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Does early publishing in top journals really predict long-term scientific success in the business field?

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Abstract
The soaring number of researchers has led to increasingly intense competition in academia. Early identification of scientists' potential is a practical but difficult issue currently attracting escalating attention. This study takes the business field as an example and explores whether early publishing in top journals is an effective yardstick to recognise scientists who will have better academic performance in their careers. We extract the career records of publication and citations for 1933 business scientists with stable and continuous publication records from the combination of the ORCID and Scopus databases. Through regression analysis and various checks, we find that researchers publishing in top journals early in their careers indeed perform better subsequently compared to peers with similar early career profiles but no top journal publications. Our research sheds light on a new perspective for early identification of potential star scientists, especially in the business field, and justifies encouraging junior researchers to devote themselves to publishing in top-ranked peer-reviewed journals.

Keywords Top journal publications · Early identification · Research performance · Academic career prediction · Citation analysis

Introduction

A great increase in the number of researchers has led to the soaring number of publications and increasingly fierce competition in academic circles. Researchers need to expend great effort to stay in academia and succeed. This phenomenon is closely related to every researcher, so it has become an issue of wide concern. In this context, studies on scientific careers (Deville et al., 2014; Jia et al., 2017; Liu et al., 2018; Sinatra et al., 2016) have gradually emerged in recent years to quantify the development dynamics of scientists over an entire career, helping scientists form a clearer understanding of their career. Some studies exploring factors related to career success have gained enormous popularity (Milojevic et al., 2018; Petersen et al., 2014; Gaule & Piacentini, 2018).

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Career success is not a simple concept, so various dimensions exist in the previous literature to measure it. For example, some studies focus on a specific position or social status, such as whether the scholar becomes a principal investigator (van Dijk et al., 2014), acquires an independent research position (Lienard et al., 2018) or becomes a top scientist (Li et al., 2019). Some other studies define the criteria for career success as the ability to maintain a long, active career in science (Milojevic et al., 2018) or the ability to attract collaboration (Zhang & Yu, 2020). Productivity and academic impact are also common indicators to measure scientific success and represent career success (Li et al., 2019; Wang et al., 2019). Academic impact is a multifaceted concept, but it is often measured in practice by citation-based indicators, including the h-index, average citation per paper, or total citation counts, even though problems are inevitable. For example, some citations are generated because of the author's reputation rather than paper quality (Hurley et al., 2013), and some scholars deliberately self-cite to promote their careers (Seeber et al., 2019). Citation-based indicators are widely used as measurements of impact (Aksnes et al., 2019; Waltman, 2016), based on the understanding of the normative theory of citing behaviour (Merton, 1979) and supported by a series of empirical research efforts (Durieux & Gevenois, 2010; Mingers & Leydesdorff, 2015; van Raan, 2006).

An important theme related to career success is predicting it by early indicators; relevant studies refer to this as early identification of the potential of scientists. This early identification capability can help funding committees and recruitment offices in universities select appropriate candidates as funding recipients or as tenured faculty from a large pool of candidates. Therefore, this topic has witnessed increasing popularity in recent years, and researchers have made efforts in this direction (Laurance et al., 2013; Lee, 2019; Zeng et al., 2017).

However, this early recognition is more intractable than short-term performance prediction. Many studies suggest using citation-based indicators as predictors of short-term scientific success at the level of authors (Danell, 2011; Mazloumian, 2012). However, when these indicators are applied to long-term prediction, the efficiency of the prediction model tends to decline greatly (Acuna et al., 2012; Petersen et al., 2012). This happens mainly because preferential attachment is the major driving force for the growth of citations (Higham et al., 2017; Newman, 2009), but it can be observed in a very limited way in the early career stage (Penner et al., 2013). Therefore, additional informative indicators, ones that do not require time to accumulate, are necessary to solve this challenge. Current studies have identified several indicators: for example, early coauthorship with top scientists (Li et al., 2019) and early setbacks (Wang et al., 2019). Some studies use high-quality journal publications to predict scholars' short-term academic performance (Lindahl, 2018; von Bartheld et al., 2015). However, research related to predicting long-term performance by early publishing in high-quality journals is still insufficient, especially in the social sciences. Further exploration is necessary to strengthen understanding of this issue.

The purpose of this study is to validate an idea that has been widely applied by academics but not scientifically tested: junior researchers who can publish in top journals tend to have scientific success in their long-term careers. We take the business field as an example to ascertain the relationship between the single event of publishing in a top journal and the future career success of a junior researcher. Regression models are used to control for disparities in early profiles other than publishing in the top journals. This research is meaningful because it provides empirical evidence for a widely adopted practice, which can enhance the confidence of institutions using the practice and reduce opposition and hesitation. Our results can also guide confused junior researchers who want to succeed in academia to reasonably plan their precious early career.

The present study is organised as follows. The second section reviews the relevant literature, and the third section describes our method of data processing and defines the variables. Then the fourth section shows the results of descriptive analysis and regression analysis, followed by the fifth section offering additional analysis of the results. The final section closes the paper with a discussion and major conclusions.

Literature review

Many publications explore factors related to an author's scientific success (e.g., van den Besselaar & Sandstrom, 2016; Way et al., 2019), and some studies pay attention to its short-term prediction (Acuna et al., 2012; Symonds, 2004), but few studies concern long-term prediction related to this theme. Current research in early identification of potential scientists has proceeded mainly in the following directions. Coauthorship, which can be observed in the author list immediately after publication, is repeatedly explored as an early indicator predicting future success. Qi et al. (2017) identified a positive relationship between the impact of collaborators in the early period and the young scholar's future academic performance. This conclusion is validated by other research, but studies also pointed out that this collaboration is not the only route to success (Amjad et al., 2017; Li et al., 2019). The effect of academic tutors as vital collaborators with junior researchers has also been focused. Analysis shows that postdoctoral mentors and the degree of intellectual synthesis between mentors in the graduate and postdoctoral stages are particularly instrumental to career success (Lienard et al., 2018). Recently identified measurements such as early-career setback (Wang et al., 2019) and publishing strategy (Zhang & Yu, 2020) have also proven relevant to long-term scientific success. The indicators presented by these studies do not require years of accumulated data; rather, they can be observed immediately once publications appear. These proposed predictors expand researchers' understanding of this topic and provide new perspectives about early identification. Even so, research on this topic is still in its infancy, and more easily observed early indicators are needed to predict long-term scientific success and provide comprehensive knowledge.

Another line of research related to publishing in high-quality journals continues to develop. The number of publications in top journals is regarded as a vital measurement of research productivity in the law field (Mishra & Smyth, 2013) and information systems field (Chen et al., 2015). Publication in leading journals is also known to be helpful for career promotion in top institutions in the marketing field (Seggie & Griffith, 2009) and finance field (Netter et al., 2018). Moreover, in economics, business, and management-related fields, publishing in top-ranked journals leads to more citations (Drivas & Kremmydas, 2020). These studies together indicate that top journal publications are of great concern in the social sciences, so junior researchers in these fields who manage to publish in top journals deserve special attention.

When predicting future academic performance, several studies focusing on natural science have mentioned publications in high-quality journals, but few relevant studies in the social sciences have done so. For example, in life sciences, researchers who publish in the journals *Nature* or *Science* in their early careers are more productive and publish in *Nature* or *Science* more frequently in the following five years (Symonds, 2004). This study, however, lacks comparisons of longer time spans or impact-related indicators. When estimating the future h-index of neuroscientists, biologists, and evolutionary researchers, Acuna et al. (2012) refer to the number of articles in *Nature*, *Science*, *Nature Neuroscience*, *Proceedings of the National Academy of Sciences*, and *Neuron*. It is interesting in this study that the accuracy of the predictions decreases over time, but the contribution of the number of top journal articles to the formula accuracy increases over time. This implies that publishing in top journals effectively predicts scholars' long-term impact. Although the number of selected top journals is very limited, these studies have yielded meaningful results.

Further, publishing two or more first-author papers in high-impact journals strongly correlates with success in a decade for 40 biomedical investigators (von Bartheld et al., 2015). Lindahl (2018) defines top journals according to a ranking by the source-normalised impact per paper (SNIP). This study indicates that the number of top journal publications during the first four years of the career is an important predictor of mathematicians' research excellence in the next four years in terms of long-term prediction. Bornmann and Williams (2017) explain that the proportion of JCR Q1 journal papers in early career can discriminate later successful researchers, but that should not be used as the only indicator due to the low to medium effect sizes. The research field of scholars in that study is not stated, so it provides limited help in determining whether high-quality journal publications early in a career predict long-career success in the social sciences. In the current study, we use journals with a high reputation among peers in the business field as a proxy for the high-quality journals to ascertain the relationship between early top journal publications and long-term scientific success for junior business researchers.

Data and methods

Data processing

Definitions and selections of journal lists

Currently, there is no widely accepted standard defining a full list of top business journals. Accordingly, we consult two widely used lists of journals (Vogel et al., 2017): (1) the Journal Citation Reports® by Clarivate Analytics (formerly Thomson Reuters): subject categories 'Business', 'Management', 'Business, Finance', 'Economics', 'Agricultural Economics & Policy', and 'Operations Research & Management Science'); and (2) the Scopus database by Elsevier (subject area 'Business, Management and Accounting' and 'Economics, Econometrics and Finance'). We focus on the union of these lists, counting journals included in one or both, which yields a set of 2633 business journals. This list is used to identify whether the research fields of each scholar in the ORCID website or Scopus dataset include business. It is reasonable to assume that a scholar's research fields include business if at least half of their papers mentioned in the ORCID website have been published in the journals on this list.

We take a widely accepted peer-reviewed ranking of journals, the FT 50 List, as the top journals in the business field, and the UT Dallas 24 List of leading business journals is used in the additional analysis (Chen et al., 2015; Tremblay et al., 2018).

Data sources and sample construction

We construct our dataset by combining the ORCID 2019 dataset (see https://doi.org/10.23640/07243.9988322.v2) and the Scopus dataset. ORCID is an open-access author identification system created to address the problem of author misidentification (Garcia-Gomez, 2012; Haak et al., 2012), and it has become an important source of data in recent studies (Gomez et al., 2020; Zhao et al., 2020). To further ensure the accuracy and comprehensiveness of sample data, Scopus, a widely recognised comprehensive citation database, is used as a complement. This database has been proved to have an advantage in addressing author name ambiguity (Baas et al., 2020; Sandberg & Jin, 2016).

This study only focuses on business researchers who stay in academia at least 20 years because this group can shed more light on academia and academic career development. This point of focus can also help filter out many scholars who voluntarily choose to drop out of academia at an early stage, which allows our study to avoid self-selection bias. We apply strict screening rules to select our research objects. By the end of 2019, the publication record indexed by Scopus and by ORCID of these scientists must meet the following criteria: (1) more than 50% of the target scholar's papers are published in the Business Journal List defined in Sect. 3.1.1; (2) the target scholar's publication record spans at least 20 years, including at least ten publications and authorship of at least one paper every five years; (3) the year of first publication for each scientist is limited to 1971–2000. The first criterion ensures these entities are recognised as business scholars, namely, at least one of the main research fields of this target scholar is business. Following the literature (Li et al., 2019; Sinatra et al., 2016), the second standard ensures that we can collect data where these business scholars experience a stable (long publication record) and an active (continuous publication record) academic career. All researchers dissatisfying this criterion are excluded because our goal is to identify a long-term performance gap between early bloomers and their peers. The third criterion is a simple sample selection procedure to avoid an overlong time interval between the career starting years of target scientists.

The above procedure resulted in 1933 scholars and a total of 109,554 documents indexed in Scopus by the end of 2019. After the document type was limited to standard articles and review articles, 88,875 are left to form our final sample. We divide this final sample into two groups according to whether the target researcher published at least one paper in FT journals within five years after the year they published their first paper. Finally, 391 scientists are assigned to the treatment group, and the remaining 1542 scientists are allocated to the control group.

For convenience, this paper uses the term *bloom* to mean 'publish in an FT journal', so scholars with a top journal publication in their early stage are referred to as *early bloomers* hereafter. We use this acronym because a person is said to bloom in English when they do something indicative of maturity or ultimate achievement in some sense, analogous to a flower that blooms (and may do so more than once).

Variables

Table 1 presents brief descriptions of all variables used in this study. Following previous studies (e.g., Lee, 2019; Li et al., 2019; Zhang & Yu, 2020), we define the starting point of a scholarly career as the year of publishing the first article. The early career is defined as the first five years in our main analysis. This study examines whether publishing in top journals in the early career stage is a valuable indicator for business scholars to predict trajectory and scientific impact in their later careers. In the main analysis, we use a dummy variable equalling 1 if the target scholar bloomed in their early career without regard to the number. Among our dataset's early bloomers, 56.52% (221) of them published only one top journal paper in their early career, and the maximum is seven.

Table 1 Variables used in this study

	Variables	Brief explanation and values
Independent variable	Early-bloom (dummy variable)	1 if target scientist bloomed (published in a top journal) in early career; otherwise 0
Covariates	Career starting year	Year when target scientist started career (published first paper in any type of journal indexed by Scopus)
	Early Institution (dummy variable)	1 if the scholar is affiliated with a top institution in early career; otherwise 0
	Early MNCS	Mean normalised citation score of papers published in early career
	No. of early papers	Total number of papers published in early career
	No. of early coauthors	Total number of different coauthors in early career
	Prop. of early first-author papers	Proportion of papers published as the first author in early career
Dependent variables	No. of top journal papers in years 6–20	Total number of papers published in top journals during career years 6–20
	MNCS in years 6–20	Mean normalised citation score of papers published during career years 6–20

In addition to early blooming, many other early factors influence subsequent research performance, so we need to control for these factors. As academia continues to evolve, academics who start their careers at different times face different competition and academic environments (Milojevic et al., 2018). Since the scholars in our dataset started their careers in different years, we control for the career starting year by introducing a year fixed effect. This makes it possible to deal separately with researchers starting their careers in different years and control for how the unique features of each year affect the result variables.

Institutions also have an important influence on scholars' subsequent careers (Heinze et al., 2009; Way et al., 2019). Therefore, we adopt the 2019 global business school ranking in FT.com to define the top institutions in the business field, and we match these top institutions with each institution the target researcher listed in early papers. If any listed institutions belong to the top 100 institutions, this scholar's early institutions score is 1; otherwise, it is 0. We include this dummy variable in subsequent regressions to exclude the long-term performance advantages associated with working at a top institution.

In addition, the quantity and impact (often measured by citations) of papers are two commonly used indicators to measure the authors' scientific performance. These two indicators in the early stage are also included in the regression models to rule out their influence on our focus path. The citation indicator, Early MNCS, is calculated based on publications in the early career of the target scientist and is normalised according to the publishing year and document type. Since only one research field is included in this study, normalisation of the field is not involved. We choose the average of ratios approach to normalise the average citations per publication (Waltman, 2016). This normalisation can solve the problem of citation inflation to a large extent, which means that the impacts of researchers who start their academic careers in different years are more comparable.

Collaboration has been proved to be related to the number of publications and citations (Larivière et al., 2015; Li et al., 2013). Further, in most disciplines, the first and last authors are the main contributors to a paper, but the rules vary between disciplines (Larivière et al., 2016). In business, the first author is always recognised as playing a more important role, especially for junior researchers. In the early stage, we use the number of coauthors (McCarty et al., 2013; Vieira & Gomes, 2010) and the proportion of publications as first author to measure the authors' academic collaboration (collaboration with top scientists is also used in the additional analysis). It is necessary to bring collaboration-related measurements into our regression models to avoid the interference of collaboration in the real relationship we are trying to validate.

This paper uses two outcome variables to measure the researchers' scientific success: number of papers in top business journals (No. of top journal papers in years 6–20) and mean normalised citation score (MNCS in years 6–20). For MNCS in years 6–20, we adopt the same normalisation procedure as for early MNCS, but it is based on subsequent career years. These indicators are determined by papers published during career years 6–20 and corresponding citations. The two variables are used to measure the academic performance of target scientists in their long-term scholarly careers from different angles: No. of top journal papers in years 6–20 measures the ability to publish high-level papers in high-quality journals; and MNCS in years 6–20 measures the average impact received by the researchers after normalisation by document type and publishing year.

Results

Descriptive results

We firstly explore in which journals and when the 88,875 papers were published by 1933 scholars. We find that the 88,875 papers were published in an array of 5614 journals; we list 28 of the journals that have at least 300 publications in Table 2. More information on the journal distribution is available upon request.

Among the 88,875 papers, 3,099 papers were published in UTD 24 journals, and 6,293 papers were published in FT 50 journals. The numbers of papers in the two top journal lists and all 5614 journals per year are shown in Fig. 1. It is obvious that the number of papers on each top journal list maintains a growth trend similar to that of the number of papers in the total sample.

Next, we explore the distributions of variables and their correlations. As shown in Fig. 2, the distributions of outcome variables are highly skewed, a feature seen in most bibliometric data (Bornmann & Leydesdorff, 2014). As for MNCS, about 90% of the values are below 2.07, but the maximum is 8.18, indicating a great difference among these scholars. Among business scientists, 57.68% do not bloom during years 6–20 of their career. For bloomers, most bloom less than six times, but a small number of scholars bloom more than 40 times (maximum: 42).

The characteristics of each variable and the relationships between variables are described in Table 3. The differences between the mean and the maximum of variables 'Early MNCS', 'No. of early papers', and 'No. of early coauthors' show that an obvious performance gap exists among scholars, even in their early careers. Further, 20% of scientists bloom in the first five years of their careers in our database, and 16% of them work in top institutions. These researchers publish an average of 5.23 papers in the first five years, their MNCS average is 0.91, their average number of unique coauthors is 3.80, and the average proportion of papers as the first author is 0.66.

Among the seven early indicators, 'Early-bloom', 'Early Institution', 'Early MNCS', and 'No. of early papers', as well as 'No. of early coauthors', are significantly correlated with both dependent variables. The Pearson correlation coefficient between the two outcome variables is 0.48, which is not strong enough to keep only one variable and rule out the other. Therefore, each variable represents a unique part of the target scientist's future research performance and behaves as an outcome variable for subsequent analysis.

In Fig. 3, we compare the difference in career performance between the two groups on eight variables: the number of papers, number of top journal publications, normalised total citations, MNCS, h-index, number of unique coauthors, proportion of papers as first author, and proportion of authors affiliated with top institutions. Early bloomers are shown in orange, and others are shown in blue. Each pair of bars (two adjacent bars) compares one index between the two groups. The left side compares the performance differences in their early career, and the right side compares performance differences in their later careers.

The relative advantages of the two groups in each index are reflected by the boundary between the two colours in each bar and the horizontal dotted line in the middle of Fig. 3. If the borderline is right on the dotted line, the two groups perform equally in that period. If the borderline is located above the dotted line, the early bloomers have worse performance. For instance, in terms of the number of papers in the later career and the proportion of papers as first author in the whole career, other scholars slightly exceed early bloomers. If the borderline is below the dotted line, obviously, the early bloomers have better

Table 2 Journals with at least 300 publications by target scholars by the end of 2019

	Journal	Frequency		Journal	Frequency
1	European Journal of Operational Research	2187	15	Economic Modelling	364
2	Economics Letters	953	16	Journal of Banking and Finance	363
3	International Journal of Production Economics	763	17	Journal of Economic Theory	359
4	Applied Economics	722	18	Journal of Optimization Theory and Applications	358
5	Computers and Operations Research	719	19	European Economic Review	351
6	Journal of the Operational Research Society	650	20	Journal of Applied Psychology	351
7	International Journal of Production Research	603	21	Energy Economics	347
8	Annals of Operations Research	564	22	Journal of Economic Dynamics and Control	341
9	Journal of Economic Behavior and Organization	461	23	Energy Policy	337
10	Applied Economics Letters	457	24	Games and Economic Behavior	336
11	American Journal of Agricultural Economics	416	25	Management Science	336
12	Tourism Management	384	26	World Development	311
13	Journal of Business Ethics	373	27	Journal of Econometrics	301
14	Journal of Business Research	372	28	Ecological Economics	300

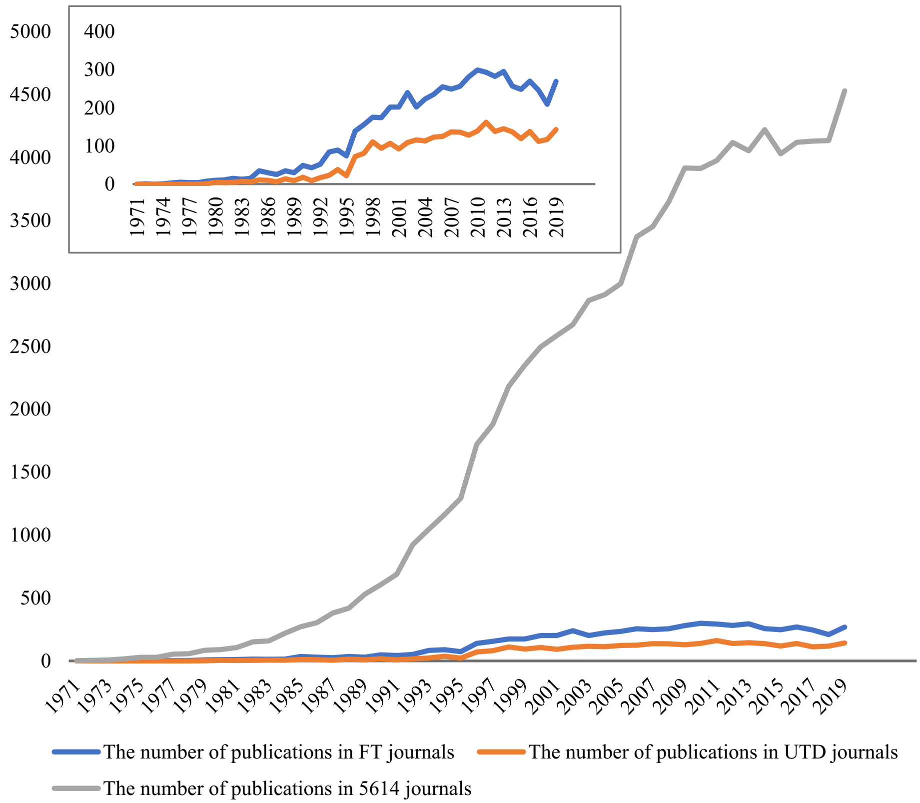

Fig. 1 Number of papers in two top journal lists and all 5614 journals from 1971 to 2019

performance. Figure 3 indicates that early bloomers have better performance on most of the indicators (such as the number of publications in top journals, normalised total citations, MNCS, and proportion of authors affiliated with top institutions) whether in the early or later stage, which is an important reason why we control for early variables in the follow-up regression analysis.

Regression results

We carry out regression analysis respectively for the two result variables. Since the number of top journal papers in years 6–20 is a counting variable with a mass of zero values, and its distribution is highly dispersed (the variance is much higher than the mean), the zero-inflation negative binomial regression model is adopted for estimation. Variable MNCS is standardised according to the document type and publishing year, and its mean roughly equals its variance, so the Poisson regression model is adopted.

Table 4 presents the results of zero-inflation negative binominal regressions using STATA 15.0 to reveal the influence of early-stage publishing in top journals on the number of top publications in the long term. Model 1 shows that early bloomers are expected to have a rate 6.81 times (odds ratio: 6.81, $p < 0.001$) greater for top journal publications when directly compared with their peers while ignoring other covariates. As shown in column 2

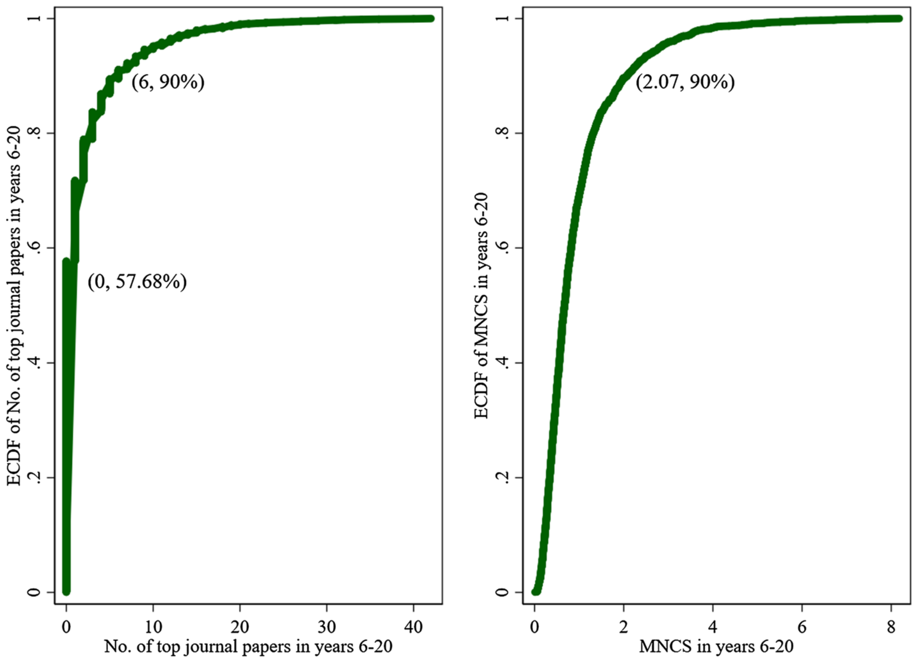

Fig. 2 Distributions of the dependent variables

of Table 4, when other covariates are included, early bloomers increase their odds of top journal publications in their later career by 395% (odds ratio: 4.95, p < 0.001). The odds ratios of Early Institution and Early MNCS are greater than 1 and significant at the 0.1% level, indicating that, for any junior scholar, working at highly reputable institutions or having higher academic impact also relates to more top journal publications in the long term.

Table 5 presents the results of Poisson regressions using STATA 15.0 to reveal the influence of early blooming on mean normalised citation score in the long term. Model 1 shows that if other early variables are not controlled for, the rate for mean normalised citation score of early bloomers increases by a factor of 1.95 in their long-term academic careers compared to those who are not early bloomers. This figure decreases in Model 2 but is still significantly positive. In addition, we can also see from Model 2 that, while holding the other variables constant in the model, junior researchers in the top 100 institutions compared to others have a rate 1.33 times greater for MNCS during career years 6–20. Similarly, with the other variables held constant in the model, if a junior researcher increases their mean normalised citation score by one point in the early career stage, the rate for MNCS in years 6–20 is expected to increase by a factor of 1.07.

Since the information provided by odds ratios is not always intuitive enough, here we use the adjusted predictions obtained by the margins command in STATA 15.0 (Williams, 2012) to convey effect sizes. The adjusted prediction values of two outcome variables for two groups are shown in Fig. 4. When we fix all other variables at their means, early bloomers are expected to publish an average of 4.25 top journal publications and receive 1.30 times as many citations as papers of the same document type published in the same year on average over the next 15 years. However, when we keep all other early variables at their means again, those who did not publish in top journals in their early stage are

Table 3 Means and standard deviations of independent variables and the correlations with two dependent variables

Variables	Mean	Standard deviation	Min	Max	No. of top journal papers in years 6–20	MNCS in years 6–20
Early-bloom	0.20	0.40	0	1	0.48***	0.34***
Career starting year	1993.18	5.61	1971	2000	– 0.02	– 0.05*
Early Institution	0.16	0.37	0	1	0.26***	0.21***
Early MNCS	0.91	1.62	0	26.26	0.31***	0.40***
No. of early papers	5.23	3.69	1	43	0.15***	0.07**
No. of early coauthors	3.80	6.54	0	202.00	0.10***	0.05*
Prop. of early first-author papers	0.66	0.32	0	1	– 0.04	– 0.03
No. of top journal papers in years 6–20	1.95	4.25	0	42	-	0.48***
MNCS in years 6–20	0.96	0.94	0.01	8.18	0.48***	-

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

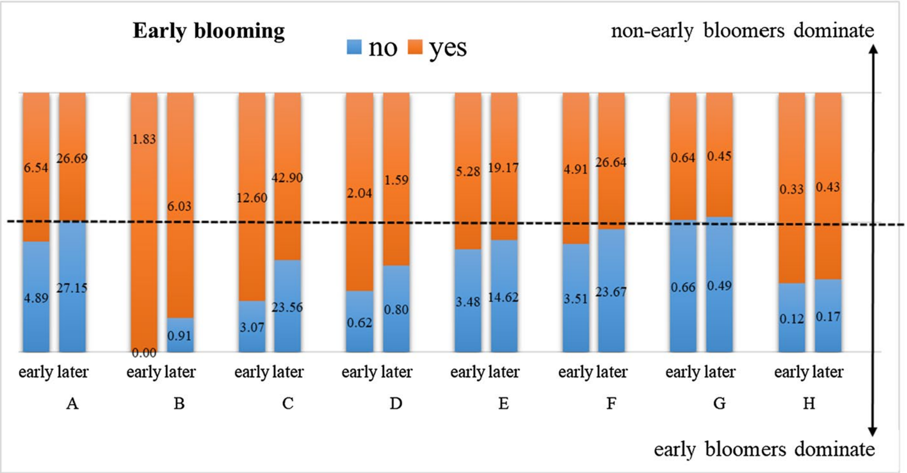

Fig. 3 Performance comparison of early bloomers and others in different career stages. Here, A refers to number of papers; B refers to number of top journal publications; C refers to Normalised total citations; D refers to MNCS; E refers to h-index; F refers to number of unique coauthors; G refers to the proportion of first-author papers; H refers to the proportion of authors in top institutions.

Table 4 Regression results of No. of top journal papers in years 6–20

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Early-bloom	6.81***	4.95***	2.03***	5.34***	9.39***	4.29***
	(21.81)	(16.72)	(13.79)	(19.72)	(16.39)	(14.34)
Early Institution		2.04***	2.11***	1.91***	2.68***	2.14***
		(6.99)	(7.08)	(6.23)	(6.79)	(6.64)
Early MNCS		1.13***	1.10***	1.03***	1.18***	1.06**
		(3.88)	(3.33)	(6.45)	(4.41)	(3.35)
No. of early papers		1.03	1.02	1.10***	1.03	1.01
		(1.69)	(1.03)	(4.41)	(1.49)	(0.45)
No. of early coauthors		1.02	1.02	1.01	1.02	1.05
		(0.87)	(0.89)	(0.95)	(0.61)	(1.46)
Prop. of early first-author papers		0.92	0.86	0.68	0.65	0.90
		(– 0.53)	(– 0.93)	(– 0.50)	(– 1.94)	(– 0.67)
Constant	0.89	0.38**	0.49*	0.12***	0.22***	0.66
Career starting year FE	No	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.19	0.25	0.24	0.35	0.23	0.16
Log pseudolikelihood	– 2874.07	– 2812.32	– 2827.17	– 1864.49	– 1792.74	– 3035.21
Number of observations	1840	1840	1840	1840	1840	1840

Odds ratios are reported, z-statistics in parentheses, *$p<0.05$, **$p<0.01$, ***$p<0.001$, FE: fixed effect. All standard errors are robust standard errors. The 93 researchers who started their scholarly careers from 1971 to 1981 are omitted here and in the later analysis because a severe multicollinearity issue would otherwise occur

Table 5 Regression results of MNCS in years 6–20

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Early-bloom	1.95***	1.61***	1.20***	1.79***	1.42***	1.71***
	(13.71)	(9.11)	(8.72)	(12.52)	(5.26)	(8.63)
Early Institution		1.33***	1.33***	1.28**	1.42***	1.39***
		(5.13)	(4.95)	(4.12)	(5.94)	(5.08)
Early MNCS		1.07***	1.08***	1.02***	1.08***	1.04***
		(4.99)	(5.63)	(8.36)	(4.98)	(4.72)
No. of early papers		1.00	1.00	1.04***	1.01	1.00
		(0.51)	(– 0.07)	(3.72)	(1.50)	(– 0.11)
No. of early coauthors		1.00	1.00	1.00	1.00	1.00
		(0.19)	(– 0.02)	(1.42)	(0.16)	(0.78)
Prop. of early first-author papers		0.94	0.93	1.04	0.93	0.87
		(– 1.11)	(– 1.28)	(0.10)	(– 1.24)	(-2.59)
Constant	0.80***	0.80	0.88	1.48**	0.85	0.93
Career starting year FE	No	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.09	0.14	0.14	0.37	0.12	0.11
Log pseudolikelihood	– 2102.35	– 2055.92	– 2052.47	– 2569.62	– 2077.03	– 2071.27
Number of observations	1840	1840	1840	1840	1840	1840

Odds ratios are reported, z-statistics in parentheses, $*p<0.05$, $**p<0.01$, $***p<0.001$, FE: fixed effect. All standard errors are robust standard errors. The 93 researchers starting their scholarly careers from 1971 to 1981 are omitted here and in the later analysis because a severe multicollinearity issue would otherwise occur

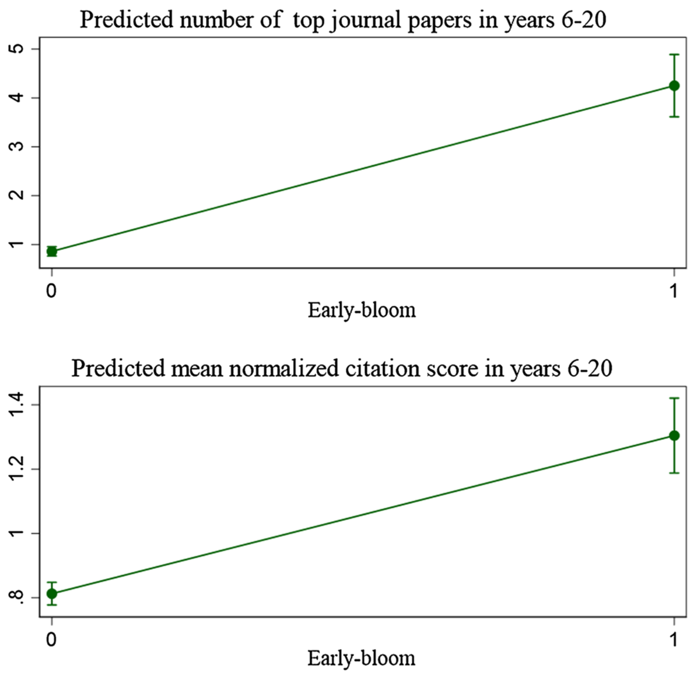

Fig. 4 Adjusted predictions with 95% CIs for two outcome variables of two groups

predicted to publish just 0.86 papers in top journals and get a mean normalised citation score of 0.81 over the next 15 years.

In summary, we find that early bloomers in the business field perform significantly better than their peers both in high-quality journal output and normalised average impact. This advantage can be observed whether through regression results or adjusted projections. It is also true after the addition of the year fixed effect and when controlling for other early factors, such as productivity, impact, working organisation, and collaboration.

Additional analysis

Analysis of alternative definitions of variables

We modify the definitions of the variables in four ways: the counting method of treatment and multi-author publications, the list of top journals, and the time span of early career. These model variations further prove the reliability of the results and exclude the possibility that our results are caused by accidental or deliberate selection of variable definitions. To observe the relationship between early blooming and long-term academic performance under different variable definitions, we recalculate each variable for the whole sample after changing these definitions one by one and follow the steps in the main analysis.

Count variables for Early-bloom

In the main analysis, we divide junior scholars into the treatment group and control group based only on whether they published in a top journal in their early stage. However, the number of top journal publications in the early stage varies, as shown in Table 6 for the detailed distribution. Therefore, in this part, we change the counting method of independent variables by using counting variables instead of binary variables. The results of regressions of two result variables are shown in the third column (Model 3) of Tables 4 and 5.

In Model 3, the coefficients of the covariates barely change while the coefficient of the independent variable decreases. This is mainly because the previous estimation measures the impact on the outcome variables from no top journal publications to having one or several top journal publications. The estimated effect size now measures the effect of each additional unit of the early top journal publications on the two outcome variables.

Table 6 Distribution of the number of top journal publications in first five years for full sample

No. of top journal publications in first 5 years	Freq	Percent	Cum
0	1542	79.77	79.77
1	221	11.43	91.21
2	88	4.55	95.76
3	41	2.12	97.88
4	20	1.03	98.91
5	13	0.67	99.59
6	4	0.21	99.79
7	4	0.21	100

Fractional counting for multi-author papers

When a paper has multiple authors, each author's contribution to the paper is different from the author's contribution in a single-author paper. If each individual author in a multi-author paper is allocated the full credit for a publication (known as full counting), the contributions are overestimated. In addition, the collaboration indicator positively correlates with the number of publications and citation rates (Larivière et al., 2015; Li et al., 2013). Therefore, it is necessary to consider credit allocation for multi-author publications to determine whether early bloomers still display better academic performance when contributions are allocated more precisely. A variety of credit allocation methods have been proposed in the literature, such as allocating different credit to the authors of a publication based on their position in the author list (Frandsen & Nicolaisen, 2010) or allocating the credits only to the first author or corresponding author (e.g. Huang & Lin, 2011; Waltman & van Eck, 2015). In this part, we apply the fractional counting method, where each author receives an equal share of the credits of publication and citations (Waltman, 2016; Wildgaard et al., 2014).

After applying fractional counting to each paper of each scholar, we repeat the process in the main analysis. The regression results for the two outcome variables are shown in the fourth column (Model 4) of Tables 4 and 5. In both models, early blooming still has a positive and significant effect on the two outcome variables, and the effect is stronger than that of the base model (Model 2). In addition, the influences of the number of papers in early stage on two result variables become significant after applying fractional counting.

Alternative definition of top journals

The UT Dallas 24 List is employed by the UT Dallas Naveen Jindal School of Management to provide top business school rankings. Like the FT 50 journals, it is one of the most widely recognised lists of leading journals in business research. The UT Dallas 24 List can be considered as a finely selected subset of the FT 50 List. Almost every journal (23 out of 24) in UT Dallas 24 List is included in the FT 50 list; the only exception is *Journal on Computing*. We replace the top journals list in our earlier analysis with the UT Dallas 24 List in this part to eliminate the objection that a deliberate choice of the top journal lists led to the conclusions.

The results are presented in the fifth column (Model 5) of Tables 4 and 5. By comparing the coefficients of the independent variables in Models 5 and 2, we find that compared with FT journals, early publication in UTD journals has a greater impact on researchers' later publications in the top journal list but less impact on obtaining higher MNCS. No matter how, the positive significant effects remain valid after changing the definition of the list of top journals, which indicates the robustness of the results.

Alternative definition of early career

We have mentioned that research definitions of career starting point vary, and we regard the year when the first academic paper was published as the starting year of a researcher's career. Meanwhile, various definitions of the length of early career appear in the literature, although it is usually defined as the first five or three years (e.g. Li et al., 2019; Qi et al., 2017). We count early variables based on data in the first five years in the main body of the paper. Here we consider an alternative definition of early career as the first three years, and the outcome variables are calculated based on publications and citations in career years 4–20. We repeat the previous model analysis, and the results are shown in the sixth column (Model 6) of Tables 4 and 5. Again, significant positive effects of early blooming on the two outcome variables do exist, suggesting that the definition (length) of early career does not change our results qualitatively.

It can be seen from what has been repeatedly verified above that the correlation of early blooming and scientific success in a long career is constant and robust. The early bloomers' advantage persists when we count the number of early top journal publications or fractional counting is applied. Also, our robustness testing showed that the advantage is not due to the intentional choice of a specific top journals list or specific choices of the length of early career.

Analysis using different time intervals

An interesting publication shows that researchers who get an opportunity to work with a well-known scholar in the later stages of their career are more productive than those who get such a collaboration in their early career (Amjad et al., 2017). This surprising correlation motivates us to clarify whether such a phenomenon also exists in our context. Therefore, considering a different time interval, we study the relationship between the chronological order of publishing in top journals and academic productivity and impact. In this extension, we not only perform a more detailed analysis of the first five years but also dispense with the idea of 'early bloom' and take all bloomers into consideration to verify whether blooming fits 'the sooner, the better'. For early bloomers, we are interested in whether their specific career age when they first bloom relates to the outcome variables. We also explore how the scholar's career stage when first blooming relates to their career performance to verify if the first blooming stage can reflect business scholars' academic performance.

We firstly focus on early bloomers and how blooming earlier in their first five years correlates to subsequent productivity. It can be seen from Fig. 5 that with the delay of the career age of the first blooming, both top journal publications and MNCS in years 6–20 show a downward trend. For early bloomers in the business field, we may infer that, at least on average, the younger their career age when first blooming, the better they perform in their subsequent career.

Our earlier focus scholars (early bloomers) are researchers publishing in top journals in career years 1–5, yet many researchers first publish in top journals not in the early stage but in the later stage. Accordingly, the next question is, in a more macroscopic time interval, does the stage of publishing in top journals relate to scientific success? In this extension, 1933 business scientists are divided into five groups according to their career stages when they first bloom. For convenience of display, we use a simple log transformation in base e of the variables. The results are presented in Fig. 6.

The top panel in Fig. 6 shows the number of publications in top journals while the bottom panel shows the MNCS. Both panels are based on publications in the whole career by business scientists who first bloom at different stages. This figure clearly shows the trend that the earlier the first blooming, the more numerous the publications in top journals and the higher the impact. Both the results support the contention that the career stage when a scholar first blooms constitutes a reliable signal of the scholar's career productivity and academic impact.

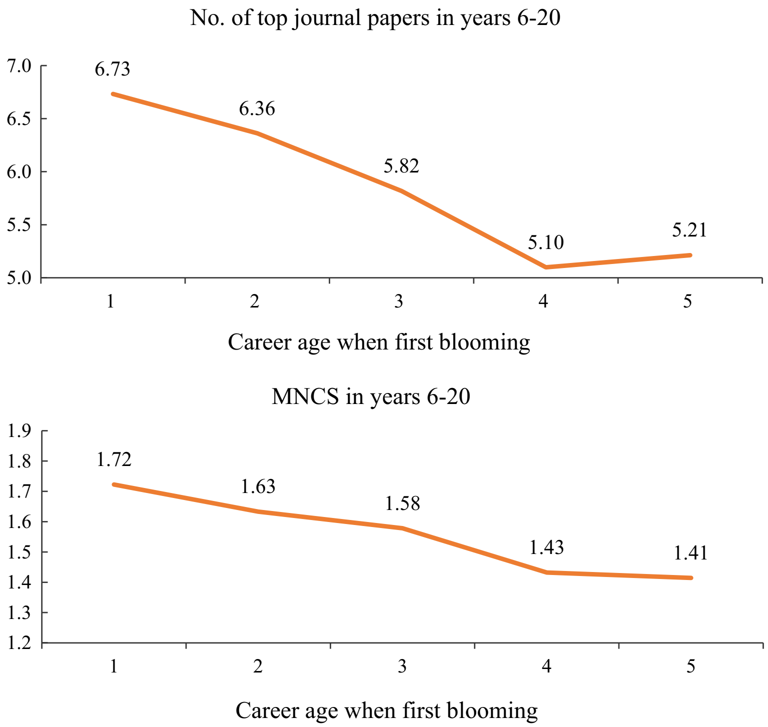

Fig. 5 Comparison of academic performances for early bloomers who first bloom at different career ages. The x-coordinate 1–5 means the career age when early bloomers first bloom. The orange line shows how the average values of result variables in career years 6–20 change with career age at first blooming

In conclusion, the content of this part provides evidence that researchers who succeed in publishing academic papers in top journals earlier tend to have long-term scientific success, whether we define ‘earlier’ using a finer time interval (one year) or a coarser time interval (career stage).

Early collaboration with top scientists

These analyses all indicate that early bloomers have better academic performance in their later careers. This result does not change with different measurements of the variables, nor with different definitions of the time interval for the term ‘early’. However, it is also worth considering whether other potential factors are influencing the early top journal publication and confusing our results. In this section, we focus on an important variable: collaboration with top scientists.

Previous studies have shown that collaborating with outstanding scientists positively impacts the academic performance of junior researchers (Amjad et al., 2017; Li et al., 2019; Qi et al., 2017). In these studies, the definition of an excellent scientist varies, with some studies using citations (Li et al., 2019; Qi et al., 2017) while others use the h-index (Amjad et al., 2017). Since this study focuses on publication in top journals and regards it as an important measure of scientists’ achievements, we identify top scientists each year based on the number of top journal publications over the past decade. Specifically, to

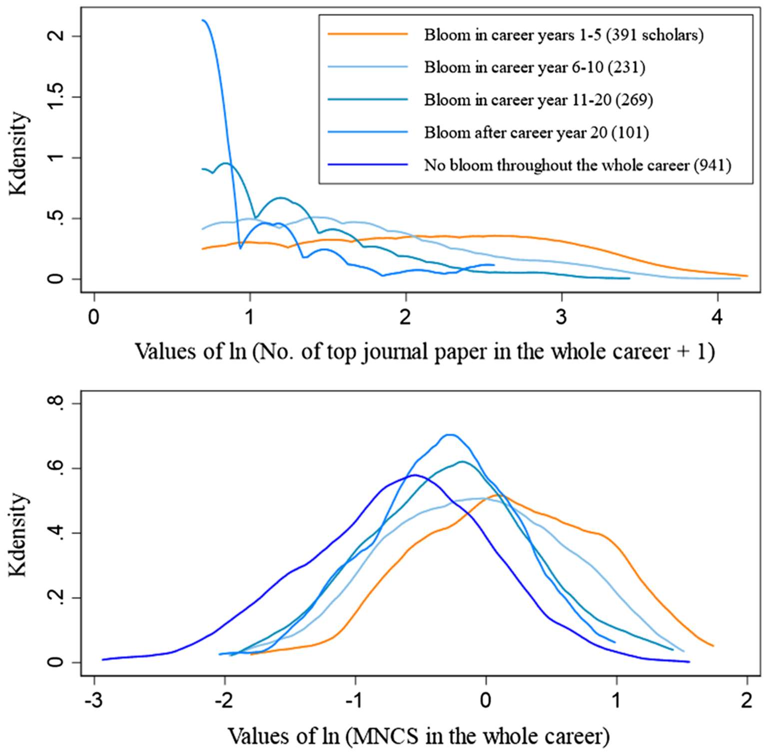

Fig. 6 Distributions of academic performance in the whole career for those who first bloom in different career stages

obtain samples of top scientists in each year, we firstly download all the articles and review articles in FT journals from the Scopus database. Then, for each given year, we locate all researchers who published in FT top journals in the last ten years. Finally, we select the top 5% of scientists who published most frequently in top journals during the previous decade as top scientists in that year. For example, the top scientists in 1981 were those who published most frequently in the FT journals between 1971 and 1980. Among our sample consisting of 1933 scholars, 5.59% (108) of the academics collaborated with top scientists in their early careers. This proportion for the early bloomer group significantly increases, reaching 12.28% (48/391).

Furthermore, we explore the relationship between early top scientist collaboration and early top journal publication, as well as its relationships with both of our outcome variables. The results are displayed in Table 7. It can be seen that early collaboration with top scientists has significantly positive correlations with early blooming and long-term academic performance (the first three columns of Table 7). This indicates that such a collaboration can be a potential confounder of our results. To rigorously measure the relationship between early blooming and two result variables, it is necessary to include early cooperation with top scientists as a covariate in the estimation models.

After we introduce early top scientist collaboration into Model 2 as a covariate (the last two columns of Table 7), the coefficients of "Early-bloom" are still positive and significant, although slight decreases occur in the coefficient sizes. This indicates that our result is

Table 7 Regression results involve early collaboration with top scientists

Variables	Early-bloom	No. of top journal papers in years 6–20	MNCS in years 6–20	No. of top journal papers in years 6–20	MNCS in years 6–20
Early-bloom				4.71***	1.56***
				(16.29)	(8.44)
Early collaboration with top scientists	2.19***	2.39***	1.37**	1.33*	1.18
	(7.86)	(5.00)	(3.36)	(2.00)	(1.89)
Early institution	0.91***	2.65***	1.42***	2.04***	1.32***
	(5.50)	(9.35)	(6.02)	(6.96)	(5.01)
Early MNCS	0.57***	1.32***	1.10***	1.13***	1.07***
	(5.81)	(6.61)	(6.22)	(3.72)	(4.99)
No. of early papers	0.10***	1.05	1.01	1.03	1.00
	(4.93)	(2.49)	(1.67)	(1.79)	(0.42)
No. of early coauthors	− 0.02	1.01	1.00	1.01	1.00
	(− 1.30)	(0.61)	(− 0.17)	(0.76)	(− 0.32)
Prop. of early first-author papers	− 0.17	0.86	0.93	0.92	0.94
	(− 0.81)	(− 0.78)	(− 1.13)	(− 0.56)	(− 1.05)
Constant	− 2.49	0.00	0.19	0.40**	0.81
Career starting year FE	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.18	0.15	0.12	0.25	0.14
Log pseudolikelihood	− 892.33	− 3071.59	− 2202.33	− 2810.97	− 2054.18
Number of observations	1933	1933	1933	1840	1840

Odds ratios are reported, z-statistics in parentheses, $^*p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$, *FE* fixed effect. All standarderrors are robust standard errors. In the last two models, 93 researchers starting their scholarly career from 1971 to 1981 are omitted here and in the later analysis because a severe multicollinearity issue would otherwise occur robust after controlling for the early coauthorship with outstanding scientists and further substantiates the main findings.

Discussion and conclusions

In this study, we investigate evidence within business field research for the widely applied but not scientifically tested idea that early publishing in top journals predicts better academic performance in subsequent long careers. The combination of the ORCID 2019 dataset and Scopus is used to collect a dataset containing 1933 business scholars with long active careers. Our comprehensive analysis reveals a significant positive correlation between early publishing in top journals and the long-term prospects of junior researchers' productivity in top journals and impact. This correlation still exists when we eliminate the impact of other early factors, when we define variables in various ways, and when we adjust the time interval of the analysis. We also consider early collaboration with top scientists in an additional analysis and verify the robustness of our results after controlling for this item.

As for the reasons and mechanisms explaining why junior researchers who succeed in publishing in top journals tend to achieve better academic performance in their careers, we offer several explanations. Firstly, even though we control for early indicators as much as possible, we cannot deny that perhaps an unobserved capability drives both early top journal publications and sustained competitive advantage. In this case, the effect we observed all comes from the impact of the researchers' academic ability. Another possible explanation is the chaperone effect proposed by Sekara et al. (2018), which highlights the vital role of experience, especially when publishing in high-impact scientific journals. From this aspect, our results may also be an example of the 'Matthew Effect' (Merton, 1968; Petersen et al., 2011), indicating a 'rich-get-richer' mechanism, as early publishing experience increases the probability that they to publish more frequently in these journals in their subsequent careers. In addition, early bloomers are more likely to attract top scientists as collaborators or get opportunities to work in prestigious institutions, which may help them achieve better performance over their careers (Qi et al., 2017; Way et al., 2019).

It is necessary to stress that we design this study only to determine whether early publishing in top journals can serve as a reliable predictor for scientific success, not to elucidate the specific mechanism. The focus of this study is to provide strong evidence that the single event of first publishing in a top journal does have a significant positive correlation with future academic performance for business researchers. This practice of considering early publication success has been widely adopted by universities, funding agencies, and other institutions, and it has been supported in other fields (Acuna et al., 2012; Bornmann & Williams, 2017).

Although previous studies identified several effective early indicators related to long-lasting academic impact (Li et al., 2019; Wang et al., 2019; Zhang & Yu, 2020), early identification of potential scientists remains a problem that suffers from a scarcity of research. Our research is a good supplement to these studies, and it can also be well applied to practice because publishing in top journals is easy to observe. Top journal publication is commonly used as an evaluation index in the social sciences (Chen et al., 2015; Mishra & Smyth, 2013) or as a short-term predictor in the natural sciences (Lindahl, 2018; von Bartheld et al., 2015). This study presents evidence that this publishing behaviour also predicts the long-term scientific performance of business researchers. Finally, this study's results are consistent with the results in other research fields (Bornmann & Williams, 2017), together showing that high-quality journal publication in an early career stage correlates with scientific success.

We believe that this study also has practical guiding significance. For researchers, our study strongly advises publishing in top-ranked peer-reviewed journals, encouraging researchers to persistently pursue high-quality research. For academic tutors advising graduate students, we recommend pushing the students to engage in high-level research work even early in their career. For relevant institutions, especially in the business field, we provide evidence to support the practice of identifying the potential success of researchers by whether they published in top journals.

As a final remark, possible limitations in this paper are acknowledged. The first limitation is the selected domain. Because of the varying difficulty and significance of publishing in the top journals in different fields, the relationship presented in this study may change slightly according to the characteristics of the junior researcher's specific field. In the future, this relationship supported by our study could be tested with data from other fields to explore whether our results remain applicable. The current paper's second limitation exists in variable operationalisation. To explore the effect of the single event of early blooming on the future academic performance of business scientists, we make efforts to utilise more early indicators available to eliminate other confounding effects. However, there are still some perplexing factors that cannot be included in our study, such as gender or the academic capability of tutors. Thirdly, we regard the year of publishing the first paper as the first year of the scholar's career, regardless of the scholar's position or physiological age. Although this is a deliberate and sensible choice made after consulting the literature, a more detailed analysis might be interesting. Finally, we cannot rule out that some business scientists with long active careers do not use or register with ORCID and therefore are not included in this study. Further studies could try to include authors more comprehensively. These limitations will be the direction of future efforts.

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Declarations

Confict of interest The authors have no fnancial or non-fnancial interests to disclose.

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