Reinventing the Older Worker: Age and Creativity Through the Lens of Patent Data

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Abstract

Previous research suggests creative ability peaks in the age decades of the 30s and early 40s, and declines thereafter, with some variation across fields. Building from the cognitive aging literature, we expect differences in the rate and quality of creative works by age. Cognitive processes show aging-related changes with increases in experience-based knowledge (pragmatics or crystallized abilities) and decreases in the ability to process novel information quickly and efficiently (mechanics or fluid abilities). We exploit a large database of U.S. inventors and the rich complexity of patent documents to explore both the rate and the nature of creative output over the life course. We extend this dataset by including information about age at patenting by combining public patent data with information on inventor ages scraped from directory websites on the web with approximately 1.2 million inventors patenting between 1976 and 2017. Our results suggest that cross-sectional and within-inventor patenting rates are similar, peaking at around the early 40s for both women and men. We find varying results for attributes of patents in relation to age some of which are consistent with cognitive aging theory. Backward citations and originality, which are connected to experience, were found to peak later in life. Forward citations and generality measures, which are more likely tied to fluid intelligence, peaked at earlier ages. These patent attributes also vary in relation to the age composition of the teams. Future goals are presented including consideration of the implications for work and retirement choices and policies.

1 Introduction

There is great interest in the implications of an aging workforce, in particular whether the growing numbers of older workers will have beneficial or adverse consequences for the economy (National Research Council, 2012). At the same time, there is much discussion about ways to support older adults remaining longer in the workforce. Government and industry are concerned that the slower maturation of younger workers and the possible declines in productivity associated with the aging workforce could have a negative impact on innovation and productivity. There is, however, no systematic evidence from the broader economy about the inventive abilities of younger and older workers. Understanding these patterns, how they vary across technological domains, and the conditions most conducive to inventive success at different ages can have significant implications for public health and public policy at the level of individuals (work, mentoring and retirement choices), organizations (retirement policies and structure of collaboration), and the economy as a whole (consequences of an aging work force for innovation and productivity). This paper examines how the extent and patent attributes of inventive activity change as inventors age. The results can inform policies to accelerate the professional growth of younger inventors and extend the effective work life, potentially improving quality of life and advancing overall innovation and growth.

1.1 Patterns of creative work over the life course

Attitudes held by employers and co-workers have an impact on older adults' decisions about whether to stay in the workforce or to retire. People may decide to retire or may be pressured to retire based on assumptions about declining creativity or productivity (Börsch-Supan & Weiss, 2016). There is a long-standing belief that one's most creative work is done early in adulthood, peaking between the ages of 30 and 40 (Beard, 1881; Dennis, 1956; 1958; Lehman, 1943;1960). Economists have studied how creative success varies over the life cycle, with the explicit goal of understanding the consequences for productivity (Galenson 2003; 2007; Galenson & Weinberg, 2000; 2001; Jones, 2009; 2010; Jones & Weinberg, 2011). Existing evidence on the age-creativity nexus focuses on the most significant achievements such as major inventions, famous artistic and literary works, or discoveries leading to a Nobel Prize. (e.g. Lehman, 1943; Dennis, 1956; Simonton, 1988). Other work examines scientific research rather than commercial invention (Packalen & Bhattacharya, 2015) or looks at innovation in the workplace using small samples with in-depth cases studies (e.g., Amabile & Kramer, 2011). The implications for age-related changes in the creative capacity of the broader population are unclear. The present study adds to the literature by looking comprehensively at a widespread and economically important creative activity that is, patenting.

1.1.1 Patents over the life course

Patenting is a widespread activity, with about 2 million U.S.-resident individuals granted patents over the 40-year period of investigation. Moreover, patents include a wealth of information about the invention and the inventor, providing a rich quantitative basis for exploring inventive success. These rich data have not been widely used to explore age-related changes in performance mainly because the publicly available patent data do not include information about birth date or inventor age. We create a new data source by harvesting information from the web to identify dates of birth for a large number of inventors. We then explore age differences and changes in inventive performance over the life course with hypotheses guided by theoretical and empirical work on cognitive aging.

The only previous studies of patents as a function of age are on Sweden (Jung & Ejermo, 2014), and two studies looking at a subsample of US inventors (Jones, 2009, Nager, et. al., 2016). Our research provides evidence on differences in inventive activities by age in a broad slice of the American workforce. Few studies have examined the within-person trajectory of creative work over the life course using large samples (Acemoglu, D, et. al. (2014)). Moreover, past studies of patenting have not investigated how the quality or impact of work changes with age. The patent dataset includes large numbers of inventions ranging from the most mundane to the very important. Additionally, we use a disambiguated dataset that allows us to identify patents that belong to a particular inventor and thus, allows us to track inventive behavior over time. Using recently developed and validated metrics of patent originality and impact, we examine not only how the rate of patenting varies with age, but also how the nature of inventions changes.

1.2 Creativity and cognitive aging

A prevalent view of older adults is that they are less creative and productive than younger adults, in part due to their declining cognitive abilities (Belbase, Sanzenbacher, & Gillis, 2015; Ng & Law, 2014; Ng &Feldman, 2012; Woolever, 2013). Age-related cognitive changes, and the possibilities for age-related complementarities in inventive teams, have important implications for the overall inventiveness and productivity of the economy, at a time when serious concerns have been raised about growing life course delays in research success and productivity, and the overall aging of the workforce (National Research Council, 2012).

There is consistent evidence from studies of adult development of a shifting balance of gains and losses in cognitive abilities throughout adulthood (Baltes et al., 2006) with increases in experience-based knowledge (pragmatics or crystallized abilities-**Gc**) and decreases in the ability to learn and process new information quickly and efficiently (mechanics or fluid abilities-**Gf**; Hartshorne & Germine, 2015; Salthouse, 2009; Schaie, 2012). However, little is known about how these ability changes might affect performance outside the lab in daily life, including the work domain. In one domain, financial decision-making (Agarwal et al., 2007), there is evidence that midlife (i.e., age 52) is a time of peak ability, despite age-related declines in memory, speed of processing, and abstract reasoning, suggesting there can be compensation for declines in the cognitive mechanics (Gf) by drawing on experience and knowledge (Gc; Lachman et al., 2015; Salthouse, 2012). We postulate that middle age is a period when there is an ideal mix of the pragmatics and mechanics of intellectual abilities, which suggests this would be a likely period of heightened creativity and inventiveness (Lachman et al., 2014).

We suggest that the rate of invention (number of patents per year) and the attributes of invention (citation-based metrics of originality, generality, forward citations, backward citations, disruptiveness, and number of independent claims) are affected by changes in inventors' cognitive abilities over their lives. In particular, both experience-based knowledge (pragmatics or crystallized abilities-**Gc**) and the ability to process new information quickly and efficiently (mechanics or fluid abilities-**Gf**) both contribute to success in creative activities such as patenting. The process of invention, of which patents are an indicator of success, is likely to reflect the interaction and balance of pragmatics and mechanics in observable ways. Invention is a cumulative process, in which inventors proceed by building upon and synthesizing what has been done before (Caballero & Jaffe, 1993), a process likely to be facilitated by a high level of pragmatic experience (Gc). At the same time, patents are, in principle, only granted for "novel" inventions, thus requiring a creative spark that is likely to be more common for inventors with a high level of fluid mechanics (Gf). Weinberg and Galenson (2005) suggest that "experimental" innovators work inductively based on experience, while "conceptual innovators" work deductively, applying abstract principles. Jones et al., (2014) recently survey work on the relationship between age and "genius," emphasizing that creativity peaks in middle age, but there is no research that systematically studies age patterns within persons over time or within teams to the best of our knowledge.

1.3 Complementarity between younger and older workers in inventor teams

Collaboration in scientific research and invention is an active research area (e.g. Wuchty et al., 2007; Freeman, et al., 2015). One theory suggesting the need for increased collaboration is the "burden of knowledge" (Jones, 2009), i.e. the rapid advance of science means more needs to be known to advance further. This suggests that differences in accumulated experience vs. newly acquired knowledge connected to age might play an important role in overall research team performance. In the realm of scientific research collaborations, researchers explore ethnicity (Freeman & Huang, 2014), benefits of international collaboration (Adams, 2013), and the comparative impact of collaborative and non-collaborative research (Hsu & Huang, 2011). Packalen and Bhattacharya (2015) find that scientific papers with a young first author and a more experienced last author are more likely to try out newer ideas than papers published by other age configurations. More recently, Yu, et al (2019) look at the citations received by a large number of papers in health sciences as a function of the 'career age' of the first and last authors. They find the typical 'inverted-U' in the raw data, but steadily declining 'quality' with age once author fixed effects were used to control for unobservable inventor characteristics. With respect to patents, Jaravel, et al., (2015) show that inventor teams are age-heterogeneous, but they do not have data on inventors' participation in teams with different age compositions over time, and so do not consider how life course changes (e.g., cognitive aging) could affect patenting activity. The patent data set we present in this paper allows us to examine whether the productivity of younger and older workers differs when participating in age-heterogeneous vs. age-homogeneous teams.

1.4 Team Composition and Patent Attributes

Theory and research on differential trajectories of cognitive aging suggest that adults at different ages would bring distinct albeit complementary abilities to the collaborative invention process. But there has been no empirical analysis in real-world settings of the extent to which these different abilities can be shared effectively within a mixed age team. The evidence from the cognitive aging field that young people have superior fluid abilities (Gf, the mechanics) while older people have superior crystallized abilities (Gc, the pragmatics) suggests that the contributions of older and younger workers are likely to be complementary in creative teams. The availability of data on the number and patent attributes of inventions of different groups of workers over their life span allows us to test this hypothesis and quantify the degree of complementarity in different contexts and circumstances. We compare the creative output of teams differing in composition by age, and also compare the creative output of individual inventors as they participate in teams with different characteristics. We examine how the originality and impact of inventions varies as a function of team participation and the age composition of teams. Significant differences when teams are age-heterogeneous compared to homogeneous can demonstrate the value of intergenerational teams in the creative workforce. Younger workers may benefit from the experience and mentoring that older workers bring to creative teams. Conversely, complementarity in teams implies that declines in Gf abilities associated with cognitive aging could be mitigated by teaming older workers with younger workers.

1.5 Aging & patenting activity

We model the interaction of rising Gc and falling Gf more formally by postulating a particular functional form for the relationship. We use a double-exponential function shown in Figure 1 to describe overall patenting activity over the life course. This suggests that patenting activity peaks during early middle age.

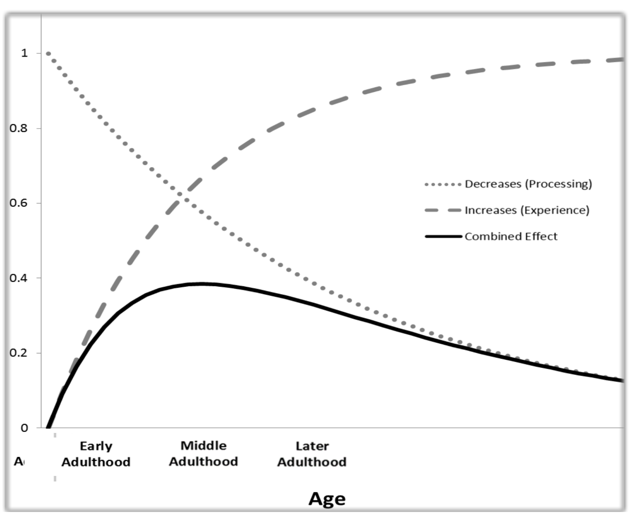

Figure 1 Double-exponential model of cognitive change

We also examine the relationship of aging and creative output with patent attributes. Each of the six patent attribute measures that we consider measures a specific aspect of the patent, and thus, have different predictions based on whether these indicators are more dependent on acquired experience or application of novel information

We predict differential relationships of age in relation to patent attributes based on cognitive aging theories. Backward citations are the number of citations a patent makes to previous patents (Griliches, 1990). This measures the previous work that a patent builds on. Thus, we expect that backward citations increase as one ages as it is based more on experience and knowledge of prior art. Originality is another measure that is dependent on prior work, and thus, similarly, we expect this measure to increase as a person ages. Originality is the technological diversity of backward citations (Jaffe, Hall, Trajtenberg, 2001). Each patent is assigned a technological field, and we use the cooperative patent classification (cpc) to designate the field. Some patents may have multiple fields as they may cover a breadth of topics. Originality measures the concentration and diversity of technological fields associated with all of the patents that it cites.

For forward citations, generality and the number of independent claims, we believe that these measures will follow our double-exponential model of cognitive change, with a peak in midlife, as these measures suggest a need for a mixture of crystalized and fluid skills. Forward citations are the number of citations received from later patents (Griliches, 1990). One can think of this as measuring how influential a patent is, and can be considered an overall quality measure of the patent. Thus, forward citations would require both experience, as inventions are cumulative, as well as novelty which are based in fluid abilities. This same reasoning applies to generality, which is another measure based on forward citations (Jaffe & Trajtenberg, 2002). It is similar to originality in that it measures the technological diversity of patents, but rather than utilizing backward citations, originality is a measure of technological diversity of forward citations. It measures the concentration of technological fields of patents for future citations (patents that cite the patent of interest). We also predict independent claims to require a mixture of fluid and crystalized skills. Independent claims are claims that add something new to the world. It is the novelty of an invention that a patent represents. Every patent must have at least one independent claim, which is stated in the patent application, in order to be considered for review. However, patents can have more than one independent claim, and the more independent claims that they have, the more new ideas are related to the patent. Knowing what is new or independent requires some understanding of previous work and experience, while also novelty requires fluid intelligence.

The last measure that we consider is disruptiveness, which in previous literature has also been called the CD index (Funk & Owen-Smith, 2016). Disruptiveness looks at the network of citations related to a patent. It evaluates all of the forward citations related to a patent and compares all of the backward citations that the forward citations cite. It compares how similar the citations of forward citations are to the patent's backward citations. If the forward citations cite the same work as the patent observed, it is *maximally consolidating* and building upon the same literature and work in the same direction. However, if the forward citations cite very different references, it is *maximally destabilizing*, and creating a new field or direction of work. We believe that disruptiveness is most dependent on novel ideas and hence connected to fluid intelligence, and thus, we predict disruptiveness to peak early in adulthood and decrease throughout the life course.

We review our predictions based on a number of indicators, but inventions are often done in teams. If, in fact, the data confirm the pattern of inventive performance predicted by cognitive theory, this then leads directly to the question of whether different cognitive abilities can be successfully pooled among the members of a creative team. If creative success is maximized by a combination of crystallized and fluid abilities, can this combination be achieved by bringing together (younger) workers with a relatively high level of fluid abilities with (older) workers with a relatively high level of crystallized abilities, or teams with predominantly middle-aged adults who have moderate levels of both types of abilities? We suggest that forward citations, generality and number of independent claims may have higher impacts in heterogeneous teams with both younger and middle-aged or older inventors since this requires a mixture of fluid and experience skills. However, for originality and backward citations, we believe that older workers will be more critical since these are more experienced based measures. Last, disruptiveness may be dominated by younger teams, although the flash of creative spark could occur at any point in life, and may not be dictated by fluid intelligence alone.

2 Data

We used the USPTO Dataset from patentsview.org. This dataset covers all patents granted between 1976-2018 and contains 8,080,135 patent-inventor pairs with 3,648,663 patents and 1,858,516 inventors.

Using disambiguated names and the location of the inventor provided on the patent application, we search for ages from three directory websites, Radaris, Spokeo and Beenverified. If the website has information about that person (or someone with that name in that location), we extract the first and last names (including any aliases), middle name or initial, city, state, and age, and compute a similarity score for each result to the information in our database.

We were able to capture age information by exactly matching the first and last name of the inventor with their associated location in 72.82% of inventors in Radaris, 64.30% of inventors for Spokeo and 66.08% of inventors for Beenverified. We find at least one age is associated with a name and location for approximately 82% of the inventors in the dataset. We could not associate an age in only 10.54 % of the cases. We also find that 29.75% of the age results are consistent across all three web-scraped sources.

Although we found ages for the majority of cases, we cannot verify that we found the correct person. After scraping the web for age related information, we create a few heuristics to calculate ages where there is disagreement between the sources we scrape. After applying these rules, we use the average of all the ages we identify for a given inventor. We subtract 2018 from that age to calculate the birth year of the inventor. For more details about how we calculate age from the information we scrape, please contact the authors. Last, we plan to address web-search errors by applying multiple over imputation that may help us understand any uncertainty of our estimated ages.

We calculate an inventor's age at patenting by subtracting their birth year from the year that they applied for a patent. We limit our dataset so that we only include those who patented before 15 and above 89, as patents at ages outside that range would be highly unlikely. After this procedure, we are left with 1,529,371 inventors with age information holding 3,558,375 patents. This dataset is what we use for our analyses that we describe in the following sections.

3 Methods

We look at two aspects of inventor patent information, the rate of patenting and the patenting attributes throughout their life course. This requires two different methods of analysis and datasets which we discuss in the remainder of this section.

3.1 Rate of Patenting over the life course

To study an inventor's rate of patenting over their life course we create a panel dataset that follows inventors patenting activity over their lifetime. This dataset covers patent applications from 1974-2017. We excluded a small number of patents applied for after 2017 as most such applications would not have been granted within the 2018 data cutoff. We ensure that individuals are within the age range of our dataset (15-89). If an inventor had not patented in a given year, they have zero patents listed, but if they were not alive in that time period they are marked as missing in that year.

We normalize patent counts to account for the fact that the number of patents granted increased over time. We use the number of utility patent applications of U.S. origin per capita per year as the normalization factor and use the year 2012 as the base year. Thus, all patents are relative to the patent application per capita of 2012.

There are two ways that we count patents when looking at an inventor's rate of patenting . A general count, which is a simple patent count for an inventor and their age at that year. We call this a *non-fractionalized patent*. Given that teamwork is an important factor in the patenting activity of an inventor, we also calculate patents as *fractionalized*, which is the patent divided by the number of co-inventors on the patent listed (1/teamsize). We sum the *fractionalized* patents for an inventor's age at that year to measure their rate of patenting while adjusting for team size.

To estimate the rate of patenting of inventors over their life course we use an inventor fixed effects model with age dummies, which we also estimate by gender and technological field. Gender is assigned using an algorithm by Blevins & Mullen (2015), which uses the US Social Security database to estimate the probability of a person being male or female given their first name and birthyear. We use the NBER classification of technological field (Jaffe, Hall, Trajtenberg, 2001). Since technological field is given at the patent level and inventors can have more than one patent in a given age category, we use the technological field of the majority of patents an inventor patented at that age. They continue with that technological field throughout their life until they start patenting more in another technological field. The simple model to estimate the rate of patenting of inventors is:

$$Prod_{ia} = \beta Age_{ika} + \alpha_i + \varepsilon_{ia}$$

Where i is the inventor and a is the age of the inventor when they patented. Age is a dummy variable indicating 1 if that inventor patented in that age category for k age groups. We group age categories by 5-year age increments, for example the age group 20-24. $Prod$ is the fractionalized or non-fractionalized patent count for that inventor in that age category. α_i is the inventor fixed effect. Last, ε is the error term. We use cluster robust standard errors.

3.2 Patent attributes

We observe the attributes of patenting activity throughout an inventor's lifetime by using six measures of patent attribute indicators, forward citations, backward citations, number of independent claims, originality, generality and disruptiveness. We merge our data about ages with patent attribute information. Forward, backward citations and the number of independent claims are provided by the USPTO through patentsview. The number of independent claims are provided within the patent application. We calculate originality and generality based on forward and backward citations using the cooperative patent classification to classify technological classes provided by the USPTO. Our measure of disruptiveness is calculated by Funk & Owen-Smith (2016), which they call the CD index. We only include patents granted before 2016 and are left with 2,810,925 patents. We select our cutoff at 2016 because the NBER technological field categories were only assigned through 2015 and our measure of disruptiveness was only calculated through 2016. For our analysis, we consider two aspects of patent attributes, patenting that is solo-authored, and patenting done in teamwork.

We constrain our dataset for solo-authored work to understand patent attributes over the life course at the individual level. We are left with 460,120 inventors holding 1,052,947 patents of which we have patent attribute information. We estimate the following model:

$$Q_p = \beta Age_{kpi} + \alpha_i + \varepsilon_{pi}$$

This model estimates the patent attribute measure Q for patent p. Age is a dummy indicator if an inventor, I, patented, p, in that age category, k. We include inventor fixed effects, α_i. This is the demeaned patent attribute average for the inventor, which includes their patent attribute for all patents, not only their solo-authored work. Last, ε_{pi} is the error term.

Our second estimation strategy for patent attribute looks at team age compositions and their impact on patent attributes. We only include patents where we know all of the ages of the inventors associated to that patent, which leaves us with 2,275,815 patents. Our estimation model is at the patent level, and is as follows:

$$Q_p = \beta_j AgeComp_{pj} + \beta_2 Gender_p + \beta_m Team_{pm} + \beta_f Field_{pf} + \beta_t Yr_{pt} + \varepsilon_p$$

We estimate the patent attribute measure, Q for patent with year (Yr_{pt}) and field ($Field_{pf}$) fixed effects. Field is the NBER technological field assigned to that patent. Year is the application year of the patent. The age composition of a team is reflected in j age composition groups in the variable $AgeComp$. This is a series of dummy variables that indicate if the team age composition. We defined age groups as, younger for those below 30 years old, middle age as 30-49, and older as above 50 years old. The middle age comparison group was based on the expected peak of creativity from previous work. Team compositions included: only younger, only middle age, only older, younger & older, younger & middle, older & middle, and all age groups (younger, middle and older). We also control for team size by using dummies for each team category (solo, couple, three, four, five, six, seven and eight+) and gender, $Gender$, which is the number of women on the patent divided by the overall team size. We use robust standard errors, and the error term included is ε_p.

4 Results

4.1 Overview

4.1.1 Patenting rate over life course dataset

Given that our dataset introduces a new variable to the patent literature, we begin our discussion of results by describing the age information contained in our new dataset and other descriptive statistics on teams and age composition. Below, Figure 2 provides an overview of the distribution of patents by ages and gender of inventors. Patents are normalized with respect to the number of applications per year per capita relative to 2012 patenting activity in order to remove the effect of the overall increasing rate of patenting with time. Patenting activity peaks in the early 40s for men and slightly earlier for women in the late 30s. Overall, men patent more than women beginning at about age 26 through the late 70s.

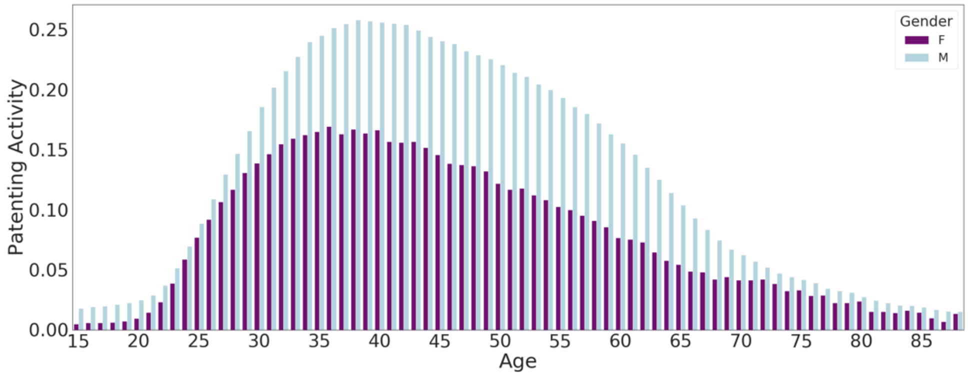

Figure 2 Patenting Activity by Age and Gender

4.1.2 ‘Career Inventors’ and patenting activity

Previous work on the life course of patenting often use year of first patent as a proxy for age (Allen et al, 2007). We explore the validity of this relationship by looking at the age of first patent for “career” inventors, who are those with more than one patent in their life time. Figure 3 only presents information for people who are born after 1959 to minimize bias caused by censoring. Since our dataset starts in 1974, we may capture some people in the middle of their career. Since we don’t have any information about their patenting activity in their earlier years, a right sided censoring problem can occur if we include all people who patent. Thus, we only include people who are born after 1959 to capture people who are patenting for their first time in their life to minimize bias in this graph. For most career inventors, their first patent is in their late 20s or early 30s, but there are a significant number of inventors that begin patenting in their 40s and beyond. Thus, the data suggest it is not appropriate to assume that the first patent occurs near the start of the inventor’s professional career, as others have done (Allen et al, 2007, Wu et al, 2018).

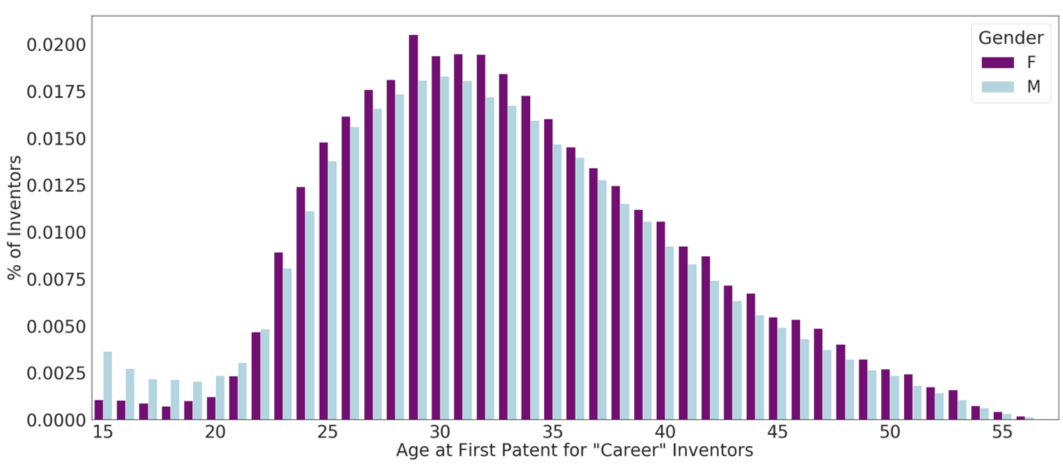

Figure 3 Age at first patent for inventors with multiple patents

We also look at the age at which an inventor first patented by decade as previous work by Jones on the ‘burden of knowledge’ has shown that the age of scientific publications and NIH research grantees have been increasing over the past few decades (2009). In contrast to the Jones findings, the results shown in Figure 5 are inconsistent with the ‘burden of knowledge’, as the age of first patent appears to have fallen in recent years for career inventors.

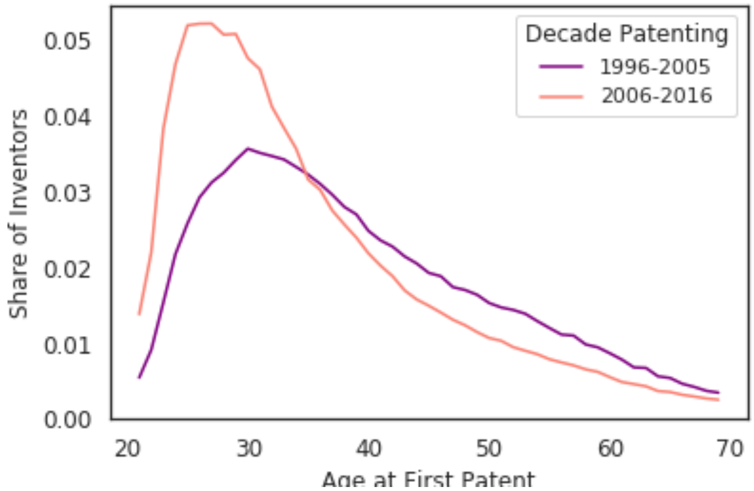

Figure 4 Age at first patent over time

An important advantage of our dataset to understand patenting patterns over the life course is that it uses a disambiguated dataset in which individuals who have multiple patents throughout their lifetime can be linked over time. The patentsview dataset uses a disambiguation algorithm, which tries to identify if someone with the same name is the same person who authored multiple patents or if they are actually authored by multiple people (Monath, McCallum et. al., 2015). The algorithm considers name spelling, patent title/abstracts, location, assignee (firm or university affiliation), and co-inventors to help identify unique inventors across time. Almost half of the inventors in the dataset have only a single patent, but given the size of the dataset there are still tens of thousands of inventors with multiple patents as presented in Figure 5. This fact enables within-person longitudinal analysis which we discuss in section 4.2. It is noteworthy that there are many fewer women inventors with multiple patents.

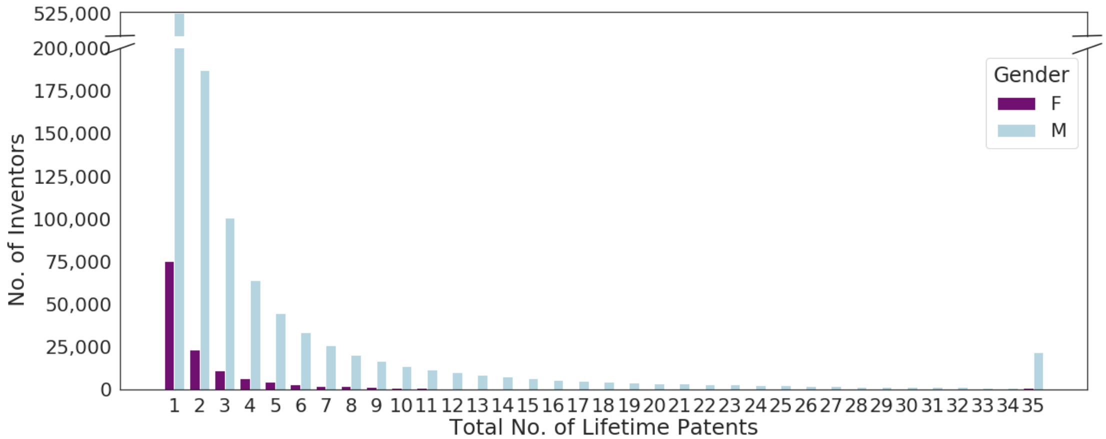

Figure 5 Lifetime Patenting by Inventor

4.2 Rate of patenting over the life course

We estimate the rate of patenting of inventors over their life course using a fixed effects model. For all our estimates, the reference group is ages 40-44. Every estimate we provide in this section is significant at the .01% level. We compare these results to our uncontrolled calculations of rate of patenting for fractionalized and non-fractionalized patent counts by age and gender. Recall that fractionalized patents include the number of inventors on the patent so that if there is a team of 5 people on a patent, it is counted as 1/5 for each inventor. Non-fractionalized patents are simply the count of a patent that doesn't adjust for team size. Figures 6 and 7 display the fractionalized and non-fractionalized patent counts by gender and age groups from our dataset. This is the average patenting rate for that age and gender group. The peak for both measures is at around 35-39 years old. For non-fractionalized counts, the peak is between 35-45 for men, but this pattern doesn't hold for fractionalized patents as the peak for men is at age 35-39. When we compare our cross-sectional averages of patenting rates in Figures 6 and 7 with our parameter estimates shown in Figures 8 and 9, the peak for both measures and genders remain at 35-39, and the parameter estimates are similar. This suggests that selection bias due to observables of inventor characteristics is not a major driver to understanding the patenting rates of inventors. If our estimated coefficients were different than our calculated averages, it would suggest that unobservable characteristics of the inventor, like their natural ability to invent or ambition, could explain their patenting rates. However, we find that this was not the case and selection doesn't seem to be a problem in this case. Further, we affirm our prediction that rate of patenting follows an inverted U-shape in our analysis in Figures 8 and 9, which displays the estimated coefficients from our fixed effects results.

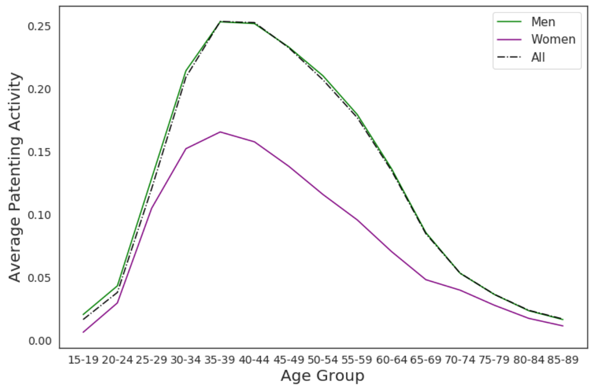

Figure 6 Average Patenting Activity by Gender, Non-Fractionalized Patent count (without standard errors)

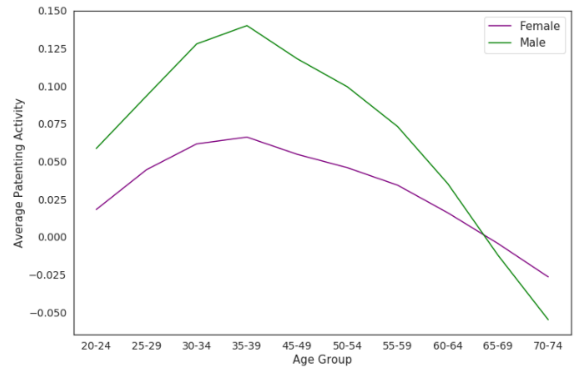

Figure 7 Average Patenting Activity by Gender, Fractionalized Patents (without standard errors)

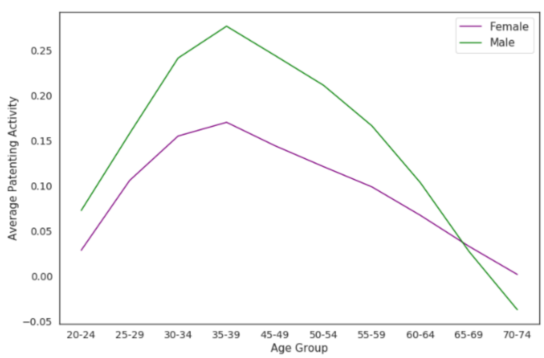

Figure 8 Estimated Patenting Activity by Gender, Non-Fractionalized Patents (without standard errors)

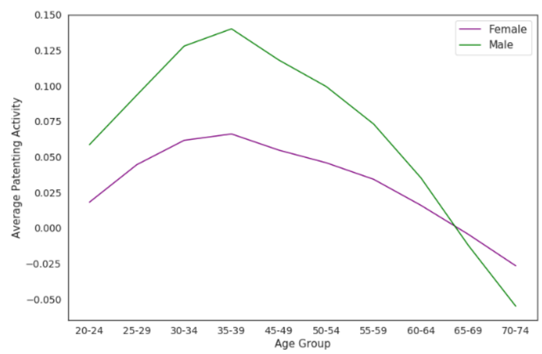

Figure 9 Estimated Patenting Activity by Gender, Non-Fractionalize Patents (without standard errors)

If we look at the overall patenting patterns without separately running regressions by gender, we see that the peak patenting rates remains at ages 35-39. Unsurprisingly, non-fractionalized patenting rates are much lower that fractionalized patenting as most patenting activity occurs in teams as we saw in Figure 2.

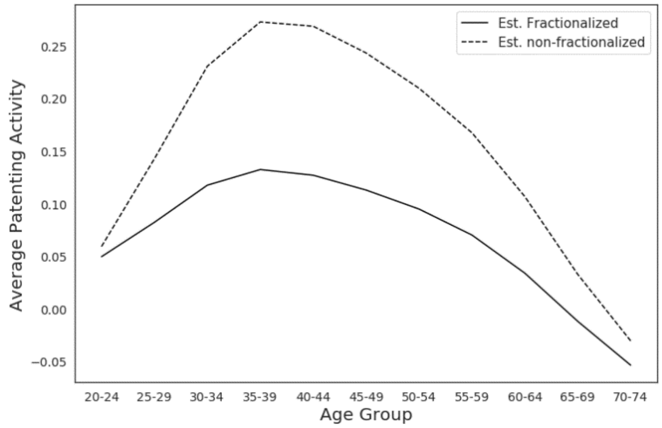

Figure 10 Patenting Productivity Estimates Over the Life Course

Across inventors, we find that peak rate of patenting typically occurs in the late 30s during middle age working years.

4.2.1 Patenting rate by technological field

We also explore patenting rates across technological fields using our fixed effects regression, but running a separate regression for technological field and gender. Technological fields are given by the NBER technological fields originating from Jaffe, Hall, and Trajtenberg (2001). There are six technological fields identified, chemical, drugs and medical, computers and communication, electrical and electronic, mechanical and other. Some technological field codes were missing, which we include in our results for transparency. Since we are unable to understand why they are missing, we do not discuss their results in detail. There are 39,447 female inventors who fell in the missing category and 300,668 male inventors. Figures 11 and 12 provide an overview of patenting rates by age and field separately for men and women.

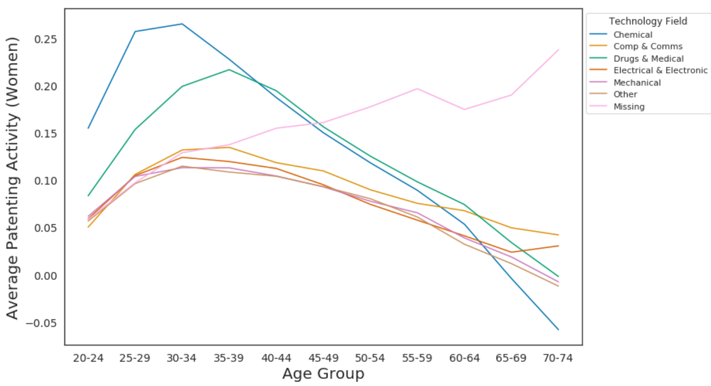

Figure 11 Productivity by Technological Field, Women

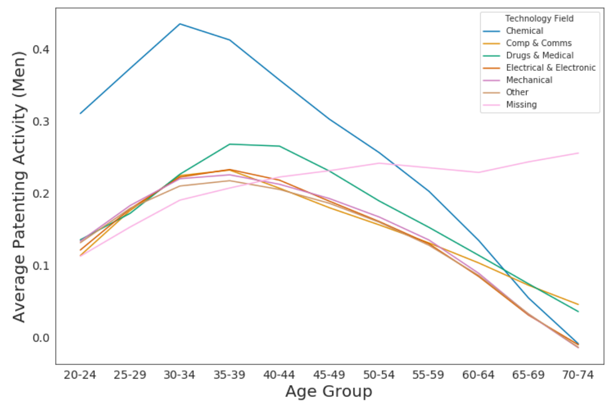

Figure 12 Productivity by Technological Field, Men

The fields with the most patenting activities for women and men are in chemical, and drugs & medical technologies. However, women tend to patent more in drugs & medical throughout their lifetimes as compared to men who tend to patent more in drugs & medical starting in their mid-life. Patenting activity has similar patterns in electrical & electronics, mechanical, computers & communications and other fields for both men and women.

4.3 Patenting attributes over the life course

We now turn to our results on the changes of patent attributes over an inventor's life course by looking at single authored patents over the life course of an inventor. Figures 13-18 display the average patent attribute over the life course. The average number of backward citations tends to increase over the life course, as expected. Forward citations are highest in early life, although they only show a slight decline with age, which is also in line with our predictions. Generality, however, continually decreases over the life course, counter to our expectations. Originality increases over the life course, as expected, but plateaus in the 60s. The number of independent claims interestingly increases over the life course until the mid-40s, where it plateaus. While we expect it to peak in midlife, we did not expect claims to plateau after midlife, but rather decrease. Finally, disruptiveness, that spark of 'genius', occurs at younger years and plateaus in the 40s, suggesting that radical ideas occur in the formative years when fluid abilities are highest.

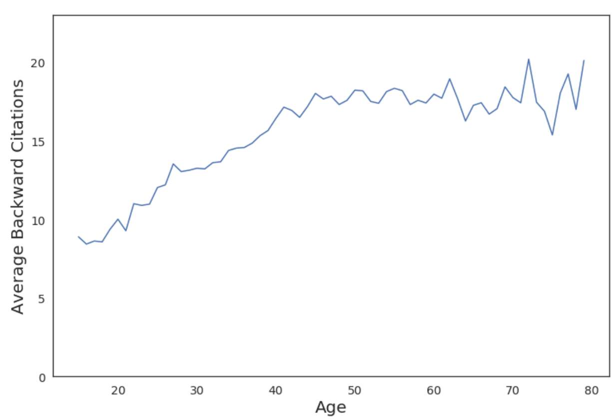

Figure 13 Patent Quality Over Life Course: Backward Citations

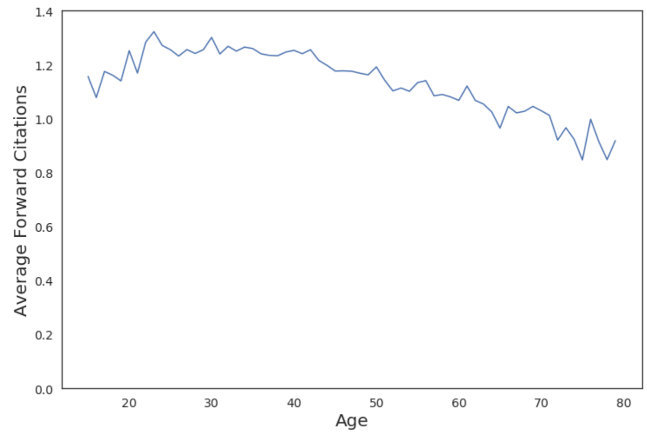

Figure 14 Patent Quality Over Life Course: Forward Citations

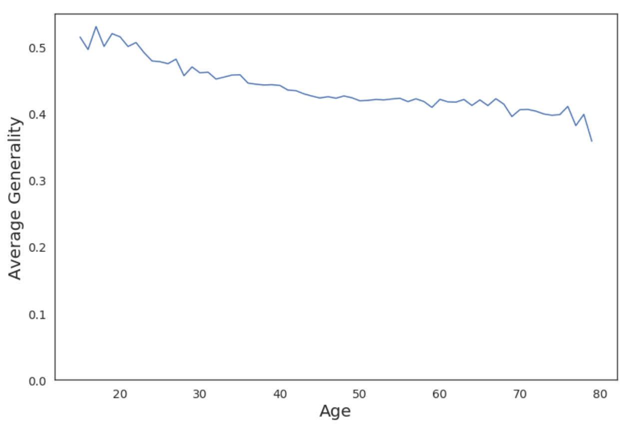

Figure 15 Patent Quality Over Life Course: Generality

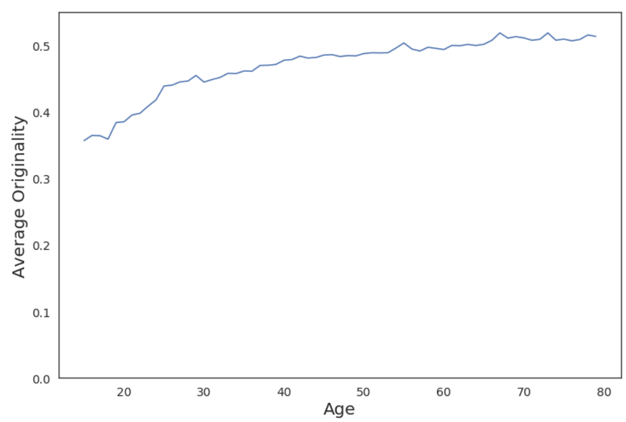

Figure 16 Patent Quality Over Life Course: Originality

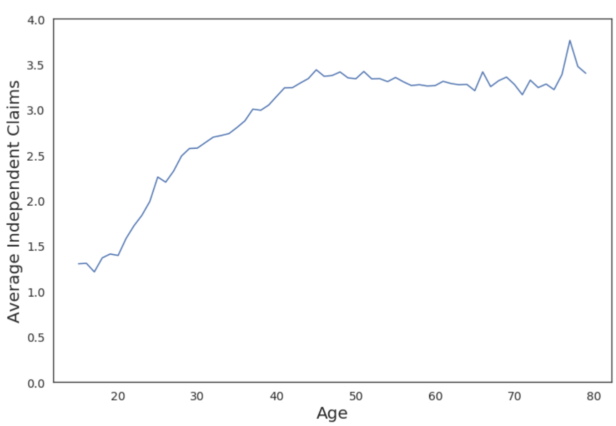

Figure 17 Patent Quality Over Life Course: Number of Independent Claims

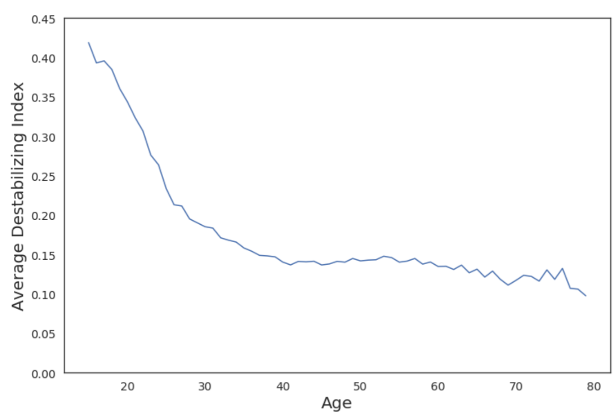

Figure 18 Patent Quality Over Life Course: Disruptiveness

4.4 Team composition and patent attributes

4.4.1 Patenting activity and teamwork

Teamwork is an important part of patenting activity as Figure 19 demonstrates. Most patenting activity occurs in teams, but there are differences in the participation rate of teamwork by gender with women working in teams and larger teams more often than men. For both genders, there is little systematic variation with the size of teams over their life course. However, the probability of having co-inventors gradually declines for both genders as they age.

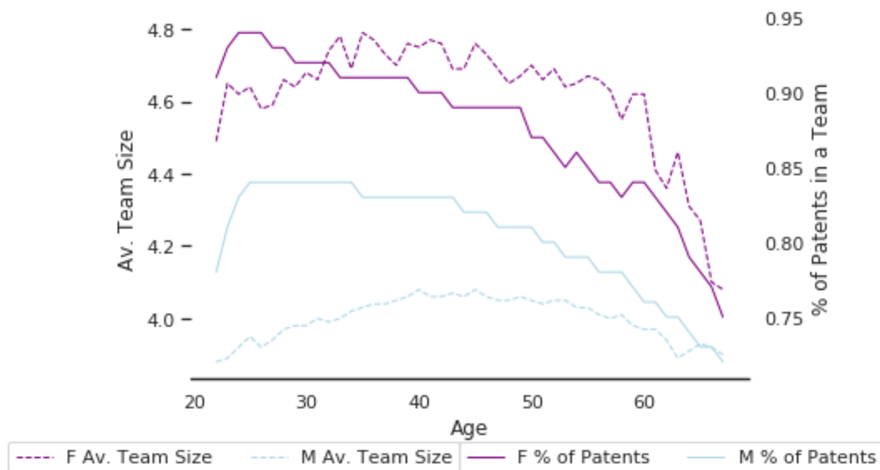

Figure 19 Team size by age at patenting

We observe the average patent attribute, in this case forward citations, by team composition in Figure 20. Forward citation is normalized by technological field and year. The size of the circle shows the size of the age group, and the color represents team composition category. In the case of forward citations, the larger the team, the more forward citations the patent has, verifying the importance of teamwork which is well known (Wu et al, 2019). Further for solo inventors, older works have fewer forward citations and middle-aged and younger inventors have similar citation patterns, while middle aged inventors tend to have higher patenting rates, confirming Figure 3. There are many patents in each of our age and team categories that allow us to analyze the relationship between age heterogeneity in team work and its impact on patent attributes.

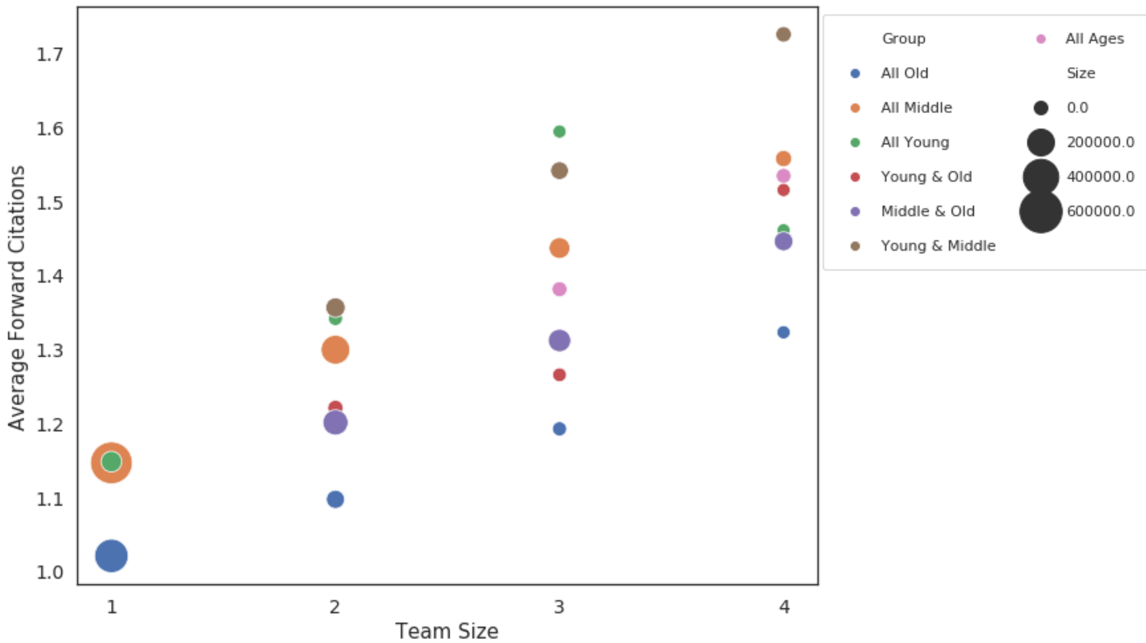

Figure 8 Team Size & Age Groups by Patent Attribute

4.4.2 Team composition and patent attribute regression results

We find that some aspects of patenting improve with age suggesting that experience or crystallized abilities contribute to innovation activity. In addition, younger inventors can add fresh ideas to produce more radical inventions. We investigate how the strengths of each age group may contribute in a team setting. Teamwork is increasingly becoming an important part of innovation activity (Wuchty, et al 2016), and even the size of a team influences types of innovation activity as large teams are likely to build upon prior work, while small teams tend to be disruptive (Wu et al, 2019). We investigate if age heterogeneous teams may increase an attribute of a patent as the mixture of team members who may have relatively stronger fluid or crystalized abilities could increase particular attributes of a patent.

We look at different age compositions of inventors within a team, all younger inventor (below 30), all middle-aged (30-49), all older (50 and above), younger and middle-aged, younger and older, middle-aged and older, and all ages (as least one team member from each age category). Figures 22-27 display the coefficient results of our age heterogeneous team regressions with their standard errors for each of our six patent attributes as described in our methods section. The team with all middle-aged inventors is the reference point in our regressions and thus have zero as the coefficient estimate. The red line in figures 22-27 is zero or when there is no estimated impact on the patent attribute. We also display the coefficient result of the female share, which is the number of women divided by the total number of people in that team.

For forward citations, which is a measure for overall quality of patents, younger and middle-aged inventors tend to produce higher quality patents than any other team composition. However, the effect is rather small with forward citations increasing by .13 forward citations. Teams with both middle aged and older inventors tend to have a little over 1 more backward citation, and as you may recall, backward citations is tied to experience. For independent claims, both middle aged and younger teams, and teams with all ages produce more novel claims than any other group, although this only increases by less than tenth of an independent claim (where on average a patent may have 2-3 independent claims). For both generality (.018 percentage points) and originality (.023 percentage points), mixed age teams with all ages have the highest contribution to these measures. For originality, teams also perform relatively better when there are teams with younger and older inventors, and middle aged and older inventors, but these teams only increase originality by approximately .02 percentage points. Interestingly, disruptiveness increases the most by approximately .021 percentage point increase when there is a larger share of women on the team, while age heterogeneous teams do not contribute, but there are positive impacts for teams with all younger or all older inventors. In general, age heterogeneous teams that are, middle and older teams, younger and middle teams, and all age teams seem to contribute to increase patent attributes, with the exception of disruptiveness, where the female share was the largest contributor. However, our effect sizes across these patent attributes are quite small.

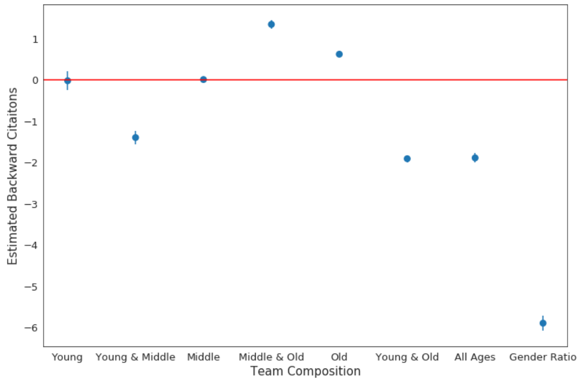

Figure 10 Age Heterogeneous Teams: Backward Citations

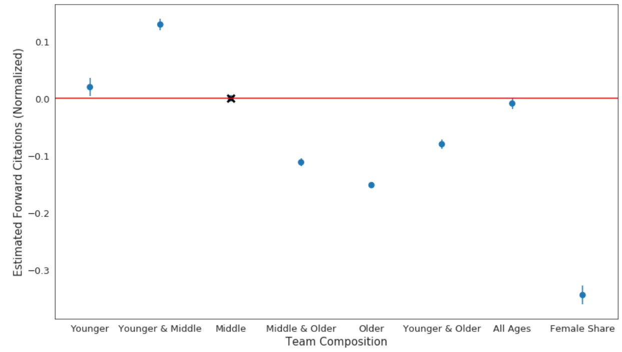

Figure 9 Age Heterogeneous Teams: Forward Citations

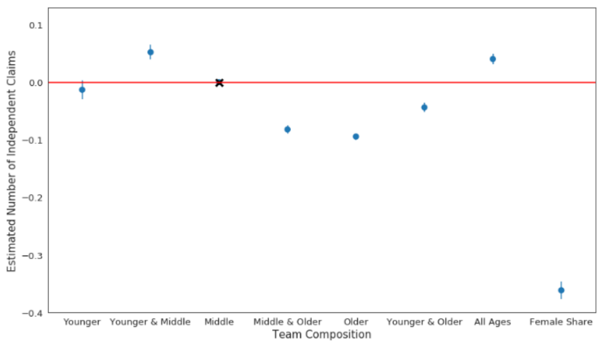

Figure 11 Age Heterogeneous Teams: Number of Independent Claims

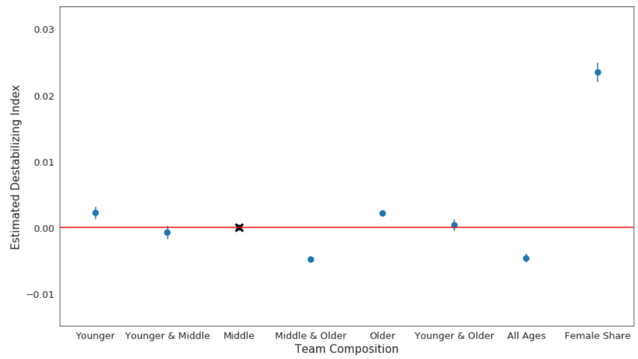

Figure 12 Age Heterogeneous Teams: Disruptiveness

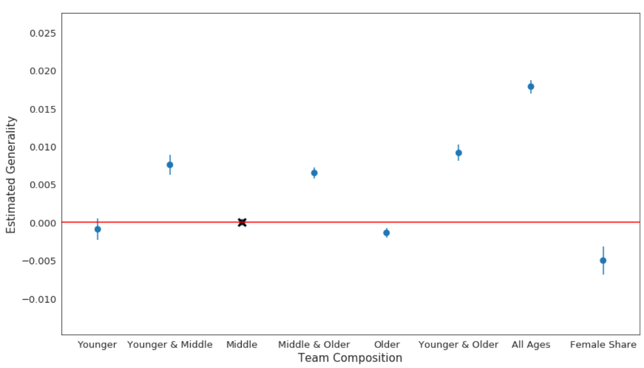

Figure 13 Age Heterogeneous Teams: Generality

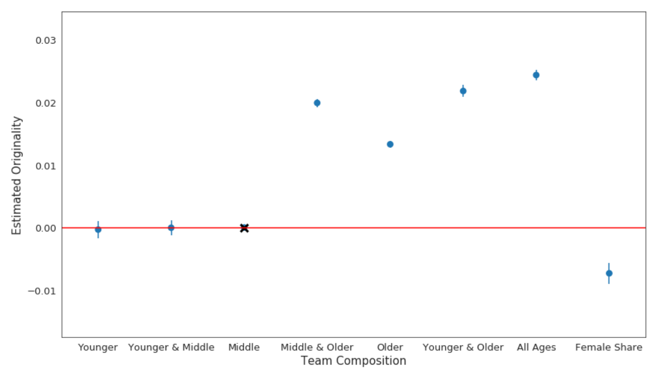

Figure 14 Age Heterogeneous Teams: Originality

5 Discussion and conclusions

Workers in many industries and professions are remaining in the work force longer than ever before. Changes in cognitive abilities as we age raise important questions about how to maintain the productivity of older workers. One important dimension of that productivity is success at creative tasks such as research and invention.

Previous work on age and creativity focuses on small and atypical groups such as Nobel prize winners, inventors of historic significance and famous artists. Our goal is to study how invention changes with aging in the entire population of U.S. inventors, both because invention is an economically significant activity in itself, and because its relationship to the aging process may be indicative of trends in other cognitive tasks involving creativity and information processing.

At the simplest level, our preliminary results confirm the pattern of productivity in relation to age that has been found in previous work. The probability that an inventor will be associated with a patent application in any given year rises during their early career, peaks around age 40, and declines after that. This pattern is similar for men and women, though the peak for women appears to be one or two years earlier. While previous work has examined this pattern mostly in data that combined within and between inventor comparisons, we find that limiting the comparison to within inventors over their life course does not change the picture substantially.

There has been much recent interest in the ‘burden of knowledge’ phenomenon (Jones, 2009). Unlike previous work in other domains such as scientific achievements, we do not find that overall inventors’ age at the time of their first patent has been rising; if anything, the peak age for first patents seems to have fallen from about 29 between 1996-2005 to about 25 from 2006-2016. Two factors that may account in part for this are: (1) the increase in team size may be making it easier for a new inventor to get their name on a patent at an earlier age; and (2) the apparent decline in the effective threshold for patentability may be making it easier to get a first patent at an earlier age. These issues merit further study.

The richness of the patent data allows us to study not just the rate of patenting, but the nature of invention. Our initial analysis of solo-inventor patents provides partial support for our hypotheses derived from cognitive aging theories. We expected that measures of invention attributes that are closely related to experience increase with age; whereas those most closely tied to rapid, novel thinking decline with age. Moreover, patent attributes that draw on both the pragmatics and mechanics of intelligence (i.e., forward citations) exhibit an inverted-U shape analogous to that for the overall rate of patenting. The experience-based measures of backward citations and ‘originality’ do increase with inventor age. Also, the number of independent claims per patent rises with age.

The most widely used measure of overall impact—forward citations—does show an inverted-U pattern, with the average citation rate peaking in the mid-twenties. Moreover, the generality of inventor citations declines with inventor age

The Funk/Owen-Smith measure of disruptiveness (Funk and Owen-Smith, 2017; Wu, Wang and Evans, 2019), decreases with the age of the inventor, consistent with the aging-related declines in efficient processing of novel and abstract stimuli.

Turning to the age composition of teams, our hypothesis is that invention attributes that draw on both experience and fluid intelligence benefit from age heterogeneous teams, in which the experience of older workers could complement the fluid intelligence of younger inventors. Once again, we find some support for the hypotheses:

- Age heterogeneous teams of, teams with middle and older inventors, younger and middle-aged inventors, and all age inventor teams seem to contribute to increase patent attributes, with the exception of disruptiveness. However, our effect sizes across these patent attributes are quite small.
- For forward citations, we find evidence of higher average citations from teams that combine younger and middle-aged workers, but we do not find much evidence of benefits from combining older and younger inventors.
- We find the strongest support for complementarity with the generality measure, for which every combination—younger with middle, younger with older, middle with older, and all ages together—shows higher average than homogenous teams.
- For number of claims, we find again a higher rate from the younger/middle combination than either all young or all middle, and evidence of complementarity for all ages.

5.1 Limitations: Issues of interpretation and generalizability

In using patents and their characteristics as indicators for age-related changes in inventive success, we face several questions regarding the significance of our findings.

There are questions of the importance or significance of the inventive activity, and the generalizability of findings about invention to other domains. Invention is economically important because of its crucial role in technological change and economic growth. Inventors represent a large and important group of professional workers, and our analysis will be based on many more individuals than have been used in any previous research on these topics. Although we cannot know how similar they are to other professional workers, they nonetheless represent a significant expansion in the scale and scope of activities for which these patterns have been studied. Moreover, our study uses well-documented patterns of aging-related changes in cognitive functioning to provide a conceptual framework for predictions about age patterns (Hughes et al., 2018).

Another issue is that at present we do not have other information about the inventors. There are limitations on our ability to distinguish the direct effect of age on cognitive function from effects on the rate of patenting that might be associated with other age-related changes such as disease, marital/parental status, or transition out of inventive activity into management or early retirement. Some of these effects (e.g. cognitive decline due to disease) are closely connected to age-related decline. Other effects (e.g. people become managers) are unconnected to cognitive decline but might still plausibly reduce the *rate* of patenting of older inventors. It is less obvious, however, that these non-cognitive changes would affect our measures of patent *attributes* or impact. The attributes of the (possibly smaller number of) patents that older workers get should be unaffected, so our conclusions about the effects of age on patent attributes should not be biased. Nonetheless, we will treat the age/patent-creativity relationship as an association rather than a causal relationship. These issues could potentially be explored further by other researchers in the future, if they were able to match the database we create to sources of information about these other conditions. Further, we do not know which inventors have stopped patenting because they have died. We are working on adding information about death dates scraped from the web as was done for dates of birth. It would be helpful to model the movement of inventors in and out of patenting and onto or off of teams, though this will be challenging without bringing in other identifying information about the inventors.

We also want to explore whether any results are sensitive to measurement error and missing data associated with the scraping of ages. Multiple-overimputation (Blackwell, Honaker and King, 2015a, 2015b) is a procedure that treats missing data and mismeasured data on a continuum. It utilizes a subset of data for which the variable measured with error is reliably known to estimate probability distributions for that variable based on observables, and then estimates the parameters of the models of interest using those distributions for the values of that variable.

Creation and cleaning of these data open up many other avenues for future research. For example, much work on research productivity effectively treats ‘age’ and ‘experience’ interchangeably, using a variable often defined as years since PhD, or years since first patent or paper. These data allow exploration of the interacting effects of chronological age and experience defined in terms of previous patenting activity. More generally, the disambiguated inventor names and associated information can be used to search for and merge in other inventor attributes such as educational attainment, allowing for broad and varied exploration of how inventive behavior evolves over the life course. When we have completed the quality control on the data set, we plan to make the patent data available publicly so that others can explore additional questions related to innovation over the life course.

In conclusion, although older adults are less likely to patent than middle-aged adults, the attributes of their patents do not decrease across the board. On measures of patent attributes that are linked to accumulated wisdom and experience, older adults in fact demonstrate higher levels of these attributes than those who are younger. Moreover, we find some evidence that age heterogenous teams that include older workers in conjunction with younger and middle-aged adults may provide higher rates of originality in patents. Age heterogeneous teams seem to produce patents increase a wide range of patent attributes and have higher rates of backward citations, forward citations, generality and number of independent claims. Disruptiveness was the only attribute that did not benefit from age heterogeneity, but did benefit from having a higher fraction of women on team. Such insights about age and inventive success can help individuals to better plan their work and retirement choices, and organizations to better design work and retirement policies. Given some suggestion of complementarities in teams of mixed ages, there may be opportunities to accelerate the performance of young workers by integrating them with older workers of greater experience, and to extend the productive life and meaningful mentoring roles of older workers by teaming them with younger workers.

References Cited

Acemoglu, D., Akcigit, U., & Celik, M. A. (2014). Young, restless and creative: Openness to disruption and creative innovations (Working Paper No. 19894). Cambridge, MA: National Bureau of Economic Research. Retrieved from http://www.nber.org/papers/w19894

Adams, J. (2013). Collaborations: The fourth age of research. *Nature*, *497*, 557–560. http://doi.org/10.1038/4975557a

Agarwal, S., Driscoll, J., Gabaix, X., & Laibson, D. (2007). The age of reason: Financial decisions over the lifecycle (Working Paper No. 07-11). Cambridge, MA: MIT, Department of Economics. Retrieved from http://dspace.mit.edu/handle/1721.1/63246

Allen, S. D., Link, A. N., & Rosenbaum, D. T. (2007). Entrepreneurship and Human Capital: Evidence of Patenting Activity from the Academic Sector. *Entrepreneurship Theory and Practice*, *31*(6), 937–951. https://doi.org/10.1111/j.1540-6520.2007.00207.x

Amabile, T., & Kramer, S. (2011). *The progress principle: Using small wins to ignite joy, engagement, and creativity at work*. Boston, MA: Harvard Business Review Press.

Baltes, P. B., Lindenberger, U., & Staudinger, U. M. (2006). Life span theory in developmental psychology. In R. M. Lerner & W. Damon (Eds.), *Handbook of child psychology. Theoretical models of human development* (*Vol. 1,* pp. 569–664). New York: John Wiley & Sons Inc. http://doi.org/10.1002/9780470147658.chpsy0111

Beard, G. M. (1881). *American nervousness: Its causes and consequences*. NY: Putnam.

Belbase, A., Sanzenbacher, G. T., & Gillis, C. M. (September, 2015). Does age-related decline in ability correspond with retirement age? Center for Retirement Research CRR WP 2015-24, Boston College, Chestnut Hill, MA. http://crr.bc.edu/wp-content/uploads/2015/09/wp_2015-24.pdf

Blackwell, M., Honaker, J., & King, G. (2015a). A unified approach to measurement error and missing data: Overview. *Sociological Methods and Research*, 1–28. http://doi.org/10.1177/0049124115589052

Blackwell, M., Honaker, J., & King, G. (2015b). A unified approach to measurement error and missing data: Overview and applications. *Sociological Methods and Research*, 1–39. http://doi.org/10.1177/0049124115585360

Börsch-Supan, A., & Weiss, M. (2016). Productivity and age: Evidence from work teams at the assembly line *The Journal of the Economics of Ageing, 7,* 7-42.

Caballero, R. J., & Jaffe, A. B. (1993). How high are the giants' shoulders: An empirical assessment of knowledge spillovers and creative destruction in a model of economic growth. *NBER Macroeconomics Annual*, *8*, 15–86. http://doi.org/10.2307/3585017

Dennis, W. (1956). Age and productivity among scientists. *Science*, *123*, 724–725. http://doi.org/10.1126/science.123.3200.724

Dennis, W. (1958). The age decrement in outstanding scientific contributions: Fact or artifact? *American Psychologist*, *13*, 457–460. http://doi.org/10.1037/h0048673

Dennis, W. (1966). Creative productivity between the ages of 20 and 80 years. *Journal of Gerontology*, *21*, 1–8. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/5901653

Freeman, R. B., Ganguli, I., & Murciano-Goroff, R. (2015). Why and wherefore of increased scientific collaboration. In A. B. Jaffe & B. Jones (Eds.), *The changing frontier: Rethinking science and innovation policy*. Chicago: University of Chicago Press.

Freeman, R. B., & Huang, W. (2014). Collaborating with people like me: Ethnic co-authorship within the US (Working Paper No. 19905). Cambridge, MA: National Bureau of Economic Research. Retrieved from http://www.nber.org/papers/w19905

Funk, R. J. & Owen-Smith, J. (2017). A dynamic network measure of technological change. *Management Science* 63, 791–817.

Galenson, D. W. (2003). The life cycles of modern artists: Theory, measurement, and implications (Working Paper No. 9539). Cambridge, MA: National Bureau of Economic Research. Retrieved from http://www.nber.org/papers/w9539

Galenson, D. W. (2007). Wisdom and creativity in old age: Lessons from the impressionists (Working Paper No. 13190). Cambridge, MA: National Bureau of Economic Research. Retrieved from http://www.nber.org/papers/w13190

Galenson, D. W., & Weinberg, B. A. (2000). Age and the quality of work: The case of modern American painters. *Journal of Political Economy*, *108*, 761–777. http://doi.org/10.1086/316099

Galenson, D. W., & Weinberg, B. A. (2001). Creating modern art: The changing careers of painters in France from impressionism to cubism. *American Economic Review*, *91*, 1063–1071. http://doi.org/10.1257/aer.91.4.1063

Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature*, *28*, 1661–1707. http://doi.org/10.1016/S0169-7218(10)02009-5

Hall, B. H., Jaffe, A. B., & Trajtenberg, M. (2001). The NBER patent citation data file: Lessons, insights and methodological tools (Working Paper No. 8498). Cambridge, MA: National Bureau of Economic Research. Retrieved from http://www.nber.org/papers/w8498

Hartshorne, J. K., & Germine, L. T. (2015). When does cognitive functioning peak? The asynchronous rise and fall of different cognitive abilities across the life span. *Psychological Science*, *26*, 433–443. http://doi.org/10.1177/0956797614567339

PMCID: PMC6057153.

Hughes, M. L., Agrigoroaei, S., Jeong, M., Bruzzese, M., & Lachman, M. E. (2018). Change in cognitive performance from midlife into old age: Findings from the Midlife in the United States (MIDUS) Study. *Journal of the International Neuropsychological Society, 24,* 805-820. Online publication Jul 18 2018. doi: 10.1017/S1355617718000425

Hsu, J., & Huang, D. (2011). Correlation between impact and collaboration. *Scientometrics*, *86*, 317–324. http://doi.org/10.1007/s11192-010-0265-x

Jaffe, A., & Trajtenberg, M. (2002). *Patents, citations and innovations: A window on knowledge economy*. Cambridge: MIT Press.

Jaravel, X., Petkova, N., & Bell, A. (2015). Team-specific capital and innovation. In *National Bureau of Economic Research Summer Institute Workshop on Innovation* July 14. Paper cited with permission of the authors.

Jones, B. F. (2009). The burden of knowledge and the “death of the renaissance man”: Is innovation getting harder? *Review of Economic Studies*, *76*, 283–317. http://doi.org/10.3386/w11360

Jones, B. F. (2010). Age and great invention. *The Review of Economics and Statistics*, *92*, 1–14. http://doi.org/10.1162

Jones, B. F., & Weinberg, B. A. (2011). Age dynamics in scientific creativity. *Proceedings of the National Academy of Sciences*, *108*, 18910–18914. http://doi.org/10.1073/pnas.1102895108

Jones, B., Reedy, E. J., & Weinberg, B. A. (2014). Age and scientific genius (Working Paper No. 19866). Cambridge, MA: National Bureau of Economic Research. Retrieved from http://www.nber.org/papers/w19866

Jung, T., & Ejermo, O. (2014). Demographic patterns and trends in patenting: Gender, age, and education of inventors. *Technological Forecasting and Social Change*, *86*, 110–124. http://doi.org/10.1016/j.techfore.2013.08.023

Lachman, M. E. (2015). Mind the gap in the middle. A call to study midlife. *Research on Human Development. 12*, 327-334. doi: 10.1080/15427609.2015.1068048

Lachman, M. E., Agrigoroaei, S., Tun, P. A., & Weaver, S. L. (2014). Monitoring cognitive functioning: Psychometric properties of the Brief Test of Adult Cognition by Telephone. *Assessment*, *21*, 404–417. http://doi.org/10.1177/1073191113508807

Lachman, M. E., Teshale, S., & Agrigoroaei, S. (2015). Midlife as a pivotal period in the life course: Balancing growth and decline at the crossroads of youth and old age. *International Journal of Behavioral Development*, *39*, 20–31. http://doi.org/10.1177/0165025414533223

Lehman, H. C. (1943). Man's most creative years: Then and now. *Science*, *98*, 393–399. http://doi.org/10.1126/science.98.2549.393

Lehman, H. C. (1960). The age decrement in outstanding scientific creativity. *American Psychologist*, *15*, 128–134. http://doi.org/http://dx.doi.org/10.1037/h0041844

Monath, N., McCallum, A., Wick, M., Sullivan, J. and Kobren, A. (2015) Discriminative Hierarchical Coreference for Inventor Disambiguation. USPTO Disambiguation Workshop Slides. Retrieved from http://www.patentsview.org/data/presentations/UMassInventorDisambiguation.pdf

Nager, Adams and Hart, David M. and Ezell, Stephen J. and Atkinson, Robert D., The Demographics of Innovation in the United States (February 24, 2016). Available at SSRN: https://ssrn.com/abstract=3066060 or http://dx.doi.org/10.2139/ssrn.3066060

National Research Council (2012). Aging and productivity and innovation. In *Aging and the macroeconomy: Long-term implications of an older population.* (pp. 106–121). *Was*hington (DC): National Academies Press (US). Retrieved from http://www.ncbi.nlm.nih.gov/books/NBK148825/

Ng, T. W., & Feldman, D. C. (2012). Evaluating six common stereotypes about older workers with meta-analytical data. Personnel Psychology, 65(4), 821-858.

Ng, E. S., & Law, A. (2014). Keeping up! Older workers' adaptation in the workplace after age 55. Canadian Journal on Aging/La revue canadienne du vieillissement, 33(01), 1-14.

Packalen, M., & Bhattacharya, J. (2015). Age and the trying out of new ideas (Working Paper No. 20920). Cambridge, MA: National Bureau of Economic Research. Retrieved from http://www.nber.org/papers/w20920

Salthouse, T. (2012). Consequences of age-related cognitive declines. *Annual Review of Psychology*, *63*, 201–26. http://doi.org/10.1146/annurev-psych-120710-100328

Salthouse, T. (2009). When does age-related cognitive decline begin? *Neurobiology of Aging*, *30*, 507–514. http://doi.org/10.1016/j.neurobiolaging.2008.09.023

Schaie, K. W. (2012). *Developmental influences on adult intelligence: The Seattle Longitudinal Study* (2nd ed.). New York: Oxford University Press. Retrieved from https://books.google.com/books?hl=en&lr=&id=44doAgAAQBAJ&pgis=1

Simonton, D. K. (1988). Age and outstanding achievement: What do we know after a century of research? *Psychological Bulletin*, *104*, 251–267. http://doi.org/10.1037/0033-2909.104.2.251

Simonton, D. K. (1990). Creativity in the later years: Optimistic prospects for achievement. *The Gerontologist*, *30*, 626–631. http://doi.org/10.1093/geront/30.5.626

Weinberg, B. A., & Galenson, D. W. (2005). Creative careers: The life cycles of Nobel laureates in economics (Working Paper No. 11799). Cambridge, MA: National Bureau of Economic Research. Retrieved from http://www.nber.org/papers/w11799

Woolever, J. (2013). Human resource departments and older adults in the workplace. In P. Brownell, J. J. Kelly, P. Brownell, J. J. Kelly (Eds.) , Ageism and mistreatment of older workers: Current reality, future solutions (pp. 111-134). New York, NY, US: Springer Science + Business Media. doi:10.1007/978-94-007-5521-5_7

Wu, L., Wang, D. and Evans, J. (2019) Large teams develop and small teams disrupt science and technology. *Nature* 566 278-382.

Wuchty, S., Jones, B. F., & Uzzi, B. (2007). The increasing dominance of teams in production of knowledge. *Science*, *316*, 1036–1039. http://doi.org/10.1126/science.1136099