

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 of creation and qualitative nature 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 describe a new database created by combining the publicly available patent data with information on inventor ages scraped from directory websites on the web for approximately 1.2 million U.S.-resident 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 increase with age. The average number of independent claims per patent also increases with age. Forward citations and generality measures, as well as a citation-based measure of disruptiveness decline on average with inventor age. We find little evidence of complementarity between workers of different ages on inventor teams, with inventor team performance generally being close to what would be expected based on the average of the expected performance of the inventors individually.

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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.

Because of the interaction of Gc and Gf in invention, we expect that a given inventor's rate of patenting will peak in middle age. The relationship between Gc and Gf and the *characteristics* of an inventor's patents is less clear *a priori*. Some characteristics—particularly those tied to backward citations—seem closely related to experience, which suggests that they would increase with the age of the inventor. Others, including forward citations, generality and the number of claims, would seem to depend on both Gc and Gf, so we might expect them so exhibit the same ‘inverted U’ pattern over the life course that we predict for the overall rate of patenting. Finally, we expect that the ‘disruptiveness’ measure—which captures by intent impactful departure from the past—might be most closely tied to Gf and hence decline with age.

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.

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 72.46% of inventors in Radaris, 64.54% of inventors for Spokeo and 66.43% of inventors for Beenverified. For subset of inventors, we also searched for additional ages using the website Peoplefinder. We find at least one age is associated with a name and location for approximately 92.6% of the inventors in the dataset. We could not associate an age in only 7.36 % of the cases. We also find that 30.32% of the age results are consistent across at least 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 1,508,676 inventors with age information holding 3,383,594 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 ($1/\text{teamsize}$). 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 the majority of their patents in an age is higher in another technological field. The simple model to estimate the rate of patenting of inventors is:

$$Prod_{ia} = \beta_k Age_{ia} + \alpha_i + \varepsilon_{ia}$$

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 2,532,562 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 begin with an analysis of single-inventor patents to understand patent attributes over the life course at the individual level. We are left with 439,822 inventors holding 763,917 patents of which we have patent attribute information. We estimate the following model:

$$Q_p = \beta_k Age_{pi} + \alpha_i + \varepsilon_{pi}$$

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 . That is, rather than estimating some parametric form for the relationship between the outcome measure and age, we allow each age or age group to have its own average. For the solo-inventor patents, we estimate separate age effects for each calendar age in years. We include inventor fixed effects, α_i so that we are estimating the differential productivity of inventors or the life course rather than the cross-sectional difference between given inventors at a certain age. 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. For this analysis, we include all patents for which we know all of the ages of the inventors associated to that patent, which leaves us with 2,532,594 patents. Our estimation model is at the patent level, and is as follows:

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

We estimate the patent attribute measure, Q for patent with year (Yr_{pt}), field ($Field_{pf}$) and inventor (α_i) 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 the team age composition. For the team analysis, because we want to look at combinations of different ages it is not practical to allow every calendar age in years to be its own group. We defined age groups as, younger for those below 35 years old, middle age as 35-49, 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: solo younger, solo middle, solo older, only younger, only middle age, only older, younger & older, younger & middle, older & middle, and all age groups (younger, middle and older). Note that our reference groups are solo middle and teams with middle aged only. We also control for team size by using dummies for each team category (solo, couple, three, four, five, six, seven and eight)¹ and $Gender$, 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.

¹ We exclude patents with more than eight inventors (approximately 1% of all patents), because in very large teams it is hard to conceptualize how age heterogeneity might play out.

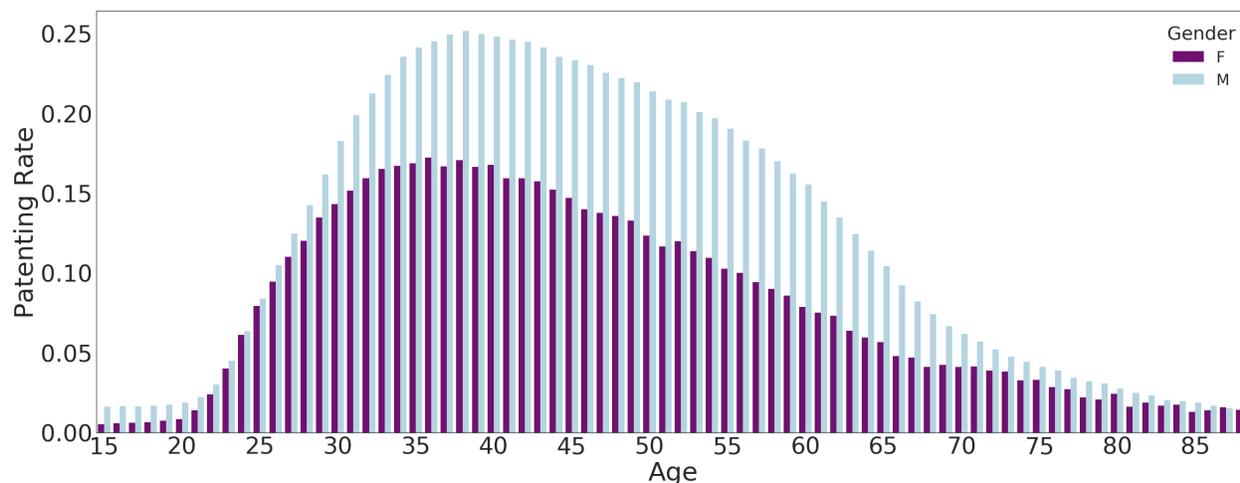


Figure 1 Patenting Activity by Age and Gender

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).

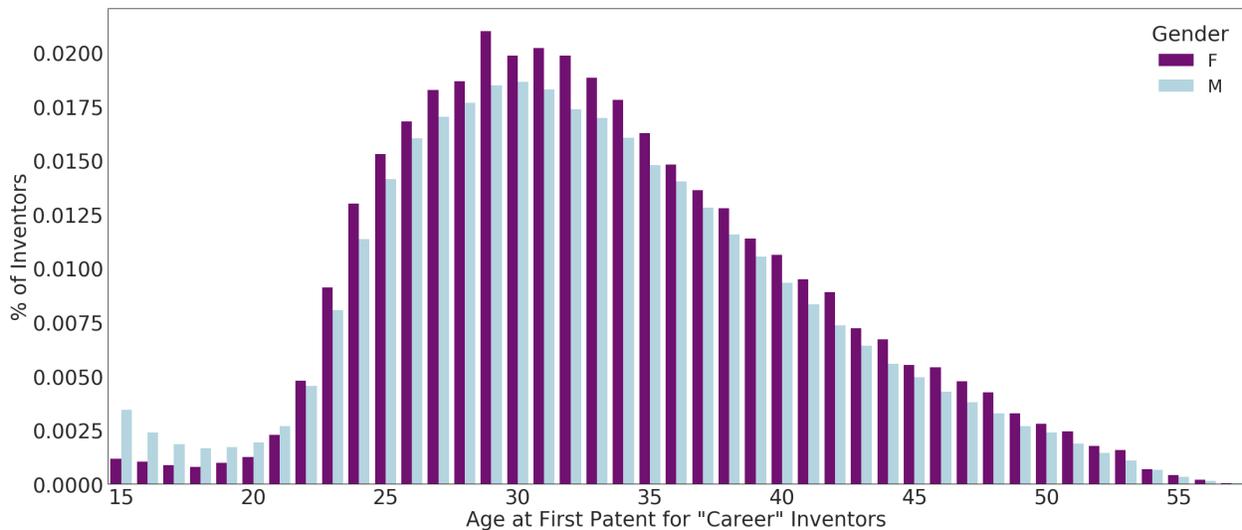


Figure 2 Age at first patent for inventors with multiple patents

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.

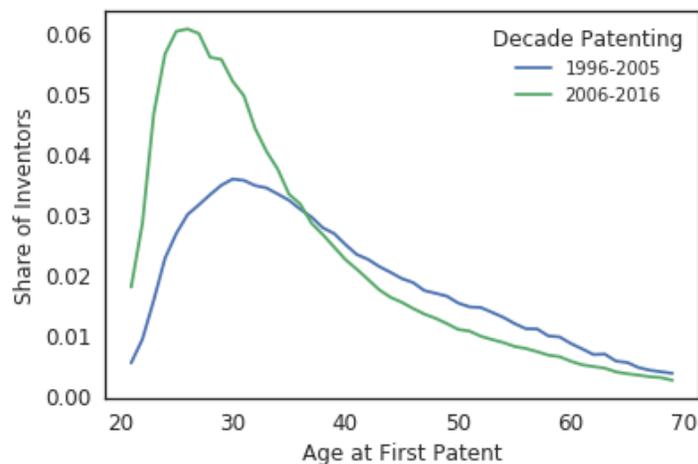


Figure 3 Age at first patent over time

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.

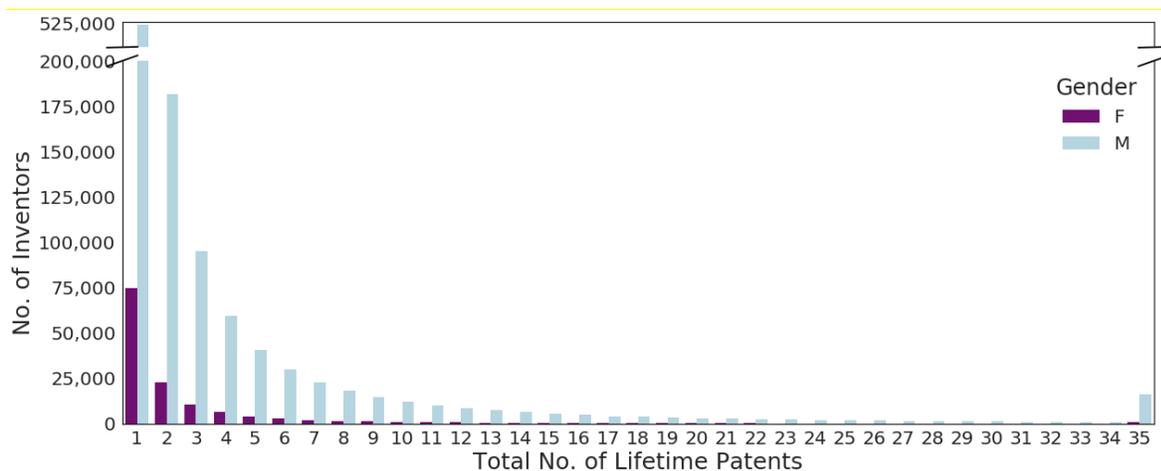


Figure 4 Lifetime Patenting by Inventor

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.

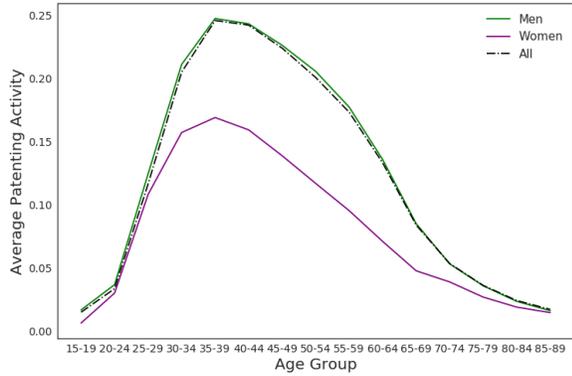


Figure 5 Average Patenting Activity by Gender, Non-Fractionalized Patent count

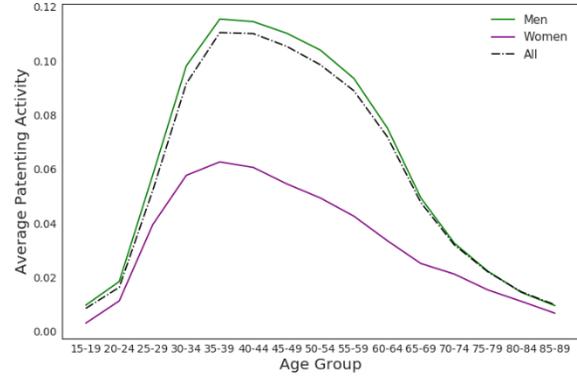


Figure 7 Average Patenting Activity by Gender, Fractionalized Patent count

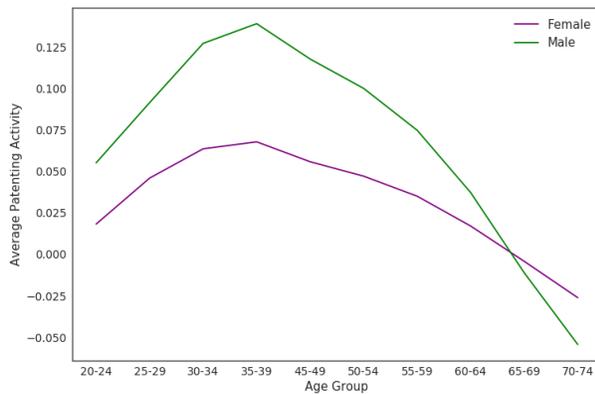


Figure 8 Estimated Patenting Activity by Gender, Fractionalized Patents

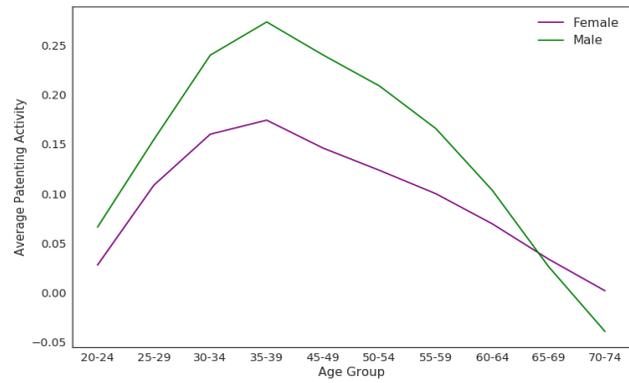


Figure 9 Estimated Patenting Activity by Gender, Non-Fractionalize Patents

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 than fractionalized patenting as most patenting activity occurs in teams as we saw in Figure 2.

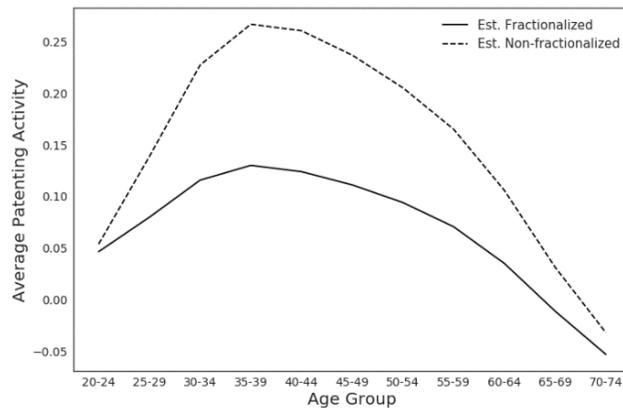


Figure 10 Patenting Productivity Estimates Over the Life Course

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.

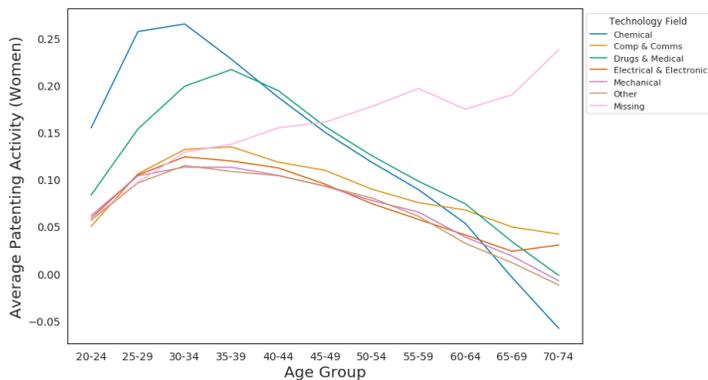


Figure 11 Productivity by Technological Field, Women

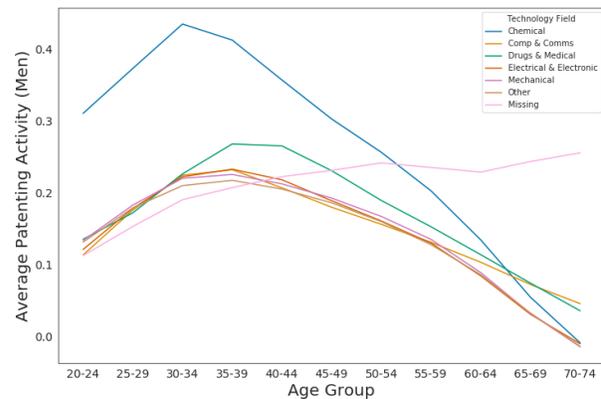


Figure 12 Productivity by Technological Field, Men

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 show that the six patent attributes divide clearly into two categories: backward citations, originality (technological diversity of backward citations) and number of independent claims increase with inventor age, while forward citations, generality (technological diversity of forward citations) and disputiveness all decline with age. The (small) vertical lines at each age point show 95% confidence intervals; given our large sample statistical precision in the classical sense is not an

issue. Note that the magnitude of these effects is also generally large: for example, the average normalized forward citation rate drops by a factor of about 2.5² over the inventor's life course.

The relationship between these results and the theory of fluid and crystallized intelligence is clearer for some measures than for others. We predicted that backward citations and originality would increase with age because they capture knowledge of and connection to the prior art, and that is indeed what we find. The mirror image of those results is that disruptiveness declines with age, suggesting that radical ideas occur in the formative years when fluid abilities are highest.

We also find that forward citations, generality and independent claims—which we expected to depend on both forms of intelligence and hence peak at some intermediate age—all have monotonic relationships to age, with forward citations and generality falling with age and number of claims rising. Interpreted strictly through the lens of our cognitive theory, this suggests that forward citations and generality are determined primarily by fluid intelligence, while the number of claims is determined primarily by crystallized intelligence or experience. Whatever the interpretation, these associations are strong and robust, and so merit further study.

² Recall that we have normalized forward citations by dividing by the average for the technology/year cohort, so an increase of 1.0 corresponds to a 100% increase in the underlying number of citations.

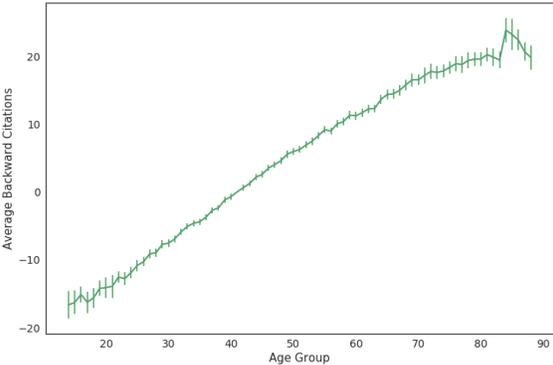


Figure 13 Patent Attributes Over Life Course: Estimated Backward Citations with Inventor Fixed Effects

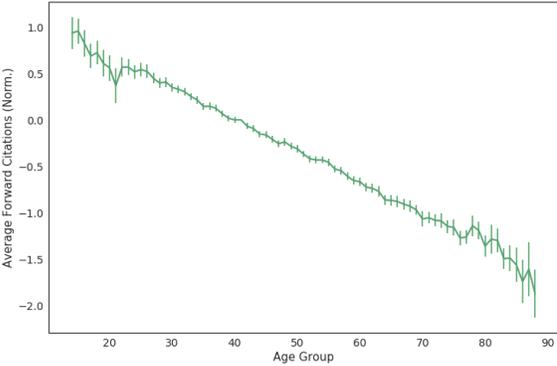


Figure 14 Patent Attributes Over Life Course: Estimated Forward Citations with Inventor Fixed Effects

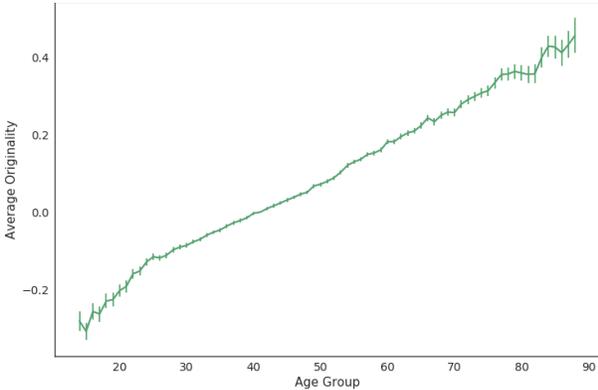


Figure 15 Patent Attributes Over Life Course: Estimated Originality with Inventors Fixed Effects

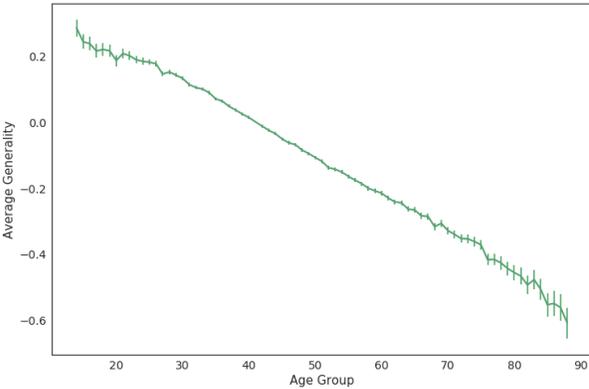


Figure 16 Patent Attributes Over Life Course: Estimated Generality with Inventor Fixed Effects

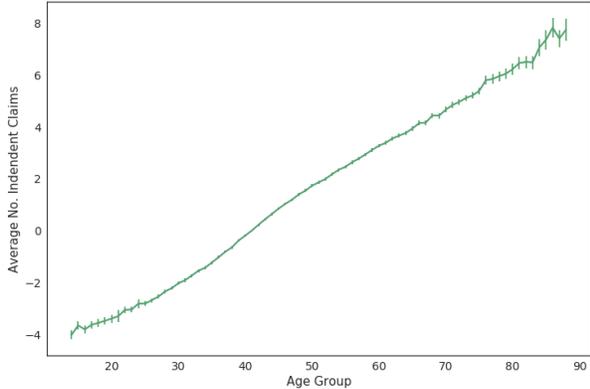


Figure 17 Patent Attributes Over Life Course: Estimated Number of Independent Claims with Inventor Fixed Effects

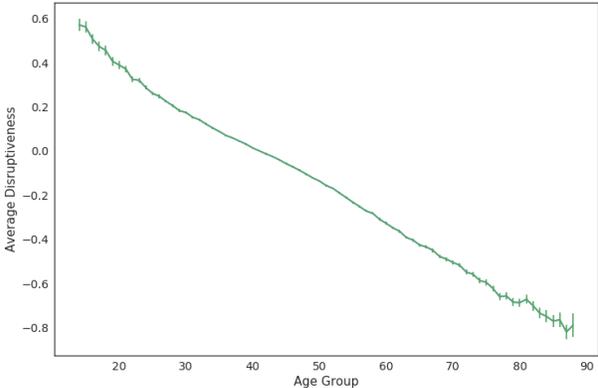


Figure 18 Patent Attributes Over Life Course: Estimated Disruptiveness with Inventor Fixed Effects

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.

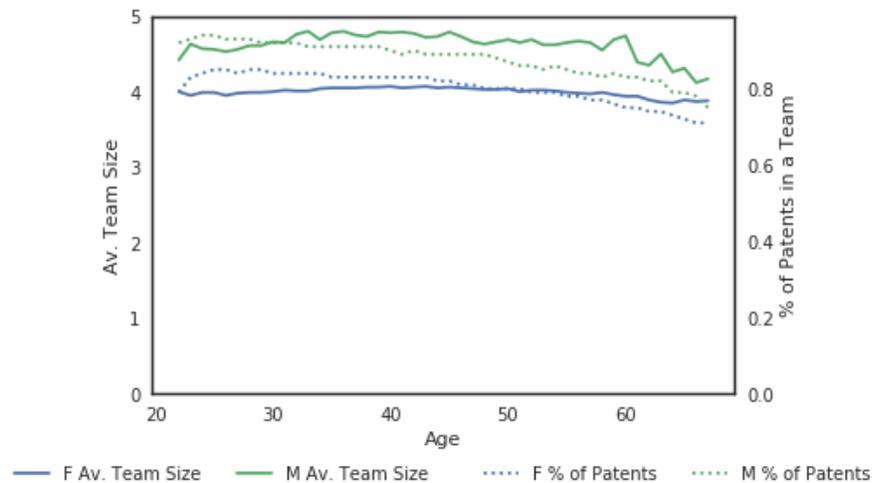


Figure 19 Team size by age at patenting

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.

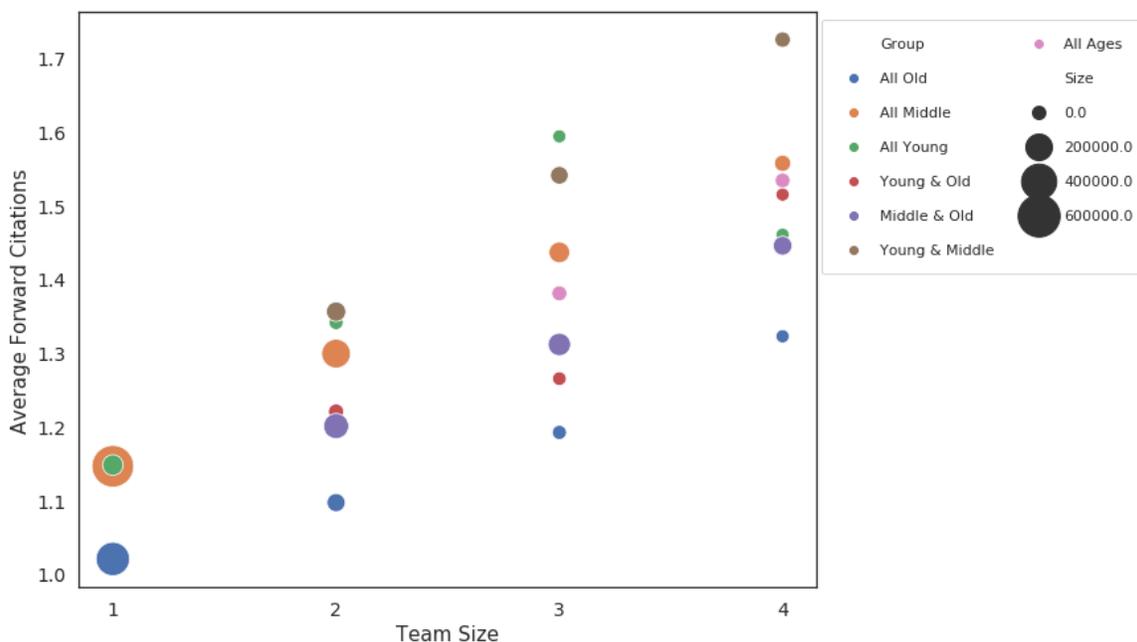


Figure 6 Team Size & Age Groups by Patent Attribute

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 35), all middle-aged (35-49), 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 9-14 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 9-14 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.

As a starting point, these results show the same overall age tendencies that we found when looking at solo-inventor patents: Backward citations, originality and number of claims are higher on teams

with older inventors, and forward citations, generality and disruptiveness are higher for teams with younger inventors. For forward citations, teams with all younger members tend to produce higher quality patents than any other team composition, with a relatively large effect as forward citations increasing by 60% compared to the reference group. Teams with both middle aged and older inventors tend to have a little over 5 more backward citations. However, older teams tend to have the most backward citations than any other team, and have about 10 more backward citations. For independent claims, older inventors tend to have 2 claims, which is more than any other team group (where on average a patent may have 2-3 independent claims). Generality, which is closely link to forward citations, shows that younger inventors tend to have the highest rates and have about 10 percentage points more than teams composed of only middle-aged inventors. Originality, which is linked to backward citations, show advantages for older teams, and have about 6 percentage points more than middle-aged inventors. Teams with younger inventors tend to have more disruptive patents than any other group with around 8 percentage points more than middle-aged teams.

In terms of gender, having more women leads to positive outcomes in terms of forward citations where teams that have a higher gender ratio have around 1.5 percent more forward citations than the mean and 7.5 more backward citations.

In general, we don't find evidence of complementarity between different age groups when they are combined in an inventor team; In general, the effect for mixed teams is approximately the average of the estimated effect for each group seperately. For example, teams that mix younger and older inventors tend to have the average effect of teams with all younger or all older inventors. Thus the basic picture in figures 9 to 14 confirms the general patterns of relationship between characteristics and inventor age that we found for solo inventors. There is little evidence that something different happens in terms of the relationship of age to characteristics when inventors are combined in teams.

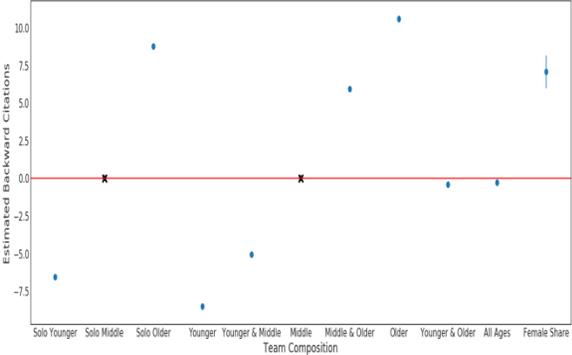


Figure 8 Age Heterogeneous Teams: Backward Citations

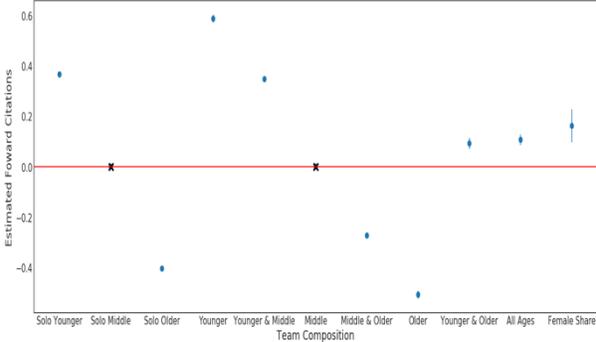


Figure 7 Age Heterogeneous Teams: Forward Citations

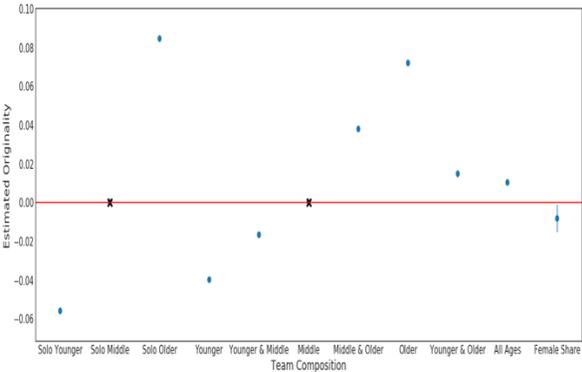


Figure 11 Age Heterogeneous Teams: Originality

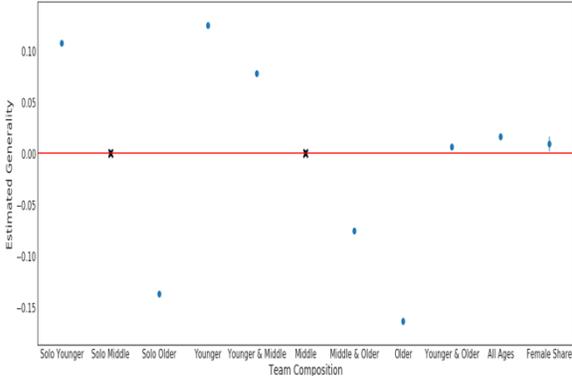


Figure 12 Age Heterogeneous Teams: Generality

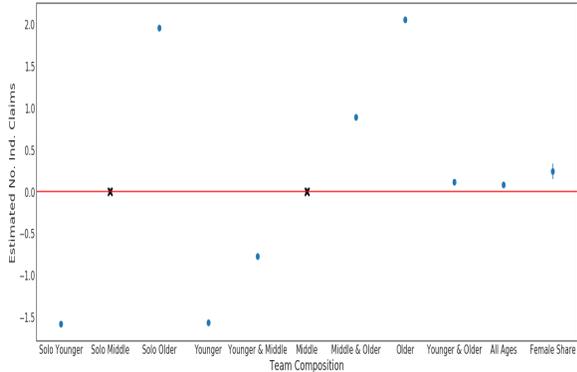


Figure 13 Age Heterogeneous Teams: Number of Independent Claims

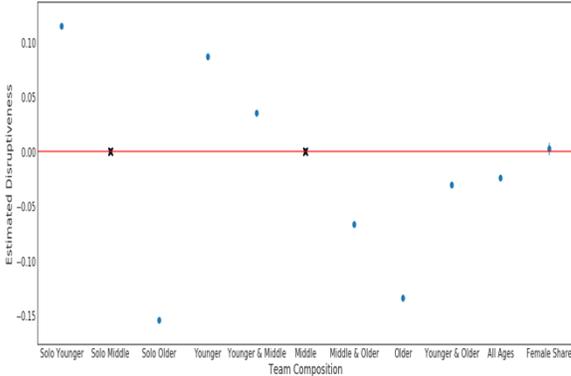


Figure 14 Age Heterogeneous Teams: Disruptiveness

4.4.3 Some sectoral results

It would be plausible that the nature of the relationship between different forms of intelligence and invention characteristics would vary across different knowledge domains. For this reason, we might expect the relationships we are estimating to differ across different fields of technology. As a preliminary exploration of the variations across technology fields, we estimated the team age composition progressions for two quite distinct technology classes: medical preparations and semiconductors. For each of these technology classes, we identified all patents in the given patent class, and estimated regressions with inventor fixed effects analogous to those above. The results are shown in figures 15 to 20 for semiconductors, and figures 21 to 26 for medical preparations. These results are surprisingly similar in both cases to the results from estimating the model on the entire corpus of patents. While this issue surely merits further investigation, the results so far do not suggest that these relationships differ greatly across patent technology fields.

Semiconductor Field Patents

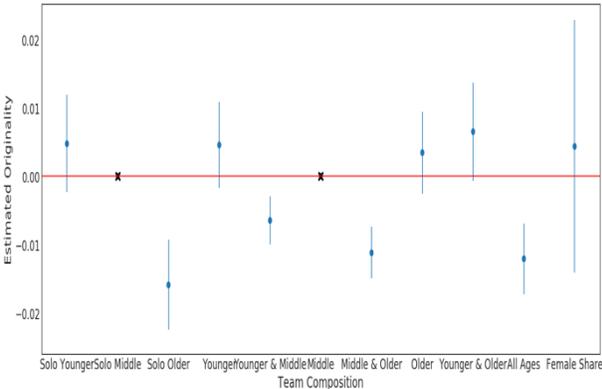


Figure 9 Semiconductors: Originality & Team Composition

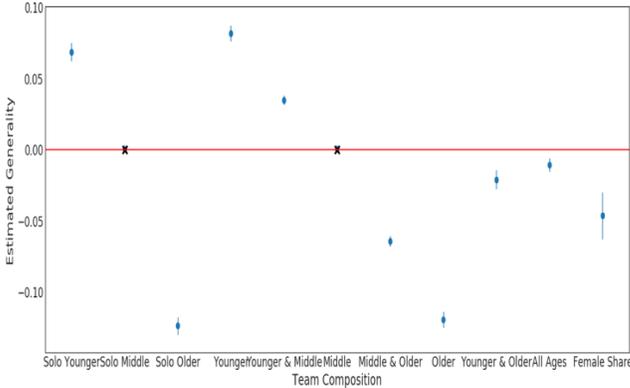


Figure 12 Semiconductors: Generality & Team Composition

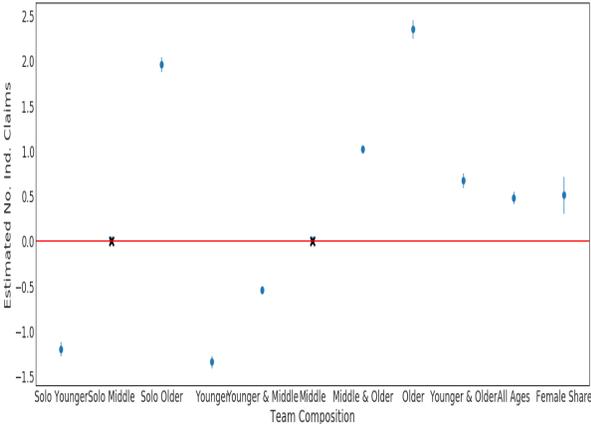


Figure 11 Semiconductors: Ind. Claims & Team Composition

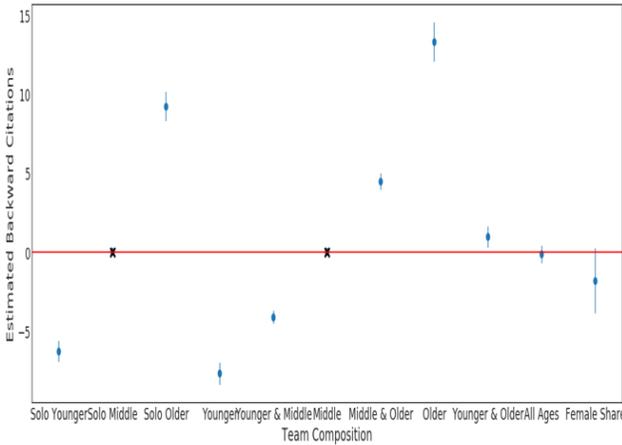


Figure 13 Semiconductors: Backward Citations & Team Composition

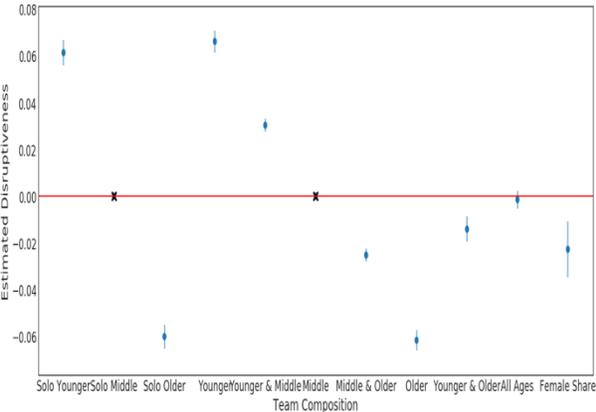


Figure 10 Semiconductors: Disruptiveness & Team Composition

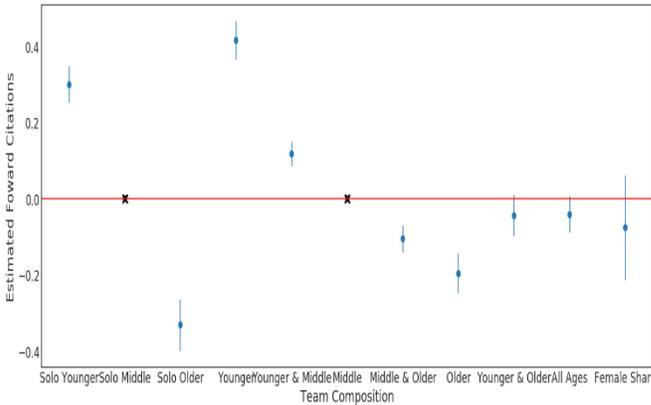


Figure 14 Semiconductors: Forward Citations & Team Composition

Medical Preparations Patents

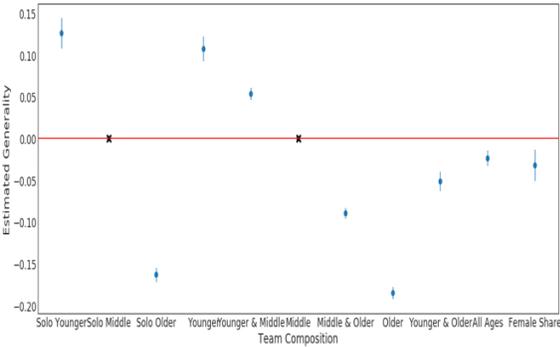


Figure 15 Medical Prep: Generality & Team Composition

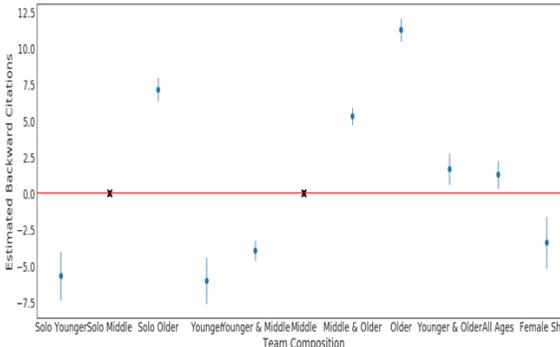


Figure 18 Medical Prep: Backward Cit & Team Composition

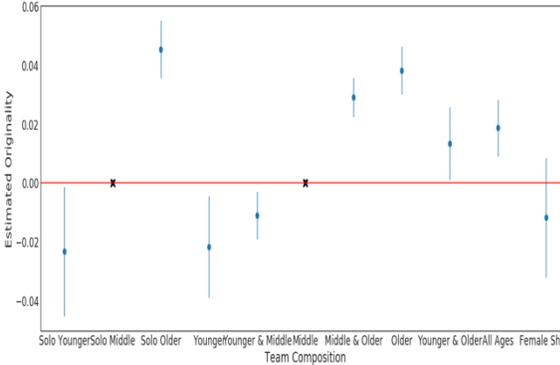


Figure 16 Medical Prep: Originality & Team Composition

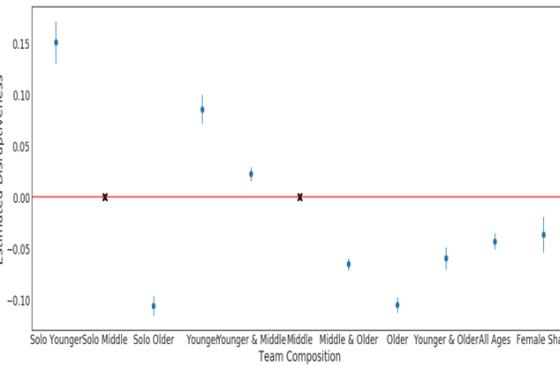


Figure 19 Medical Prep: Disruptive & Team Composition

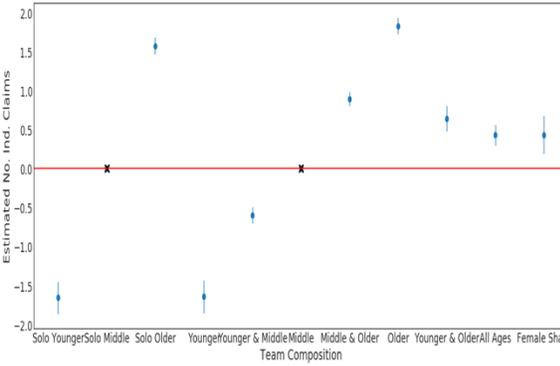


Figure 17 Medical Prep: Ind. Claims & Team Composition

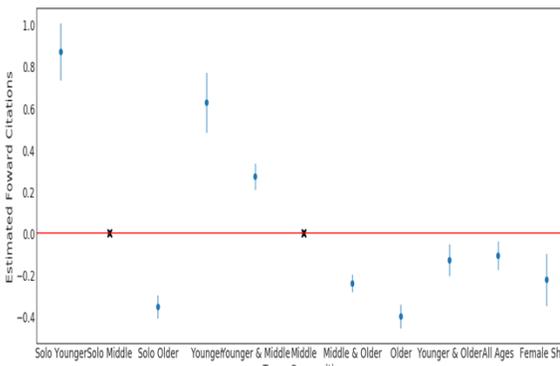


Figure 20 Medical Prep: Forward Citations & Team Composition

5 Conclusion

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.

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 would increase with age; whereas those most closely tied to rapid, novel thinking would decline with age. We had also hypothesized that some patent characteristics depend on both forms of intelligence and would therefore peak in middle age. We did indeed find that measures associated with backward citations increase with age, consistent with their dependence on crystallized intelligence. We also found that disruptiveness declines with age, consistent with its dependence on fluid intelligence. We did not, however, find any attribute that first increased with age and then decreased as predicted if a measure were dependent on both crystallized and fluid intelligence. We found instead that forward citations and generality both decline with age. The decrease in forward citations with age is consistent with the recent finding of Yu, et al (2109) for scholarly papers in the Life sciences.

An intriguing finding is that the number of independent claims increases with age. The interpretation of this finding is unclear. Perhaps the greater experience of older inventors allows them to exploit more thoroughly or more completely the ramifications of their inventive ideas.

Turning to the relationship between the age composition of teams and the characteristics of their inventions, our findings suggest the same relationships we found in solo-inventor patents playing out. We had originally hypothesized that the crystallized intelligence of older inventors and the fluid intelligence of younger inventors might complement each other in age-heterogeneous teams. This hypothesis was predicated, however, on the expectation that some patent attributes would depend on *both* forms of intelligence. Since we found no characteristic that exhibited the inverted-U age relationship that we associate with dependence on both forms of intelligence, it is perhaps not surprising that we find no evidence of complementarity. In other words, for any characteristic that either increases or declines monotonically with age, there is no reason to expect that combining inventors of different ages on a team would yield complementarity. Our results are internally consistent in that we find all measures either increase or decrease monotonically, and we find no measure for which significant complementarity seems to be present.

In interpreting our results, several constraints and caveats should be kept in mind. 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.

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6 Appendix

Table 1 Patent Attribute & Age Group Teams Regressions

	Forward	Backward	Disruptiveness	No. Claims	Originality	Generality
Solo Younger	0.366 (0.013)	-6.584 (0.161)	0.115 (0.001)	-1.588 (0.015)	-0.056 (0.001)	0.107 (0.001)
Solo Older	-0.405 (0.010)	8.727 (0.153)	-0.155 (0.001)	1.952 (0.013)	0.084 (0.001)	-0.138 (0.001)
Younger & Middle	0.347 (0.011)	-5.089 (0.138)	0.035 (0.000)	-0.780 (0.013)	-0.017 (0.001)	0.078 (0.001)
Middle & Older	-0.274 (0.011)	5.900 (0.154)	-0.067 (0.000)	0.885 (0.013)	0.038 (0.000)	-0.076 (0.001)
Younger & Older	0.587 (0.021)	-0.447 (0.232062)	-0.031 (0.001)	0.109 (0.020)	0.015 (0.001)	0.006 (0.001)
All Ages	0.106 (0.021)	-0.313 (0.256)	-0.024 (0.001)	0.077 (0.021)	0.010 (0.001)	0.016 (0.001)
All Younger	0.587 (0.015)	-8.533 (0.199)	0.087 (0.001)	-1.572 (0.019)	-0.040 (0.001)	0.124 (0.001)
All Older	-0.509 (0.014)	10.551 (0.238)	-0.134 (0.001)	2.051 (0.017)	0.072 (0.001)	-0.164 (0.001)
Female Share	0.161 (0.065)	7.044 (1.107)	0.002 (0.005)	0.237 (0.092)	-0.008 (0.007)	0.009 (0.007)
Team Size	0.110 (0.004)	2.158 (0.052)	-0.002 (0.000)	0.130 (0.004)	0.003 (0.000)	0.003 (0.000)
Chemical	-0.196 (0.014)	-2.233 (0.167)	0.006 (0.001)	-0.016 (0.013)	0.005 (0.001)	0.054 (0.001)
Comp & Comm.	-0.196 (0.016)	-3.321 (0.203)	0.002 (0.000)	0.503 (0.015)	0.001 (0.001)	0.076 (0.001)
Drugs & Med.	-0.815 (0.028)	-1.703 (0.322)	-0.012 (0.001)	0.153 (0.018)	-0.011 (0.001)	0.033 (0.001)
Elec	0.166 (0.013)	-3.808 (0.168)	0.013 (0.000)	0.163 (0.013)	-0.007 (0.001)	0.069 (0.001)
Other	0.365 (0.016)	-2.415 (0.169)	0.009 (0.000)	0.068 (0.011)	0.005 (0.001)	0.052 (0.001)
Unassigned	0.049 (0.003)	-0.415 (0.042)	0.000 (0.000)	-0.003 (0.003)	0.002 (0.000)	0.013 (0.000)
Constant	-0.009 (0.001)	0.037 (0.020)	0.000 (0.000)	0.001 (0.001)	-0.001 (0.000)	-0.002 (0.000)
Year FE	Y	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y	Y
N	2,532,594	2,532,594	2,532,562	2,532,594	2,532,594	2,532,594
RMSE	2.078	27.297	0.176	2.684	0.208	0.223

Table 2 Fractionalized & Non-Fractionalized Patenting Rates by Age Group Regressions

Table 1: Patenting Rate Over Life Course Regressions

	(1)	(2)	(3)	(4)
	FE: Non-Frac	OLS: Non-Frac	FE: Frac	OLS: Frac
15-19	-0.229*** (0.001)	-0.249*** (0.001)	-0.0837*** (0.000)	-0.138*** (0.000)
20-24	-0.206*** (0.001)	-0.226*** (0.001)	-0.0773*** (0.000)	-0.122*** (0.000)
25-29	-0.122*** (0.001)	-0.138*** (0.001)	-0.0440*** (0.000)	-0.0787*** (0.000)
30-34	-0.0332*** (0.001)	-0.0456*** (0.001)	-0.00821*** (0.000)	-0.0320*** (0.000)
35-39	0.00628*** (0.001)	-0.000746 (0.001)	0.00609*** (0.000)	-0.00618*** (0.000)
45-49	-0.0236*** (0.001)	-0.0140*** (0.001)	-0.0128*** (0.000)	0.000689** (0.000)
50-54	-0.0552*** (0.001)	-0.0328*** (0.001)	-0.0299*** (0.000)	-0.00149*** (0.000)
55-59	-0.0952*** (0.001)	-0.0558*** (0.001)	-0.0533*** (0.001)	-0.00733*** (0.000)
60-64	-0.154*** (0.001)	-0.0932*** (0.001)	-0.0887*** (0.001)	-0.0217*** (0.000)
65-69	-0.228*** (0.001)	-0.140*** (0.001)	-0.135*** (0.001)	-0.0434*** (0.000)
70-74	-0.292*** (0.001)	-0.169*** (0.001)	-0.177*** (0.001)	-0.0564*** (0.000)
75-79	-0.346*** (0.001)	-0.184*** (0.001)	-0.215*** (0.001)	-0.0638*** (0.000)
80-84	-0.393*** (0.002)	-0.194*** (0.001)	-0.250*** (0.001)	-0.0680*** (0.000)
85-89	-0.434*** (0.002)	-0.195*** (0.001)	-0.282*** (0.001)	-0.0683*** (0.000)
Cons.	0.260*** (0.001)	0.256*** (0.001)	0.124*** (0.000)	0.0886*** (0.000)
N	55355343	55355343	55355343	55355343
Within R^2	0.0130		0.0120	
Between R^2	0.00164		0.0175	
Overall R^2	0.00755		0.00341	
Adj. R^2	0.0130	0.0103	0.0120	0.0103

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3 Solo-Inventor & Patent Attributes Over the Life Course

	(1) Forward.	(2) Disruptiveness	(3) Backward.	(4) Ind. Claims	(5) Originality	(6) Generality
Age 14	1.030*** (0.132)	0.319*** (0.020)	-19.34*** (1.365)	-5.354*** (0.134)	-0.111*** (0.019)	0.374*** (0.020)
Age 15	1.052*** (0.115)	0.307*** (0.018)	-19.02*** (1.228)	-5.012*** (0.126)	-0.136*** (0.016)	0.335*** (0.018)
Age 16	0.912*** (0.127)	0.275*** (0.016)	-17.68*** (0.966)	-5.074*** (0.115)	-0.100*** (0.016)	0.323*** (0.017)
Age 17	0.771*** (0.110)	0.244*** (0.015)	-18.70*** (1.144)	-4.834*** (0.106)	-0.109*** (0.015)	0.297*** (0.016)
Age 18	0.796*** (0.115)	0.259*** (0.015)	-17.71*** (1.106)	-4.601*** (0.129)	-0.0982*** (0.014)	0.291*** (0.015)
Age 19	0.678*** (0.127)	0.227*** (0.014)	-16.21*** (0.930)	-4.462*** (0.105)	-0.105*** (0.013)	0.283*** (0.014)
Age 20	0.625*** (0.112)	0.223*** (0.013)	-15.94*** (1.261)	-4.302*** (0.117)	-0.0918*** (0.013)	0.249*** (0.014)
Age 21	0.425*** (0.149)	0.223*** (0.011)	-15.57*** (1.336)	-4.127*** (0.152)	-0.0936*** (0.012)	0.264*** (0.012)
Age 22	0.619*** (0.076)	0.189*** (0.010)	-14.03*** (0.730)	-3.792*** (0.103)	-0.0695*** (0.010)	0.252*** (0.011)
Age 23	0.617*** (0.063)	0.196*** (0.008)	-14.17*** (0.756)	-3.735*** (0.081)	-0.0702*** (0.009)	0.236*** (0.009)
Age 24	0.561*** (0.059)	0.176*** (0.007)	-13.12*** (0.627)	-3.429*** (0.144)	-0.0551*** (0.008)	0.226*** (0.008)
Age 25	0.580*** (0.057)	0.160*** (0.006)	-11.97*** (0.716)	-3.375*** (0.069)	-0.0483*** (0.007)	0.220*** (0.007)
Age 26	0.560*** (0.059)	0.150*** (0.006)	-11.38*** (0.583)	-3.221*** (0.062)	-0.0536*** (0.006)	0.214*** (0.007)
Age 27	0.481*** (0.046)	0.142*** (0.005)	-10.07*** (0.606)	-3.015*** (0.059)	-0.0564*** (0.006)	0.178*** (0.006)
Age 28	0.426*** (0.043)	0.128*** (0.005)	-9.832*** (0.512)	-2.778*** (0.056)	-0.0464*** (0.005)	0.182*** (0.006)
Age 29	0.437*** (0.042)	0.110*** (0.004)	-8.560*** (0.511)	-2.623*** (0.052)	-0.0424*** (0.005)	0.170*** (0.005)

	(1) Forward.	(2) Disruptiveness	(3) Backward.	(4) Ind. Claims	(5) Originality	(6) Generality
Age 30	0.375*** (0.035)	0.108*** (0.004)	-8.285*** (0.437)	-2.395*** (0.050)	- (0.005)	0.158*** (0.005)
Age 31	0.352*** (0.033)	0.0921*** (0.004)	-7.610*** (0.412)	-2.247*** (0.051)	- (0.005)	0.137*** (0.005)
Age 32	0.324*** (0.032)	0.0881*** (0.004)	-6.499*** (0.386)	-2.027*** (0.047)	- (0.004)	0.125*** (0.005)
Age 33	0.270*** (0.030)	0.0757*** (0.004)	-5.612*** (0.361)	-1.803*** (0.045)	- (0.004)	0.118*** (0.004)
Age 34	0.231*** (0.031)	0.0633*** (0.003)	-5.083*** (0.357)	-1.657*** (0.045)	- (0.004)	0.105*** (0.004)
Age 35	0.158*** (0.029)	0.0539*** (0.003)	-4.784*** (0.372)	-1.424*** (0.043)	- (0.004)	0.0841*** (0.004)
Age 36	0.157*** (0.030)	0.0440*** (0.003)	-4.033*** (0.330)	-1.181*** (0.044)	- (0.004)	0.0744*** (0.004)
Age 37	0.134*** (0.027)	0.0368*** (0.003)	-2.963*** (0.335)	-0.949*** (0.042)	- (0.004)	0.0571*** (0.004)
Age 38	0.0721*** (0.025)	0.0280*** (0.003)	-2.535*** (0.321)	-0.739*** (0.039)	- (0.004)	0.0437*** (0.004)
Age 39	0.0224 (0.025)	0.0201*** (0.003)	-1.294*** (0.290)	-0.443*** (0.037)	- (0.004)	0.0293*** (0.004)
Age 40	0.00221 (0.024)	0.00686** (0.003)	-0.781*** (0.280)	-0.231*** (0.037)	0.000723 (0.003)	0.0169*** (0.004)
Age 42	-0.0702*** (0.023)	-0.00978*** (0.003)	0.683** (0.315)	0.254*** (0.037)	0.00593* (0.003)	-0.0136*** (0.004)
Age 43	-0.0969*** (0.027)	-0.0173*** (0.003)	1.358*** (0.309)	0.499*** (0.038)	0.0100*** (0.003)	-0.0279*** (0.004)
Age 44	-0.159*** (0.025)	-0.0263*** (0.003)	2.336*** (0.323)	0.724*** (0.040)	0.0133*** (0.004)	-0.0402*** (0.004)
Age 45	-0.170*** (0.027)	-0.0387*** (0.003)	2.813*** (0.341)	0.966*** (0.041)	0.0181*** (0.004)	-0.0582*** (0.004)
Age 46	-0.219*** (0.026)	-0.0473*** (0.003)	3.794*** (0.352)	1.172*** (0.044)	0.0211*** (0.004)	-0.0716*** (0.004)

	(1) Forward.	(2) Disruptiveness	(3) Backward.	(4) Ind. Claims	(5) Originality	(6) Generality
Age 47	-0.269*** (0.027)	-0.0561*** (0.003)	4.383*** (0.369)	1.371*** (0.043)	0.0246*** (0.004)	-0.0796*** (0.004)
Age 48	-0.253*** (0.030)	-0.0653*** (0.003)	5.032*** (0.416)	1.611*** (0.044)	0.0239*** (0.004)	-0.0987*** (0.004)
Age 49	-0.303*** (0.030)	-0.0753*** (0.003)	6.084*** (0.442)	1.798*** (0.048)	0.0353*** (0.004)	-0.112*** (0.004)
Age 50	-0.332*** (0.031)	-0.0825*** (0.003)	6.551*** (0.467)	2.027*** (0.046)	0.0349*** (0.004)	-0.127*** (0.004)
Age 51	-0.392*** (0.029)	-0.0949*** (0.003)	6.927*** (0.421)	2.202*** (0.046)	0.0374*** (0.004)	-0.141*** (0.004)
Age 52	-0.446*** (0.030)	-0.0996*** (0.004)	7.674*** (0.452)	2.373*** (0.046)	0.0412*** (0.004)	-0.163*** (0.004)
Age 53	-0.462*** (0.030)	-0.112*** (0.004)	8.332*** (0.519)	2.609*** (0.048)	0.0497*** (0.004)	-0.171*** (0.004)
Age 54	-0.466*** (0.031)	-0.124*** (0.004)	9.256*** (0.506)	2.823*** (0.049)	0.0616*** (0.004)	-0.183*** (0.005)
Age 55	-0.495*** (0.034)	-0.136*** (0.004)	10.24*** (0.484)	2.996*** (0.050)	0.0639*** (0.004)	-0.200*** (0.005)
Age 56	-0.571*** (0.032)	-0.149*** (0.004)	10.12*** (0.508)	3.205*** (0.051)	0.0666*** (0.004)	-0.214*** (0.005)
Age 57	-0.590*** (0.035)	-0.161*** (0.004)	11.26*** (0.536)	3.395*** (0.051)	0.0732*** (0.005)	-0.227*** (0.005)
Age 58	-0.654*** (0.037)	-0.164*** (0.004)	11.67*** (0.542)	3.604*** (0.053)	0.0722*** (0.005)	-0.245*** (0.005)
Age 59	-0.704*** (0.039)	-0.184*** (0.004)	12.72*** (0.590)	3.818*** (0.058)	0.0759*** (0.005)	-0.255*** (0.005)
Age 60	-0.717*** (0.037)	-0.194*** (0.004)	12.71*** (0.578)	4.015*** (0.055)	0.0915*** (0.005)	-0.265*** (0.005)
Age 61	-0.779*** (0.040)	-0.207*** (0.005)	13.24*** (0.569)	4.173*** (0.058)	0.0867*** (0.005)	-0.283*** (0.006)
Age 62	-0.796*** (0.041)	-0.213*** (0.005)	13.89*** (0.619)	4.385*** (0.066)	0.0928*** (0.005)	-0.298*** (0.006)

	(1) Forward.	(2) Disruptiveness	(3) Backward.	(4) Ind. Claims	(5) Originality	(6) Generality
Age 63	-0.830*** (0.048)	-0.235*** (0.005)	14.02*** (0.570)	4.523*** (0.063)	0.0984*** (0.005)	-0.302*** (0.006)
Age 64	-0.926*** (0.044)	-0.239*** (0.005)	15.44*** (0.636)	4.673*** (0.064)	0.0984*** (0.006)	-0.325*** (0.006)
Age 65	-0.933*** (0.045)	-0.254*** (0.005)	16.25*** (0.699)	4.886*** (0.068)	0.108*** (0.006)	-0.330*** (0.007)
Age 66	-0.948*** (0.048)	-0.260*** (0.006)	16.43*** (0.652)	5.123*** (0.074)	0.126*** (0.006)	-0.350*** (0.007)
Age 67	-0.980*** (0.047)	-0.269*** (0.006)	17.00*** (0.724)	5.177*** (0.072)	0.112*** (0.007)	-0.354*** (0.007)
Age 68	-1.003*** (0.051)	-0.291*** (0.006)	17.88*** (0.746)	5.488*** (0.083)	0.124*** (0.007)	-0.388*** (0.008)
Age 69	-1.045*** (0.046)	-0.297*** (0.007)	18.67*** (0.844)	5.512*** (0.086)	0.129*** (0.007)	-0.379*** (0.008)
Age 70	-1.146*** (0.072)	-0.305*** (0.007)	18.76*** (0.715)	5.780*** (0.085)	0.123*** (0.008)	-0.404*** (0.009)
Age 71	-1.134*** (0.049)	-0.313*** (0.007)	19.46*** (0.980)	5.985*** (0.091)	0.142*** (0.008)	-0.417*** (0.009)
Age 72	-1.165*** (0.055)	-0.338*** (0.008)	20.13*** (0.958)	6.144*** (0.091)	0.149*** (0.008)	-0.433*** (0.010)
Age 73	-1.174*** (0.062)	-0.342*** (0.008)	20.04*** (0.848)	6.333*** (0.099)	0.154*** (0.009)	-0.436*** (0.011)
Age 74	-1.234*** (0.056)	-0.364*** (0.009)	20.32*** (0.852)	6.452*** (0.101)	0.158*** (0.010)	-0.445*** (0.011)
Age 75	-1.248*** (0.071)	-0.368*** (0.010)	20.92*** (0.819)	6.673*** (0.104)	0.161*** (0.011)	-0.459*** (0.012)
Age 76	-1.362*** (0.063)	-0.393*** (0.010)	21.49*** (1.037)	7.097*** (0.140)	0.180*** (0.011)	-0.504*** (0.013)
Age 77	-1.357*** (0.062)	-0.412*** (0.012)	21.52*** (1.077)	7.216*** (0.144)	0.188*** (0.012)	-0.509*** (0.014)
Age 78	-1.236*** (0.090)	-0.409*** (0.012)	22.14*** (1.026)	7.332*** (0.146)	0.191*** (0.013)	-0.519*** (0.016)

	(1) Forward Cit.	(2) Disruptiveness	(3) Backward Cit.	(4) Ind. Claims	(5) Originality	(6) Generality
Age 79	-1.291*** (0.081)	-0.428*** (0.013)	22.41*** (0.878)	7.477*** (0.149)	0.191*** (0.014)	-0.539*** (0.016)
Age 80	-1.463*** (0.091)	-0.425*** (0.013)	22.51*** (0.869)	7.691*** (0.163)	0.183*** (0.015)	-0.555*** (0.018)
Age 81	-1.391*** (0.122)	-0.402*** (0.015)	23.28*** (0.936)	7.992*** (0.193)	0.175*** (0.016)	-0.570*** (0.019)
Age 82	-1.408*** (0.103)	-0.429*** (0.015)	22.94*** (1.101)	8.044*** (0.186)	0.175*** (0.017)	-0.597*** (0.022)
Age 83	-1.602*** (0.082)	-0.461*** (0.017)	22.50*** (1.073)	8.027*** (0.197)	0.215*** (0.020)	-0.581*** (0.023)
Age 84	-1.602*** (0.114)	-0.455*** (0.020)	27.11*** (1.490)	8.696*** (0.245)	0.231*** (0.021)	-0.617*** (0.024)
Age 85	-1.676*** (0.140)	-0.482*** (0.019)	26.46*** (1.816)	9.002*** (0.293)	0.233*** (0.023)	-0.664*** (0.027)
Age 86	-1.856*** (0.184)	-0.470*** (0.025)	25.67*** (1.336)	9.470*** (0.290)	0.214*** (0.025)	-0.660*** (0.030)
Age 87	-1.729*** (0.243)	-0.509*** (0.024)	24.15*** (1.181)	9.152*** (0.251)	0.224*** (0.027)	-0.680*** (0.031)
Age 88	-1.993*** (0.136)	-0.486*** (0.037)	23.27*** (1.594)	9.485*** (0.312)	0.254*** (0.035)	-0.726*** (0.036)
Cons	1.205*** (0.019)	0.168*** (0.002)	10.84*** (0.274)	1.854*** (0.030)	0.486*** (0.003)	0.512*** (0.003)
N	763917	763909	763917	763917	763917	763917
R ²	0.0106	0.243	0.0236	0.121	0.0857	0.0607
RMSE	1.239	0.150	15.01	1.870	0.169	0.182
Year FE	Y	Y	Y	Y	Y	Y

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$