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INVENTION AND THE LIFE COURSE:
AGE DIFFERENCES IN PATENTING

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Invention and the Life Course: Age Differences in Patenting
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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. For solo inventors, backward citations and originality, which are connected to experience, were found to increase with age. Forward citations, number of claims, and generality measures, as well as a citation-based measure of disruptiveness decline on average with inventor age. A similar pattern was found for performance in teams based on the average age of inventors in the team. Exploration of age diversity showed that teams with a wider age range had patents that are slightly more important (i.e., with more forward citations). The findings have the potential to advance scholarship on the life course of innovation with implications for workplace policies.

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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 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 attributes of patent activity change as inventors age.

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 only previous studies of patents as a function of age are in Sweden (Jung & Ejermo, 2014), and two studies looking at a subsample of US inventors (Jones, 2009, Nager, et. al., 2016). Most of this work is cross-sectional, looking at the age distribution of creators within samples of achievements. Such analysis confounds how the abilities of individuals change over their life with selection into and out of the creative activity (Yu, et al 2019). By looking at 3 million patents associated with 1.4 million inventors over the period 1976-2018, we can complement cross-sectional comparisons with fixed-effects estimation that mitigates selection issues.

Consistent with prior related work, we find that the *rate* at which inventors successfully patent rises on average in the first decades of work life, and then begins to decline at around age 40. Surprisingly, however, we find that the *nature* of inventions changes more or less monotonically with age, with invention attributes related to experience (backward citations, originality) rising with age, and patent attributes related to creativity (forward citations, disruptiveness, generality, and number of claims) falling with age. We find that patents generated by teams of inventors show patterns basedon the mean age of the team that are consistent with the patterns that are related to the age of solo inventors. Yet, we did find that the diversity of age within teams had small effects on the attributes of team patents. The largest effects of age variability within teams was found for forward citations, suggesting that mixed age teams produce more important inventions.

The following section grounds this analysis in the theoretical and empirical literature on how cognitive abilities change with age. Section 3 describes the construction of the data and Section 4 provides an overview of the empirical approach. Section 5 presents results, and Section 6 analyzes the robustness of the results to errors introduced in our search for inventor ages. Section 7 provides discussion and Section 8 gives concluding comments. Complete documentation of the data collection process is given in Kaltenberg, et al (2021)

2 Innovation and the Life Course

2.1 Invention 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). 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). Much of this work has been done using standardized cognitive test batteries in cross-sectional or longitudinal studies or in laboratory studies using experimental designs. However, little is known about how these ability changes might affect performance on tasks in daily life, including the work domain (Hertzog, 2020). 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). A possible explanation for performance peaking in middle age is that this 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 patent attributes such as, forward citations, backward citations, disruptiveness, number of claims, originality and generality) 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 important contribution of both of Gc and Gf abilities 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*. If a characteristic depends on *both* Gc and Gf, then we would expect it similarly to peak in middle age, where inventors can best draw on both abilities. If, however, a given characteristic is determined largely by only one form of ability, then we might it expect it to either rise with age (if it depends on Gc) or fall with age (if it depends on Gf).

2.2 Age Diversity and Innovation in Inventor Teams

Collaboration in scientific research and invention is an active research area (e.g. Wuchty et al., 2007; Freeman, et al., 2015; Ahmadpoor and Jones, 2019). 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.

Given the aging of the population and the increased number of older adults remaining in the workforce beyond traditional retirement age, there has been interest in examining the effects of age diversity in the workplace (Salas, & Paoletti, 2019). The results generally show there are benefits to having age diversity for innovation and productivity (Gomez et al., 2019; Hammermann et al., 2019; Li et al., 2020). Yet, there are also moderating factors such as firm size, job security and type of industry that affect whether or not diversity is beneficial (Garnero et al., 2014 Meulenaere et al., 2015).

The relationship between team age structure and patent attributes should, again, be conditioned by how the attributes are related to Gc and Gf. If there are attributes that depend on both forms of ability, this suggests the theoretical possibility of age complementarity or benefits of age diversity. That is, we would expect that attributes requiring both Gc and Gf might be most easitly produced by teams who have younger members (with high Gf) *and* older members with high Gc or primarily middle-aged adults, who typically would have moderate to high levels of both Gc and Gf. The patent data set we present in this paper allows us to examine whether the productivity of workers differs when participating in age-heterogeneous vs. age-homogeneous teams.

3 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 searched 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 extracted the first and last names (including any aliases), middle name or initial, city, state, and age, and computed a similarity score to the information in our database for each result.

We were able to capture age information by exactly matching the first and last name of the inventor with their associated location in 72% of inventors in Radaris, 65% of inventors for Spokeo and 66% of inventors for Beenverified. For a subset of inventors, we also searched for additional ages using the website Peoplefinder. Across all databases, we found at least one age to be associated with a name and location for approximately 93% of the inventors in the dataset. About 30% of the age results are consistent across at least three web-scraped sources. In Section 6, we present an analysis of the extent to which the inventors we failed to find differ systematically from those we did find.

After scraping the web for age related information, we created a few heuristics to calculate ages where there is disagreement between the sources we scraped. We use the average of all the ages we identify for a given inventor, if the difference was less than three years. We subtracted the age from 2018, the year the searches were done, to calculate the birth year of the inventor.

We calculated an inventor's age at patenting by subtracting their birth year from the year that they applied for each patent. We limited our dataset so that we exclude inventors for whom the age we found suggests that they applied for a patent before age 15 or 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.[1] In Section 6, we consider whether the possibility of matching errors in the data construction is likely to be having a significant impact on the results.

4 Methods

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

4.1 Rate of Patenting over the life course

To study an inventor's rate of patenting over their life course we created 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. 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 patent applications per capita in 2012.

We counted patents two different ways when looking at an inventor's rate of patenting. A general count, which counts every patent on which the individual appeared as an inventor in a given year. We call this the *non-fractionalized patent* count. Given that teamwork is an important factor in patenting activity, we also calculated *fractionalized* patents, for which each patent counts only as the reciprocal of the team size. Thus an inventor who appeared in. a given year on one solo patent, one with 1 other inventor and 1 as part of a team of 5 would have a non-fractionalized count of 3 and a fractionalized count of 1.7 in that year.

To estimate the rate of patenting of inventors over their life course we used an inventor fixed effects model with age dummies, which we also estimated by gender and technological field.

[1] For more detail on the matching and cleaning procedures, see Kaltenberg, et al (2021).

To estimate the rate of patenting of inventors over their life course we used an inventor fixed effects model with age dummies, which we also estimated 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 used 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 used 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:

Equation 1

$$Prod_{ia} = \sum_a \beta_a Age_{ia} + \alpha_i + \varepsilon_{ia}$$

where i is the inventor and a is the age of the inventor when they patented. $Prod$ is the fractionalized or non-fractionalized patent count for that inventor at that age. Age is a dummy variable set to unity for observations corresponding to age a. α_i is the inventor fixed effect. That is, rather than estimating some parametric form for the relationship between patent production and age, we allow each age to have its own average productivity. Lastly, ε is the error term. We use cluster robust standard errors.

4.2 Patent attributes

We observe the attributes of patenting activity throughout an inventor's lifetime by using citation-based indicators: forward citations, backward citations, number of total claims, disruptiveness, generality, and originality. Forward and backward citations and the number of independent claims are provided by the USPTO through patentsview. The number of forward citations received by a patent are widely used as a measure of 'importance' and the number of backward citations made by the patent indicate the depth of connection to previous technology. Generality and originality are measures of the technological diversity of, respectively, the forward and backward citations. They are calculated as one minus the sum of squared shares of patents by patent class, so they are equal to zero if all of the citing/cited patents are in the same class, and they approach one as the patents are spread across classes (Trajtenberg, et al, 1997; Squicciarini, et al, 2013).[2]

The claims in a patent represent the legal statement(s) as to what object, composition or method is specifically claimed for patent protection. A larger number of claims may indicate an invention of broader scope, and the number of claims has been used as an indicator of patent scope

[2] The simple calculation of generality and originality is biased towards towards zero for patents with few citations. We apply the bias correction described in Hall, et al (2001) to correct for this bias.

or breadth. (Squicciarini, et al, 2013).[3] Because the number of citations and the number of claims in U.S. patents varies by technology field and has been rising over time, we normalize these three measures by dividing the actual number by the mean for that indicator across all patents applied for in the given year and patent class. In order to calculate these citation metrics, we include only patents granted before 2016 as more recent years of patent citations are more likely to have errors and are left with 2,532,562 patents.

The disruptiveness measure was proposed by Funk & Owen-Smith (2016). This metric, which they call the CD index, captures the extent to which the patent represents an important new technology trajectory. It is based on the extent to which the patents represented by the forward citations also cite the patents represented by the backward citations. It ranges between the value of -1 (all of the patents making the forward citations also contain citations to patents receiving the backward citations—minimally disruptive) to 1 (none of the patents making the forward citations contain citations to the patents receiving the backward citations—maximally disruptive).

For our analysis, we consider two aspects of patent attributes, patenting that is solo-authored, and patenting by all inventors.

4.2.1 Solo-authored inventors

We begin with an analysis of single-inventor patents to understand patent attributes over the life course at the individual level. The data include 439,822 inventors holding 763,917 solo-inventor patents for which we have patent attribute information. We estimate the following model:

Equation 2

$$Q_{pi} = \sum_k \beta_k Age_{pi} + \sum_f \beta_f Field_{pi} + \alpha_i + \varepsilon_{pi}$$

This model estimates the patent attribute measure Q for patent p invented by inventor i. Dummies for each age are included as before, allowing for a completely flexible relationship between age and each indicator variable. 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.

4.2.2 All inventors

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

[3] Claims can be 'independent' or 'dependent'. Dependent claims narrow the scope of the independent claim on which they depend. Thus, the number of independent claims is probably a better measure of patent scope than the total number of claims. However, the Patentsview website did not have a consistent time series for independent claims as of the time of this analysis.

ages of the inventors associated with that patent, which leaves us with 2,532,594 patents. [4] Our estimation model is at the patent level, and is as follows:

Equation 3

$$Q_p = \sum_j \beta_j Age_{pj} + \beta_s SD_p + \beta_2 Gender_p + \sum_m \beta_m Team_{pm} + \sum_f \beta_f Field_{pf} + \alpha_i + \varepsilon_p$$

We estimate how the patent attribute measure Q varies with the mean age of the members of the inventor team, using dummies for mean age rounded to the nearest integer, to allow complete flexibility in the shape of the age-attribute relationship as before. We also include the standard deviation of age across the members of the team in order to test for effects of age heterogeneity within the team.[5] Although there are other measures used to examine age diversity (e.g., Blau index, coefficient of variation), the standard deviation has been suggested as most appropriate to examine the extent of age separation in a team in contrast to the disparity or variety (Harrison & Klein, 2007; Orlando and Shelor, 2002; Solanis et al., 2012). We were most interested in whether having both younger and older adults on the same team would be an advantage, given that they would bring different cognitive abilities. Thus, given our focus on the potentially complementary skills brought by younger and older adults, we examined whether diversity in terms of a larger degree of age separation on teams would be associated with higher quality patents. *Gender* is the fraction of the team members who are female. Previous work has found that citations and other significance measures are increasing in the size of the inventor team, so we include a full set of dummies for each team size up to 8. We also include 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. We use robust standard errors, and the error term included is ε_p.

Estimation of Eq. (3) presents computational challenges because of the unusual way in which the inventor fixed effects enter. Unlike the typical panel data situation, each inventor is connected to a varying number of patents, and each patent has a varying cast of associated inventors. This makes estimation by demeaning or absorbing the fixed effects impossible. In principle, it could be estimated including dummy variables for each inventors, but the very large number of inventors makes this infeasible. To solve this problem, we partialed out each variable with respect to each

[4] We exclude the very small number (1.20%) of patents with more than 8 inventors, as it is not clear how to think about the effects of age composition for large teams.

[5] Theoretically, the effect of age heterogeneity on team performance could be more complex than would be captured by simply including the standard deviation of age, particularly if the age-attribute relationship is nonmonotonic at the individual level. We did test for such effects by estimating versions of the model with dummies for particular combinations of ages, e.g. teams with someone below 35 and someone over 50. These age-combination effects were always close in magnitude to the simple average of the effects associated with the groups being combined. This is not surprising *ex post*; as discussed below, we find the age-attribute relationships in the individual regressions to be monotonic.

of the covariates to reflect the contribution of the average patent quality of each inventor. The approach is similar to solving high-dimensional fixed effects by Correia (2017).[6]

Table 1 presents summary statistics for key variables in the datasets used for analysis.

Table 1a Summary Statistics for Inventors

	count	mean	std	min	25%	50%	75%	max
Birthyear	1,508,676	1957.65	16.30	1883	1948	1959	1969	2001
Gender (1 = Female)	1,228,900	0.11	0.31	0.0	0.0	0.0	0.0	1.0
Lifetime Pat.	1,508,676	4.56	12.26	1	1	2	4	1787

Table 1b Summary Statistics for Patent Attributes (Solo Inventors, N Inv = 444,559)

	count	mean	std	min	25%	50%	75%	max
Appl. Year	978405	1995.364	10.985	1974	1987	1997	2004	2015
Age	978405	45.384	12.254	15	36	44	54	89
Forward Cit. (Norm.)	978405	1.071	2.379	0.000	0.191	0.532	1.173	226.494
Backward Cit. (Norm.)	978405	1.169	1.846	0.000	0.424	0.795	1.359	125.968
Disruptiveness	978391	0.165	0.336	-1.000	0.000	0.015	0.167	1.000
N. Claims	978301	1.045	0.799	0.047	0.536	0.930	1.317	63.072
Originality	978405	0.474	0.333	0.000	0.000	0.542	0.740	1.000
Generality	978405	0.345	0.365	0.000	0.000	0.228	0.694	1.000
Gender	978405	0.038	0.190	0.000	0.000	0.000	0.000	1.000

[6] We would like to acknowledge Sergio Correia who helped solve this computational issue.

Table 1c Summary Statistics for Patent Attributes (All, N Inv = 1,314,716)

	count	mean	std	min	25%	50%	75%	max
Appl. Year	5124784	1999.708	9.793	1974	1994	2001	2007	2015
Team Avg. Age	5124784	42.972	9.156	15	37	42	48	89
Forward Cit. (Norm)	5124784	1.354	3.514	0.0	0.167	0.570	1.365	339.159
Bakward Cit. (Norm)	5124784	1.391	2.754	0.0	0.351	0.752	1.454	345.994
Disruptiveness	5124732	0.103	0.275	-1.0	-0.002	0.002	0.072	1.000
N. Claims	5123773	1.144	0.845	0.0	0.628	1.029	1.391	63.072
Originality	5124784	0.490	0.334	0.0	0.138	0.572	0.763	1.000
Generality	5124784	0.272	0.350	0.0	0.000	0.000	0.616	1.000
Gender Ratio	5124784	0.023	0.111	0.0	0.000	0.000	0.000	1.000

5 Results

5.1 Overview

5.1.1 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 1 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. For this purpose, multi-inventor patents are ‘credited’ fully to each inventor on the team. Patenting activity peaks in the early 40s for men and slightly earlier for women in the late 30s. It is also noteworthy that both men and women continue to patent throughout adulthood in later life, although at lower rates. Overall, men patent more than women beginning at about age 26 through the late 70s. At their peaks, the average male inventor in the dataset is associated with about one patent every four years, and the average female about one every six years.

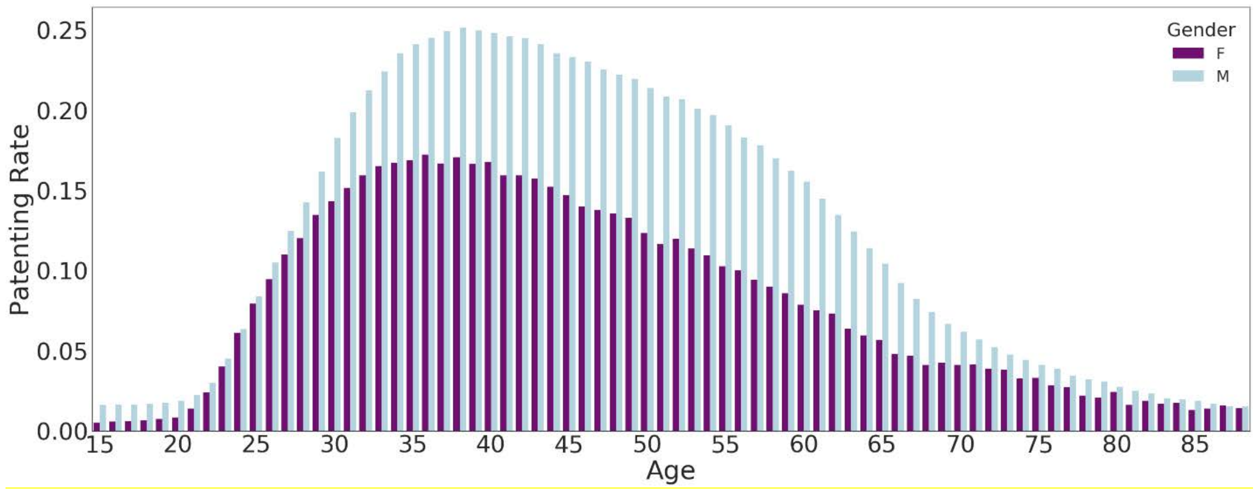

Figure 1 Patenting Activity by Age and Gender (patents per year per inventor, normalized to the overall patenting rate in 2012)

5.1.2 Career Inventors' and patenting activity

Previous work on the life course of patenting often uses elapsed time since the 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, defined as those with more than one patent in their life time. Figure 2 only presents information for people who are born after 1959 to minimize bias caused by censoring.[7] 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).

[7] Inventors born before 1959 could plausibly have had their first patent before our data start in the mid 1970s.

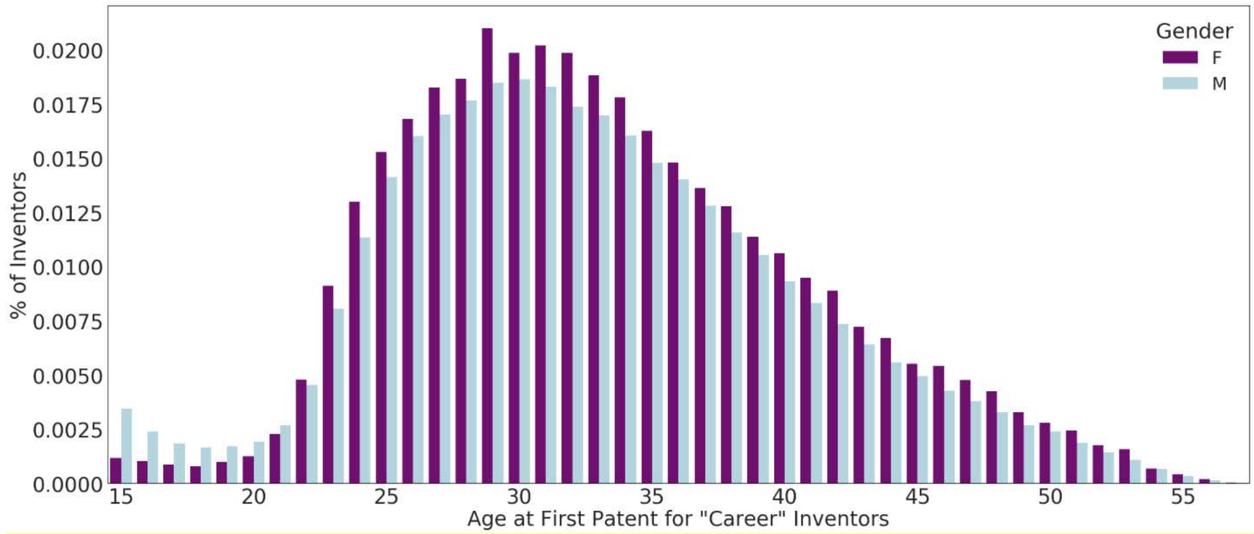

Figure 2 Age at first patent for inventors with multiple patents

Previous work on the ‘burden of knowledge’ has shown that the age at which scientists get their first publications and NIH research has been increasing over the past few decades (Jones, 2009). Figure 3 presents an analogous comparison for first patents. It shows the opposite trend, with the age at first patent for inventors with multiple patents being younger in the most recent decade than the previous decade. There are several possible explanations for this. First, the overall rate of patenting has been rising rapidly, possibly suggesting that the USPTO standard for granting a patent has been falling. This might lead to younger inventors having their first success at a lower age. Second, inventor team sizes have been rising; since we give full credit to all inventors on a team, this may have lead to it being easier for a younger inventor to get their name on a patent earlier in their career.

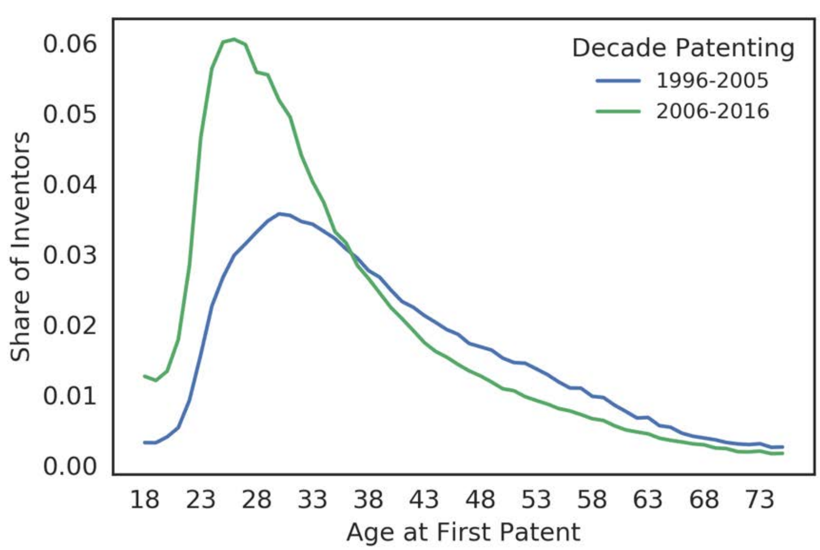

Figure 3 Age at first patent over time

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 different 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 4. This fact enables within-person longitudinal analysis which we discuss in section 5.2. It is noteworthy that there are many fewer women inventors with multiple patents.

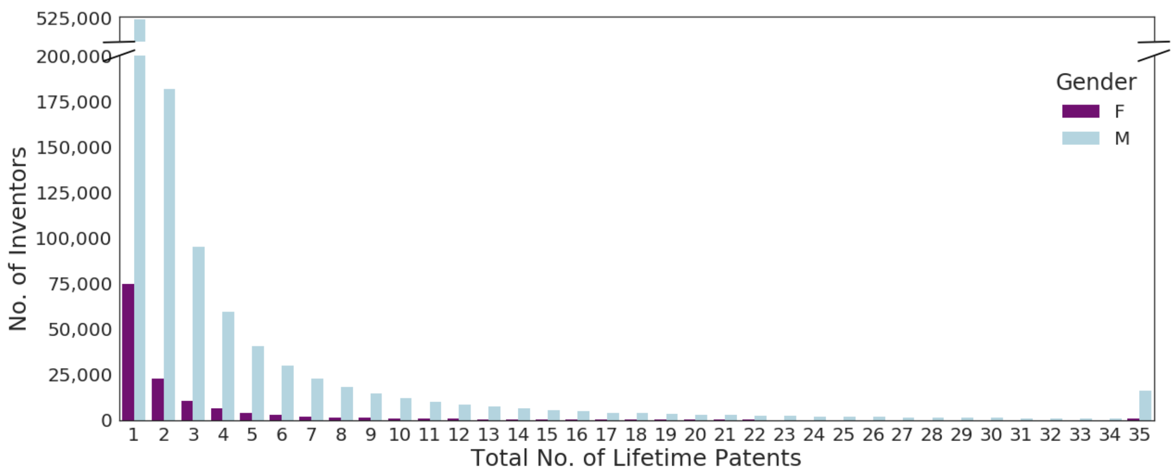

Figure 4 Lifetime Total Patents by Inventor

5.2 Rate of patenting over the life course

We estimate the rate of patenting of inventors over their life course using a fixed effects model as presented in Eq. (1). For all our estimates, the reference group is age 41. Every estimate we provide in this section is significant at the .01% level. Much previous work on age and creativity has been based on cross-sectional rather than longitudinal comparisons. It is therefore interesting to compare the fixed effects results to the raw counts by age of inventor, to see how much difference controlling for the heterogeneous quality of inventors makes.

As noted, in counting inventors' productivity, we need to choose how to count multi-inventor patents. We can count multi-inventor patents as a full patent credited to each of its inventors, or we can fractionalize the patent counts, so that each inventor gets credit for 1/n of a patent, where n is the number of inventors on the patent. The age-patenting profiles produced by the two methods might differ, particularly if inventors of different ages have systematically different proclivities to participate in teams (a question we explore further below). As it turns out, the age profiles for fractionalized and non-fractionalized counts are quite similar. For brevity we display here the results for the fractionalized counts; the profiles for the non-fractionalized counts are presented in Appendix Figure A1.

Figures 5a and 5b compare the patenting-age profiles for the raw data and the fixed effect estimates. The profiles are remarkably similar. We might have thought, for example, that there is some amount of patenting at young ages by people who really are not very good inventors, who then figure out that they are not good at it and drop out. To the extent this were true, it would generate an apparent decline in patenting with age that would disappear in the fixed effects estimates, because the latter measure only the *relative* rate of patenting at different ages for a given inventor. The fact that the fixed-effect estimates are so similar to the raw data suggests that selection out of (or into) patenting activity is not highly correlated with innate ability to patent.

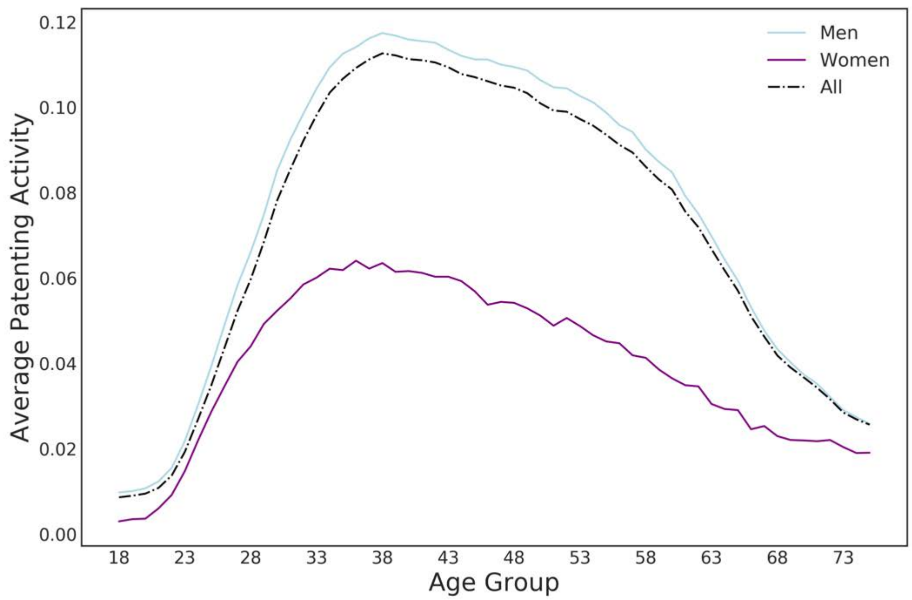

Figure 5a Raw Average Patenting Activity by Age and Gender (fractionalized patent count)

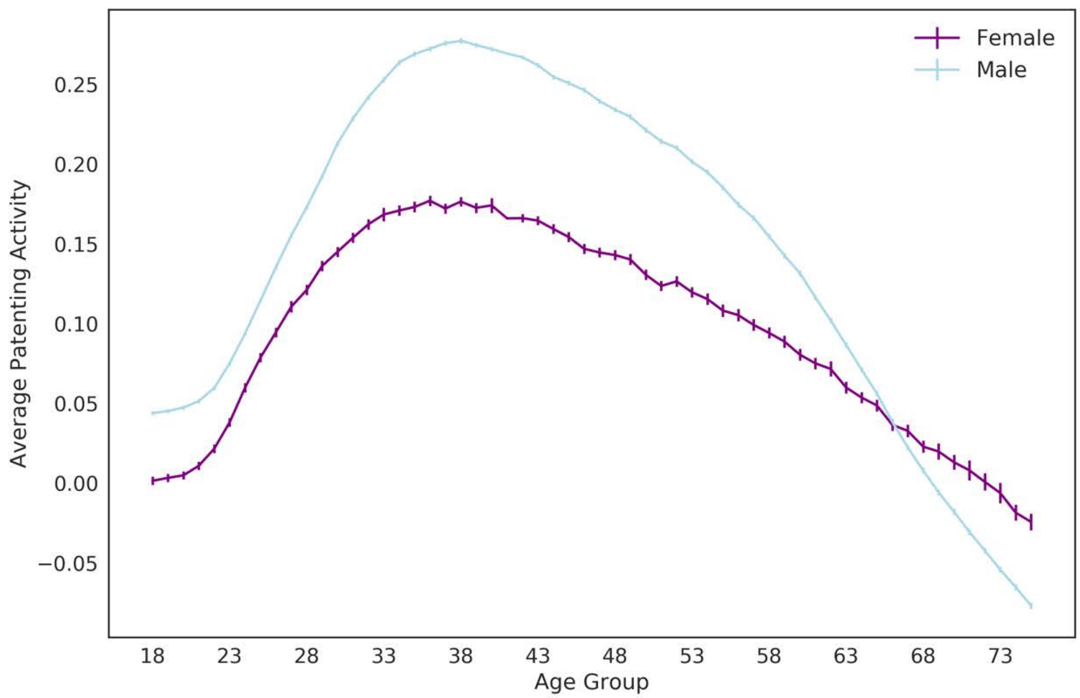

Figure 5b Patenting Activity by Age and Gender, Estimated with Inventor Fixed Effects (fractionalized patent count)

5.2.1 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. Figure 6 provides an overview of patenting rates by age and field separately for men and women.

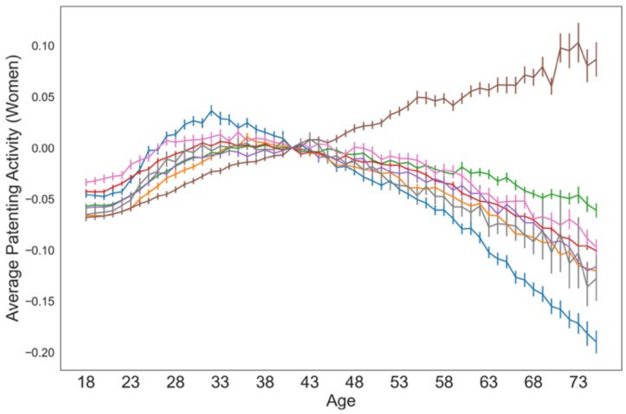

Figure 6a Patent Productivity by Age and Technological Field, Women

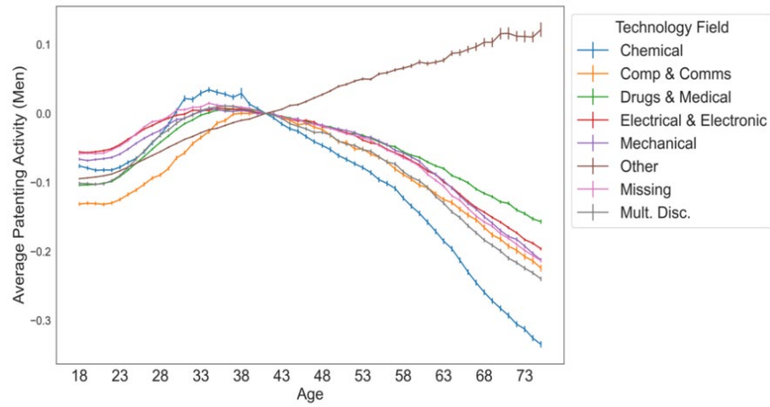

Figure 6b Patent Productivity by Age and Technological Field, Men

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.

5.3 Patent attributes over the life course for solo inventors

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 7-12 display the coefficients on the age dummies from estimating Eq. (2) for the six patent attributes. The omitted age is 41, so all of the estimates represent the average difference at a given age relative to average age 41. The estimates are from regressions with inventor fixed effects, so the interpretation of the coefficients is the relative performance for a given inventor at different ages[8] Complete regression results are presented in Appendix Table A1. None of these attributes exhibits a pattern of rising to a peak in middle age and then declining, as found for the frequency of patenting. Forward citations, number of claims, disruptiveness and generality all exhibit monotonic decline in age, except for some 'noise' in the estimates at very young and very old ages, likely due to the relatively small number of observations at those ages. In contrast, backward citations and originality show a monotonic increase (again after noisy estimates below age 20), peaking at about age 70, with some evidence of a decline after that.

The effects for forward citations, disruptiveness, backward citations generality and originality are quite large. Because the citation counts have normalized relative to the mean for the technology-year cohort, the estimated forward citations coefficient of about .5 ages in the early 20s indicate that on average a given inventor's patents receive about 50% more citations at this

[8] Estimates without inventor fixed effects (not reported) are not qualitatively different.

age than that inventor's patents when they are 41; when the inventor reaches their late 50s, their patents will receive about half as many as at age 41.

As noted, disruptiveness is bounded between -1 and 1; its standard deviation in our dataset is .275. The estimates indicate that the patents of the inventor in their early 20s are about .2 more disruptive, and those of the inventor in their early 60s .3 less disruptive, than those of a 41-year old. For backward citations, the average rate of citations made by an inventor in their mid 60s is about 1.4 times the number for an inventor in their early twenties. Generality and originality both vary from zero (all citations in the same technical field) to an asymptote of one (citations infinitely distributed across different fields). So the decrease in generality of about .6 and the increase in originality of about .4 are quite large.

The effect for number of claims, while quite monotonic is quite small: a decrease of something like .2 claims on average over the life course, against an average number of claims of about 1.14.

The findings of monotonic relationships with age for all of these attributes suggests that each attribute is linked more strongly to one or the other of the cognitive abilites Gf and Gc. Forward citations—which is typically interpreted as capturing technological impact or importance—and disruptiveness seem to be linked to fluid intelligence (Gf or the ability to learn and process new information quickly and efficiently), which makes sense if such rapid thinking and processing is the source of important new concepts. Backward citations appear closely linked to crystalized intelligence (Gc or experience-based knowledge), which makes sense if more experienced inventors produce new inventions more thoroughly grounded in previous technology.[9] It is less clear to us why the number of claims would be linked to fluid intelligence, but since the effect is small in magnitude the connection appears insignificant in any case. Finally generality (the technological diversity of the forward citations) appears linked to Gf and originality (the technological diversity of the backward citations) appears linked to Gc. We note in this regard that the nomenclature of 'originality' and 'generality' is conventional and is based on an untested notion that inventions that connect to a wide diversity of earlier technologies can be thought of as 'original' and those that connect to a wide range of future technologies can be thought of as 'general'. The empirical fact is that as inventors age, their inventions tend to draw on a a wider range of technological fields, but are connected to a narrower technological range of future inventions. Our data do not themselves provide any interpretation of these tendencies.

[9] Note that patent citations differ from citations in scholarly papers in that they are placed in the patent by the patent examiner, based on a combination of citations noted by the applicant and the examiner's own search of the prior art. Depending on the time period, something like half of citations are added by the examiner. Thus, the finding of a higher rate of citation by older inventors does not mean (only) that they literally are more knowledgeable about prior patents, but more generally that they are undertaking inventions that are more extensively connected to prior technology.

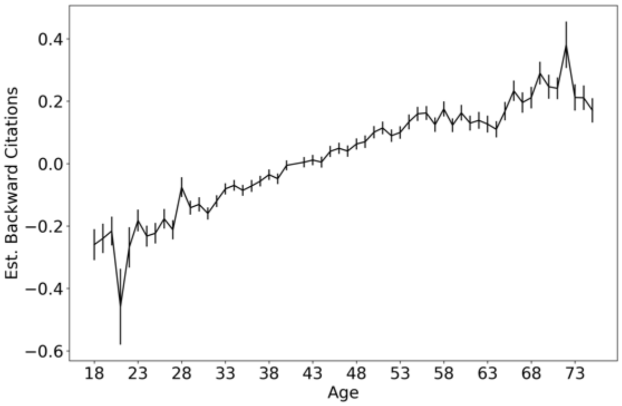

Figure 7: Backward citations by age for solo inventors, fixed effects estimates

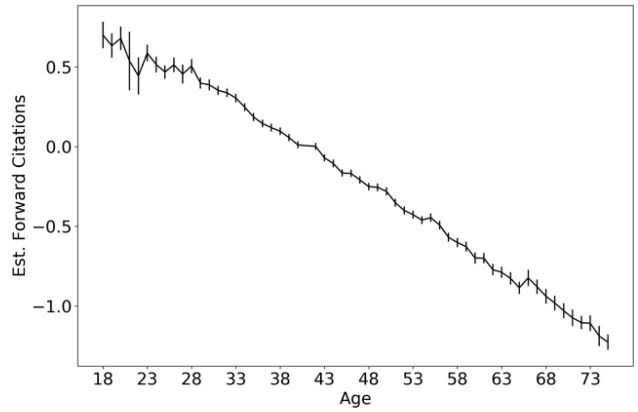

Figure 8: Forward citations by age for solo inventors, fixed effects estimates

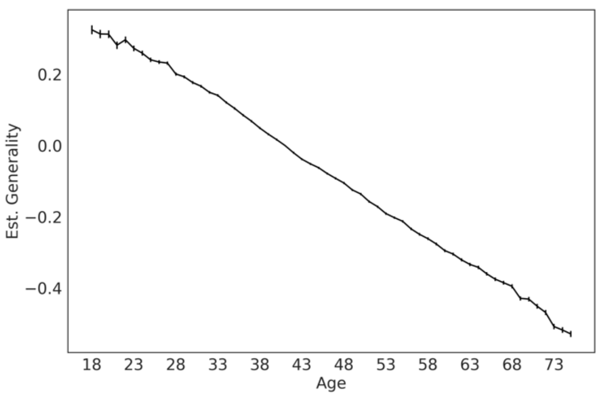

Figure 9 Number of claims by age for solo inventors, fixed effects estimates

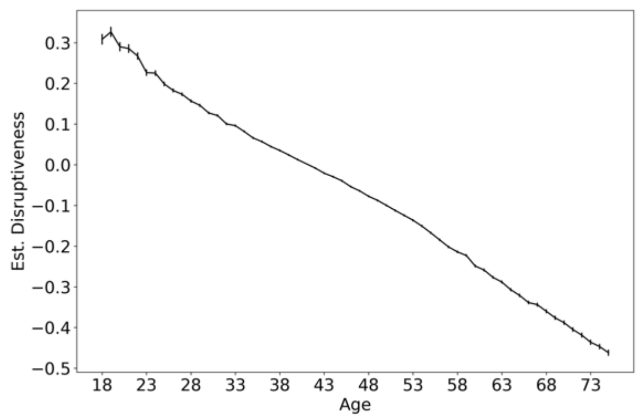

Figure 10: Disruptiveness by age for solo inventors, fixed effects estimates

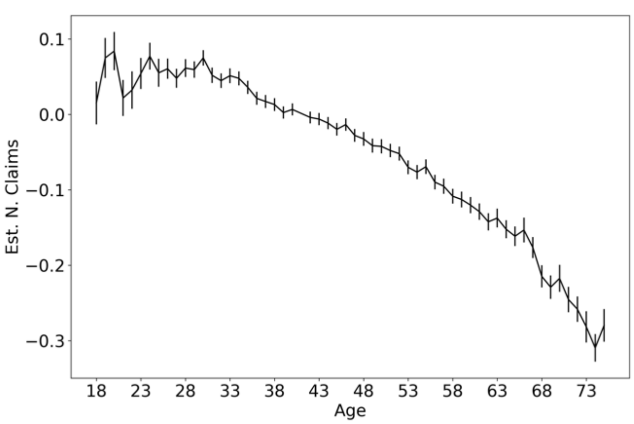

Figure 11 Generality by age for solo inventors, fixed effects estimates

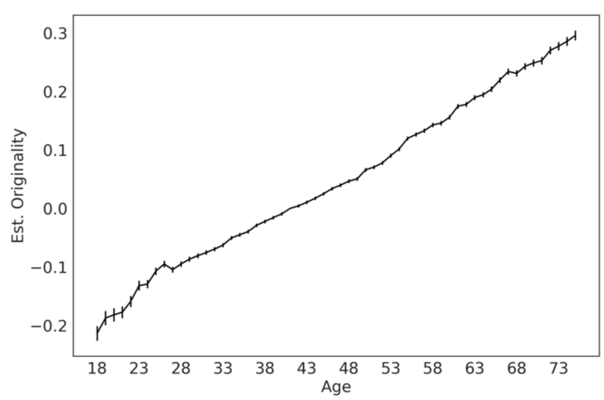

Figure 12 Originality by age for solo inventors, fixed effects estimates

5. 4 Team composition and patent attributes

5.4.1 Patenting activity and teamsize

Teamwork is an important part of patenting activity. Figure 13 shows the fraction of each inventor's patents that came from a team, and the average team size (for those patents that were not solo), as a function of age and gender. Teamwork is quite common; overall about 80% of a given male inventor's patents come from a team, and 90% for women.[10] There is a slight tendency for the likelihood of being on a team to decline with age, particularly after about age 50. Men experience teams with an average size of about 4; for women about 4.5. There is little systematic variation in the size of teams over their life course for either gender.

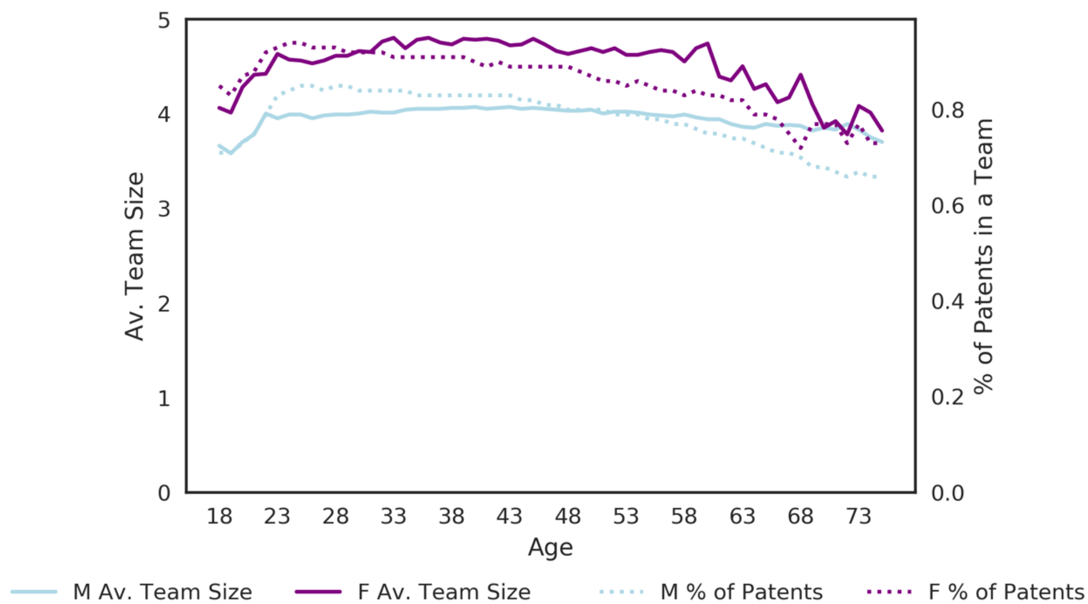

Figure 13 Inventor Team size by age and gender

5.4.2 Age and gender composition of teams and attributes

We turn now to estimation of the relationship between team age composition and patent attributes using Eq. (3). The resulting mean age dummy coefficient estimates from the inventor-fixed-effects regression are displayed in Figures 14-19. Complete regression results are presented in Table 2. The Figures all show patterns qualitatively quite similar to the corresponding Figure for the solo-inventor patents. The effects are, however, quantitatively larger except for

[10] This is not saying that 80-90% of *patents* are team patents. As noted above, solo inventor patents are about 33.23% of the total in our sample. But when looked at from the perspective of the inventors, each multiple-inventor patent is counted multiple times, so the fraction of inventor experiences that are on teams is higher than the fraction of patents from teams.

disruptiveness. Comparing a team with average age of 25 to one whose average age is 60, the former produces patents that on average receive about 4 times as many forward citations, make about 1 more claim, exhibit disruptiveness about .5 higher, make about one quarter the number of backward citations, have about .2 less originality, and have about .05 more generality . The generally larger effects are perhaps not surprising, as a team of several people with an *average* age of 20 (or 60) is more unusual than a single inventor having that age. This rarity of extreme values of the average is also the reason why the estimates are noisy for average ages below 25 and above 70.

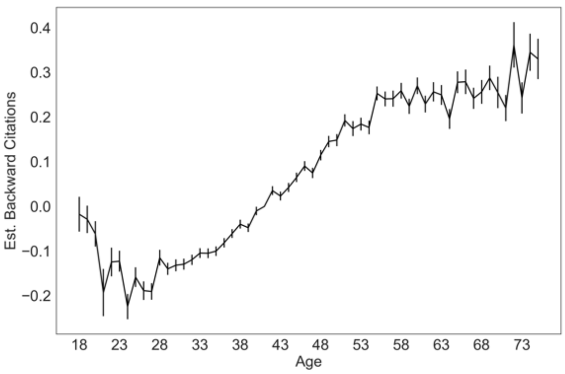

Figure 14 Backward citations by age for all inventors, fixed effects estimates

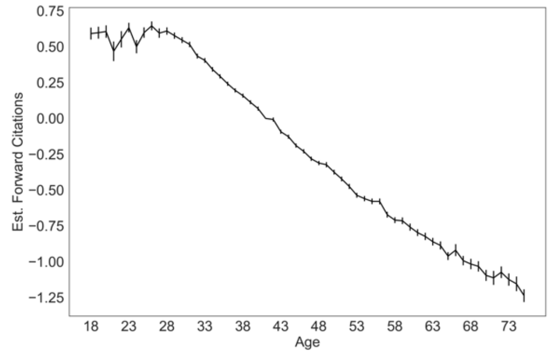

Figure 15 Forward citations by age for all inventors, fixed effects estimate

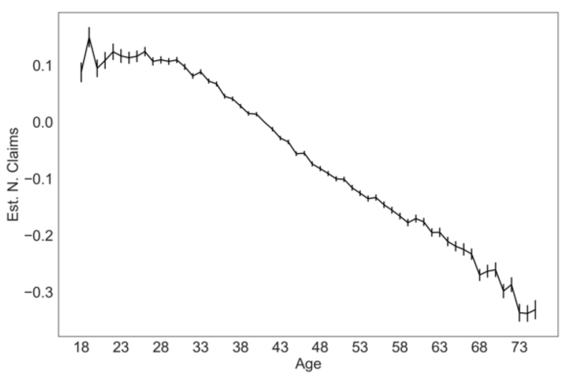

Figure 16 Number of Claims by age for all inventors, fixed effects estimates

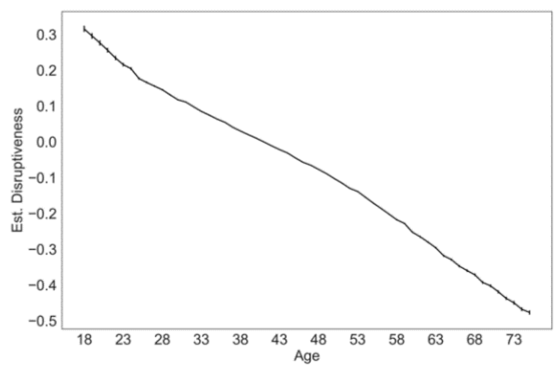

Figure 17 Disruptiveness by age for all inventors, fixed effects estimates

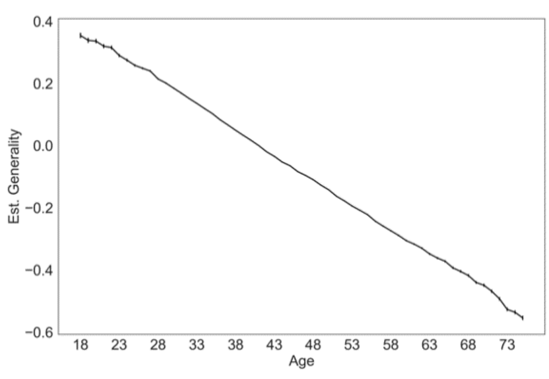

Figure 18 Generality by age for all inventors, fixed effects estimates

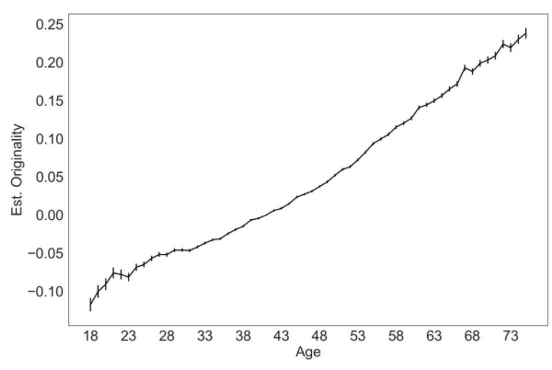

Figure 19 Originality by age for all inventors, fixed effects estimates

Table 2 Regressions of Patent Attributes with Inventor Fixed Effects

	Forward	Disruptiveness	Backward	N Claims	Generality	Originality
SD Age	0.0043	-0.0015	0.0061	0.0023	0.0004	0.0012
	0.0008	0.0001	0.0005	0.0002	0.0001	0.0001
Age: 15	0.8554	0.3960	0.0552	0.1517	0.4128	-0.1479
	0.0606	0.0115	0.0429	0.0232	0.0107	0.0114
Age: 20	0.6066	0.2769	-0.0614	0.0950	0.3365	-0.0907
	0.0432	0.0072	0.0284	0.0155	0.0071	0.0079
Age: 25	0.5989	0.1775	-0.1582	0.1163	0.2588	-0.0649
	0.0363	0.0033	0.0221	0.0102	0.0037	0.0040
Age: 30	0.5468	0.1180	-0.1316	0.1096	0.1852	-0.0458
	0.0209	0.0018	0.0133	0.0054	0.0020	0.0022
Age: 35	0.2937	0.0641	-0.1000	0.0674	0.1033	-0.0311
	0.0152	0.0013	0.0107	0.0043	0.0015	0.0016
Age: 40	0.0688	0.0107	-0.0102	0.0142	0.0172	-0.0042
	0.0141	0.0011	0.0095	0.0038	0.0014	0.0014
Age: 45	-0.1895	-0.0443	0.0649	-0.0559	-0.0643	0.0235
	0.0144	0.0012	0.0105	0.0039	0.0014	0.0015
Age: 50	-0.3747	-0.1023	0.1485	-0.0999	-0.1418	0.0522
	0.0163	0.0014	0.0134	0.0046	0.0017	0.0017
Age: 55	-0.5785	-0.1710	0.2530	-0.1331	-0.2216	0.0935
	0.0197	0.0017	0.0157	0.0055	0.0020	0.0020
Age: 60	-0.7581	-0.2521	0.2701	-0.1702	-0.3054	0.1268
	0.0249	0.0022	0.0186	0.0068	0.0025	0.0025
Age: 65	-0.9608	-0.3289	0.2779	-0.2190	-0.3716	0.1652
	0.0273	0.0030	0.0244	0.0089	0.0034	0.0034
Age: 70	-1.0949	-0.4022	0.2551	-0.2604	-0.4489	0.2030
	0.0387	0.0041	0.0351	0.0130	0.0047	0.0047
Age: 75	-1.2363	-0.4766	0.3302	-0.3309	-0.5539	0.2381
	0.0446	0.0059	0.0451	0.0168	0.0065	0.0069
Age: 80	-1.3053	-0.5504	0.2638	-0.3589	-0.6179	0.2794
	0.0503	0.0084	0.0586	0.0205	0.0090	0.0096
Age: 85	-1.3492	-0.6046	0.2106	-0.4007	-0.6797	0.3171
	0.1038	0.0142	0.0566	0.0313	0.0145	0.0156
Team: 2	0.1080	-0.0008	0.0771	0.0413	0.0003	0.0018
	0.0073	0.0006	0.0056	0.0020	0.0008	0.0008
Team: 3	0.2215	-0.0018	0.1658	0.0766	0.0023	0.0041
	0.0092	0.0008	0.0068	0.0024	0.0009	0.0010

	Forward	Disruptiveness	Backward	N Claims	Generality	Originality
Team: 4	0.3120	0.0006	0.2223	0.1033	0.0054	0.0034
	0.0111	0.0009	0.0081	0.0028	0.0011	0.0012
Team: 5	0.3752	0.0032	0.3025	0.1223	0.0068	0.0055
	0.0145	0.0011	0.0099	0.0034	0.0013	0.0015
Team: 6	0.5308	0.0050	0.3454	0.1433	0.0089	0.0038
	0.0202	0.0013	0.0128	0.0043	0.0016	0.0018
Team: 7	0.5042	0.0018	0.4843	0.1759	0.0136	0.0107
	0.0244	0.0017	0.0182	0.0059	0.0020	0.0023
Team: 8+	0.6241	0.0055	0.5602	0.1947	0.0168	0.0052
	0.0405	0.0023	0.0249	0.0079	0.0027	0.0030
Gender Ratio	0.0039	0.0007	0.0019	0.0024	0.0005	0.0003
	0.0095	0.0008	0.0072	0.0024	0.0009	0.0009
Cmp & Cmm	0.4944	-0.0010	-0.1162	0.0163	0.0097	0.0233
	0.0133	0.0011	0.0096	0.0034	0.0013	0.0015
Drgs & Med	-0.5217	-0.0108	-0.5741	0.0502	-0.0120	-0.0059
	0.0243	0.0014	0.0150	0.0042	0.0015	0.0017
Elec	0.3585	0.0092	0.0797	0.1021	0.0025	-0.0034
	0.0093	0.0008	0.0077	0.0024	0.0010	0.0011
Mech	0.5649	0.0025	-0.1191	0.1285	0.0077	0.0224
	0.0144	0.0009	0.0095	0.0031	0.0012	0.0013
Other Field	0.4476	-0.0078	-0.3379	0.1117	0.0154	0.0267
	0.0117	0.0010	0.0091	0.0032	0.0013	0.0014
Missing Field	-0.0522	0.0216	0.1526	0.0584	-0.0277	-0.0287
	0.0215	0.0010	0.0139	0.0028	0.0012	0.0015
Cons.	-0.0030	0.0002	-0.0045	-0.0010	0.0000	-0.0003
	0.0012	0.0001	0.0009	0.0004	0.0001	0.0001
N	2,748,172	2,748,141	2,748,172	2,747,689	2,748,172	2,748,172
r2	0.0117	0.0599	0.00668	0.00677	0.0709	0.0102
RMSE	2.0569	0.180	1.502	0.579	0.214	0.220

As seen in Table 2, larger inventor teams produce patents that make more backward citations, receive more forward citations and have more claims. The magnitude of the team size effects are significant, but generally not as large as the age effects. For example, the difference between the youngest and oldest teams in terms of forward citations is on the order of a factor of 4, whereas the difference between a team of 8 and a team of 2 is a factor of about 1.75. Team size is an important factor in all of the measures. For forward citations, backward citations, number of claims, generality, and originality, larger teams have higher outcomes. However, smaller teams, especially solo-authors, tend to have more disruptive patents than larger groups.

The gender composition of teams does not have a measurable association with any of these attributes. Age diversity (as measured by the standard deviation) has a positive coefficient with respect to forward citations, claims, generality and originality, and a negative coefficient for disruptiveness and backward citations. All of these estimates are statistically significant but with the exception of forward citations, the effects are quite small. For forward citations, the estimate is small but not trivial. Consider a hypothetical team of four 40-year olds, and the hypothetical replacement of one of these with a 20-year old and one with a 60-year old. This would increase the standard deviation of age on this team by about 16, which, by the estimate in Table 2, would increase the expected forward citations by about 25%--a noticeable increase associated with a possible (though admittedly rather extreme) increase in team age diversity. Thus, for a given average age of team membership, greater diversity, i.e., a wider age range, is associated with a modestly higher level of forward citations, often used as a measure of patent quality.

The standard deviation of age on a team is an arbitrary measure of age variation. As a different way of looking for effects of age composition of teams on team performance, we examined whether (controlling for team size), specific combinations of ages (younger with older, younger with middle age, middle age with older) exhibit differences in average patent attributes. We found that average performances on the difference attributes for such combinations were very close to the mean of the performance of solo inventors with each attribute. For example, a team with an older and a younger member had average forward citations very close to halfway between the mean for an older solo inventor and an a younger solo inventor. Thus this approach provided no additional evidence of meaningful complementarities or other interactions between inventors of different ages on a given team.

6 Robustness Checks

Our matching of web-scraped ages to the patent data potentially creates measurement problems that could affect our results. First, to the extent that the inventors that were matched differ systematically from those that could not be matched, our results could be unrepresentative of the underlying population. Second, some of the matches are likely mis-matches, meaning that age in the dataset is likely measured with some amount of error. This could bias the estimates of the relationship between age and the variables of interest. Measuring the size of these problems would require, by definition, information we don't have, so we cannot ultimately determine how serious they are. In this section we undertake two analyses that do not fundamentally measure the size of these problems, but which do shed light on whether they are likely to seriously bias the results.

To address the issue of selection based on successful matching of the inventor to individuals with ages found on the web, we simply compare those patent-inventor pairs that were matched to those that were not using all available information. Table 4 presents a logistic regression of age found/not found for each patent-inventor pair, using as regressors all observable attributes of the patent-inventor pair and displays the average partial effects. The results suggest that the only variable that has an impact on predicting our ability to find an age for an individual is gender. Other variables--patent attributes, year of application, team size or field of the patent—have effects that are statistically distinguishable from zero because of the large sample size, but which are small in magnitude. Finding the age of women, in particular, can be particularly difficult because women are more likely to change their name throughout their lifetime. In addition, we rely on two algorithms – one that pools patents to a unique inventor, and another that identifies gender. It is possible that a woman patents under two different names and consequently, that algorithm creates two separate inventor ids. As a result, there may be more difficulty in finding ages for women as there may be more public information for one name than a another.

Table 3 Logistic regression for Selection (Displaying Average Partial Effects)

Logistic Regression for Selection

Variable	APE/SE	Variable	APE/SE	Variable	APE/SE
Lifetime Tot Pat	-0.003***	Yr: 1976	0.007	Yr: 1996	0.066***
	0.00		-0.013		-0.01
Female	1.247***	Yr: 1977	0.055***	Yr: 1997	0.091***
	-0.007		-0.013		-0.009
Cmp & Cmm	-0.066***	Yr: 1978	0.031*	Yr: 1998	0.110***
	-0.003		-0.013		-0.009
Drgs & Med	-0.034***	Yr: 1979	0.007	Yr: 1999	0.104***
	-0.004		-0.014		-0.009
Elec	-0.006	Yr: 1980	0.016	Yr: 2000	0.105***
	-0.004		-0.013		-0.009
Mech	0.057***	Yr: 1981	0.02	Yr: 2001	0.099***
	-0.004		-0.012		-0.008
Other Field	0.041***	Yr: 1982	0.003	Yr: 2002	0.084***
	-0.004		-0.013		-0.008
Missing Field	-0.028***	Yr: 1983	0.016	Yr: 2003	0.084***
	-0.008		-0.013		-0.008
Team: 2	-0.010**	Yr: : 1984	0.02	Yr: 2004	0.083***
	-0.003		-0.012		-0.008
Team: 3	-0.032***	Yr: 1985	0.000	Yr: 2005	0.080***
	-0.003		-0.012		-0.009
Team: 4	-0.045***	Yr: 1986	-0.008	Yr: 2006	0.082***
	-0.004		-0.012		-0.008
Team: 5	-0.041***	Yr: 1987	0.021	Yr: 2007	0.070***
	-0.004		-0.011		-0.008
Team: 6	-0.040***	Yr: 1988	0.002	Yr: 2008	0.068***
	-0.005		-0.012		-0.008
Tean: 7	-0.026***	Yr: 1989	0.027*	Yr: 2009	0.037***
	-0.006		-0.011		-0.008
Team: 8+	-0.013**	Yr: 1990	0.037***	Yr: 2010	0.036***
	-0.005		-0.011		-0.008
Forward Cit.	-0.001*	Yr: 1991	0.040***	Yr: 2011	0.025**
	0		-0.011		-0.008
Backward Cit.	0.004***	Yr: 1992	0.055***	Yr: 2012	0.015*
	0		-0.01		-0.008
N. Claims	0.008***	Yr: 1993	0.075***	Yr: 2013	0.005
	-0.001		-0.01		-0.007
Disruptiveness	-0.023***	Yr: 1994	0.072***	Yr: 2014	0.002
	-0.004		-0.01		-0.007
		Yr: 1995	0.071***		
			-0.01		
N: 6656934	Log likelihood	-3095173.966			

To address the possible effect of age mismeasurement within the dataset of matched inventors, we explore empirically the extent to which the re sults seem to change using subsamples of the data in which the extent of age mismeasurement is likely to be low and high. For a ‘low measurement error’ sample, we utilize those inventors that were successfully matched to invididuals on 3 different web sites, and for which we found the same birth date on all three sites. We also require that the match on all three sites was exact, including middle initial, state, and city. This ‘low measurement error’ sample is a sub-sample of the data used for the analysis above. For a ‘high measurement error’ sample, we utilize those inventors for which we found matches on different web sites, with the different web sites indicating different birth dates for the individual. These inventors were not used in the analysis above, but for this robustness check we choose one of the differing birth dates at random and include them in the anslysis as if it were the correct birth date. While we do not know exactly how much measurement error is in these datasets, we are confident that the ‘low measurement error’ sample has less than our baseline analysis dataset (which includes, for example, many inventors that were found on only one site), which in turn has less measurement error than the ‘high measurement error’ sample.

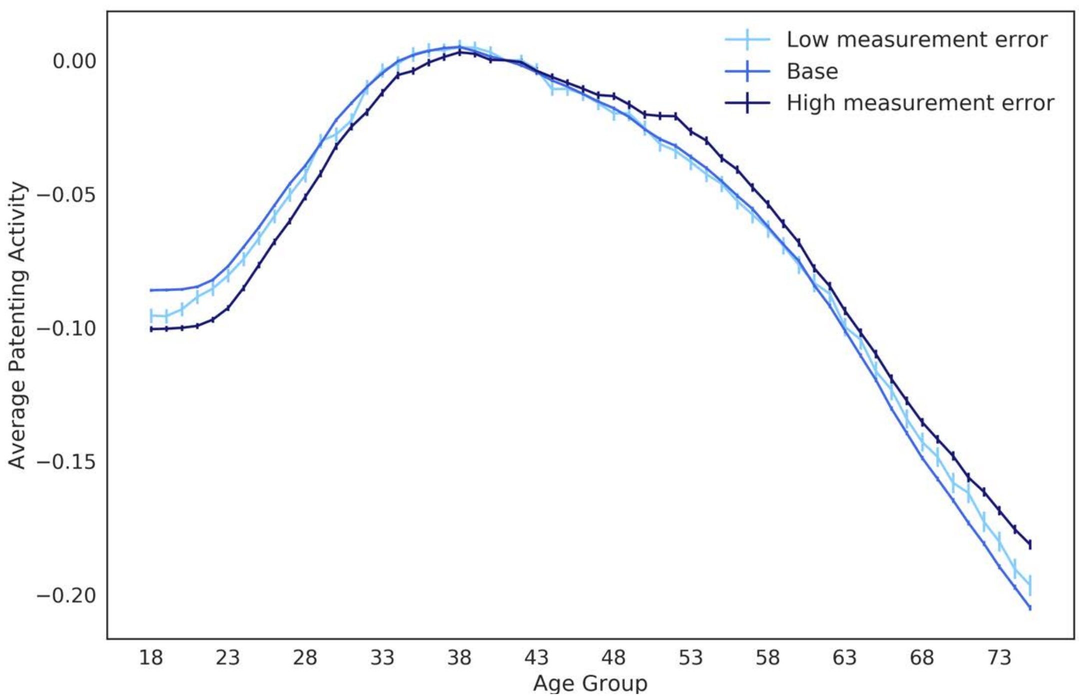

Figure 20 Patenting Activity by measurement error sample, Estimated with Inventor Fixed Effects (fractionalized patent count)

Figure 20 shows the results for the fixed-effect estimates of the rate of patent production over the life course. For the prime work years of 25-65, the estimates are essentially indistinguishable. They deviate modestly for very young and very old inventors, likely because of relatively small sample sizes. But because of this sample size issue, we had already chosen not to place much weight on these estimates in the tails of the age distribution.

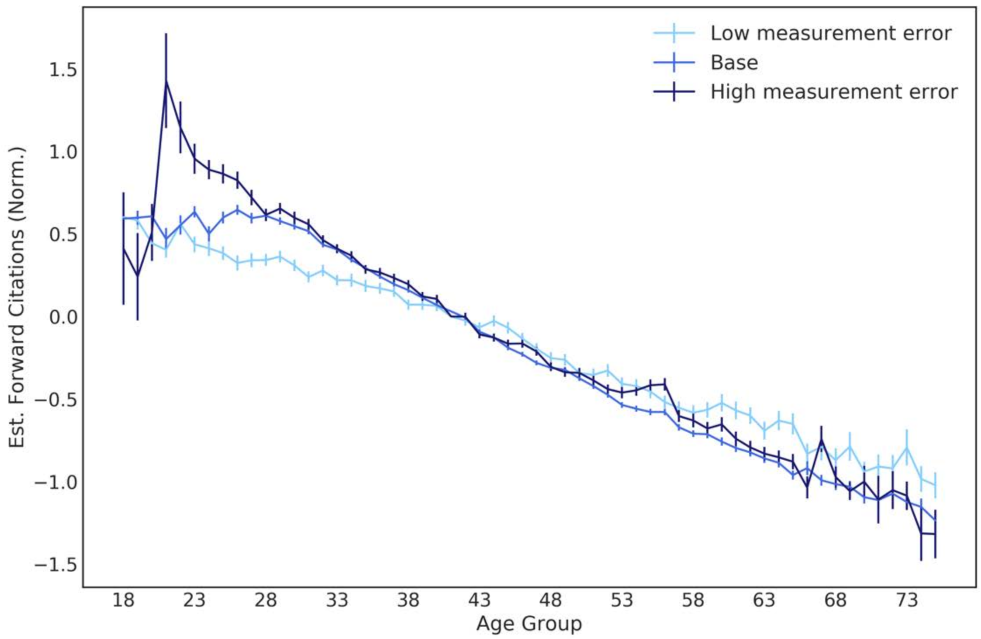

Figure 21 Normalized forward citations by measurement error sample, Estimated with Inventor Fixed Effects

Figure 21 shows analogous results for the forward citation team patent regression. Here the range of ages for which all three sets of results track closely is somewhat narrower, roughly age 30 to 50. For ages below 30 the low measurement error results show an even larger advantage for the younger inventors. For ages 50-60, both the high and low measurement error groups show an even more rapid decline than our baseline results.

Overall, these results suggest that measurement error may have some effect on the exact magnitude of the age effects, particularly for the lowest and highest age groups. However, the qualitative picture of the results is quite robust even to what seems like quite a large swing in the amount of measurement error present in the data.

7 Discussion

We contribute to the literature on creativity and aging, by exploring how the extent and qualitative nature of patents changes as inventors age. Because of the size and richness of our data, we are able to explore several important dimensions of this relationship. First, we have longitudinal data on many inventors over many years, which allows us to resolve the extent to which apparent patterns in the data are due to variations across individuals as distinct from variations with age for a given individual. Second, we have data on several different qualitative attributes of patents, which allows us to examine not just how the rate of creativity activity changes as people age, but also how the nature of those activities change. Finally, because we observe inventors participating in many changing inventor teams over time, we can explore how the ages of the members of a team interact to affect the activities of the team.

We first confirm the previously observed pattern, from more exceptional or specialized samples including geniuses, that the rate of patenting peaks at approximately age 40. This pattern is similar for men and women, and it is similar when viewed longitudinally. Interestingly, we find that the age at which inventors get their first patent has been falling over the last couple of decades, in contrast to scientific research where the age of first publication has been rising.

When we look at how the attributes of patents vary with the age of their inventors, we find clear and monotonic relationships for all of the attributes we examined. As inventors age, they produce patents that yield more forward citations, are more disruptive of the existing technology, and which have slightly broader scope as measured by the number of claims. For forward citations and disruptiveness these effects are quantitatively large, bigger, for example than the effects previously identified as associated with the size of inventor teams.

The number of backward citations and originality, on the other hand, rise significantly as inventors age. While it is perhaps surprising that all of these attributes exhibit monotonic relationships while the rate of patenting rises and then falls after a peak in middle age, the particular pattern of associations confirms the relavence of the formulation of cognitive aging process in terms of rising crystallized intelligence and declining fluid intelligence, assuming we are comfortable associating forward citations, generality, and disruptiveness with fluid intelligence and backward citations and origianality with crystalized intelligence. As Hertzog (2020) has pointed out, the increased knowledge and expertise associated with later life may also restrict the number of important or novel contributions. Older inventors may work on incremental changes to ideas or patents developed earlier in life, rather than beginning a novel and revolutionary or disruptive line of work

Turning to the analysis of teams, the results are straightforward. In terms of age effects, teams behave pretty much as the average of their members. Teams with lower average age produce patents that receive more forward citations, are more disruptive, general, and have somewhat more claims. Teams with older members produce patents that make more backward citations and more originality.With regard to age heterogeneity of teams, for forward citations there is a small but non-trivial effect of age diversity that can be layered on top of these larger effects associated with average age. That is, for a given average age, greater diversity is associated with a modestly higher level of forward citations.

There has been some mixed evidence for the role of age and diversity with regard to innovation. For example, Hammermann et al., (2019) found that the average age of a company's workforce had a negative impact on innovation, but age diversity measured by the standard deviation of age increases the innovation of a company. Moreover, the effects of age diversity vary as a function of the type of work that is being done (Garnero et al., 2014). Thus, in future work it will be of interest to explore the role of team age diversity across different technological fields.

The team results are not surprising given the nature of the associations between age and attributes at the individual level. If a given attribute required a mixture of Gc and Gf, then we might expect that more age diverse teams combining older and younger members could rely on the respective strengths of each. But if a given attribute required an emphasis on one component of intelligence, then we would expect performance with respect to that attribute to change with age monotonically. Our finding that all attributes change monotonically with age suggests that each attribute depends primarily on only one aspect of intelligence as the patterns by average age of the team members are consistent with that found for solo inventors of that age. At the same time, however, a wider age range seems to have a small advantage for the quality of an invention.

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 is based on many more individuals than have been used in 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.

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 later in life) 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*. 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 view the age/patent-creativity relationship as an association rather than a causal relationship.

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 or work history, allowing for broad and varied exploration of how inventive behavior evolves over the life course.

8 Conclusions

By adding information about age and gender to the U.S. patent database, we are able to show the age and gender distributions of inventors over a period of 40 years. This allows us to examine how creative productivity varies both between and within persons. We find that about 6% of the inventors for whom we found ages are granted patents after age 65. About 22% of the sample received their *first* patent after age 50. In addition, the new data provide interesting information about how the attributes of inventions vary across age and the age heterogeneity in teams. We find that older workers bring different innovative skills to bear on the inventive process than younger adults. Moreover, teams that include a wider age range have some advantage compared to age homogeneous teams in terms of producing more widely cited inventions. The results have implications for work and retirement choices and employer policies such as maintaining older workers longer and including them in mixed age teams.

We expect findings from this project have the potential to advance the scholarship on creativity and aging, but also to generate policy implications for promoting and acknowledging the life course of innovation in the workplace. The results show that although more inventions are made by those in early and middle adulthood, there are many older adults who continue to receive patents for inventions, working alone or in mixed age teams. The inventions by younger adults are cited more widely by future patents. In contrast, inventions by older adults draw more heavily on a wider range of previous inventions. This suggests that inventions of older adults rely more on connections and integration with earlier patents, which depends on having more expansive knowledge and experience. Although we did not find strong evidence for the added value of mixed age teams, there was some evidence that teams with a more diverse age range had patents that are more important (i.e., with more forward citations). Future work that explores these relationships within different technology fields may help to clarify the contributions of age diversity.

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Appendix

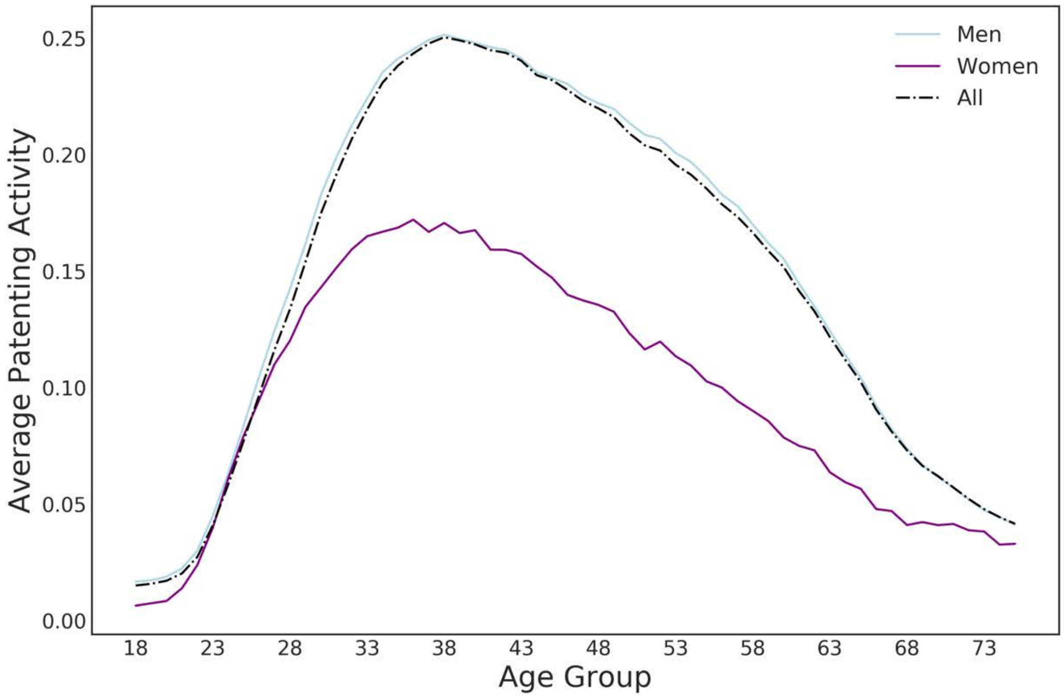

Figure A.1. Raw Average Patenting Activity by Age and Gender (total patent count)

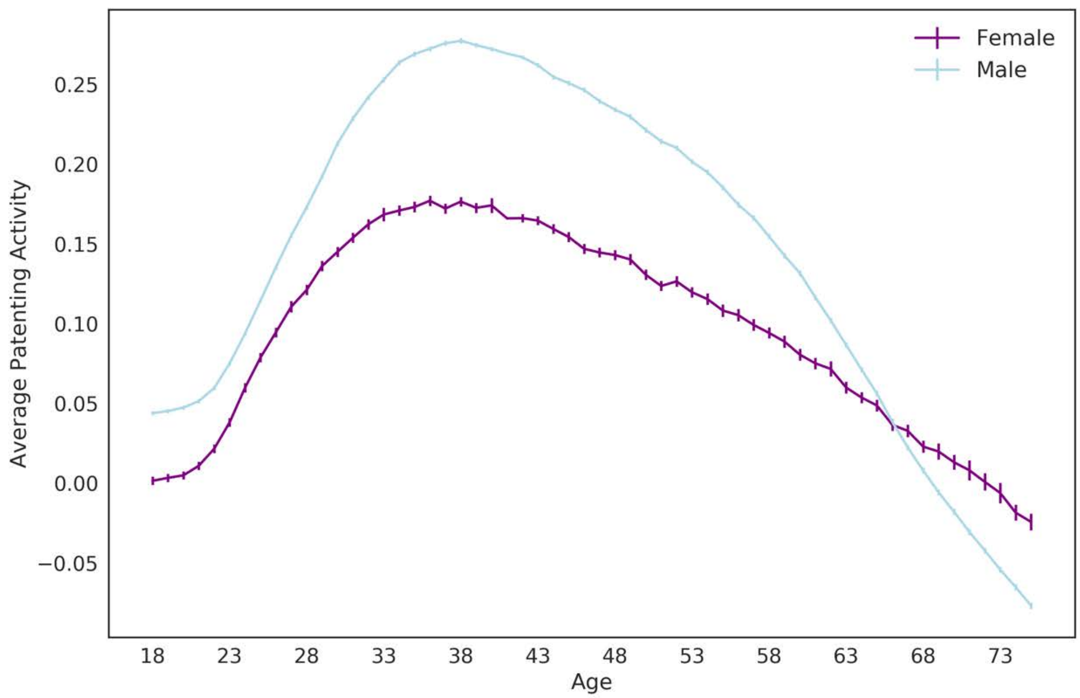

Figure A.2. Patenting Activity by Age and Gender, Estimated with Inventor Fixed Effects (fractionalized patent count)

Table A1. Full Regression table for solo inventors

	(1) Forward	(2) Disruptiv.	(3) Backward	(4) N. Claim	(5) Originality	(6) Generality
Age 15	0.865***	0.545***	-0.0798	0.00931	-0.271***	0.382***
	(0.099)	(0.018)	(0.058)	(0.032)	(0.016)	(0.015)
Age 16	0.815***	0.517***	-0.188***	0.0674**	-0.259***	0.352***
	(0.084)	(0.016)	(0.068)	(0.032)	(0.014)	(0.014)
Age 17	0.512***	0.460***	-0.190***	-0.0167	-0.204***	0.337***
	(0.063)	(0.015)	(0.041)	(0.028)	(0.014)	(0.013)
Age 18	0.626***	0.414***	-0.211***	0.00690	-0.213***	0.325***
	(0.074)	(0.013)	(0.045)	(0.026)	(0.013)	(0.012)
Age 19	0.544***	0.415***	-0.207***	0.0655**	-0.187***	0.313***
	(0.072)	(0.012)	(0.044)	(0.026)	(0.012)	(0.012)
Age 20	0.566***	0.365***	-0.195***	0.0443*	-0.182***	0.313***
	(0.068)	(0.011)	(0.043)	(0.025)	(0.011)	(0.011)
Age 21	0.436***	0.352***	-0.402***	0.0196	-0.177***	0.282***
	(0.166)	(0.011)	(0.110)	(0.024)	(0.010)	(0.010)
Age 22	0.389***	0.332***	-0.237***	0.0345	-0.159***	0.297***
	(0.106)	(0.009)	(0.060)	(0.024)	(0.010)	(0.009)
Age 23	0.534***	0.284***	-0.158***	0.0591***	-0.132***	0.273***
	(0.051)	(0.008)	(0.033)	(0.020)	(0.008)	(0.008)
Age 24	0.459***	0.279***	-0.199***	0.0698***	-0.129***	0.260***
	(0.047)	(0.007)	(0.032)	(0.017)	(0.007)	(0.007)
Age 25	0.415***	0.248***	-0.198***	0.0503***	-0.107***	0.241***
	(0.040)	(0.006)	(0.031)	(0.018)	(0.006)	(0.006)
Age 26	0.462***	0.228***	-0.152***	0.0537***	-0.0949***	0.235***
	(0.043)	(0.005)	(0.030)	(0.013)	(0.006)	(0.005)
Age 27	0.414***	0.219***	-0.187***	0.0433***	-0.105***	0.232***
	(0.056)	(0.004)	(0.029)	(0.012)	(0.005)	(0.005)
Age 28	0.459***	0.195***	-0.0640**	0.0554***	-0.0949***	0.201***
	(0.044)	(0.004)	(0.031)	(0.012)	(0.005)	(0.004)
Age 29	0.363***	0.179***	-0.128***	0.0506***	-0.0866***	0.193***
	(0.034)	(0.004)	(0.022)	(0.011)	(0.004)	(0.004)
Age 30	0.353***	0.158***	-0.120***	0.0688***	-0.0808***	0.177***
	(0.033)	(0.003)	(0.022)	(0.010)	(0.004)	(0.004)

Age 31	0.320***	0.152***	-0.151***	0.0484***	-0.0753***	0.167***
	(0.027)	(0.003)	(0.019)	(0.011)	(0.004)	(0.004)
Age 32	0.306***	0.129***	-0.111***	0.0430***	-0.0694***	0.149***
	(0.026)	(0.003)	(0.018)	(0.010)	(0.004)	(0.004)
Age 33	0.282***	0.119***	-0.0708***	0.0543***	-0.0627***	0.141***
	(0.026)	(0.003)	(0.017)	(0.010)	(0.003)	(0.003)
Age 34	0.226***	0.101***	-0.0619***	0.0451***	-0.0505***	0.121***
	(0.024)	(0.003)	(0.017)	(0.009)	(0.003)	(0.003)
Age 35	0.170***	0.0827***	-0.0790***	0.0298***	-0.0449***	0.104***
	(0.025)	(0.003)	(0.017)	(0.009)	(0.003)	(0.003)
Age 36	0.132***	0.0706***	-0.0638***	0.0200**	-0.0395***	0.0855***
	(0.023)	(0.003)	(0.018)	(0.009)	(0.003)	(0.003)
Age 37	0.111***	0.0549***	-0.0507***	0.0166*	-0.0288***	0.0685***
	(0.024)	(0.003)	(0.017)	(0.009)	(0.003)	(0.003)
Age 38	0.0894***	0.0418***	-0.0328**	0.0125	-0.0222***	0.0491***
	(0.023)	(0.003)	(0.016)	(0.008)	(0.003)	(0.003)
Age 39	0.0554**	0.0293***	-0.0447***	0.00553	-0.0157***	0.0321***
	(0.022)	(0.003)	(0.017)	(0.008)	(0.003)	(0.003)
Age 40	0.00856	0.0154***	-0.00374	0.00817	-0.00924***	0.0166***
	(0.021)	(0.002)	(0.015)	(0.008)	(0.003)	(0.003)
Age 42	0.00128	-0.0105***	0.00325	-0.00315	0.00442	-0.0201***
	(0.021)	(0.002)	(0.016)	(0.008)	(0.003)	(0.003)
Age 43	-0.0615***	-0.0247***	0.0130	-0.00144	0.0107***	-0.0382***
	(0.022)	(0.003)	(0.016)	(0.008)	(0.003)	(0.003)
Age 44	-0.0937***	-0.0356***	0.00471	-0.00690	0.0175***	-0.0512***
	(0.023)	(0.003)	(0.017)	(0.008)	(0.003)	(0.003)
Age 45	-0.146***	-0.0497***	0.0360**	-0.0164**	0.0252***	-0.0623***
	(0.022)	(0.003)	(0.017)	(0.008)	(0.003)	(0.003)
Age 46	-0.152***	-0.0665***	0.0458***	-0.00948	0.0339***	-0.0783***
	(0.023)	(0.003)	(0.017)	(0.008)	(0.003)	(0.003)
Age 47	-0.192***	-0.0801***	0.0331*	-0.0235***	0.0398***	-0.0919***
	(0.022)	(0.003)	(0.018)	(0.009)	(0.003)	(0.003)
Age 48	-0.230***	-0.0958***	0.0536***	-0.0284***	0.0467***	-0.105***
	(0.023)	(0.003)	(0.017)	(0.009)	(0.003)	(0.003)

Age 49	-0.233***	-0.111***	0.0622***	-0.0345***	0.0506***	-0.125***
	(0.024)	(0.003)	(0.019)	(0.009)	(0.003)	(0.003)
Age 50	-0.250***	-0.127***	0.0879***	-0.0389***	0.0661***	-0.136***
	(0.025)	(0.003)	(0.019)	(0.009)	(0.003)	(0.003)
Age 51	-0.321***	-0.141***	0.101***	-0.0420***	0.0707***	-0.157***
	(0.025)	(0.003)	(0.020)	(0.009)	(0.003)	(0.003)
Age 52	-0.362***	-0.160***	0.0774***	-0.0462***	0.0779***	-0.171***
	(0.025)	(0.003)	(0.019)	(0.009)	(0.003)	(0.003)
Age 53	-0.391***	-0.174***	0.0840***	-0.0593***	0.0904***	-0.191***
	(0.024)	(0.003)	(0.019)	(0.009)	(0.003)	(0.003)
Age 54	-0.422***	-0.192***	0.115***	-0.0667***	0.102***	-0.202***
	(0.024)	(0.003)	(0.023)	(0.009)	(0.003)	(0.003)
Age 55	-0.408***	-0.213***	0.140***	-0.0600***	0.120***	-0.213***
	(0.026)	(0.003)	(0.022)	(0.010)	(0.003)	(0.003)
Age 56	-0.448***	-0.235***	0.141***	-0.0815***	0.127***	-0.234***
	(0.027)	(0.003)	(0.021)	(0.010)	(0.003)	(0.004)
Age 57	-0.525***	-0.254***	0.106***	-0.0868***	0.133***	-0.249***
	(0.028)	(0.003)	(0.022)	(0.010)	(0.004)	(0.004)
Age 58	-0.549***	-0.271***	0.154***	-0.0978***	0.143***	-0.262***
	(0.029)	(0.003)	(0.024)	(0.010)	(0.004)	(0.004)
Age 59	-0.573***	-0.282***	0.101***	-0.106***	0.146***	-0.276***
	(0.031)	(0.003)	(0.021)	(0.010)	(0.004)	(0.004)
Age 60	-0.642***	-0.310***	0.141***	-0.109***	0.156***	-0.295***
	(0.035)	(0.004)	(0.024)	(0.011)	(0.004)	(0.004)
Age 61	-0.639***	-0.325***	0.106***	-0.116***	0.175***	-0.305***
	(0.030)	(0.004)	(0.023)	(0.011)	(0.004)	(0.004)
Age 62	-0.704***	-0.345***	0.112***	-0.129***	0.178***	-0.321***
	(0.034)	(0.004)	(0.026)	(0.011)	(0.004)	(0.004)

Age 63	-0.725***	-0.360***	0.100***	-0.121***	0.190***	-0.334***
	(0.033)	(0.004)	(0.026)	(0.012)	(0.004)	(0.004)
Age 64	-0.754***	-0.384***	0.0827***	-0.138***	0.194***	-0.342***
	(0.038)	(0.004)	(0.025)	(0.012)	(0.004)	(0.005)
Age 65	-0.818***	-0.400***	0.142***	-0.145***	0.204***	-0.360***
	(0.038)	(0.004)	(0.028)	(0.013)	(0.005)	(0.005)
Age 66	-0.758***	-0.420***	0.198***	-0.139***	0.220***	-0.375***
	(0.049)	(0.005)	(0.031)	(0.016)	(0.005)	(0.005)
Age 67	-0.811***	-0.427***	0.164***	-0.159***	0.234***	-0.385***
	(0.044)	(0.005)	(0.032)	(0.014)	(0.005)	(0.005)
Age 68	-0.869***	-0.445***	0.172***	-0.198***	0.231***	-0.395***
	(0.045)	(0.005)	(0.033)	(0.015)	(0.005)	(0.006)
Age 69	-0.898***	-0.465***	0.249***	-0.213***	0.243***	-0.429***
	(0.045)	(0.005)	(0.035)	(0.015)	(0.006)	(0.006)
Age 70	-0.940***	-0.479***	0.209***	-0.199***	0.249***	-0.431***
	(0.045)	(0.006)	(0.037)	(0.018)	(0.006)	(0.006)
Age 71	-0.985***	-0.497***	0.206***	-0.225***	0.253***	-0.451***
	(0.050)	(0.006)	(0.034)	(0.017)	(0.006)	(0.007)
Age 72	-1.011***	-0.511***	0.340***	-0.235***	0.270***	-0.469***
	(0.040)	(0.006)	(0.072)	(0.017)	(0.007)	(0.007)
Age 73	-1.010***	-0.533***	0.173***	-0.262***	0.277***	-0.508***
	(0.048)	(0.007)	(0.041)	(0.020)	(0.007)	(0.007)
Age 74	-1.087***	-0.544***	0.172***	-0.292***	0.286***	-0.518***
	(0.062)	(0.007)	(0.038)	(0.018)	(0.007)	(0.008)
Age 75	-1.118***	-0.568***	0.136***	-0.261***	0.296***	-0.529***
	(0.047)	(0.008)	(0.038)	(0.022)	(0.008)	(0.008)
Age 76	-1.082***	-0.577***	0.100***	-0.281***	0.303***	-0.545***
	(0.056)	(0.008)	(0.033)	(0.020)	(0.009)	(0.009)
Age 77	-1.179***	-0.596***	0.119**	-0.286***	0.318***	-0.582***
	(0.052)	(0.009)	(0.047)	(0.023)	(0.009)	(0.010)
Age 78	-1.169***	-0.635***	0.0560	-0.285***	0.333***	-0.591***
	(0.046)	(0.010)	(0.042)	(0.026)	(0.010)	(0.010)
Age 79	-1.111***	-0.634***	0.0495	-0.327***	0.338***	-0.606***
	(0.067)	(0.010)	(0.042)	(0.026)	(0.011)	(0.011)
Age 80	-1.168***	-0.652***	0.0517	-0.327***	0.340***	-0.603***
	(0.061)	(0.011)	(0.039)	(0.027)	(0.012)	(0.012)

Age 81	-1.271***	-0.664***	0.0649	-0.345***	0.326***	-0.631***
	(0.068)	(0.011)	(0.044)	(0.030)	(0.012)	(0.012)
Age 82	-1.188***	-0.640***	-0.0226	-0.347***	0.334***	-0.641***
	(0.093)	(0.014)	(0.055)	(0.036)	(0.014)	(0.014)
Age 83	-1.194***	-0.680***	-0.0380	-0.402***	0.344***	-0.667***
	(0.092)	(0.013)	(0.049)	(0.033)	(0.014)	(0.015)
Age 84	-1.352***	-0.708***	-0.116**	-0.369***	0.372***	-0.676***
	(0.071)	(0.015)	(0.045)	(0.034)	(0.017)	(0.017)
Age 85	-1.309***	-0.721***	0.0875	-0.383***	0.420***	-0.686***
	(0.120)	(0.018)	(0.064)	(0.043)	(0.018)	(0.019)
Age 86	-1.414***	-0.731***	0.139	-0.429***	0.409***	-0.741***
	(0.112)	(0.018)	(0.126)	(0.038)	(0.019)	(0.020)
Age 87	-1.628***	-0.731***	-0.0661	-0.469***	0.410***	-0.711***
	(0.131)	(0.022)	(0.054)	(0.043)	(0.022)	(0.024)
Age 88	-1.533***	-0.777***	-0.0855	-0.446***	0.419***	-0.732***
	(0.189)	(0.024)	(0.070)	(0.047)	(0.024)	(0.026)
Age 89	-1.698***	-0.788***	-0.246***	-0.459***	0.449***	-0.799***
	(0.170)	(0.034)	(0.070)	(0.052)	(0.032)	(0.031)
Chemistry	0.493***	-0.00408*	-0.0523***	-0.00174	0.0162***	0.0200***
	(0.020)	(0.002)	(0.016)	(0.006)	(0.003)	(0.003)
Drugs & Med	-0.333***	-0.0188***	-0.387***	0.0255***	-0.0136***	-0.0206***
	(0.038)	(0.003)	(0.024)	(0.008)	(0.003)	(0.003)
Elec	0.321***	0.0112***	0.0686***	0.0972***	0.00206	0.0139***
	(0.015)	(0.001)	(0.012)	(0.005)	(0.002)	(0.002)
Mech	0.484***	0.00853***	-0.105***	0.113***	0.00857***	0.0110***
	(0.020)	(0.002)	(0.014)	(0.006)	(0.002)	(0.002)
Other Field	0.405***	-0.00420**	-0.258***	0.0971***	0.0114***	0.0188***
	(0.018)	(0.002)	(0.013)	(0.005)	(0.002)	(0.002)
Missing Field	-0.0572	0.0600***	0.169***	0.0474***	-0.0430***	-0.0310***
	(0.044)	(0.002)	(0.029)	(0.006)	(0.003)	(0.003)
N	978404	978390	978404	978300	978404	978404
r2_w						
rmse	1.584	0.185	1.162	0.555	0.208	0.210

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