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Influence in Economics and Aging

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Influence in Economics and Aging

Pavel Jelnov and Yoram Weiss*

March 30, 2021

Abstract

We study the relationship between age and influence in a closed group of leading economists. We consider, as a measure of influence, monthly RePEc rankings and address the dynamics of rankings within the top group as a function of age. We find that the rankings peak at age 60 or 30 years after Ph.D. graduation. Differently from other leaders, current and future Nobel laureates do not experience deterioration of the rankings if their works and citations are discounted by recursive impact factor, and their ranking with respect to the breadth of citations across fields improves at old age.

JEL code: J24

Keywords: aging; citations; influence; Nobel; research productivity

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1 Introduction

The measurement of scientists’ productivity as a function of age dates back at least to [Dennis \(1956\)](#). Scientists accumulate experience, reputation, and a professional network, but their productivity decreases because of age-related factors ([Desjardins and Warnke, 2012](#), [Barrett and Riddell, 2016](#), [Green and Riddell, 2013](#), [Skirbekk et al., 2004](#)).¹ Young scientists stand on the shoulders of their older counterparts but are healthier, strongly incentivized, easily adopt new technology and methods, and are likely to generate novel concepts ([Weinberg and Galenson, 2019](#)).²

However, influence is not the same as productivity. Although scientists become less innovative as they age, the number of their papers in highly cited journals and among highly cited papers continues to rise ([Gingras et al., 2008](#), [Cui and Zhong, 2013](#), [Rauber and Ursprung, 2008](#)).³ Thus, it may be asked whether the influence of scientists reflects the Matthew effect of accumulated advantage, where “the rich get richer and the poor get poorer” ([Allison et al., 1982](#), [Ek and Henrekson, 2019](#)), or whether it reflects a non-monotonic trend.

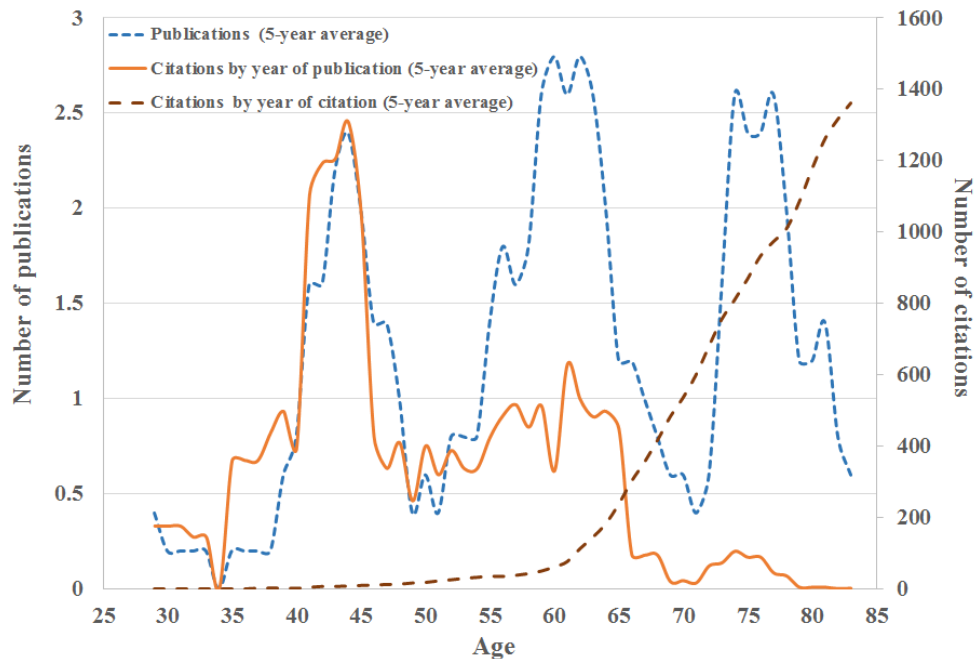
The question in this paper is what does the average relationship between age and influence of leading economists look like. Our motivation is beautifully illustrated by the example of Gary Becker. [Figure 1](#) shows Becker’s publications and citations by year of publication and by year of citation. Becker had three particularly productive periods in terms of the number of publications: in his mid-40s, in his early 60s, and in his late 70s. The most frequently cited papers were published during the first of the three peaks. However, the number of citations took off only when he was in his 60s.

¹[Börsch-Supan and Weiss \(2016\)](#) present evidence that disagrees with decline of productivity at least up to age 60.

²[Fortunato et al. \(2018\)](#) describe science as “a complex, self-organizing, and evolving network of scholars, projects, papers, and ideas.” Correspondingly, the complex nature of institutional science motivates some authors to use models from physics, biology, and other disciplines to address the spread of citations across papers (see, for example, [Clough et al., 2015](#), [Goldberg et al., 2015](#), [Klosik and Bornholdt, 2014](#), and [Zeng et al., 2017](#)).

³By contrast, [Sinatra et al. \(2016\)](#) model the impact of a scientific article as a product of constant ability and age-independent luck and find that this model fits data.

Figure 1: Publications and citations of Gary Becker



Note: The figure presents the 5-year moving average of Gary Becker’s publications and citations, listed on his RePEc author page, by Becker’s age.

Becker (1962) predicted that “The next few years should provide much stronger evidence on whether the recent emphasis placed on the concept of human capital is just another fad or a development of great and lasting importance.” The human capital theory was motivated by the contemporary economic growth (Weiss, 2015), but the rise of its influence was also affected by external factors, i.e., emergence of high-quality microdata and cheap computational power, which led to the development of structural econometric methods and from there to an enormous body of empirical work based on Becker’s theory.⁴ Accordingly, Becker received the Nobel Prize in 1992 at age 62.

The external factors that can explain the time lag between Becker’s most in-

⁴See also Biddle and Hamermesh (2017), who assess the post-WWII evolution of microeconomic research.

fluent publications and their citations do not apply to all leading economists. Yet arguments with respect to the effect of external factors are made in [Jones and Weinberg \(2011\)](#), who write that “age–creativity relationship varies substantially more over time than across fields,” in [Chiappori and Levitt \(2003\)](#), [Jones et al. \(2014\)](#), [Azoulay et al. \(2010\)](#), and in [Reschke et al. \(2018\)](#). Moreover, [Aizenman and Kletzer \(2011\)](#) find that although deceased authors lose potential citations (an observation that shows that citing is a strategic decision), influence of Fischer Black and Amos Tversky soared posthumously, indicating the role of external factors.⁵

Our second observation comes from comparison between disciplines. In [Figure 2](#), we compare Nobel laureates in economics to Nobel laureates in physics and literature. The horizontal axis is the age at the time of receipt of the Nobel (the figure considers prizes awarded from 1990 to 2019). The vertical axis for laureates in economics and physics is the number of years since Ph.D. graduation and for laureates in literature it is the number of years since publication of the first book. The figure shows that the distribution of ages at the time of receipt of the Nobel varies across disciplines. All Nobelists in economics except Esther Dufflo were at least 50 years old. Nobelists in literature had a similar age range as economists but a wider range of experience. By contrast, a significant number of Nobelists in physics were younger than 50 and had less than 20 years of experience, even if some Nobelists in physics were very old, including the oldest person ever to receive the prize. In this sense, economists are more similar to writers than to physicists. In our context, the lack of young Nobelists in economics indicates uncertainty about the influence of economic research. This observation refers to the discussion in [Friedman \(1953\)](#) about similarity (and dissimilarity) of economics and physics, which is essentially the question whether economics is “story telling” rather than a positive science. What makes the reference to Friedman’s essay even more intriguing is the fact

⁵There exists also a literature that discusses the historical dynamics of influence of prominent authors, such as Adam Smith ([Wight, 2002](#)), Frank Ramsey ([Duarte, 2009](#)), and the list of the economists from the *1985 Calendar of Great Economists* ([Anderson et al., 1989](#)).

that it was published fifteen years before the Nobel prize in economics was even established. Yet decades of Nobel Committee’s decisions perfectly fit Friedman’s hypothesis.

Our research design departs from the dynamics of influence within a closed group of leading economists. The approach is to consider the overall influence as a constant term that is distributed between top authors. We aim at the identification of the intergenerational competition. We employ to this end a rich and systematic database of RePEc⁶ monthly rankings. We estimate the gradient of the rankings with respect to age when we control for individual fixed effects and autoregression of the residuals.⁷

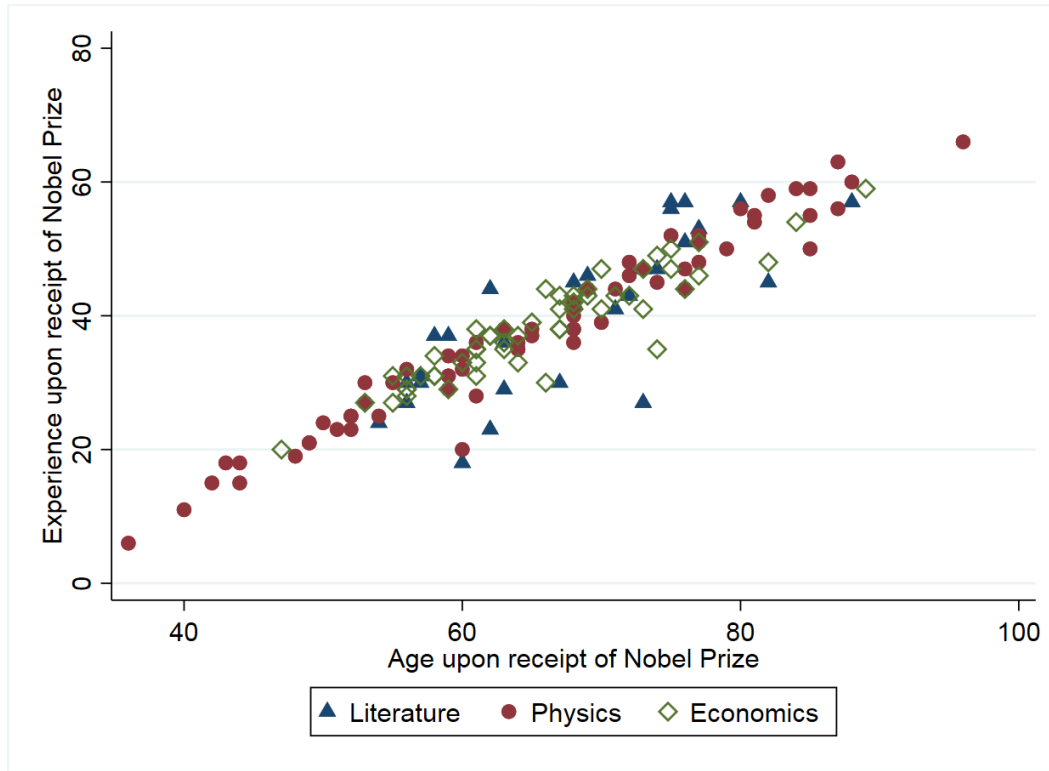
RePEc calculates the 37 rankings from its data on citations, publications, journal pages, abstract views, downloads, scientific network, and number of students. The citations and the publications are measured by a set of indices, which use different weighting schemes along the quantity / quality/ coauthorship/ time lag dimensions. Constrained by the RePEc policy of publishing explicit rankings of only top 5% of its members, the agents that we analyze are economists that are continuously included in this group. Yet this group is not small. The largest possible (in terms of $N \times T$) balanced panel that can be constructed from these data consists of 1,335 economists who are ranked over 100 months.

We find that the relationship of rankings with age follows a U-shape, where

⁶RePEc (Research Papers in Economics) is a database that currently includes more than 55,000 economists, and describes itself as “a collaborative effort of hundreds of volunteers in 99 countries to enhance the dissemination of research in Economics and related sciences. The heart of the project is a decentralized bibliographic database of working papers, journal articles, books, book chapters, and software components, all maintained by volunteers. ... So far, over 2,000 archives from 99 countries have contributed about 2.6 million research pieces from 3,000 journals and 4,600 working paper series. Over 50,000 authors have registered and 75,000 email subscriptions are served every week.” See [Orazbayev \(2017\)](#) for a descriptive presentation of the data available on RePEc and related services.

⁷Of course, there are different types of influence, and RePEc rankings do not capture all of them. For instance, [Angrist et al. \(2020\)](#) and [Aistleitner et al. \(2019\)](#) consider interdisciplinary influence of economists, and [Groot and van den Brink \(2019\)](#) discuss their influence in media. In particular, Nobel laureates enjoy popularity in the general public after being awarded.

Figure 2: Age and experience: Nobel laureates in economics, literature, and physics



Note: The figure covers Nobel Prizes awarded from 1990 to 2019. The level of experience for Nobel laureates in economics and physics is the number of years since Ph.D. graduation. The level of experience for Nobel laureates in literature is the number of years since publication of the first book or the equivalent.

the lowest point indicates the best ranking. This “optimal” age is 60, which corresponds to around 30 years after Ph.D. graduation.⁸ Therefore, our results indicate that a twenty-year lag between peak of productivity, which is around age 40 (Gingras et al., 2008, Cui and Zhong, 2013, and Rauber and Ursprung, 2008), and peak of influence, discussed above for the case of Garry Becker, is the average pattern among leaders.

In the empirical analysis, we distinguish between Nobelists and other top RePEc members. The Nobel Prize is an external recognition of the scientist’s “unquestionable” influence (Hirsch, 2005), independent of RePEc. It is therefore not easy to find a proper comparison group for the Nobel laureates. A natural comparison group would be the nominees who did not win the prize (Baffes and Vamvakidis, 2011), but this data is released with a 50-year lag. Therefore, we take an advantage of the fact that in RePEc data, Nobel laureates can be consistently compared to top non-Nobelists.⁹ We find that differently from other leaders, current and future Nobelists do not expe-

⁸We refer to the number of years that passed since a scholar graduated from a Ph.D. program because of the practical purposefulness of this variable: all authors in our data completed Ph.D. in economics or related, and we found the year of graduation for 96% of them.

⁹The Nobel Prize is studied in empirical research using two approaches. The first approach is to see the prize as a deterministic achievement, to try to figure out what is special about the laureates’ background and life cycle, and to ask whether the winners can be predicted (Gingras and Wallace, 2009; Wagner et al., 2015; Baffes and Vamvakidis, 2011; Van Dalen, 1999; Stephan and Levin, 1993; Shavinina, 2004; Rothenberg, 2005; Weinberg and Galenson, 2019; Ham and Weinberg, 2008). In addition, the Nobel prize is sometimes used as a benchmark to investigate the efficiency of a certain ranking methodology (Krapf et al., 2012), trends in the profession (Boettke et al., 2012), creativity (Weinberg and Galenson, 2019), and knowledge diffusion (Bjork et al., 2014). The second approach is to consider the Nobel Prize as a semi-experimental setup, where the winner and the timing of the award are, to some extent, exogenous. This approach uses the prize to estimate the effect of a positive status shock on outcomes such as collaboration, productivity, and health (Rablen and Oswald, 2008; Chan et al., 2014; Chan et al., 2015; Frandsen and Nicolaisen, 2013; Zuckerman, 1967). The effect of honors on performance was studied also for the John Bates Clark Medal and the Fellowship of the Econometric Society (Chan et al., 2014). We follow the former approach. We do not estimate the effect of the prize, because an external intervention cannot immediately affect the aggregates that determine the RePEc rankings. Rather, we investigate whether Nobelists (even before receiving the prize) are different from other leading economists in terms of the effect of age on their rankings.

rience a U-shaped relationship of age with rankings for indices of the number of works and citations discounted by recursive impact factor. That is to say, the marginal effect of age on their rankings does not deteriorate with age. Moreover, for breadth of citations across fields, the marginal effect of age on Nobelists’ rankings improves with age.¹⁰

The rest of the paper is organized as follows. In Section 2, we introduce the data and provide descriptive statistics. In Section 3, we describe the estimation procedure. In Section 4, we present the results. Section 5 concludes.

2 Data

RePEc Author Rankings

Our data source is the collection of rankings of the top 5% of RePEc members for the period from August 2000 to June 2020. RePEc publishes the explicit ranking of only top 5% of its members. However, this data constraint is in agreement with the concept that only a small proportion of scientists are influential (Azoulay et al., 2010). Yet the top 5% are not a tiny group. The number of RePEc members was initially small, but has exploded. Correspondingly, the number of the top 5% of the members grew from 18 in the first ranking to over 3,000 twenty years later.

RePEc publishes the aggregate ranking and the rankings with respect to each of the 37 underlying indices, listed in Table 1. The aggregate ranking is a harmonic mean of the 37 rankings. The indices consider the number of works, citations, published pages, abstract views and downloads from RePEc, the quality of professional network, and the number of graduate students. Although most (but not all) existing literature considers citations as a sole measure of influence,¹¹ we argue that other indices are also important. Num-

¹⁰We use the verbs “deteriorate” and “improve” and not “increase” and “decrease” to avoid confusion: the better rankings are the lower ones, so an increase of a ranking is bad.

¹¹Citations mean influence in Hilmer et al. (2015) and many others. However, there is a big discussion on how citations should be counted (Hirsch, 2005, Hamermesh, 2018,

ber of publications indicates influence, because acceptance rates in economic journals are very low. Thus, publications mean that one’s work receives exposure and prestige at the expense of the work of many others.¹² Number of PhD students is important, because supervision of PhD dissertations generates a direct spread of the supervisor’s fields of interest, ideas, and methods. Finally, research network is important for a similar reason.

Although it may happen that a relatively minor economist ranks well in RePEc, it would be an exception. For instance, the list of top 10 RePEc authors includes only very influential economists, such as James J. Heckman and Jean Tirole. Moreover, as we show below, Nobelists (even before the receipt of the prize) rank much better on average than others in the top 5% group. This evidence also advocates the validity of RePEc rankings as a measure of influence.

Efficient Panel

In order for the rankings of the economists that we analyze not to be biased by newcomers to RePEc, we choose the range of months that maximizes the number of observations in a strongly balanced panel (*authors* \times *months*). Thus, we study the dynamics of influence in a closed group, where individuals are ranked every month with respect to each other. This is important, because we interpret our empirical analysis as an investigation of competition within a closed group. Accordingly, we restrict the sample to RePEc members that are continuously ranked among the top 5%, and the selection of months range is such that the resulting data set is as large as possible. Because RePEc continues to rank its members posthumously, we restrict the sample to economists who were alive at the time of ranking.

Bornmann and Wohlrabe, 2019, Perry and Reny, 2016, Besancenot et al., 2019).

¹²Bosquet and Combes (2013) and Michalska-Smith and Allesina (2017) explore the causal relationship between the number of publications and the number of citations. In addition, Henrekson and Waldenström (2011) consider seven methods of measurement of economists’ performance.

The range of months that we analyze is from March 2012 to June 2020. It provides the maximal possible balanced panel with $N = 1,335$, including 30 Nobel laureates, $T = 100$, and $N \times T = 133,500$. We normalize the rankings within this group, and, for convenience of reading the regression coefficients, rescale the normalized ranking by multiplying it by 100. Therefore, the top economist in our data has the ranking of $\frac{100}{1,335}$, while the rankings of other economists are uniformly distributed between $\frac{200}{1,335}$ and 100.

Our analysis addresses the variables of age and the number of years since Ph.D. graduation. We use different sources to find these data: curriculum vitae, personal and institutional websites, the RePEc genealogy project, Wikipedia, and the Prabook project. We found the year of birth for 997 authors (74.7%) and the year of Ph.D. in economics (or equivalent) graduation for 1,280 authors (95.9%). Hence, the sample with age consists of $997 \times 100 = 99,700$ observations, and the sample with the number of years since graduation consists of $1,280 \times 100 = 128,000$ observations. The authors in the sample have a wide range of ages from 32 to 95 for non-Nobelists and from 39 to 92 for Nobelists (see the summary statistics in Panel A of Table 2).

Robustness Check: Long Panel

A natural robustness check of the results is estimation of the model with a different sample. We recall that in the efficient panel $T = 100$ and $N = 1,335$. For the robustness check, we increase T by 50% at the expense of a lower N . Thus, we reestimate the model with $T = 150$ (January 2008 to June 2020). The largest N for a balanced panel in this period of time is 633 authors, for 531 (83.9%) of whom we know the year of birth and for 624 (98.6%) of whom we know the year of graduation. There are 27 Nobelists in this sample. For ease of notation, we refer to this sample as the “long panel,” and its summary statistics are shown in Panel B of Table 2.

Figure 3 illustrates the data. The axes are month of ranking and number of authors. The line shows the evolution of the overall number of top 5% RePEc

authors, and the two rectangles indicate the efficient and the long panels.

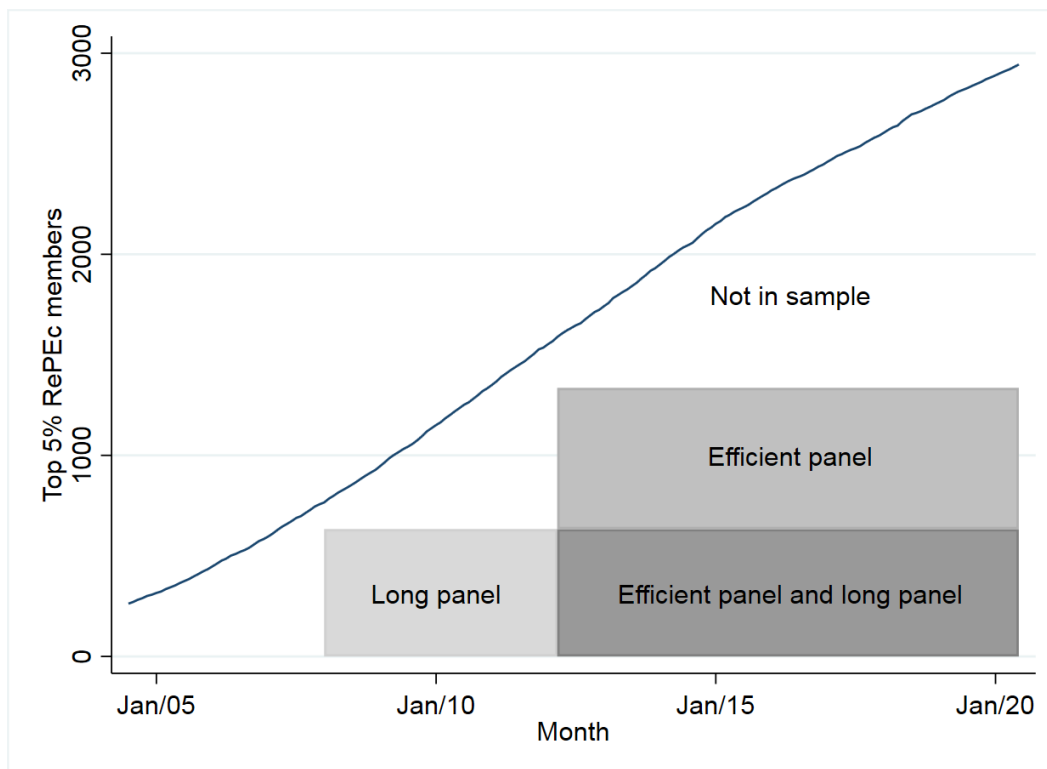
Descriptive Graphs

We start from descriptive graphs that show stylized facts with regard to the average rankings of the top 5% of RePEc members. In Figure 4, we plot the average aggregate ranking by age. As seen in the figure, the average ranking improves i.e., decreases, until about age 60 and deteriorates afterwards. Compared to non-Nobelists, Nobelists have higher and stabler average rankings (not declining until their late 70s).

Figure 4 shows separately three birth cohorts of non-Nobelists and two cohorts of Nobelists. The overlaps between the cohorts show to which extent we can separate cohort effects from age effects. RePEc is a relatively new resource and does not cover complete life cycles. In particular, our efficient panel covers only a period of 100 months. Thus, cohort effects cannot be fully separated from age. However, as seen in Figure 4, the overlapping regions have coinciding ranking patterns. Therefore, although we do not interpret our findings as robust to all birth cohorts, we cannot reject the possibility that this is the case.

One can also plot the components of the aggregate ranking separately. In Figure 5, we consider two of the 37 indices. The figure shows the average ranking in terms of the simple number of citations and the number of distinct works by age and by the number of years since Ph.D. graduation. We see almost no difference between Nobelists and other top economists in the average ranking in terms of the number of works as a function of age and as a function of academic experience. However, there is a significant difference in the ranking of Nobelists and other top economists in terms of the number of citations. There is a big advantage for Nobelists at all ages and at all levels of academic experience.

Figure 3: Full data set, the efficient, and the long panels



Note: The figure shows the number of top 5% RePEc members in terms of the aggregate monthly ranking. The two rectangles show the largest possible (in terms of $N \times T$) balanced panel (“efficient panel”) and a balanced panel with a 50% longer time window than in the efficient panel (“long panel”). For some authors, we do not know the year of birth and the year of Ph.D. graduation. They are taken into account for normalization of monthly rankings within the panel but are not included in regression analyses.

Table 1: RePEc indices used to rank authors

Index	Description
<i>A: Number of Citations</i>	
1	nbcites Number of Citations
2	dcites Number of Citations, Discounted by Citation Age
3	scites Number of Citations, Weighted by Simple Impact Factor
4	dscites Number of Citations, Weighted by Simple Impact Factor, Discounted by Citation Age
5	wscites Number of Citations, Weighted by Recursive Impact Factor
6	wdscites Number of Citations, Weighted by Recursive Impact Factor, Discounted by Citation Age
7	anbcites Number of Citations, Weighted by Number of Authors
8	adcites Number of Citations, Weighted by Number of Authors, Discounted by Citation Age
9	ascites Number of Citations, Weighted by Number of Authors and Simple Impact Factors
10	adscites Number of Citations, Weighted by Number of Authors and Simple Impact Factors, Discounted by Citation Age
11	awscites Number of Citations, Weighted by Number of Authors and Recursive Impact Factors
12	awdscites Number of Citations, Weighted by Number of Authors and Recursive Impact Factors, Discounted by Citation Age
13	hindex h-index
14	ncauthors Number of Registered Citing Authors
15	rcauthors Number of Registered Citing Authors, Weighted by Rank (Max. 1 per Author)
16	euclid Euclidean Citation Score
17	nepcites Breadth of Citations across Fields
<i>B: Number of Works and Journal Pages</i>	
1	nbworks Number of Works
2	dnbworks Number of Distinct Works
3	scworks Number of Distinct Works, Weighted by Simple Impact Factor
4	wscworks Number of Distinct Works, Weighted by Recursive Impact Factor
5	anbworks Number of Distinct Works, Weighted by Number of Authors
6	ascworks Number of Distinct Works, Weighted by Number of Authors and Simple Impact Factors
7	awscworks Number of Distinct Works, Weighted by Number of Authors and Recursive Impact Factors
8	nbpages Number of Journal Pages
9	scpages Number of Journal Pages, Weighted by Simple Impact Factor
10	wscpages Number of Journal Pages, Weighted by Recursive Impact Factor
11	anbpages Number of Journal Pages, Weighted by Number of Authors
12	ascpages Number of Journal Pages, Weighted by Number of Authors and Simple Impact Factors
13	awscpages Number of Journal Pages, Weighted by Number of Authors and Recursive Impact Factors
<i>C: Miscellaneous</i>	
1	absviews Number of Abstract Views in RePEc Services over the Past 12 months
2	downloads Number of Downloads through RePEc Services over the Past 12 months
3	aabsviews Number of Abstract Views in RePEc Services over the Past 12 months, Weighted by Number of Authors
4	adownloads Number of Downloads through RePEc Services over the Past 12 months, Weighted by Number of Authors
5	close Closeness Measure in Co-authorship Network
6	betweenn Betweenness Measure in Co-authorship Network
7	students Record of Graduates

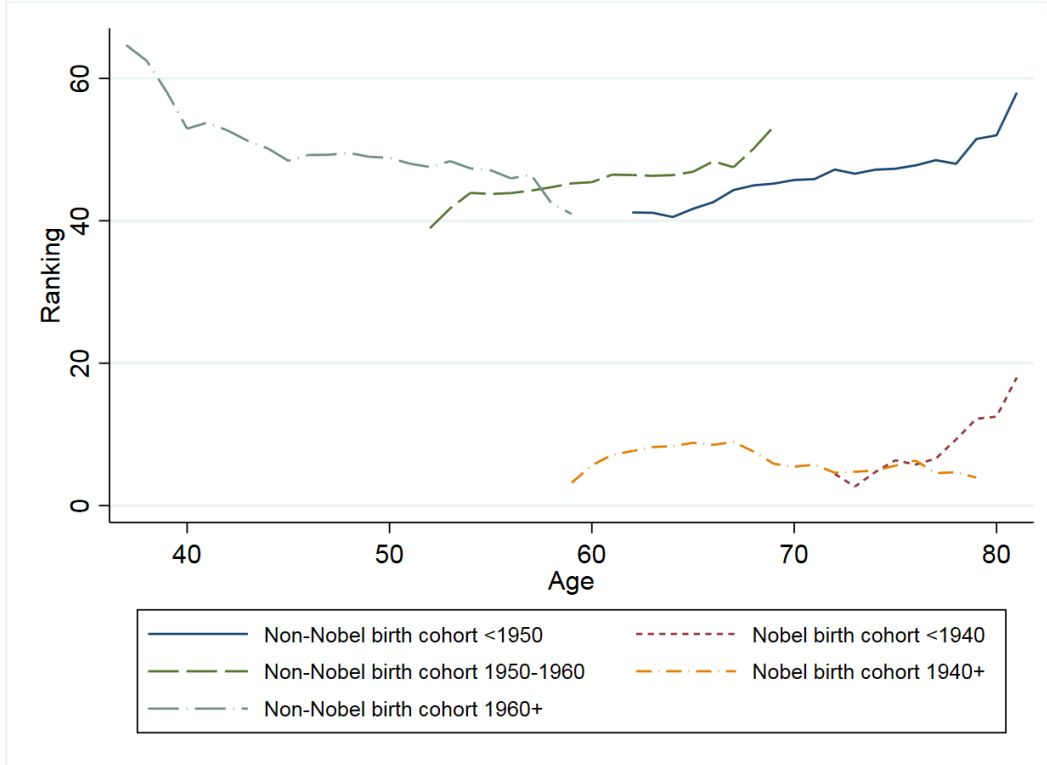
Note: The names and the description of the indices are given according to RePEc.

Table 2: Summary statistics

	Mean	Std.	Min.	Max.	Number of obs.
<i>A: Efficient panel (March 2012 to June 2020)</i>					
<i>Non-Nobelists</i>					
Age	60.1	9.5	32	95	96,700 (967)
Years since Ph.D.	30.1	9.8	2	69	125,000 (1,250)
<i>Nobelists</i>					
Age	71.2	9.7	39	92	3,000 (30)
Years since Ph.D.	45.0	10.0	12	64	3,000 (30)
<i>B: Long panel (January 2008 to June 2020)</i>					
<i>Non-Nobelists</i>					
Age	59.3	9.1	29	95	75,600 (504)
Years since Ph.D.	30.2	9.3	-1	69	89,550 (597)
<i>Nobelists</i>					
Age	70.0	8.8	43	92	4,050 (27)
Years since Ph.D.	43.8	9.1	15	64	4,050 (27)

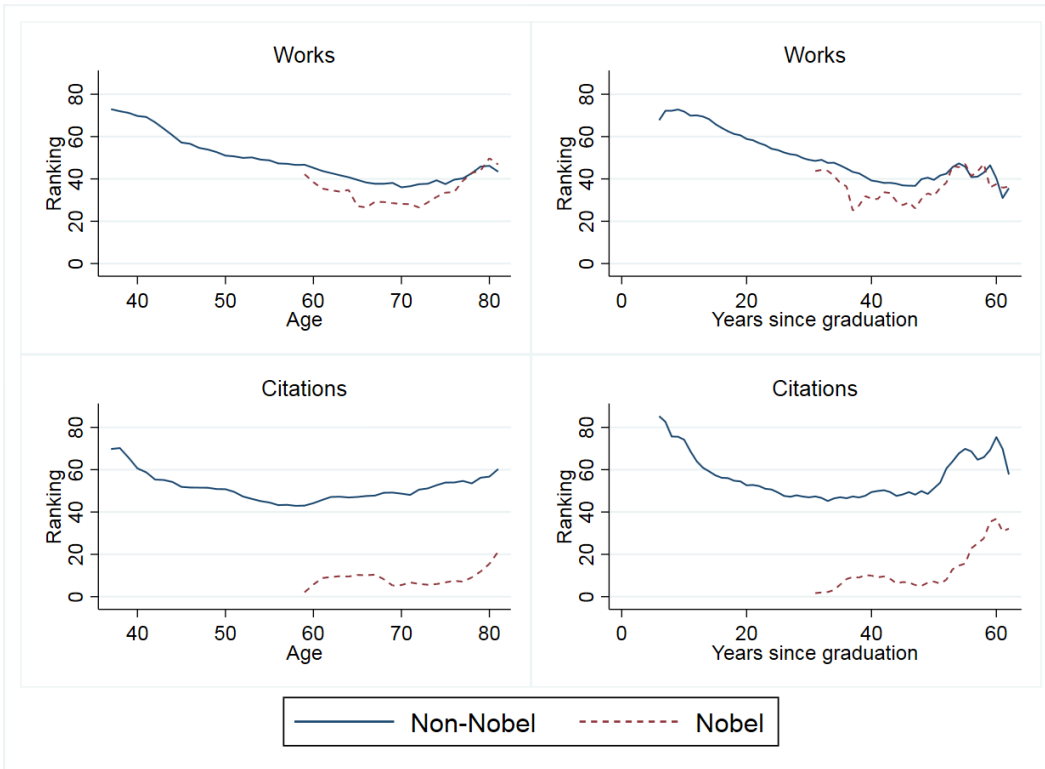
Note: The table shows the descriptive statistics of age and years since receipt of Ph.D. in economics or an equivalent degree. The efficient panel is the largest (in terms of $N \times T$) balanced panel that can be derived from the top 5% of RePEc aggregate rankings. The long panel has a by-50%-larger T than the efficient panel has at the expense of a smaller number of economists. The Nobelists are laureates and future laureates at the time of ranking. The figures in parentheses next to the number of observations indicate the number of authors. All the authors in the efficient and the long panels are alive in June 2020.

Figure 4: Average aggregate ranking of top economists by age



Note: The figure shows the average normalized monthly aggregate ranking (multiplied by 100) in the efficient panel (from March 2012 to June 2020), by age and birth cohort. The aggregate ranking is a harmonic mean of 37 rankings with respect to indices, listed in Table 1. The sample for this figure consists of all economists in the efficient panel whose year of birth is known: 967 non-Nobelists and 30 Nobelists during 100 months, 99,700 observations overall (see the summary statistics in Panel A of Table 2).

Figure 5: Average ranking of top economists in terms of the number of distinct works and the number of citations, by age and years since Ph.D. graduation



Note: For graphs by age, see the note to Figure 4. For graphs by year of graduation, the sample consists of all economists in the efficient panel whose year of Ph.D graduation is known: 1,250 non-Nobelists and 30 Nobelists during 100 months, 128,000 observations overall (see the summary statistics in Panel A of Table 2)

3 Estimation

Econometric Model

In this section, we strip the rankings from individual fixed effects and from autocorrelation of the error term and test whether the U-shaped pattern is still there. We estimate a model where we consider, as the outcomes of interest, the 37 RePEc rankings, normalized within the closed group of authors in the efficient or long panels. We depart from the U-shaped relationship, observed in Figure 4, and estimate a quadratic specification¹³

$$R_{it} = \beta_1 Age_{it} + \beta_2 Age_{it}^2 + Nobel_i \times (\beta_3 Age_{it} + \beta_4 Age_{it}^2) + \mu_i + \varepsilon_{it}, \quad (1)$$

where R_{it} is the normalized ranking of economist i in month t , Age is age in years, and $Nobel$ is a dummy variable for being the author a current or future Nobel laureate. The disturbance is allowed to be first-order autoregressive within each author.¹⁴

Individual fixed effects are captured by μ_i . By controlling for individual fixed effects, we absorb any differences in initial conditions between economists of different ages, so that it only matters what happened during the considered period. Therefore, we estimate the gradient of influence by age during 100 months (150 in the long panel) and abstract from historical conditions, such as publication and citation patterns in pre-Internet era, relevant for old but not for young authors.¹⁵

We also estimate Equation (1), where we replace age by the number of years since Ph.D. graduation. Age and number of years since graduation are fully

¹³Any non-linear or non-parametric specification could be identified but not a linear model, because the age of all authors increases at the same rate over time, while the average ranking within the closed group remains constant.

¹⁴We use the STATA function *xtregar* for estimation.

¹⁵Affiliation is also related to influence. It is not included in the model, because if an economist did not change her affiliation during the sample period, the effect of affiliation is absorbed by the individual fixed effect. If she changed her affiliation, such a change is likely to be endogenous to her influence.

correlated in presence of individual fixed effects, and their simple correlation is as high as 0.96, so we refer to these variables interchangeably. However, we found the year of graduation for 95.9% of the efficient panel and for 98.6% of the long panel, compared to, respectively, 74.7% and 83.9% for year of birth. Therefore, estimation with the number of years since graduation adds to the statistical analysis, because any selection issues that may bias the estimates of Equation (1) parameters are not present in the estimation with the number of years since graduation instead of age. An additional reason to estimate the model with the number of years since graduation is to find the optimal level of this variable when the quadratic model is statistically significant.

Interpretation of the Coefficients

Equation (1) captures the relationship of age with normalized rankings, where a normalized ranking ranges between $\frac{100}{1,335}$ and 100, the lower the better. A negative coefficient means a better ranking as a function of the explanatory variable. Because of the normalization of rankings, we interpret the coefficients as percentage points in the uniform distribution of the authors according to each ranking.

As discussed in Section 2, the RePEc ranking data is still too short to follow the complete life cycles of leading economists. Therefore, age effect in this data cannot be fully separated from cohort effect beyond controlling for cohort-specific mean ranking using individual fixed effects.¹⁶ We illustrated this problem in Figure 4. Thus, our estimates should be interpreted as gradients of influence within a closed group of leading economists of different ages sampled for a period of 100 (for the efficient panel) or 150 (for the long panel) months. By saying “the effect of age on the ranking,” we mean the trajectory of rankings over the distribution of ages in RePEc data, when we control for the author-specific mean ranking and the autoregressive disturbance.

¹⁶This is *not* the age-time-cohort problem in the identification of structural parameters in life-cycle models (Schulhofer-Wohl, 2018). There is no time dimension in our data, because the average monthly ranking within the closed group is constant over time.

4 Results

Table 3 presents the results of estimation of Equation (1) for the number of citations. The columns correspond to the indices, listed in Panel A of Table 1. The quadratic form is statistically significant for all 17 citation indices. The coefficients imply a U-shaped relationship with optimum (the best ranking) at age 60. When one replaces age by the number of years since Ph.D. graduation, the optimal value is 30 years. These results are robust to the estimation using the long panel.

Nobelists do not have a different relationship of age with their citation rankings, unless one weights the citations by recursive impact factor (columns 5, 6, 11, and 12). For these indices, the U-shape disappears, indicating no deterioration of their rankings at old age. Nobelists do not follow a U-shaped pattern also for the number of citations, weighted by the number of authors and simple impact factor and discounted by citation age (column 10). An even stronger difference for Nobelists is observed for breadth of citations across fields (column 17). Nobelists rankings *improve* at old age. The results in columns 5, 6, 11, 12, and 17 make an interesting link to the discussion in the introduction, because they emphasize that for Nobelists, citations of their past research, captured by the recursive impact factor, and the spillovers of their research across fields, slow down the deterioration of their influence.

Table 4 presents the results for the number of works and journal pages. The relevant indices are listed in Panel B of Table 1. The quadratic form is statistically significant for all 13 indices in the efficient panel, and for 12 out of 13 indices in the long panel. Also for these indices, the optimal age is 60, and the optimal number of years since graduation is 30. Similarly to the results for citation indices, Nobelists do not experience a U-shaped relationship or rankings with age when their work is weighted by recursive impact factor (columns 4, 7, and 13). Other Nobelists effects, observed in the efficient panel, are not robust to the long panel.

Table 5 presents the results for the number of abstract views and downloads

from RePEc, the network indices, and the number of graduate students. These indices are listed in Panel C of Table 1. The U-shaped relationship with age is not observed for rankings with respect to the simple number of abstract views and the number of downloads, but is observed when the abstract views and downloads are weighted by the number of authors. It is also observed for the network indices. Finally, the U-shape is not observed with respect to the number of graduate students. Nobelists do not have different coefficients for any of the indices in this table.

5 Conclusions

In this paper, we use the rich and growing RePEc database to capture several years of implicit competition for higher ranking between leading economists of different ages. We find that the relationship between age and rankings follows a U-shape. Economists reach the peak of their ranking at age 60, around 30 years after Ph.D. graduation. It is about twenty years after the productivity (or creativity) peak, which is, according to [Gingras et al. \(2008\)](#), [Cui and Zhong \(2013\)](#), and [Rauber and Ursprung \(2008\)](#), around age 40. Moreover, scientists whose exceptional influence is recognized externally by the Nobel Committee do not experience a deterioration in their rankings when their works and citations are discounted by the recursive impact factor. For breadth of citations across fields, their rankings even improve at old age. It may indicate the effect of the prize or the other way around, the spread of influence across fields may make the Nobel prize more likely. But it may also be related to their individual traits, correlated with the propensity to receive the prize.

What can explain the time lag between the productivity and the influence peaks? First, spreading new ideas may take time. Technology such as the internet may help to facilitate the process. Second, some of the innovative works solve research questions that are quite different from the main stream ones (e.g., behavior economics in the 1980s), or they may use a specific

Table 3: Regression results: citations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
	nbcsites	dcites	scites	discites	wscites	wdiscites	ambcites	adcsites	ascites	adscites	awscites	awdiscites	hindex	ncauthors	rcauthors	euclid	ncpites
<i>A: Efficient panel</i>																	
<i>Age</i>	-0.936*** (0.123)	-2.129*** (0.156)	-1.168*** (0.112)	-2.191*** (0.147)	-3.933*** (0.083)	-3.584*** (0.124)	-0.881*** (0.138)	-2.268*** (0.168)	-0.989*** (0.124)	-2.144*** (0.158)	-3.681*** (0.100)	-3.337*** (0.139)	-1.409*** (0.172)	-0.645*** (0.100)	-1.085*** (0.106)	-0.997*** (0.158)	-1.879*** (0.176)
<i>Age</i> ²	0.008*** (0.001)	0.018*** (0.001)	0.010*** (0.001)	0.018*** (0.001)	0.033*** (0.001)	0.030*** (0.001)	0.007*** (0.001)	0.019*** (0.001)	0.008*** (0.001)	0.018*** (0.001)	0.031*** (0.001)	0.028*** (0.001)	0.012*** (0.001)	0.005*** (0.001)	0.009*** (0.001)	0.008*** (0.001)	0.016*** (0.001)
<i>Age</i> × <i>Nobel</i>	0.310 (0.816)	0.731 (1.038)	0.493 (0.745)	1.075 (0.972)	2.614*** (0.550)	2.802*** (0.824)	0.639 (0.917)	2.148* (1.111)	0.899 (0.822)	1.788* (1.045)	3.693*** (0.660)	3.184*** (0.918)	1.492 (1.144)	0.128 (0.665)	0.547 (0.704)	0.247 (1.040)	3.947*** (1.162)
<i>Age</i> ² × <i>Nobel</i>	-0.003 (0.006)	-0.006 (0.007)	-0.005 (0.005)	-0.009 (0.007)	-0.022*** (0.004)	-0.022*** (0.006)	-0.006 (0.006)	-0.017** (0.008)	-0.007 (0.006)	-0.014* (0.007)	-0.029*** (0.005)	-0.025*** (0.006)	-0.011 (0.008)	-0.002 (0.005)	-0.005 (0.005)	-0.004 (0.007)	-0.030*** (0.008)
Optimal age (std. err.)	60.31 (1.227)	60.32 (0.679)	60.56 (0.900)	60.69 (0.623)	59.96 (0.192)	60.40 (0.318)	59.53 (1.446)	59.73 (0.676)	59.90 (1.161)	60.24 (0.679)	59.86 (0.246)	60.16 (0.380)	58.52 (1.120)	60.28 (1.453)	60.18 (0.908)	61.61 (1.423)	60.20 (0.848)
Optimal value (std. err.)	30.16 (1.263)	30.13 (0.713)	30.28 (0.938)	30.23 (0.648)	30.38 (0.175)	30.41 (0.326)	30.26 (1.227)	30.31 (0.580)	30.39 (1.008)	30.37 (0.585)	30.44 (0.201)	30.45 (0.332)	27.64 (1.192)	30.35 (1.718)	30.42 (1.045)	32.34 (1.898)	30.59 (0.741)
<i>B: Long panel (robustness check)</i>																	
Optimal age (std. err.)	59.07 (3.089)	59.88 (1.725)	59.94 (2.698)	60.25 (1.397)	59.52 (0.435)	60.16 (0.831)	59.03 (2.152)	59.20 (1.379)	59.27 (1.988)	59.72 (1.272)	59.33 (0.528)	59.83 (0.866)	55.70 (3.789)	60.60 (5.470)	60.60 (5.470)	62.49 (3.711)	61.03 (2.257)
<i>Nobel</i> effects					Robust	Robust	Robust	Not robust	Robust	Robust	Robust	Robust					Robust
Optimal value (std. err.)	31.27 (2.891)	31.66 (2.021)	31.05 (2.458)	31.29 (1.469)	30.47 (0.399)	30.92 (0.827)	30.90 (2.060)	31.23 (1.458)	30.93 (1.843)	31.10 (1.309)	30.43 (0.489)	30.75 (0.833)	24.98 (4.258)	30.75 (0.833)	30.75 (0.833)	30.75 (0.833)	32.20 (1.740)

Notes: The estimation procedure controls for author fixed effects and allows for within-author AR(1) disturbance. Optimal age is the one that maximizes the ranking according to the estimated marginal effect. Optimal number of years since Ph.D. graduation is the one that maximizes the ranking according to the estimated marginal effect. Optimal age and number of years since Ph.D. graduation are shown only in columns where the quadratic form is statistically significant. Standard errors are given in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table 4: Regression results: works and journal pages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	nbworks	dnbworks	scworks	wscworks	anbworks	ascworks	awsworks	nbpages	scpages	wscpages	anbpages	ascpages	awscpages
<i>A: Efficient panel</i>													
<i>Age</i>	-0.610*** (0.090)	-1.234*** (0.100)	-1.249*** (0.128)	-2.353*** (0.103)	-0.731*** (0.118)	-1.058*** (0.130)	-1.990*** (0.105)	-0.844*** (0.121)	-1.499*** (0.155)	-3.141*** (0.133)	-0.706*** (0.134)	-1.330*** (0.156)	-2.687*** (0.130)
<i>Age</i> ²	0.005*** (0.001)	0.010*** (0.001)	0.010*** (0.001)	0.020*** (0.001)	0.006*** (0.001)	0.009*** (0.001)	0.017*** (0.001)	0.007*** (0.001)	0.013*** (0.001)	0.026*** (0.001)	0.006*** (0.001)	0.011*** (0.001)	0.022*** (0.001)
<i>Age</i> × <i>Nobel</i>	-2.472*** (0.595)	-2.213*** (0.661)	-0.357 (0.846)	2.672*** (0.686)	-0.893 (0.782)	0.325 (0.859)	4.694*** (0.697)	-2.164*** (0.800)	1.197 (1.031)	6.370*** (0.883)	-1.277 (0.888)	2.169** (1.032)	8.882*** (0.860)
<i>Age</i> ² × <i>Nobel</i>	0.016*** (0.004)	0.015*** (0.005)	0.001 (0.006)	-0.019*** (0.005)	0.005 (0.005)	-0.004 (0.006)	-0.035*** (0.005)	0.015*** (0.006)	-0.009 (0.007)	-0.043*** (0.006)	0.008 (0.006)	-0.016** (0.007)	-0.061*** (0.006)
Optimal age (std. err.)	59.08 (1.354)	59.15 (0.739)	59.72 (0.941)	59.87 (0.399)	59.43 (1.481)	59.50 (1.127)	59.80 (0.480)	59.59 (1.322)	59.82 (0.957)	59.47 (0.384)	60.27 (1.771)	60.28 (1.087)	60.00 (0.439)
<i>Years since Ph.D.</i>													
Optimal value (std. err.)	29.72 (1.509)	30.08 (0.648)	30.27 (0.883)	30.56 (0.358)	30.11 (1.341)	30.16 (1.028)	30.44 (0.373)	30.22 (1.503)	30.65 (0.911)	30.87 (0.349)	30.16 (1.799)	30.68 (0.992)	30.94 (0.366)
<i>B: Long panel (robustness check)</i>													
Optimal age (std. err.)	59.70 (2.170)	59.77 (1.508)	60.06 (2.310)	62.73 (2.490)	59.53 (2.527)	59.70 (2.279)	59.70 (0.373)	59.66 (2.434)	59.42 (1.883)	59.87 (0.770)	59.38 (3.200)	59.73 (2.036)	60.53 (1.084)
<i>Nobel</i> effects	Not robust	Not robust	Not robust	Robust	Robust	Robust	Robust	Not robust	Not robust	Not robust	Not robust	Not robust	Robust
<i>Years since Ph.D.</i>													
Optimal value (std. err.)	30.92 (1.953)	30.78 (1.187)	30.89 (2.020)	30.67 (1.844)	30.86 (2.067)	30.34 (2.033)	31.43 (2.416)	31.43 (2.416)	31.06 (1.869)	31.23 (0.614)	31.12 (2.583)	30.85 (1.965)	31.21 (0.816)

Notes: The estimation procedure controls for author fixed effects and allows for within-author AR(1) disturbance. Optimal age is the one that maximizes the ranking according to the estimated marginal effect. Optimal number of years since Ph.D. graduation is the one that maximizes the ranking according to the estimated marginal effect. Optimal age and number of years since Ph.D. graduation are shown only in columns where the quadratic form is statistically significant. Standard errors are given in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table 5: Regression results: views, downloads, network, and students

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	absviews	downloads	aabsviews	adownloads	close	betweenn	students
<i>A: Efficient panel</i>							
<i>Age</i>	-0.050 (0.120)	0.022 (0.150)	-0.733*** (0.163)	-0.566*** (0.180)	-2.466*** (0.191)	-2.168*** (0.144)	-0.045 (0.147)
<i>Age</i> ²	0.000 (0.001)	-0.000 (0.001)	0.006*** (0.001)	0.005*** (0.001)	0.020*** (0.002)	0.018*** (0.001)	0.000 (0.001)
<i>Age</i> × <i>Nobel</i>	-0.290 (0.794)	-0.261 (0.996)	0.661 (1.084)	0.644 (1.193)	-0.640 (1.268)	1.017 (0.952)	1.872* (0.971)
<i>Age</i> ² × <i>Nobel</i>	0.001 (0.006)	0.001 (0.007)	-0.005 (0.008)	-0.005 (0.008)	0.003 (0.009)	-0.010 (0.007)	-0.012* (0.007)
Optimal age (std. err.)			60.45 (2.094)	61.63 (3.079)	61.38 (0.731)	61.16 (0.618)	
<i>Years since Ph.D.</i>							
Optimal value (std. err.)			30.93 (1.905)	31.34 (3.102)	31.52 (0.590)	32.55 (0.527)	
<i>B: Long panel (robustness check)</i>							
Optimal age (std. err.)			57.09 (2.884)	58.48 (3.011)	62.27 (1.319)	62.88 (1.019)	
<i>Years since Ph.D.</i>							
Optimal value (std. err.)			31.45 (1.918)	31.49 (2.179)	34.61 (1.015)	34.76 (0.799)	

Notes: The estimation procedure controls for author fixed effects and allows for within-author AR(1) disturbance. Optimal age is the one that maximizes the ranking according to the estimated marginal effect. Optimal number of years since Ph.D. graduation is the one that maximizes the ranking according to the estimated marginal effect. Optimal age and number of years since Ph.D. graduation are shown only in columns where the quadratic form is statistically significant. Standard errors are given in parentheses. ***p<0.01, **p<0.05, *p<0.1.

methodology that is not commonly used at the time (e.g., the structural approach in the health economics in the early 2000s). It may also depend on how open-minded the main-stream are in embracing new perspectives. Third, one may develop a larger social network and receive wider recognition over time.

An additional factor that can explain the time lag between productivity and influence peaks is the Matthew effect. It takes time for an article to achieve the sort of status that leads to it being habitually cited. Many highly cited articles gradually become iconic and are cited just because everybody cites them. At the same time, after a few decades, the results of extremely influential articles become so canonical that they are not even cited any more, e.g., [Samuelson \(1954\)](#) on public expenditure.

However, we document that it is hard to maintain the growth of influence after age 60. At this age, the leaders start to get overtaken by their younger colleagues.

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