown by inventors between the ages of 30 and 50, depending on the domain. Industrial invention in knowledge-intensive fields, as well as great invention, seem to be young men's games, whereas in the more experience-based fields, innovative performance peaks later, and remains stable until late in the career. However, descriptive age-invention profiles should be interpreted with great caution, as they do not necessarily reflect age-specific performance only, but also mirror the age distribution in the workforce.

Due to the lack of age data in official patenting statistics, only the PatVal dataset has, up to now, provided a sound econometric approach that allows us to study the performance of inventors of different ages, and control for other relevant determinants of performance at the individual and organizational levels. Accordingly, the number of patents first increases with age, peaks at around 50 years or age, and then slowly levels off[10]. A similar pattern is found for the quality of patents, although the decline at older ages has not been unanimously confirmed.

However, a remaining drawback of these studies, which we discuss below, is the presence of different kinds of selectivity effects leading to upward or downward biases in the estimates for age-specific performance at older ages. Furthermore, the only PatVal study that adopts a real life course approach is Hoisl (2007a), whereas others look at the total amount of inventions produced by inventors of different ages that are fixed at a certain point in time.

As discussed previously, age-specific inventive performance at older ages may, on the one hand, be upwardly biased if only the most prolific remain actively involved in the generation of technological novelties, while the less productive drop out of the innovation business, or those hampered by health impairments leave the labor force. On the other hand, the likelihood of working in innovation-related occupations and fields is generally lower for older than for younger workers (Mariani and Romanelli 2007, p. 1137, fn. 12). The probability of bringing forth technological novelties at later ages is therefore reduced by nature. To what extent age invention profiles proxy age-specific inventive productivity in this context rather depends on why older people are less engaged in activities directly related to the production of inventions: if potential inventors are selected into non-innovative sectors over their careers due to a lower inventive productivity, a decreasing number of patents produced at older ages actually reflects lower inventive productivity.

Alternatively, technological change could have simply widened the gap between the technological frontier where novel inventions are more likely to arise, and the fields or organizations in which older workers are employed. A lower number of patents at older ages is, therefore, not necessarily related to a lower capacity to innovate. Instead, older workers could simply have fewer chances to produce patents resulting from employment in fields and by companies that do not operate close to the current technological frontier. In this case, empirical measures for age-specific performance are downwardly biased for older ages due to omitted confounding factors that differ by age (unobserved heterogeneity).

Finally, a promising direction for further research relates to the reasons why inventive performance differs across ages. The studies of Weinberg (2004) and Giuri et al. (2007) indicate that age effects may not only be present in the generation of technological novelties, but also in the age-specific capacity to absorb recent technological knowledge that may be built upon. The slight decline in inventive performance found in some of the reviewed studies may, therefore, reflect not only the age-specific capacity to innovate, as reflected by knowledge and experience, but also the capacity to adopt new knowledge through formal and informal interactions with other innovators.

3 Workforce age and innovation in firms and regions

[10] Unfortunately, sector-specific differences in the age pattern of inventive performance based on this dataset have not yet been studied in detail.

While studies at the firm and country levels generally do not attribute innovative performance to single workers, but rather to a group of workers of a certain age, they allow us to identify effects that go beyond the direct contribution of individuals as measured, for example, by the number of patents produced.

In this context, we may think of older workers as enabling younger workers to produce economically relevant novelties by sharing their experience (see e.g. Hetze and Kuhn 2007; Kuhn and Hetze 2007). Similarly, younger workers could contribute by providing ideas and up-to-date formal knowledge that their older counterparts may transform into patentable and marketable products.

In both cases, the skills of both younger and older workers jointly lead to innovation, but the inventors cited in the patent application or the key performers who receive high scores in peer and management rankings may not account for these more indirect and less visible channels of innovative performance (see also Oberg 1960).

The following part of the review focuses on age effects on innovation and technological change at the aggregate level. We start with evidence on workforce age and firm-level productivity in general (3.1), and then focus on the age-dependency of productivity and technology adoption in high-tech firms (3.2). To complete the picture, we touch on studies dealing with the question of whether technological change depends on the age composition of the total population in general, or of the workforce in particular at the country and regional levels (3.3). We again conclude with a short summary (3.4).

3.1 Workforce age and productivity at firm level

The relationship between firms' productivity and the age composition of their workforces has been abundantly studied for a great number of countries[11] (for reviews, see, for example, Skirbekk 2004; Schneider 2006). This research draws upon linked employer-employee datasets to analyze how firms' productivity, as measured by output or value added per worker, is related to the characteristics of their respective workforces.

A main controversy in this context is whether productivity enhancements through the accumulation of general and (firm-)specific work experience over the course of workers' lives outweighs potential negative effects caused by declines in cognitive skills, or the depreciation of human capital (Malmberg et al. 2008; Daveri and Maliranta 2007).

However, age-related differences in productivity can either result from age-specific work performance in general, or emerge from age-specific capacity to bring forth or adopt new, productivity-enhancing technology. As a consequence, these two effects cannot be properly disentangled. Still, this line of research offers valuable insights into the application of firm-level production functions with age and quality adjusted labor inputs. We therefore first outline the general methodology and results of the relevant studies.

[11] E.g. Hellerstein and Neumark (1995) for Israel, Hellerstein et al. (1999) and Haltiwanger et al. (1999) for the US, Haegeland and Klette (1999) for Norway, Aubert and Crépon (2003a) and Crépon et al. (2003) for France, Prskawetz et al. (2005) as well as Malmberg et al. (2008) for Sweden, Schneider (2006) for Germany, Dostie (2006) for Canada, Ilmakunnas et al. (2004), Daveri and Maliranta (2007) as well as Ilmakunnas and Maliranta (2007) for Finland as well as Prskawetz et al. (2007a,) and Mahlberg et al. (2007) for Austria.

The methodological basis, put forth by Hellerstein and Neumark (1995), as well as by Hellerstein et al. (1999), and later refined by Crépon et al. (2003) and Aubert and Crépon (2003b), has been adopted by the great majority of studies that investigate age effects on firm-level productivity. The authors suggest modeling a production function that relates firm output to capital and material input, as well as labor input of different types and quality. With respect to the latter, the workforces of the firms are divided into groups according to age and other characteristics, such as education, race, sex, or occupation. Based on this "labor quality aggregate" (Hellerstein and Neumark 1995, p. 91), the average contribution of these groups to overall firm output is estimated to determine productivity differentials (see also Aubert and Crépon 2003a, p. 99).

A main assumption in these models is full substitutability between different subgroups of workers. This means that, theoretically, a certain group of workers (i.e., young engineers) could be completely replaced by workers of other subgroups. The gain or loss in productivity thereby corresponds to the productivity differential between the two groups of workers, and remains the same for each swapped worker, no matter how many workers are left in the original subgroup.

Most of these studies find that the contribution to firm productivity is highest for workers in their thirties or forties, whereas it is somewhat lower for older workers, when compared to their prime age counterparts[12] (for reviews see Skirbekk 2004; Schneider 2006).

With more detailed data becoming available, the age-productivity pattern has been found to differ across gender, occupational groups, by firm size, and by industrial sector. For example, among French firms, age effects tend to be more pronounced in services and commerce than in industry (Aubert and Crépon 2003a, p. 109). In a second example, a study on Swedish plants between 1985 and 1996 by Malmberg et al. (2008, pp. 242, 253) suggests that all age groups seem to have a stronger and more positive influence in larger plants. One explanation the authors provide is that the opportunity to interact and to exchange ideas between age groups increases with the number of workers.

Furthermore, some studies explicitly control for what we suggest may be called age-specific quality of human capital, i.e., age effects within groups of workers of a certain educational or occupational group (e.g., Aubert and Crépon 2003a; Crépon et al. 2003; Schneider 2006). Referring to the earlier studies of Hellerstein and Neumark (1995) and Hellerstein et al. (1999), these authors estimate what they call the "extended" model, in contrast to the previously used "simple" model: each of the different types of labor specified in the labor quality aggregate is now characterized by a specific coefficient, which is not necessarily a decomposition of simpler coefficients. More concretely, the marginal productivity of older highly skilled workers can, for example, differ from the product of the marginal productivity of older workers, multiplied by the marginal productivity of highly skilled workers.

[12] In the very pioneering studies of Hellerstein and Neumark (1995) for Israeli firms, and Hellerstein et al. (1999) for US data, productivity increases monotonically with age. However, the discrepancy when compared to the other studies, which find an inversely-u-shaped relationship between age and productivity, probably results from unobserved heterogeneity (e.g., a high influx of young immigrants with lower productivity), poor data quality, or the specification of the output variable (for a discussion see Skirbekk 2004).

However, age, occupational, and educational patterns in firm-level productivity seem to operate independently of each other. This has been shown by robustness checks regarding the assumption that the ratio of the productivity differentials between age groups is constant with respect to many other worker characteristics (see e.g. Hellerstein et al. 1999, pp. 431, 437 or Prskawetz et al. 2007b, p. 605; Crépon et al. 2003, p. 6 discuss the simple vs. extended model, and present estimation results for the latter model). In essence, this means, for example, that age effects for both academic workers and unskilled workers follow a similar, inversely u-shaped pattern.

Instead of making use of a labor quality aggregate, an alternative approach to model age effects on productivity is to relate firm output as measured by an index of total factor productivity (TFP) to multi-order polynomials of workforce mean age and to other control variables (Ilmakunnas et al. 2004, Malmberg et al. 2008, Daveri and Maliranta 2007, pp. 132, 134 in particular for a comparison of the two methods of calculating age-productivity profiles at the plant level). Ilmakunnas et al. (2004, p. 262) show for Finnish firms that productivity increases up to an average age of around 40, and then slightly declines. Furthermore, productivity is found to be lower for less experienced workers with a shorter tenure in the current plant (Ilmakunnas et al. 2004, p. 271). A similar discussion about the importance of productivity enhancements through learning-by-doing is provided by Malmberg et al. (2008).

Going one step further, Daveri and Maliranta (2007) show that workers' age is not by itself related to productivity. Splitting the age component into tenure and a measure for potential labor force experience (the number of years after the last completed degree), they find that firm- or occupation-specific experience, as captured by tenure, seems to drive productivity, whereas potential experience does not.

Albeit abundant, empirical evidence is far from conclusive, and the main criticisms will therefore be discussed[13]. As argued by, for example, Aubert and Crépon (2003a, pp. 99, 106), Skirbekk (2008, p. 193) and Daveri and Maliranta (2007, p. 137), disentangling age effects from other drivers of firm-level productivity may be difficult (unobserved heterogeneity). First, there may be some unobserved structural heterogeneity among firms, for example, with respect to their initial technological equipment. Workforces grow older with the plants in which they are employed, i.e., older plants tend to produce less up-to-date technology and older workforces (e.g., Malmberg et al. 2008, p. 244). Similarly, unobserved year-specific effects can arise if the workforce is aging over time, and if, at the same time, productivity changes due to an omitted time-varying factor.

Second, unobserved common factors, such as, for example, managerial ability, may lead to a spurious correlation between age and productivity, as they may simultaneously affect firms the age structure and their productivity: prolific managers may boost productivity, and at the same time, attract and hire young workers (Daveri and Maliranta 2007, p. 137). Such unobserved effects may be picked up by the age variables, and low or

[13] Other aspects not raised in this paper are: the use of fairly rough age groups, or, when modeling age effects based on workers' mean ages, the very general functional relationships assumed; Daveri and Maliranta (2007) and Aubert and Crépon (2003a) additionally shed light on implementation difficulties such as attenuation, panel attrition, measurement error as a source of endogeneity, as well as selectivity with respect to plants remaining in the panel. Furthermore, the results for age effects are not only sensitive to the econometric strategies chosen to tackle simultaneity and unobserved heterogeneity, but also regarding general specification issues (e.g., choice of productivity indicator, adjustment of labor input by hours worked).

even negative (positive) productivity estimates for older (younger) workers may simply be spurious correlations between age and productivity.

Furthermore, since most of these studies are based on cross-sectional data or short time series, a young age structure could also be the result, rather than the cause, of the firms' success. This could, for example, be the case if younger workers have a preference for leaving inefficient companies in order to work for highly productive firms. Similar to this sorting mechanism for younger mobile workers, older workers remaining in plants may be positively selected if their less productive counterparts have dropped out over time due to early retirement or unemployment (Daveri and Maliranta 2007, p. 138). In both cases, a firm's productivity also determines its age structure, and not only the other way round (reverse causation).

In the econometric literature, the above-discussed issues are subsumed by endogeneity, i.e., the one or several explanatory variables are correlated with the error term (see, for example, Wooldridge, 2002, p. 50). Malmberg et al. (2008, pp. 241-249) provide a clear-cut empirical illustration of how far controlling, or failing to control, for endogeneity may lead to biased—or even to completely reversed estimates for age effects on firm-level productivity.

In a first step, straightforward panel regression, plants with a dominance of prime age workers are found to be the most productive, whereas younger workers are seen to have a less favorable, or even a detrimental influence on plant productivity. However, the age composition of the workforce is not independent of unobserved characteristics of the plant that, at the same time, also affect productivity.

In particular, the age structure of a plant's workforce may be closely related to how long it has been in operation, and may, therefore, indirectly reflect its technological age. After controlling for fixed plant effects, increases in younger groups of the workforce hamper productivity, whereas the contribution of 50+-year-olds is now positive, albeit only about one-third as strong as for the prime age group of workers. The effect of workers' mean age on productivity – formerly negative – then turns positive.

As a last step, the authors argue that, controlling to fixed effects may induce a dynamic bias into estimates. Take, for example, a plant that lays off workers due to a negative productivity shock, with most of the dismissed workers being old – not because they are less productive, but because they have alternative options, such as early retirement.

As including fixed effects is basically the same as demeaning explanatory variables within a plant over time, productivity will be positively – but artificially – correlated with the share of older workers in the same period, as future values are also taken into account in the fixed effects methodology. In addition to the dynamic bias problem, the authors point out that omitted year-specific variables, such as demand effects, may have biased the results in the fixed effects estimation.

Re-estimating the model by instrumental variable (IV) regression, as well as using fixed time effects, leads to even stronger positive effects of age. Consequently, the previous estimates of age-specific productivity tend to be downwardly (upwardly) biased for older (younger) workers if unobserved plant effects and endogeneity are not, or are not adequately, controlled for. However, a major drawback of the IV estimation strategy is that no strong instruments for the age share model could be found, and instrumentation of the squared mean age term would be precarious, as it is highly correlated with the linear term of mean age. In the IV specification, age effects were, therefore, only modeled through the mean age of the workforce in its linear form. Moreover, reverse causation is still not tackled in this and similar studies based on short time series, i.e., age effects may be biased resulting from the sorting of younger workers into the most efficient firms, or of selectivity of older workers over their careers.

Another issue arising from the short period of analysis in most studies is that age-specific productivity is implicitly assumed to be constant for subsequent birth cohorts. However, over the last decade, each generation of senior workers has enjoyed higher educational attainment, better health conditions, more recent work experience, and even higher cognitive skills than the preceding one. The productivity of senior workers may, therefore, change over time. Similarly, Skirbekk (2008) points out that age-productivity profiles are not static, but subject to changes of labor market requirements over time.

What can we learn from this line of research, apart from how to model age effects (i.e., labor-quality-aggregate vs. mean-age approach), that sound empirical analyses on age differentials in productivity require long time series, and the difficulties we should avoid in econometric implementation? Assuming that high-tech firms draw heavily upon their workforces' capacity to innovate, we can conceive productivity as an indirect measure of innovative performance. Consequently, firm-level studies on the age-dependency of productivity that differentiate between high- and low-tech firms should provide valuable insights into the age-dependency of innovative performance. We will do so in the following section.

3.2 Age-dependency of productivity and technology adoption in high-tech firms

Daveri and Maliranta (2007) compare the age-dependency of productivity across industries for Finnish firms between 1995 and 2002. As explained earlier, they do not focus on workers' age composition, but on the plant averages of two components of human capital, i.e., general work experience, as reflected in an indicator of potential experience, as well as firm- and occupation- specific experience as measured by workers' tenure.

In electronics, a high-tech industry characterized by rapid technological change, productivity rises with average tenure of workers in the plant up to a certain level. In plants where the workforce already has an average tenure of six years or more, further increases hamper productivity. In more traditional industries, no such pattern is detected: in forestry, additional years of tenure seem to enhance productivity, even if average tenure in a plant is already high. In industrial machinery, instead of a tenure effect, general labor market experience appears to foster productivity, though the results are only significant in the cross-sectional estimation.

To sum up, a certain amount of firm-specific experience seems to be of particular importance in high-tech firms (here: electronics), whereas general work experience matters less. We suggest one possible, twofold explanation for this pattern: on the one hand, freshly acquired knowledge and experience through learning on the job in the specific technological field the plant operates in are a prerequisite for high productivity. On the other hand, assuming that learning is most intense in the early years of tenure and slows down subsequently, rapid technological change leads to a negative effect of tenure after some years.

A novel approach in firm-level studies on age effects in productivity, both in high-tech and in traditional firms, has been suggested by Ilmakunnas and Maliranta (2007). They are not concerned with the relationship between the age composition of the workforce itself, but focus on the productivity effects of flows of labor from and into the firm, i.e., the hiring and dismissal of younger, prime age, and older workers, respectively.

Results show that, in firms operating in the information and communication technology (ICT) industry sector, dismissals of older workers (ages 49+) with potentially outdated skills enhance productivity, whereas dismissals of prime age workers hamper it. The fact that these effects are about twice as pronounced in the ICT industry as in the non-ICT industry highlights the importance of employing prime age workers with an adequate mix of up-to-date knowledge and work experience for the achievement of high productivity levels in the ICT industry.

Bertschek and Mayer (2008) follow a more conventional approach to investigating age-productivity patterns related to ICT, using data from the ICT survey of the Center for European Economic Research (ZEW) for 1,039 German firms in 2004 and 2007. In line with the previously discussed labor quality aggregate studies on workforce age and productivity, they simultaneously relate firm productivity to the use of ICT, and to the age structure of employees. Two results are of particular interest. First, fewer older than younger workers use IT, but those who do are more productive than older non-users. Second, interaction effects between IT intensity and the proportion of older workers do not become significant in the estimation, which suggests that older workers do not obstruct IT-enabled productivity.

Based on the same data, Meyer (2008) shifts the attention from the production of technological novelties to the question of to what extent the adoption of technology is related to workforce age. For 374 German firms in the ICT and knowledge-intensive sector in 2005, she finds that, the higher the share of employees under the age of 30, and the lower the share of 40- to 55-year-old workers, the higher the likelihood is that the firm will adopt new technologies or software. The following is an example for the strength of this effect: if all other determinants are held constant, a 10% increase in the share of the workforce between the ages of 40 and 55 decreases the probability of technology adoption by 2.5 percentage points[14]. However, the author recommends careful interpretation because, due to the cross-sectional nature of the data, endogeneity may have biased the estimates.

Up to now, the only study investigating whether an age-heterogeneous workforce is conducive to productivity is Veen and Backes-Gellner (2008). They use linked employee-employer data for several thousand German firms from 1993 to 2001. For knowledge-intensive and innovative sectors, they find that the more age-diverse a firm's workforce is, as measured by two alternative diversity indices, the higher its productivity. A 10 percentage points higher heterogeneity in the age composition of the workforce, would, according to their results, *ceteris paribus* lead to an increase in productivity of around

[14] Note that this is the 'gross' effect that does not take into account that changes in the share of one age group automatically implies changes in the other age shares. The net effect therefore additionally depends on whether an age group with a higher or a lower adoption probability is assumed to ingest the released share.

3%. In contrast to this result, age-heterogeneity is found to be detrimental with respect to productivity in more traditional sectors.

As an explanation, the authors propose that inefficiencies in cooperation and communication among workers may increase with the degree of age-heterogeneity in the workforce[15]. However, in contrast to sectors where standardized routine tasks prevail, innovative firms seem to over-compensate for these influences by improved and flexible problem solving in a dynamic context, which may be attributed to a higher diversity of cognitive skills and other competences provided by mixed-age workforces. Another study in the context of innovative firms and the role of workforce age is by Schneider (2008). Based on the same data as those used by Veen and Backes-Gellner (2008), he analyzes the marginal effects of increases in the mean age of firms' workers on the probability that the firm will produce an innovation in the respective year for a cross-section of 1,000 German firms in 2004. He confirms the inversely u-shaped relationship between age and innovative performance found at the individual level. According to his findings, the probability of creating market novelties and new products peaks at around a mean age of 40, and decreases subsequently. The capacity for improving existing products (incremental innovation) remains constant between 30 and 50 years of age, and only then starts to decline. Comparing the effect of an increase in the mean age in a firms' total workforce with an increase in the mean age of engineers and skilled technicians, age-performance profiles only differ in the upper part of the age distribution: technical staff display a longer plateau of high performance than the overall workforce. Performance with respect to incremental innovation even seems to be more or less independent of age.

It should be emphasized that Schneider (2008), on the subject to the generation of innovation, and Meyer (2008), on technology adoption, are the first of the studies discussed in this section to move a step towards a more direct assessment of innovation. However, measuring innovation by a binary variable remains highly unsatisfactory. This is because, for example, in large firms, the likelihood of producing or adopting at least one new technology can be assumed to be close to one, and is, therefore, rather independent of the age composition of the workforce. Still, these results are in line with the age pattern found in productivity studies for high-tech industries. In particular, the probability that a firm will pioneer more radical innovations, such as completely new products or even market novelties, seems to be higher, on average, with a younger workforce, while more incremental innovation resulting in improvements of existing products tends to be much less sensitive to workforce age.

3.3 Workforce/population aging and technological change in countries and regions

While studies at the firm level have focused on the interplay between workforce age composition and firm productivity, macro-level studies have – while giving special consideration to innovative productivity in a few cases – hitherto studied the consequences of demographic change on economic performance from a much broader

[15] Similar evidence is provided by Börsch-Supan et al. (2006) and Düzgün (2008): error rates at the assembly line of a large automotive manufacturer are more probable in age-heterogeneous teams than in teams consisting of mainly older or mainly younger workers.

perspective. The main concern of these studies has been in assessing to what extent aging and shrinking of the *total* population hampers economic growth. But before we can address this question, we must first consider how economic growth is related to innovation. Increases in national output that cannot be explained by increases of quantity or quality in labor and capital input, the so-called Solow residual, are commonly interpreted as technological change, and measured by upwards trends in the total factor productivity.

In this context, demographic change can influence economic growth through various channels: decreasing labor supply, life-cycle effects in savings behavior and its effects on capital investment, age-related consumption and demand, and human capital accumulation or expenditure. Additional issues with respect to interest rates, exchange rates, and the balance of payments arise when an open economy is assumed.

For developed economies, results point again towards the well-known hump-shaped relationship between the age structure of the population and economic performance. Examples include Prskawetz et al. (2007) for the EU countries, and Brunow and Hirte (2006) for 197 regions in the EU-15. It is, therefore, the prime age group (ages 30-40), or even the 50- to 64-year-olds, who contribute most to economic growth (Brunow and Hirte 2006, p. 17; Prskawetz et al. 2007, p. 8), while high shares of 65+ year-olds and a large young population negatively affect economic growth. In this context, the total population is in the spotlight, so that a main growth driver lies in the share of workforce. For reviews on demographic change and economic growth, see also McMorrow and Roeger (2004), Czechl and Henseke (2007), or, with a particular focus on population aging (Fent et al., 2008).

Some recent studies dig deeper, and specifically explore the interplay between countries' total factor productivity and the age composition of their workforces. Feyrer (2008), for example, looks at a panel of 87 countries between 1960 and 1990. He finds that 40- to 49-year-old workers contribute the most to total factor productivity, whereas increases in all other age groups are associated with fewer or no productivity enhancements. For example, over a 10-year period, a shift of 5% from age group 30 to 39 to age group 40 to 49 would add about 16% to per worker output in each year.

In this study, Feyrer (2008) argues that the social return of experience goes beyond the individual return, as measured, for example, by earnings. He hypothesizes (pp. 88, 96) that externalities from the age composition of the workforce, particularly positive ones from workers at the highly productive ages, arise through age-specific capacity to innovate, or the stock of managerial knowledge available according to a country's age composition. However, evidence supporting the assumption that prime age workers are most prolific in terms of innovation, as well as in managerial skills, remains purely descriptive, and refers to individual-level evidence.

Again, what can we learn from these findings about workforce age and innovative performance on an aggregate level? As at the firm level, increases in the total factor productivity of countries may result not only from technological change, but also, for example, from improved labor productivity (i.e., better educated workers). In what ways workforce aging affects either of them or both, and to what extent, cannot be properly disentangled. Moreover, we have to be aware of the fact that life-cycle savings and investment behavior, age-specific demand and consumption patterns, and human capital accumulation work through the age composition of the workforce or the population.

Consequently, research should address much more specifically the age effects on innovation and technological change on the country level. In this context, one strand of research tackles the effect of population aging on the *demand for innovation*. We closely follow McMorrow and Roeger (2004, p. 47) for the purposes of this discussion. Some authors argue that technological change is hampered by population aging, as an older population is less dynamic and innovative, and declining markets for capital goods decrease the profitability of innovation (see e.g. Romer 1990a; Jones 2002). In contrast to this view, Cutler et al. (1990) believe that, scarcity being the mother of invention; declines in labor supply will then induce higher levels of innovation. In conclusion, these results, though ambivalent, indicate that population aging can affect the demand for innovation through various transmission mechanisms. However, we are still not at the core of our question: namely, what influence does the age composition of the workforce (and not population aging) have on the production of new knowledge (and not the demand for it). To our knowledge, two studies have tackled more explicitly the task of studying the age-dependency of innovative performance and technological change.

First, Prskawetz et al. (2007) and Fent et al. (2008) focus on the adoption of technology in the EU-25 countries between 1950 and 2005. Accounting for the gap between these countries' current technological frontiers, and that of the US, which is assumed to be the state-of-the-art globally, they model catching-up processes through the adoption of technology. High shares of 15-29-year-olds in the population, according to the authors, tend to foster technology adoption, whereas countries with high shares of prime age and older workers are associated with rather lower absorption rates. Another main conclusion is that "it is highly educated youngsters who drive the absorption process while mature adults drive the productivity process." (Fent et al. 2008, p. 10).

The second study is concerned with the emergence of new innovative businesses in German regions as a driver of technological change. Bönte et al. (2007) find that the number of knowledge-based (high-tech) startups in German regions is related to the age composition of their working-age population, whereas no such relationship can be seen for firm births in other industries. In particular, more individuals in their twenties, as well as more individuals between the ages of 40 and 50, drive regional innovation, as mirrored in the number of high-tech startups.

The results again indicate that an adequate mix in the stock of up-to-date knowledge and work experience are driving innovation on an aggregate level. However, it remains to be seen in how far endogeneity of the age structure drives these findings: if innovative regions attract mostly younger and well educated work migrants from less innovative regions, the causality between the age composition and the region's performance in innovative entrepreneurship is reversed, and estimates for the role of younger (older) age groups for regional innovative entrepreneurship may be upwardly (downwardly) biased.

While promising, the previous studies do not yet touch the core of our question: i.e. how workforce aging may affect innovation and technological change. First, the studies relating workforce aging to changes in total factor productivity (e.g., Feyrer 2008) cannot differentiate between productivity enhancements resulting from improved labor quality, and those actually resulting from innovations. Still, we credit this line of research for highlighting that the adoption of new knowledge, as well as the starting of innovative businesses, may be a young man's game, and that, in studies at the regional or country levels, the effects of age-specific innovative performance should be carefully disentangled from other influences related to age.

3.4 Summary and discussion

The previous sections have focused on the role of workforce age in innovation at the levels of firms, countries, and regions. Such aggregate level studies have some advantages over the purely individual perspective on age and innovation. First, they are able to relate innovative performance to the age-composition of the total workforce. This means that age differentials in the average capacity to innovate of groups of workers of different ages can be disentangled from pure demographic effects caused by the weight of this age group in the overall workforce, as well as of age-related confounding factors, such as educational attainment.

From a conceptual perspective, the aggregate perspective also comprises more indirect contributions to innovation, such as the transfer of knowledge or experience, that are left out if the number of publications or patents produced by individual innovators is analyzed. In this context, the role of knowledge transmission and spillover in workforces depending on their age composition may be of particular interest.

Furthermore, the potential upward bias in inventive performance at older ages due to positive selectivity of inventors over the life course seen at the individual level in studies based on PatVal data should be reduced, as less productive workers are not necessarily dropping out of the innovation business, even if they may contribute more indirectly to measurable innovative performance, through, for example, the transmission of knowledge and experience to younger generations of workers.

To some extent, however, positive selectivity at older ages may still exist through the age-specific probability of being employed in innovative sectors. This applies if we assume that workers are, over the course of their lives, selected into or out of innovation-relevant jobs and sectors according to their innovative capacity, and not, as discussed earlier, simply because they have drifted away from the technological frontier together with their firms (see Section 3.1).

Key findings of the aggregate-level studies are as follows: the inversely u-shaped relationship between workforce age and innovative performance – as measured by productivity in high-tech sectors, the adoption of new technology, firms' probability of innovating, or the emergence of innovative businesses – is confirmed on the firm, country, and regional levels. In most studies, the age of peak performance, 30-40 years old, tends to be somewhat earlier for technology adoption and innovative performance than for general firm-level productivity, or increases in total factor productivity.

An additional insight is that radical innovation tends to be more a young man's game than is the case for more incremental innovation. Furthermore, the mix of different age groups in the firms' workforce, i.e., age heterogeneity, has been found to foster productivity for firms operating in creative and innovative sectors. Finally, for different innovation-relevant occupations, technical staff displays a longer plateau of greater contributions to the firm's innovative performance than do the overall workforce.

Thus, differentiating between the effects of age, tenure (as a proxy of firm-specific experience), and general labor market experience seem to be of particular importance.

Some evidence points towards the joint effect of freshly acquired firm-specific knowledge and experience through learning-on-the-job in the specific technological field the plant operates in. However, if learning happens in the initial years at a new employer, rapid technological change can lead to a negative effect of tenure after some years.

The previous studies on the age-dependency of innovation are a first step towards a deeper understanding of this topic, but, due to a lack of appropriate measures for innovation and the absence of longer time series, serious methodological restrictions continue to apply.

4 Looking back and looking ahead

Individual level studies on age and innovative, or inventive, performance provide valuable insights into the question of how inventors' age is related to their capacity to produce novelties. Empirical evidence points towards an inversely u-shaped relationship between workers' ages and innovative performance, with the highest performance shown between the ages of 30 and 50, depending on the domain. Industrial invention in knowledge-intensive fields, as well as great invention, seems to be a young man's game, whereas in the more experience-based fields, innovative performance peaks later and remains stable until late in the career. Moreover, the quality of invention does not necessarily decrease at older ages.

However, the lack of data places limits on future research. On the one hand, few studies adopt a veritable life course perspective. On the other hand, selectivity or unobserved heterogeneity may bias the results. Appropriate data dealing with potential selectivity should comprise the whole statistical population of potential innovators. Moreover, it necessarily requires longer periods of time to study the evolution of innovative capacities over workers' careers. Finally, it necessary to consider not only indicators for age and innovative performance, but also potential confounding factors, such as education or occupation. As no such data is currently available, it can only be gathered through costly and time-consuming primary data collection in innovative companies or other R&D establishments.

Meanwhile, the aggregate levels of firms, regions and countries provide opportunities to explore the relationship between workforce age and innovation based on available data, and to prepare the ground for such costly but in-depth individual-level analyses. Moreover, these data allow us to look beyond the individual capacity to bring forth economically relevant novelties and to adopt existing innovations.

And indeed, previous research has shed some additional light on the question of whether the age composition the workforce influences productivity in knowledge intensive sectors or technology adoption at the firm, regional, or country levels. A main result is that young professionals drive knowledge absorption, innovation, and technological progress, whereas more experienced workers are more relevant in mature technological regimes.

However, due to the cross-sectional approach adopted in many studies or short time series, the existence of serious methodological drawbacks, such as endogeneity biases caused by unobserved heterogeneity, reverse causation, or dynamic biases induced by fixed effects estimation, demand careful interpretation of the results. Future research should attempt to deal with these technical issues.

Despite these promising attempts, many conceptual issues remain unaddressed. Except for some scattered general reasoning about the decline of cognitive skills at older ages or the obsolescence of engineering knowledge, there is no comprehensive conceptual framework to explain why the innovative capacities of firms, regions or countries should be related to the age composition of their workforces:

- The *transmission channels* through which workforce age becomes effective are worthy of further exploration. As has become clear, innovation and technological change is a phenomenon on different levels, and in various guises. So how, then, is the success of firms, regions and countries with respect to invention, productivity in innovative sectors, and the emergence of new innovative businesses, related to the age composition of workers in corporate R&D laboratories, high-tech workers in general, or potential founders of knowledge-intensive new businesses?

- The majority of studies dealing with aggregate innovative performance do not account for the possibility that the contributions to technological progress made by workers of different age provide may *also differ across educational or occupational groups,* such as engineers, managers, clerks, manual workers, or unskilled labor. Does the knowledge of technology workers have a shorter half-life with respect to innovative achievements than that of managers? Or is there a universal, skill-independent impact of workers' ages, that may, for example, be driven by the evolution of the achievement motivation over workers' careers?

- Finally, the *functional relationship* between workforce age and innovative performance, and how to model it, remains unclear. Previous approaches range from simply including age as a linear variable or additionally accounting for higher-order polynomials to proxy the assumed hump-shape of the age-performance profile, to using shares of workers in different age categories. But are workers of different ages and knowledge backgrounds complementing each other? If so, what are the consequences if the share of younger workers falls below a certain threshold? Or will we be able to compensate for the impact of declining workforces rather easily by filling open positions with older, experienced workers instead of younger professionals?

In conclusion, the issues that are of top priority in firms' business practices have been neglected up to now. A framework on the transmission channels of age on innovative performance would be a first step toward creating a conceptual underpinning of future empirical research on the issue. A particular focus could, therefore, be on the role of the specific set and quality of human capital, as provided by workers of different ages and occupations, including the substitutability and complementarity between different subgroups of workers. Research pinpointing such issues will not only advance scientific knowledge about the relationship between workforce age and innovative performance, but also allow for more substantiated assessments on the true impact of demographically driven skills shortages for high-tech firms and innovation-based economies.

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