

The Production Economics of The Economics Production

Yushan Hu
Renmin University of China

Ben G. Li
University of Massachusetts Lowell

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Department of Economics
University of Massachusetts Lowell
<http://www.uml.edu/economics>
Twitter: @uml_econ Phone: 978-934-2780

The Production Economics of The Economics Production*

Yushan Hu¹ and Ben G. Li²

¹School of Economics, Renmin University of China, Beijing, P. R. China

²Department of Economics, University of Massachusetts, Lowell, Massachusetts

Abstract

How is new economic knowledge produced over time? That depends on how the expertise of authors is managed within economic journals. Using data from 41 major economics journals spanning 21 years (1994-2014), we find that both the intensive margin (article length) and extensive margin (article number) of the discipline have been growing. In particular, the extensive margin has outgrown the intensive margin, such that each article produces absolutely more but relatively less knowledge. This pattern is highly consistent with a model of within-journal specialization. As predicted by the model, the share of an individual article shrinks less in general interest journals and in more prestigious journals, where expertise is less substitutable across topics.

JEL codes: A11, D43, L80

Keywords: Division of labor, within-firm specialization, academic publishing

1 Introduction

Readers' willingness to pay for journals is declining. Discontinuing print journals is a current trend in university libraries. Electronic journals are sold online, though their unit of sale is the article. This is anything but surprising. Working papers now become freely accessible online long before being published, and many final drafts remain freely accessible after being published. Journals are diminishing in their role as knowledge disseminators and instead are transitioning to a role as quality-controlled repositories of knowledge.¹ An average page in a journal receives less attention

*Corresponding author: Ben G. Li, Email: benli36@gmail.com, Address: Department of Economics, University of Massachusetts, Lowell, MA 01854. We are grateful to the editor, one anonymous coeditor, two anonymous referees, Jim Anderson, Sultan Orazbayev, Matthias Weber, and Penglong Zhang for valuable comments. All remaining errors are our own.

¹See [Friberg \(2014\)](#) and [Zilibotti \(2014\)](#) for discussions on the changing role of economic journals. This trend is also obvious in the sciences. For example, in mathematics and physics, nearly all papers are freely accessible through

now than in the pre-internet era when researchers relied on journals to stay on the frontier of research advancements.

This study is concerned with how the annual outputs of journals, including their length and number of published articles, have evolved in the new age. Our data cover 41 prestigious economic journals, spanning two decades (1994-2014) that coincided with the time when the World Wide Web and online search engines revolutionized individual information intake.² We find that journal length, article length, and number of published articles have been steadily increasing, and more importantly, the page share of an average article within a journal has been decreasing. Think of every journal as a knowledge-making firm that charges consumers for every page of knowledge they read, journal length as its total output, and articles as its knowledge-making teams. The observed data pattern suggests that every team produces absolutely more but relatively less.

The observed data pattern is consistent with what an analogical within-firm specialization model predicts. As readers' attention on every published page declines, their willingness to pay reduces. In response, journals raise their outputs to compensate for the lost revenues. Suppose that introducing a team of experts (an article) incurs a fixed cost, and letting a few teams produce all the output overstretches their expertise. Then, as a tradeoff, every journal has an optimal number of teams (number of articles) every year, conditional on its annual output. When journals produce greater annual total outputs, the fixed costs of additional teams (articles) are economized. As a result, a greater number of articles are published, each being more focused on its core expertise. Therefore, both journal length and article number grow, with the latter margin growing more to reduce every article's output (page) share; that is, the extensive margin outgrows the intensive margin as the amount of economic knowledge increases over time.

Up to this point, within-journal specialization is just one possible explanation. We next derive unique predictions from it. Within a journal's scope, if the expertise is less substitutable across topics, the fixed costs of publishing more articles will be less economized, so that the page share of individual articles should decrease less. Conceivably, the expertise on one topic is more discounted on other topics (i) in general-interest journals than in field journals, and (ii) in journals with stronger expertise overall. Thus, the page-share decrease should be less in general-interest journals and in better ranked journals. These hypotheses are found to be supported by the data, and our findings are robust to the use of different estimation methods, subsamples, and journal rankings.

Apart from type and ranking, there are two other journal characteristics that relate to the substitutability of expertise across topics within a journal. One is whether a journal imposes a page limit on initial submissions. We find the journals with such page limits highly conforming to our earlier hypotheses, while the patterns from the journals without page limits are weaker. This is

the arXiv repository (<https://arxiv.org>).

²In April 1993, the CERN (European Organization for Nuclear Research), where the World Wide Web was born, announced that the World Wide Web would be freely accessible to every internet user. Search engines were born later that year, including `W3Catalog` in September and `Aliweb` in November.

consistent with the thesis of [Card and DellaVigna \(2014\)](#) on revealed preferences in submissions — authors shorten their submissions following the imposed page limits if they have no better outlets that match their papers’ qualities. A natural implication of their thesis is that journals would not impose page limits if the risk of having authors extend beyond their expertise is not a significant concern. In other words, for journals that impose page limits on initial submissions, submissions longer than the page limits overstretch the expertise that the journals believe those submissions to have.

The other journal characteristic that relates to the substitutability of expertise across topics is the degree of specialization of the researchers. In research fields that have more specialized researchers, the cross-topic expertise loss is expected to be less, so that the decrease in the page share of individual articles should be greater. In other words, letting more-specialized experts author articles in their fields runs a lower risk of overstretching expertise. We use the field-specific specialization index compiled by [Ellison \(2002a\)](#) and find evidence in support of our hypothesis.

The key mechanism of within-journal specialization is that journals, in a highly competitive environment, push articles to be short and focal. [Dixit \(1998\)](#) has an eloquent anecdote on this tendency:

As an editor of the *Review of Economic Studies*, (Frank) Hahn asked the author to cut down his paper from 40 pages to its essential core of three pages. When the author wrote a long and indignant letter, Hahn responded in two sentences: “Crick and Watson described the structure of DNA in three pages. Kindly explain why your idea deserves more space.”

The analogy used by Frank Hahn may not be entirely appropriate, because the writing in economics, unlike that in hard sciences that build on lab experiments, usually needs more detailed descriptions, explanations and justifications. Nevertheless, his analogy exemplifies a key tradeoff in the business of academic publishing: a longer article is richer but easily strays from its central insights, and delivering more insights in fewer pages is the key to publishing a successful journal.

The first contribution of this paper is demonstrating the specialization patterns in the production of economic knowledge. Economics is a discipline about specialization and its own evolution exemplifies specialization. Starting as “an inquiry into the nature and causes of the wealth of nations” ([Smith, 1776](#)), economics has grown to be a modern social science that has 849 clusters of research topics (defined by JEL codes) and 2,527 journals (according to RePEc registrations).³ The 41 economics journals covered by our 21-year sample published 55,244 research articles. These articles specialized in distinct topics, which went far beyond the “nature and causes of the wealth of nations,” and no modern economist can claim that she understands all of these articles even at a superficial level. Adam Smith referred to such a phenomenon as a division of labor.

³These statistics were accessed in July 2019.

There exist various approaches to formulating Adam Smith’s division of labor. We built a variant of [Chaney and Ossa \(2013\)](#) to guide our empirical study.⁴ The approach taken by [Chaney and Ossa \(2013\)](#), featuring monopolistic competition, introduces different teams, instead of pure labor, into the firms that make differentiated products. Launching more teams incurs more fixed costs, but letting teams specialize in certain parts of production reduces variable costs. This informs the importance of optimizing the structure of teams (essentially, expertise units) in the production of any expertise-intensive product. As teams become more specialized, they each are responsible for less, but more teams are contributing at the same time and every team is becoming more productive. Think of a research project as a team that adds to the body of economic knowledge. We believe that most economists agree with us on the increasing sophistication of economics papers, the narrowing breadth of research topics, and at the same time the remarkably rapid growth of modern economic knowledge.

This paper also sheds light on the operation of the economics profession. Economists have studied the whole production line in their own profession, from authorship ([Hamermesh, 2013](#)) and coauthorship ([Laband and Tollison, 2000](#); [Rosenblat and Mobius, 2004](#); [Ray and Robson, 2018](#); [Weber, 2018](#)), to page limits on initial submissions ([Card and DellaVigna, 2014](#)), editing and refereeing ([Brogaard, Engelberg, and Parsons, 2014](#); [Cherkashin, Demidova, Imai, and Krishna, 2009](#); [Orazbayev, 2017](#); [Welch, 2014](#)), journal response time ([Azar, 2007](#); [Ellison, 2002a,b](#); [Leslie, 2005](#)), and citations ([Einav and Yariv, 2006](#); [Feenberg, Ganguli, Gaule, and Gruber, 2017](#); [Huang, 2014](#); [van Praag and van Praag, 2008](#)). We consider such a thorough self-study of the profession not as a sign of the profession’s narcissism, but as a deep inquiry into whether this profession, born for understanding and improving the efficiency of resource allocation, operates itself efficiently.⁵ Any deviation from economic efficiency in the profession reflects either a collective inadequacy in understanding efficiency, or a collective failure in correcting incentives. This being said, a careful self-study is warranted.

Our paper departs from the existing introspection in three ways. First, we demonstrate the functional differences between general-interest journals and field journals. Having both types of journals, which is common in many sciences and social sciences, does not necessarily mean that different types of articles are published in them. General-interest journals could, as in some disciplines, publish high-quality articles, whether their topics are general or not. In that case, journal type is no different from journal ranking. Many economists feel that this is also the trend in economics. At present, many articles in general-interest economic journals are as specialized as those in field journals, and whether their topics are general is oftentimes a subjective matter. In our study, general-interest journals turn out to be indeed unique. Our results show that conditional on journal rankings, the value of an average article in general-interest journals is more robust than its counterpart in field journals in this internet age. In other words, articles in general-interest journals

⁴See [Young \(1928\)](#), [Stigler \(1951\)](#), [Becker and Murphy \(1992\)](#), and [Yang \(2001\)](#) for alternative approaches.

⁵Economists also study the business of other intellectuals, including mathematicians ([Head, Li, and Minonдох, 2019](#)), scientists ([Haeussler and Sauer mann, 2016](#)), lawyers ([Garicano and Hubbard, 2009](#)), and the academic publishing industry overall ([Edlin and Rubinfeld, 2005](#); [Jeon and Rochet, 2010](#); [Nevo, Rubinfeld, and McCabe, 2005](#)).

are less substitutable with each other, not only intellectually but also in generating profits for the publishing business.

Second, we examine the journal and article length. Perhaps surprisingly, economists have rarely examined this direct measure of knowledge output. To our knowledge, [Card and DellaVigna \(2013, 2014, 2018\)](#) are the only few exceptions that utilize the information contained in the length of economic works. [Card and DellaVigna \(2014\)](#) note that, all else held equal, longer submissions are more likely to receive revise-and-resubmit verdicts and more citations afterwards, both suggesting a higher quality. [Card and DellaVigna \(2013, 2018\)](#) summarize the time trends in the length and number of articles published in top-five economics journals. Our paper is different from theirs in several important ways. One, we are interested in the relative length of publications while they are interested in absolute length and its determinants. Two, we inspect 41 quality journals (including the top ones) where most good papers written by most good economists are published. Three, apart from demonstrating the time trends in these journals, we aim to provide a stylized framework to analyze how journals organize their outputs and compete against each other.

Third, our theory and empirics can also be applied to analyzing other respects of the profession. For example, we rationalize time trends in journal subscription prices and job market of economists in [Section 5](#). Our model is perhaps not the best tools for those analyses but it points to the possibility of combining different facets of the profession into a unified analytical framework in the future.

The rest of the paper is organized as follows. In [Section 2](#), we derive testable hypotheses from a stylized model of within-journal specialization. We describe our data in [Section 3](#) and report our empirical results in [Section 4](#). In [Section 5](#), we extend our theory and empirics to let them speak to the journal market of economics and the job market of economists. In [Section 6](#), we conclude.

2 Conceptual Framework and Estimating Equation

In this section, we present a stylized model to guide our later empirical study. Our model, as a variant of [Chaney and Ossa \(2013\)](#), follows a simple idea. As the attention paid by readers to an average published page declines, their willingness to pay for journals reduces, reducing the markups charged by journals. To compensate for the lost revenues, journals publish more pages and the additional pages are from both (1) additional articles and (2) additional pages per article. The former margin outgrows the latter, owing to further within-journal specialization. As a result, the page share of an individual article shrinks. The page-share decrease is less in journals where expertise is less substitutable across topics. We specify the major regression at the end of the section, which will be estimated in [Section 4](#).

2.1 Setup

Readers “consume” N economics journals. Readers have identical income and utility function: $U = \sum_{i=1}^N u(x_i)$, where $u(x_i)$ is the utility obtained from reading x_i pages of journal i . $u(x_i)$ is differentiable, increasing, and concave in x_i . The elasticity of demand is $\epsilon(x_i) = \frac{-u'(x_i)}{x_i u''(x_i)}$, where $\epsilon(x_i) > 1$ and $\epsilon'(x_i) < 0$ for any $x_i > 0$. In other words, the demand curves for x_i are less convex than constant. Readers do not read all pages in a journal but selectively choose a fraction $1/b$ to read. That is, if a journal has y_i pages, $x_i = y_i/b$ pages are read by readers (different readers may choose different x_i pages to read). $1/b$ is a parameter that characterizes readers’ attention. The smaller $1/b$ is, the less attention is paid to the publication and thus the fewer pages are read.

Consider a representative journal, the subscript i of which is omitted for convenience. It produces $y = \sum_{a=1}^n y(a)$ pages, where $y(a)$ is the length of article a , and n is the number of articles published in the journal. We abstract away from cross-page differences within a journal. Specifically, all pages within an article are symmetric, and all articles in a journal are symmetric; therefore, all pages in a journal are symmetric.⁶

Two types of costs are incurred in the production of a journal. The first type is logistics costs, represented by f , incurred per article. They refer to the journal’s own services devoted to every published article, including editing, refereeing, proofreading, typesetting, and printing services.⁷ The second type is expertise costs. Journals are written by authors using their expertise, and the expertise related to one research topic does not fully carry over to another. We denote the scope of every journal by $[0, 1]$, which is a continuum of research topics. Every published article addresses a core topic and a few adjacent topics, and the adjacent topics farther from the core topic incur a higher expertise cost per topic. Formally, the expertise cost of a journal that consists of n articles is $\int_0^{1/n} z^\gamma dz$ per page, and the positive constant γ specifies the growth rate of expertise cost on adjacent topics. When n rises, the journal is written by a greater number of experts who focus more on their core expertise.

The above cost structure illustrates a clear tradeoff between article number and article length within a journal. A journal with $n = 1$ has the lowest logistics costs, because all its pages are written by the same author(s) who covers the entire journal scope $[0, 1]$. That would incur the highest expertise costs per page $\int_0^1 z^\gamma dz$. To the contrary, a journal with a huge n has extremely high publishing costs but very low expertise costs per page, because the journal is divided into numerous articles, each one written using the most relevant expertise. To strike a balance between the two polar cases, there exists an optimal number of articles conditional on any journal length y .

⁶In the data, within-journal variation in article length is quite small. The standard deviation of article length equals approximately a third of the average article length (mean: 0.32; median: 0.35).

⁷The costs of refereeing service include both the costs of referee management and referee expertise. The costs of referee management, such as the costs of searching, monitoring, and compensations paid to referees, are counted as logistics costs. The costs of referee expertise costs have been reflected in the expertise costs of published articles, since authors of published articles are typically chosen to be referees (i.e., the expertise in writing papers is also the expertise in referring papers).

Formally, the total cost function of the journal production is

$$C(y) = y \int_0^{1/n} z^\gamma dz + nf, \quad (1)$$

and the optimal article number is

$$n = \left(\frac{y}{f}\right)^{\frac{1}{\gamma+2}}, \quad (2)$$

conditional on journal length y .

To determine journal length y , we integrate the above demand (reader) side and supply (journal) side in a market where journals compete monopolistically with each other. By equations (1) and (2), there is a free-entry (FE) condition under which price equals average total cost:

$$p = \left(1 + \frac{1}{\gamma+1}\right) \left(\frac{f}{y}\right)^{\frac{\gamma+1}{\gamma+2}}. \quad (\text{FE})$$

That is, given a market price p , journals that cannot publish every page with a cost lower than this level would not survive. At the same time, journals price their pages at the level

$$p = \frac{1}{\gamma+1} \times \frac{\epsilon(x)}{\epsilon(x)-1} \left(\frac{f}{y}\right)^{\frac{\gamma+1}{\gamma+2}}, \quad (\text{PM})$$

in order for profit-maximization (PM), where $\frac{\epsilon(x)}{\epsilon(x)-1}$ represents the journal's markup. Recall $x = y/b$, so that the markup equals $\frac{\epsilon(y/b)}{\epsilon(y/b)-1}$. The above FE and PM schedules constitute a system whose equilibrium is denoted by (p^*, y^*) . We impose $\epsilon(0) > 1 + \frac{1}{\gamma+1}$ to ensure the existence and uniqueness of the equilibrium (p^*, y^*) .

By solving the FE-PM system, we obtain

$$\epsilon(y^*/b) = 1 + \frac{1}{\gamma+1}, \quad (3)$$

where y^* is endogenously determined. With y^* solved, x^* and p^* are solvable, as are number of articles n^* and number of journals N^* . Notice that the article length, namely $\frac{y^*}{n^*} = f^{\frac{1}{\gamma+2}} y^{*\frac{\gamma+1}{\gamma+2}}$, is increasing in the journal length y^* , indicating within-journal specialization.

Our later empirical analysis involves journal length y^* , number of articles n^* , and article length $\frac{y^*}{n^*}$. We focus on the average page share of individual articles in the journal where they are published. This page share is constructed using our journal data, theoretically informed by

$$S^* \equiv \frac{y^*/n^*}{y^*} = \frac{1}{n^*} = \left(\frac{f}{y^*}\right)^{\frac{1}{\gamma+2}}. \quad (4)$$

S^* is neutral to the different page styles used by journals that may confound their y^* and y^*/n^* . We collect data on both y^* and y^*/n^* to construct S^* in our empirical study. As implied by equation

(4), the variation in the length share S^* comes eventually from the variation in the number of articles published n^* .⁸

A Note on the decision n . Our model above is a partial equilibrium variant of [Chaney and Ossa \(2013\)](#). Labor is not introduced into our model. The aforementioned scope $[0, 1]$ of a journal represents a continuum of research topics targeted by the journal. For example, consider a journal in the field of international trade. The research topics in this field include cross-industry trade, within-industry trade, tariffs, trade agreements, and so on. The journal does not have to publish an article on each of those topics since the readership on a single topic may be too limited in size. Instead, the journal can group some of the topics, such as covering both cross-industry trade and within-industry trade in a combined “trade pattern” article, and covering both tariffs and trade agreements in a combined “trade policy” article. Apparently, combining topics would incur a higher cost, attributed to the search required to identify experts in both topics (captured by the expertise cost parameter γ). Meanwhile, not combining topics would result in having too many articles that each have too limited a readership. This trade off is reflected in the endogenous choice of n , namely the number of “teams” in the model.

The term “team” used above does not necessarily involve the labor of authors. In our model, a team is just a personified way to describe a combination of topics chosen by the journal to be covered in an article. In essence, it is no different from an interval of product features combined by a firm in one product but not in other products. Introducing labor formally into the model could enrich the term. A simplistic approach in this vein is to assume that each research topic has one unit of authors who have the greatest expertise on that topic. Authors that are the best fit for one topic can write on topics adjacent to the topic, but can only do so with an elevated expertise cost. Then, by assuming a given stock of labor (i.e., economists in the field) uniformly distributed across the niche topics, the labor market of the journal can be analyzed. Fields in economics are different in size, and thus have their own labor markets as such, with varying stocks of economists available as the authors of their journals (general-interest journals have even larger labor markets). Formally introducing such labor markets would alter neither the theoretical predictions nor the empirical results in this study. We chose not to add them and to leave the model a partial-equilibrium one.

The model has also abstracted away from the editorial process of journals. A journal in our model is a decision maker that embodies its editor and publisher. This decision maker decides the number of teams n to keep the knowledge production cost-efficient. In other words, the journals in our model are production units without personnel. The editorial process, especially the interaction between editors and authors, has been modeled in the literature, such as [Ellison \(2002b\)](#), [Faria and Goel \(2010\)](#), and [Faria, Mixon, and Upadhyaya \(2018\)](#). We find the approach of [Faria et al. \(2018\)](#) particularly appealing because their approach also models every journal as a production process.

⁸Compared with n^* , S^* has the additional merit that the original number of articles has been adjusted (notice that $dS^* = \frac{-1}{n^{*2}}dn^* \neq \frac{1}{dn^*}$). For example, publishing 10 additional articles has different implications for a journal that initially published 20 articles per year compared to a journal that initially published 200 articles per year. S^* captures that difference while n^* does not.

Extending our model in that direction is feasible but goes beyond the scope of this paper. The model we built above is intended to inform how different journals organize knowledge production differently, as detailed in the next subsection.

2.2 Different Journals

We now link the growth rate of expertise cost γ to the types and rankings of journals. Introducing heterogeneous costs into a monopolistic competition model usually renders the equilibrium number of firms N_i and the composition of entrants indeterminable. However, our study tracks a highly stable selection of journals over time, so that changing journal number and composition are not a concern. Put differently, the following specifications and the resulting comparative statics are based on a given time-invariant equilibrium.

The parameter γ is linked to journal type ω and ranking value R :

$$\gamma = \omega - \tau R, \tag{5}$$

where $\tau > 0$ is a positive constant that fixes the importance of R relative to ω . With R held equal, the γ of general-interest (G) journals is greater than that of field (F) journals, or

$$\omega_G > \omega_F. \tag{6}$$

This is because general-interest journals publish articles that answer a larger variety of research topics than field journals, so that within the given journal scope $[0, 1]$, the expertise associated with one topic is less relevant to others in the journal. At the same time, with type (ω) held equal, in journals written using less expertise overall (i.e., weaker journals), the expertise related to one topic attenuates less when applied to other topics. Note that a larger rank value R means a weaker ranking: the journal ranked 10th ($R = 0.1$) is weaker than the journal ranked 1st ($R = 0.01$).

By inserting equation (5) into equation (3), one can immediately see that (1) given the same type, a weaker journal has a higher demand elasticity and thus a lower markup, and (2) given the same ranking, a field journal has a higher demand elasticity and thus a lower markup, in comparison with a general-interest journal.

2.3 Hypotheses and Estimating Equation

Hypotheses. Now consider a marginal decline in $1/b$, representing a decrease in the attention paid by readers to individual journal issues. What interest us is the resulting comparative statics. First and foremost, by equation (3), the marginal decline in $1/b$ causes an increase in y^* .⁹ Intuitively, the decline in attention lowers the willingness to pay and thus markup, so that journals raise their output (length) y^* to compensate for lost revenues. When y^* rises, the number of articles n^* rises

⁹The PM schedule may be either upward- or downward-sloping, which however both lead to an increase in y^* in this setting.

according to equation (2). That is, letting published articles be more specialized (i.e., involving fewer topics per article) helps to reduce the marginal cost per page. Recall that publishing more articles brings more fixed costs, which are however economized by the larger output y^* here. As a net effect of a greater y^* and a greater n^* , the page share of each article within the journal reduces. Formally,

$$\frac{dS^*}{d(1/b)} = \underbrace{\frac{dS^*}{dy^*}}_{<0} \underbrace{\frac{dy^*}{d(1/b)}}_{<0} > 0. \quad (7)$$

The rising y^* , rising n^* , rising y^*/n^* , and declining S^* are the first sets of predictions that we will test using our data.

In our later empirical study, we will use a time-trend variable to proxy for the declining $1/b$. Although the declining attention accords with our experience as readers, the time-trend variable inevitably captures other trends in the publishing industry. Therefore, our major specification has to count on at least one other variation that can identify the trend specific to the declining $1/b$. This is why the types and rankings of journals are introduced:

$$\left| \frac{dS^*}{dy^*} \right|_G < \left| \frac{dS^*}{dy^*} \right|_F, \quad (8)$$

and

$$\frac{d^2 S^*}{dy^* dR} > 0, \quad (9)$$

where the inequalities follow from equations (4) and (5). Notice that the second term in inequality (7), namely $\frac{dy^*}{d(1/b)}$, does not vary with journal type or journal ranking. Then inequalities (8) and (9) lead to our major hypotheses:

Hypotheses. *In response to a negative attention shock $d(1/b) < 0$, S^* shrinks less (i) in general-interest journals than in field journals, and (ii) in journals that have a better ranking (i.e., a smaller ranking value R).*

The intuition behind the hypotheses are as follows. A journal with less substitutable expertise across its topics — either because it is a general-interest journal or it has stronger expertise on all its topics — will find publishing more articles less useful in curtailing costs. In other words, facing the same f per article, soliciting more articles is less economical for journals with a higher γ . For them, the number of published articles may still rise, but to a lesser degree.

Estimating Equation. Hereafter, we omit the asterisk in superscripts for convenience. The above hypotheses inform a difference-in-differences regression:

$$S = \beta \cdot (-1/b) + \bar{\theta} \cdot \begin{bmatrix} G \\ R \end{bmatrix} + \bar{\delta} \cdot (-1/b) \cdot \begin{bmatrix} G \\ R \end{bmatrix} + v, \quad (10)$$

where G is a general-interest dummy, R is the ranking value, $-1/b$ represents the aforementioned declining attention, and v is the error term. As noted earlier, we use a time-trend variable to proxy for the decreasing attention $-1/b$. Denote the time-trend variable by T_t , then a full-fledged regression follows:

$$S_{it} = \beta \cdot T_t + \bar{\theta} \cdot \begin{bmatrix} G_i \\ R_i \end{bmatrix} + \bar{\delta} \cdot T_t \cdot \begin{bmatrix} G_i \\ R_i \end{bmatrix} + \xi' X_{it} + \eta_t + v_{it}, \quad (11)$$

where i indexes journal, t indexes year, X_{it} represents control variables, and η_t is a year fixed effect. In particular, the fixed cost (per article) parameter f will be proxied for using the submission fees of journals. Our major hypotheses pertain to the estimated coefficients of interaction terms: $\hat{\delta} = [\hat{\delta}_G > 0, \hat{\delta}_R < 0]'$.

The rest of the regression (11), despite not being our major interest, are still noteworthy. First, the coefficient of the pure time trend β is not identifiable. The marginal effect of the time-trend variable T_t on S_{it} is

$$\frac{\partial S_{it}}{\partial T_t} = \beta + \delta_G G_i + \delta_R R_i. \quad (12)$$

The coefficient of the field-journal indicator ($G_i = 0$) and the coefficient of the best journal are mixed with the pure time trend β (i.e., the effect of declining attention $-1/b$), rendering none of the three separately identifiable.

Second, the coefficients of the non-interacted G_i and R_i , namely $\hat{\theta}_G$ and $\hat{\theta}_R$, are interesting but are not our focus. Equations (3) and (5) suggest that general-interest journals and better ranked journals have a smaller S_{it} :

$$\hat{\theta}_G < 0, \hat{\theta}_R > 0, \quad (13)$$

which are actually supported by our empirical results. However, such coefficients also capture other cross-sectional differences between journals that have different types and rankings. We caution against interpreting them as evidence of our model, and focus our study instead on the interaction terms.

Third, one may wonder if the effect of R on γ differs between general-interest journals and field journals. When such a difference exists, the previous equation (5) has a more general form:

$$\gamma = \omega - \tau_\omega R, \quad (14)$$

where the slope of R , now denoted by τ_ω , differs between general-interest and field journals. To investigate whether τ_ω is journal-type specific, we will experiment with introducing a triple difference term $T_t \cdot G_i \cdot R_i$ into regression (11). Its estimated coefficient will be unequal to zero if τ varies by journal type.

Lastly, the error term v_{it} will be clustered, following the method of [Cameron, Gelbach, and Miller \(2011\)](#), to allow arbitrary clustering along the i and t dimensions. This addresses both the

within-journal autocorrelation, within-year correlation, and a combination of the two in the error term.

We next move on to describe our data and some basic data patterns of y_{it} , n_{it} , y_{it}/n_{it} and S_{it} .

3 Data

3.1 Sources

Our primary data source is the tables of contents (TOCs) of journals. Through web scraping, we obtained the TOCs of 41 economics journals during the 1994-2014 period. A list of the journals and their available years are provided in **Table A1**. The four newest journals have a few missing years because they did not exist at first. Overall, the pool of journals is highly stable over time. We excluded published entries in journals that do not make original contributions, such as editorials, award announcements, minutes, and addenda.¹⁰ After cleaning, our dataset contains TOC information for 55,244 published articles.

The selection of the 41 journals was based on two major considerations. The first is their reputations in the economics profession. We use the union set of three journal classifications as the range of journal candidates: (1) the top-30 journals in the RePEc aggregate rankings, (2) the A+, A and B journals in the Kiel Institute’s journal list, and (3) the journals classified by [Engemann and Wall \(2009\)](#) as where “ambitious economists” publish. These three classifications are widely perceived to be objective, and offer different perspectives on evaluating journals. The former two classifications also provide the ranking values that will be used in our later regression analysis.¹¹ Between the two rankings, the RePEc rankings are our primary measure of R because their values are numeric and continuous, while the Kiel Institute’s rankings have only three discrete ratings.¹² The second consideration is the scrapability of their TOCs. Not all journals make all of their online TOCs publicly available. There are journal websites that might purposely hide their TOC information from repeated downloading. Such journal candidates are excluded from our dataset.¹³

The discipline of economics in this study is broadly defined to include finance, marketing, and accounting. Economists in these three fields are typically affiliated with business schools (b-schools) of universities. They receive training similar to (sometimes the same as) economists affiliated with

¹⁰See Appendix ?? for details.

¹¹The classifications compiled by [Engemann and Wall \(2009\)](#) are located in their Table 3. The RePEc journal rankings can be found at https://ideas.repec.org/top/top_journals.all.html, while the Kiel institute’s rankings can be found at <https://www.ifw-kiel.de/forschung/internal-journal-ranking>. Notice that both rankings change over time. The ranking values that we use were accessed in July 2015.

¹²All journal rankings are controversial to some extent, having their own strengths and weaknesses. This is because journal rankings rely on the ranking methods in use, which inevitably involve judgments made by the researchers who compile the rankings.

¹³When conducting our data collection, we were unable to download TOCs from the websites of *Journal of Business & Economic Statistics* and *Journal of Business*. The exact reasons remain unknown. We speculate that the earlier website had a script that blocked repeated downloading. Such scripts are usually written to prevent overloading of web servers, and have been increasingly used in websites. The latter case is possibly related to the discontinuation of the journal in 2006.

economics departments. In the economics profession, there is neither a clear division between economics-department economists and b-school economists, nor a strict criterion to designate a research paper as an economics-department paper as opposed to a b-school paper.¹⁴ We have no intention to create such divisions among economists and their works. However, journals in those fields do share some characteristics that distinguish them from other economics journals, such as higher submission fees, a relatively smaller audience, and being house journals of professional associations separate from economic associations. Therefore, we refer to them as “b-school journals,” as opposed to other economics journals (which are referred to as “pure economics journals”). This distinction is used mainly in robustness checks to determine whether there exist potential differences between the two groups of journals.

3.2 Variables

The descriptive statistics of our working dataset are reported in **Table 1**, where most variables are self-explanatory. Below, we elaborate on a few variables. One is the number of pages, which is our measure of journal length. It is a simple count of pages provided in the TOCs of journals. In **Figure 1**, we plot the number of pages of every journal against time (the 21 years). Among the 42 plots, the first is concerned with the total pages of all the 41 journals and each of the following 41 plots corresponds to one single journal. The total of all journals has a significantly upward trend, which is also the case for most journals during the two decades.

Despite the revealing patterns, we should be aware that the number of pages is incomparable across journals. The incomparability results from two factors. First, journals use different page styles (e.g., typeface, font size, line space, and page margin), such that one page in a journal is not an equivalent of one page in another.¹⁵ Second and more subtly, theoretical/empirical inclination often influences the length of articles and thus journals. Empirical articles are typically longer because data charts and tables take larger amounts of space than text. Moreover, some journals encourage putting detailed proofs in appendices (usually having smaller fonts and narrower line spaces) or require detailed proofs be provided as online appendices that are not published in the journals. This may make theoretical articles even shorter. Of course, the opposite may also happen. If a journal requires additional tables and data charts to be put in online appendices but keeps full-fledged proofs in the text, its empirical articles would be shorter than theoretical ones. In sum, articles and journals, even typesetted using the same page style, may still be incomparable in length. Therefore, as discussed in Section 2, our major interest is in S_{it} , namely the page share of an average article within its journal-year duplet. Unlike journal and article length, the page-share variable S_{it} has automatically adjusted for cross-journal differences in both page styles and

¹⁴In the US higher education system, the majority of academic economists are affiliated with economics departments.

¹⁵Card and DellaVigna (2014) nicely addressed this type of incomparability by extracting word counts from the pdf files of original submissions. We are unable to extract word counts for many journals because their articles published in the 1990s were converted into pdf files as scanned images rather than using word-processing software. Using images as source files makes word-counting infeasible (current OCR technologies are not helpful in this case).

Table 1: Summary Statistics

<i>Overview</i>			
Number of years			9-21¶
Number of papers			55244
Number of journals			41
Number of publishers			13
<i>Descriptive statistics*</i>			
	N	Mean	St.D
<i>At the journal-year duplet level</i>			
Number of papers	831	66.48	44.67
Number of pages	831	1368.56	803.59
Number of pages per paper	831	22.28	6.99
Page share of an average paper	831	0.02	0.01
Time index A	831	10.18	6.04
Time index B	831	4.06	2.00
Time index C	831	2.02	0.82
<i>At the journal level</i>			
Ranking value#	41	0.21	0.20
Pure-economics journal dummy	41	0.88	0.33
Top-5 journal dummy	41	0.12	0.33
Page limit (on initial submissions) dummy	41	0.32	0.47
Submission fee (unit: 100 US dollars)§	41	0.87	1.12
General-interest journal dummy	41	0.32	0.47
Ellison specialization index Δ	24	0.27	0.11

Notes: * Further details are in the text. ¶ Most journals have 21 years. Details of the journals and their year spans are provided in Table A1. # It refers to the RePEc rankings. § The only other currency used in submission-fee payments is euro. We use 100 euros=112 US dollars in conversion. Δ The index was obtained from Table 9 in Ellison (2002a).

theoretical/empirical inclination.

It is important to note that some journals switched to a more compact page style during our sample period.¹⁶ By using a more compact page style, a journal can squeeze in more articles per year, which tends to raise the number of articles published per year and thus reduces the page shares of individual articles. Such changes make S_{it} of journal i not comparable with itself over time. However, the page-style changes are, by themselves, in line with what our model predicts —

¹⁶The typeset change of the Dutch publisher Elsevier in 2009 is a good example (see footnote 27 for details).

the denser text fits more articles in journal issues. Therefore, it is not an empirical concern in our later empirical analysis, even though it might cause the uptrend of journal length in Figure 1 to be understated.

Also noteworthy are the time-trend variables that we constructed. Remember that the time-trend variable is used to proxy for the declining attention of readers. A more rigid trend variable (e.g., incremental by one every seven years rather than every year) is more likely to secure a solid trend, but meanwhile has less variation for econometric use. To strike a balance between the two considerations, we constructed three different trend variables, hereafter referred to as time indexes A, B and C. Time index A starts from 0 and increases by one every calendar year, while Time indexes B and C increase every three years and seven years, respectively.

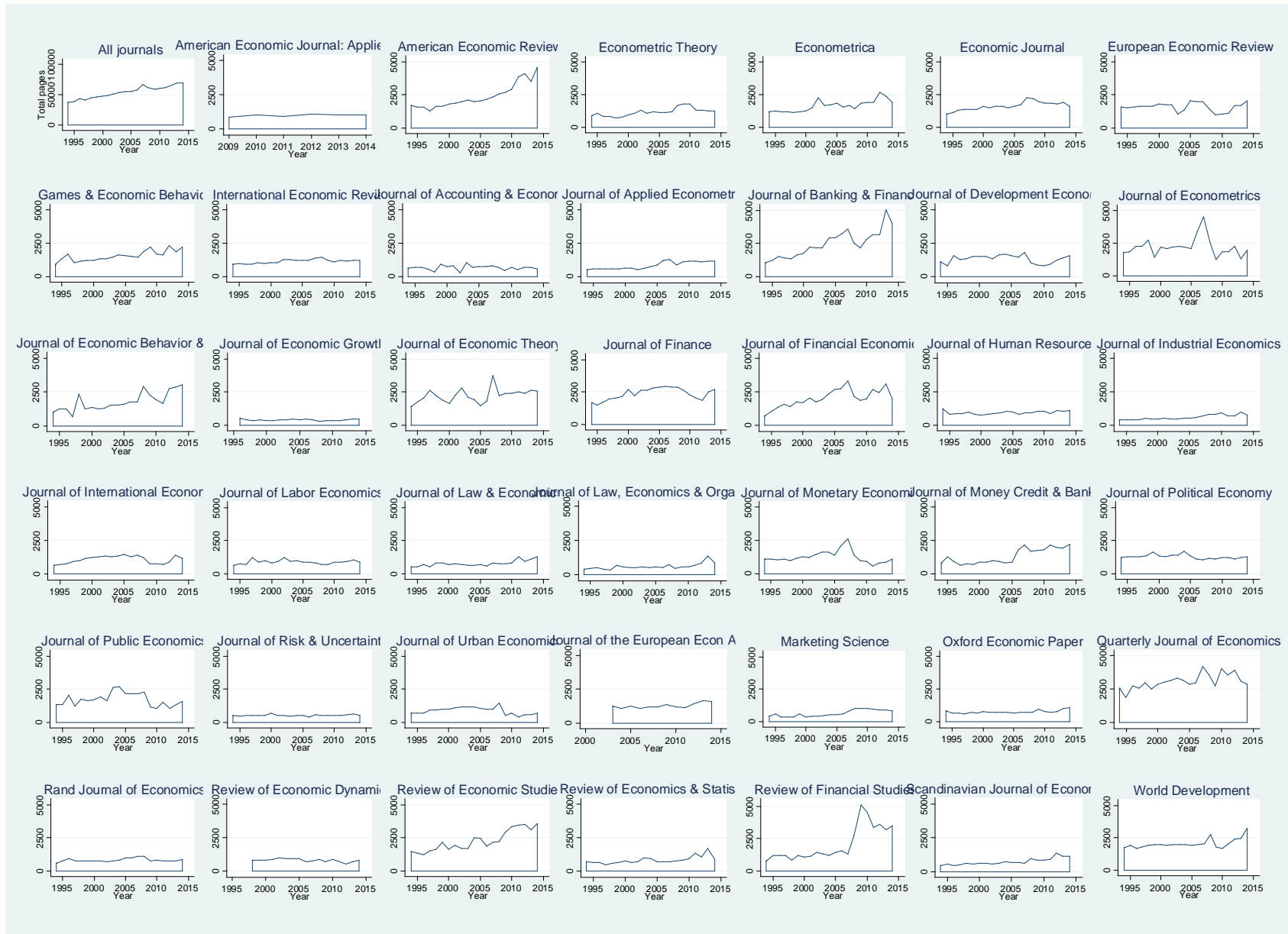
There were 13 publishers involved in the production of the 41 journals during the sample period.¹⁷ In our later regression analysis, we always include publisher fixed effects (or journal fixed effects if applicable, which are more stringent than publisher fixed effects). Notice that some journals in the sample changed publishers during the sample period. We use their latest publishers to construct those fixed effects. However, using their previous publishers does not alter our findings.¹⁸

We found the information on submission fees (if applicable) from journals' guidelines for authors. The original fees were in either US dollars or euros, and we converted fees in euros to US dollars using the exchange rate 100 euros=112 dollars. Lastly, Table 1 also mentions the page limits on initial submissions and the Ellison specialization index. We will explain them in detail when they are used (see Section 4.3).

¹⁷The American Economic Association (AEA), the American Finance Association (AFA), and the European Economic Association (EEA) publish their house journals independently, while other house journals use commercial publishers as official publishers. In our sample, the *American Economic Review* (AER) and the *American Economic Journal: Applied Economics* are published by the AEA. The *Journal of Finance* is published by the AFA. The *Journal of the European Economic Association* (JEEA) is published by the EEA.

¹⁸Acquisitions of publishers suggest reduced price margins, revenues, and profits of the acquired publishers. This is consistent with the outcome of readers' declining attention and willingness to pay in our model.

Figure 1: Total Page Length of Economics Journals



3.3 The Flourishing Economics

In the rest of this section, we investigate how the economic publications in our sample grew during the 21-year period. This investigation is motivated by two considerations. First, knowing the basic time patterns of the publications in our sample is meaningful in its own right, as they represent most of the new economic knowledge produced in the last two decades. Second and more importantly, this exercise illustrates whether the model we described in Section 2 is appropriate for rationalizing recent economic knowledge production. The model predicts longer journal y_{it} , more articles n_{it} , longer articles y_{it}/n_{it} , and shrinking page share per article S_{it} . If these patterns are refuted by the data, a different model should be sought and thus there would be no point to test the hypotheses derived from the model.

In **Table 2**, four margins of the economic publications are regressed on the time trend index A.¹⁹ We use the most stringent fixed effects — journal fixed effects — together with year fixed effects. As mentioned earlier, following the method of [Cameron et al. \(2011\)](#), we cluster the error term and allow arbitrary clustering along the i and t dimensions. This addresses both the within-journal autocorrelation and within-year correlation in the error term.

A positive and statistically significant time trend is found in journal length, number of articles, and article length under all specifications. They correspond to their theoretical counterparts y_{it} , n_{it} , and y_{it}/n_{it} , respectively. An average journal publishes 37.72 more pages and 1.38 more articles every year (columns (2) and (4)). Notice that the 37.72 pages here are based on an “average page style,” so that the magnitude should not be taken literally. As a net effect of the two, the page share of an average article S_{it} decreases by approximately 0.024 percentage point per year (column (8)), which means about a half percentage point decrease over a 21-year period. Recall that in Table 1, an average article in an average journal-year accounts for two percent of its total pages, with one percent being the corresponding standard deviation. So, a half-percentage-point decrease is a substantial decrease.

It is important to notice that the above patterns of S_{it} stem from the fact that article length y/n increases less than journal length y does. They are not driven by shrinking article length y/n . In fact, rising article length y/n is found in the same table (see columns (5)-(6) of Table 2). An average article is 0.28 pages longer per year (again, based on an average page style), equating to 5.9 pages longer over a 21-year period. With any page style, the fact that an average article becomes six pages longer represents a considerable change for a journal.

In **Table 3**, we compare the three margins across journal groups. Panel A demonstrates a comparison between high-ranking journals and low-ranking journals, and Panel B between pure-economics journals and b-school journals. Since both ranking-related variables and the pure-economics/b-school dummy are time-invariant journal characteristics, we cannot use journal fixed effects here. Instead, we include (1) publisher fixed effects, which control for market powers and

¹⁹The findings are similar when the other two time indexes are used.

Table 2: Growth in Economics Publications along Different Margins

	(1)	(2)	(3)	(4)
Dep. Variable:	Total pages published in a year		Number of articles published in a year	
Time index§	34.45*** (12.75)	37.72*** (6.508)	1.194** (0.476)	1.378*** (0.408)
Year fixed effects	Y	Y	Y	Y
Journal fixed effects	N	Y	N	Y
Observations	831	831	831	831
R-squared	0.061	0.744	0.039	0.760
	(5)	(6)	(7)	(8)
Dep. Variable:	Average pages per article in a year		Average page share per article within journal-year duplets	
Time index§	0.285* (0.157)	0.276*** (0.0685)	-0.000161* (9.40e-05)	-0.000243*** (7.88e-05)
Year fixed effects	Y	Y	Y	Y
Journal fixed effects	N	Y	N	Y
Observations	831	831	831	831
R-squared	0.022	0.715	0.009	0.855

§ Time index A is used here (the other two indexes give similar results). Standard errors are reported in parentheses, allowing for arbitrary clustering across journals and years. *** p<0.01, ** p<0.05, * p<0.1.

other publisher differences and (2) year fixed effects, which control for time-varying differences (including time trend). Not using journal fixed effects also enables us to include submission fees as a control variable in our regressions.

Panel A of Table 3 shows that top-five journals (the *American Economic Review*, the *Econometrica*, the *Journal of Political Economy*, the *Quarterly Journal of Economics*, and the *Review of Economic Studies*) publish longer journal issues and more articles, and an average article in them accounts for a smaller share of the journal length. We will further discuss how top-five journals perform in our theory and empirics in Section 4.2. Panel B of Table 3 compares the aforementioned pure-economics journals with b-school journals. Overall, pure-economics journals publish longer journal issues and more articles than b-school journals, but shorter articles. There is no significant difference in page share S_{it} between the two groups. The last four columns in Panel B control for ranking values, which results in a decrease in the observed differences.

Interestingly, in both panels A and B, the submission fee has negative coefficients in the regressions of total pages and number of articles, and positive signs in the regressions of page shares. This is consistent with our model’s implications: a higher submission fee suggests a higher fixed cost f , which reduces the number of articles and raises the page share of an average article (see equations (2) and (4)).²⁰

²⁰Our model does not predict an effect of f on y , which however can be rationalized as a supply-side effect in the background. That is, a high submission fee charged by a journal discourages all potential authors from publishing papers in that journal. This supply-side effect may reduce journal length y .

Table 3: Margins of Different Journal Groups

Dep. Variable:	Total pages published in a year	Num. of articles published in a year	Ave. pages per article in a year	Ave. page share per article within journal-year duplets	Total pages published in a year	Num. of articles published in a year	Ave. pages per article in a year	Ave. page share per article within journal-year duplets
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Panel A: Different quality groups</i>								
Top-5 dummy	1,353*** (259.3)	52.00*** (14.91)	5.012 (3.157)	-0.0156*** (0.00272)				
Ranking value§					-439.3*** (82.26)	-23.86*** (7.435)	0.834 (1.022)	0.00843*** (0.00187)
Fee	-467.0*** (147.5)	-25.93*** (8.861)	0.943 (1.092)	0.00898*** (0.00248)	-2,996*** (376.4)	-86.37*** (18.30)	-17.12*** (4.015)	0.0280*** (0.00629)
Year FEs¶	Y	Y	Y	Y	Y	Y	Y	Y
Publisher FEs¶	Y	Y	Y	Y	Y	Y	Y	Y
Observations	814	814	814	814	814	814	814	814
R-squared	0.596	0.578	0.572	0.708	0.596	0.578	0.572	0.708
<i>Panel B: Different affiliation groups</i>								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pure-econ dummy	877.6** (409.0)	90.74*** (15.19)	-8.238*** (0.858)	-0.0119 (0.00767)	349.0** (176.0)	70.28*** (10.62)	-8.048*** (1.725)	0.000719 (0.00474)
Ranking value§					-2,984*** (371.1)	-83.90*** (14.63)	-17.40*** (3.846)	0.0280*** (0.00630)
Fee					-393.4*** (98.03)	-14.60*** (5.444)	-0.226 (0.901)	0.00853*** (0.00237)
Year FEs¶	Y	Y	Y	Y	Y	Y	Y	Y
Publisher FEs¶	Y	Y	Y	Y	Y	Y	Y	Y
Observations	814	814	814	814	814	814	814	814
R-squared	0.438	0.538	0.563	0.595	0.634	0.595	0.642	0.696

§ A larger ranking value means a weaker ranking. ¶ FEs are short for fixed effects. Standard errors are reported in parentheses, allowing for arbitrary clustering across journals and years. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To summarize, we find that both the intensive margin (article length) and extensive margin (article number) of the discipline have been growing. In particular, the extensive margin has outgrown the intensive margin. With the overall patterns confirmed, we now move on to the main body of our empirical study that focuses on the share variable S_{it} .

4 Empirical Results

4.1 Main Findings

We now run regression (11) using the data described in Section 3. Our main results are reported in Table 4. We use each of the three time indexes and control for submission fees. Since journal type G_i and ranking value R_i are time-invariant, journal fixed effects cannot be used here. Instead,

publisher fixed effects are included in all regressions. Also, we keep year fixed effects in all columns as before. We start with a specification that excludes the interaction terms. Its results are reported in column (1), where the page share of an average article turns out to be smaller in general-interest journals and better ranked journals. This is consistent with our theory (recall inequalities (13)), though such a cross-sectional comparison is not our main interest, as noted earlier.

Table 4: Page Share within Journal-Year Duplets

	(1)	(2)	(3)	(4)
Dep. Variable: average page share within journal-year duplets				
General-interest dummy	-0.00784*** (0.00302)	-0.0116*** (0.00291)	-0.0123*** (0.00304)	-0.0133*** (0.00308)
Ranking value§	0.0199* (0.0107)	0.0296*** (0.0108)	0.0315*** (0.0110)	0.0348*** (0.0111)
Time index A	-0.000171 (0.000107)	-7.46e-05 (0.000183)		
Time index A × General-interest dummy		0.000375** (0.000171)		
Time index A × Ranking value		-0.000967** (0.000488)		
Time index B			-0.000395 (0.000504)	
Time index B × General-interest dummy			0.00112** (0.000485)	
Time index B × Ranking value			-0.00291** (0.00136)	
Time index C				-0.000838 (0.00119)
Time index C × General-interest dummy				0.00273** (0.00110)
Time index C × Ranking value				-0.00745** (0.00302)
Fee	0.00208 (0.00148)	0.00208 (0.00147)	0.00208 (0.00148)	0.00208 (0.00148)
Year fixed effects	Y	Y	Y	Y
Publisher fixed effects	Y	Y	Y	Y
Observations	831	831	831	831
R-squared	0.582	0.596	0.596	0.597

§ A larger ranking value means a weaker ranking. Standard errors are reported in parentheses, allowing for arbitrary clustering across journals and years. *** p<0.01, ** p<0.05, * p<0.1.

More important findings are presented in columns (2)-(4), where the interaction terms are included and each column uses a different time index. The estimated coefficients of the interaction terms are in line with our major hypotheses: $\hat{\delta}_G > 0$, $\hat{\delta}_R < 0$. That is, the page share of an average article shrinks less per year in general-interest journals and better ranked journals. This holds in all three columns. The coefficients of submission fee are statistically insignificant in these columns.

In **Table 5**, we experiment with the three-way interaction $T_t \cdot G_i \cdot R_i$ mentioned earlier. We insert it into regression (11) to identify whether the role of journal ranking differs between general-

Table 5: Difference-In-Difference-In-Differences Estimates

Dep. Variable: average page share within journal-year duplets	(1)	(2)	(3)
General-interest dummy	-0.0135*** (0.00429)	-0.0140*** (0.00433)	-0.0145*** (0.00441)
Ranking value§	0.0242 (0.0197)	0.0264 (0.0198)	0.0305 (0.0197)
General-interest dummy × Ranking value (I)	0.00804 (0.0194)	0.00709 (0.0197)	0.00442 (0.0201)
Time index A	-4.25e-05 (0.000203)		
Time index A × General-interest dummy (II.A)	0.000278 (0.000251)		
Time index A × Ranking value (III.A)	-0.00111* (0.000579)		
Time index A × General-interest dummy × Ranking value (IV.A)	0.000527 (0.000703)		
Joint significance [p-value]			
(II.A)+(III.A)	[0.002]		
(I)+(IV.A)	[0.641]		
(I)+(II.A)+(III.A)+(IV.A)	[0.004]		
Time index B	-0.000301 (0.000566)		
Time index B × General-interest dummy (II.B)	0.000831 (0.000732)		
Time index B × Ranking value (III.B)	-0.00333** (0.00164)		
Time index B × General-interest dummy × Ranking value (IV.B)	0.00155 (0.00202)		
Joint significance [p-value]			
(II.B)+(III.B)	[0.001]		
(I)+(IV.B)	[0.630]		
(I)+(II.B)+(III.B)+(IV.B)	[0.002]		
Time index C	-0.000568 (0.00135)		
Time index C × General-interest dummy (II.C)	0.00191 (0.00172)		
Time index C × Ranking value (III.C)	-0.00869** (0.00355)		
Time index C × General-interest dummy × Ranking value (IV.C)	0.00444 (0.00464)		
Joint significance [p-value]			
(II.C)+(III.C)	[0.000]		
(I)+(IV.C)	[0.542]		
(I)+(II.C)+(III.C)+(IV.C)	[0.000]		
Fee	0.00198 (0.00161)	0.00198 (0.00162)	0.00198 (0.00162)
Year fixed effects	Y	Y	Y
Publisher fixed effects	Y	Y	Y
Observations	831	831	831
R-squared	0.601	0.601	0.602

§ A larger ranking value means a weaker ranking. The ".A" denotes that the time index A is used here (the same for later ".B" and ".C"). Standard errors are reported in parentheses, allowing for arbitrary clustering across journals and years. *** p<0.01, ** p<0.05, * p<0.1.

interest journals and field journals in determining the trend in S_{it} . The regression is otherwise the same as the original regression (11). The three-way interaction term is added as the last regressor (labeled “IV.A/B/C”) in all columns. It is not significantly different from zero, regardless of the specification in use, indicating that the role of journal ranking in determining the trend is not different between general-interest journals and field journals. That is, speaking of equation (14), $\tau_\omega = \tau$ is suggested by the data.

Notice that there are in total four interaction terms here, three two-way interactions (labeled I, II, and III in Table 5) and one three-way interaction (labeled IV in Table 5). A possible concern arises as to whether the heavy non-linearity introduced by them into the regression deprives the statistical significance of the three-way interaction term. This concern is legitimate, since the coefficient of the two-way interaction term $T_t \cdot G_i$, which is statistically significant in the previous Table 4, now loses statistical significance. To address the concern, we conduct joint-significance tests on three different combinations of coefficients: II+III, I+IV, and all-four.

We reach two findings from the joint-significance tests. One, the all-four combination shows clear joint significance. Two, the all-four joint significance is mainly driven by the joint significance of combination II+III rather than that of I+IV. These two findings corroborate the conclusion we drew above. That is, the role of ranking value in determining the trend is no different between general-interest journals and field journals. They also corroborate our findings from Table 4 by demonstrating that the significance of two-way interactions $T_t \cdot G_i$ and $T_t \cdot R_i$ (i.e., combination II+III here) is not caused by mis-specified functional forms.

4.2 Robustness

We check the robustness of the results in Table 4 in three ways.²¹ The first check is on the estimation method. The dependent variable S_{it} , as a share variable, has a data range between 0 and 1. The previous Table 4 uses linear regressions, which do not econometrically constrain the range of the dependent variable. We experiment with the fractional logit estimation that constrains the dependent variable between 0 and 1. The results are reported in **Table 6**, where marginal effects (calculated at the means of all regressors) are reported. The estimated signs are the same as in Table 4, while the estimated magnitudes are quite similar to those in Table 4. The drawback of the fractional logit estimation is that, given its non-linear functional forms, the choice of regressor values in the marginal-effect calculation is largely arbitrary. Thus, we use it only as a robustness check.

The next robustness check focuses on the ranking values, and its results are reported in **Table 7**. In columns (1)-(4) of the table, the regressions in Table 4 are rerun with top-five journals excluded from the sample. This is to address the fact that top-five journals, which are general-

²¹In addition, there is one relatively new journal (*American Economic Journal: Applied Economics*, which began publishing in 2009) in our sample. We checked the robustness of the results in Table 4 by excluding the journal (six corresponding observations) from the regressions. The regressions produce the same findings (available upon request).

Table 6: Robustness I: Fractional Logit Model

Dep. Variable: average page share within journal-year duplets	(1)	(2)	(3)	(4)
General-interest dummy	-0.00765** (0.00079)	-0.01160** (0.00108)	-0.01239** (0.00124)	-0.01344** (0.00145)
Ranking value§	0.01695** (0.00271)	0.02407** (0.00324)	0.02556** (0.00354)	0.02798** (0.00398)
Time index A	-0.00017 (0.00011)	-0.00008 (0.00013)		
Time index A × General-interest dummy		0.00040** (0.00010)		
Time index A × Ranking value		-0.00073** (0.00023)		
Time index B			-0.00029 (0.00043)	
Time index B × General-interest dummy			0.00120** (0.00030)	
Time index B × Ranking value			-0.00219** (0.00070)	
Time index C				-0.00095 (0.00121)
Time index C × General-interest dummy				0.00292** (0.00072)
Time index C × Ranking value				-0.00559** (0.00171)
Fee	0.00230** (0.00046)	0.00230** (0.00046)	0.00230** (0.00046)	0.00230** (0.00046)
Year fixed effects	Y	Y	Y	Y
Publisher fixed effects	Y	Y	Y	Y
Observations	831	831	831	831

§ A larger ranking value means a weaker ranking. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$.

interest journals, have the best rankings (i.e., the smallest ranking values R_i) among all economics journals. As a result, when R_i takes on these smallest values, it has a mechanical correlation with G_i . This causes a potential “top-general-interest journal effect” that may hide behind the estimates in Table 4. It is no longer an issue when top-five journals are excluded. As shown in columns (1)-(4), the findings from Table 4 remain.

Our identification relies on cross-journal variations through the two interaction terms. Top-five journals have the lowest ranking values and meanwhile are general-interest journals. Thus, we cannot formulate a separate robustness check for them. According to our theory, they have the least tendency to increase the number of articles published, as their intellectual values come more from quality than from quantity.²² Indeed, [Card and DellaVigna \(2013, 2018\)](#) find that the total number of articles published in top-five journals is actually lower during our sample period than it was in the 1970s. This might be related to the fact that the attention given to the top-five journals in this profession rose rather than declined ([Heckman and Moktan, 2020](#)). Nevertheless, their resilience to the trend is consistent with what our theory predicts.

²²Technically, the articles in top-five journals have the maximal γ (see equation (5)) and thus the least variation in S^* as shown by equation (4).

Table 7: Robustness II: Alternative Rankings

Dep. Variable: average page share within journal-year duplets								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample:	Non-top-five journals				Full			
Ranking:	Benchmark				Kiel			
General-interest dummy	-0.00596 (0.00364)	-0.00972** (0.00386)	-0.0104*** (0.00397)	-0.0117*** (0.00401)	-0.00543* (0.00303)	-0.00916*** (0.00316)	-0.00989*** (0.00332)	-0.0109*** (0.00347)
Ranking value§	0.0144 (0.0155)	0.0243 (0.0151)	0.0263* (0.0152)	0.0299** (0.0152)	0.0109*** (0.00300)	0.0125*** (0.00336)	0.0127*** (0.00353)	0.0131*** (0.00367)
Time index A	-0.000245*** (8.09e-05)	-7.23e-05 (0.000184)			-0.000190 (0.000116)	-0.000206 (0.000202)		
Time index A×General-interest dummy		0.000376*** (0.000144)				0.000370** (0.000173)		
Time index A×Ranking value		-0.000986* (0.000514)				-0.000165 (0.000194)		
Time index B			-0.000206 (0.000520)				-0.000813 (0.000543)	
Time index B×General-interest dummy			0.00112*** (0.000401)				0.00111** (0.000508)	
Time index B×Ranking value			-0.00296** (0.00149)				-0.000470 (0.000534)	
Time index C				-0.000798 (0.00123)				-0.00199 (0.00127)
Time index C×General-interest dummy				0.00285*** (0.000853)				0.00272** (0.00116)
Time index C×Ranking value				-0.00773** (0.00328)				-0.00113 (0.00116)
Fee	0.00185 (0.00174)	0.00185 (0.00173)	0.00185 (0.00174)	0.00185 (0.00174)	0.00257 (0.00170)	0.00255 (0.00172)	0.00255 (0.00172)	0.00255 (0.00172)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Publisher fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	726	726	726	726	831	831	831	831
R-squared	0.586	0.595	0.595	0.596	0.594	0.602	0.601	0.601

§ A larger ranking value means a weaker ranking. Standard errors are reported in parentheses, allowing for arbitrary clustering across journals and years. *** p<0.01, ** p<0.05, * p<0.1.

In columns (5)-(8) of **Table 7**, the ranking values are from the journal rankings compiled by the Kiel Institute. The A+, A, and B+ journals rated by the Kiel Institute are coded as ranking values 0, 0.5, and 1, respectively. Having only three levels in the ranking value reduces the variations in R_i . The coefficient of its interaction with the time index, namely $\hat{\delta}_R$, is now negative but statistically insignificant. However, the coefficient of the ranking value itself, namely $\hat{\theta}_R$, remains positive and statistically significant as before (the significance level actually rises a bit). The results related to journal type G_i , either interacted or not, also remain as before.

The last robustness check is concerned with the potential differences between pure-economics journals and b-school journals. In **Table 8**, columns (1)-(3) correspond to pure-economics journals, while columns (4)-(6) correspond to b-school journals. Since b-school journals are all field journals,

we cannot include G_i in the regressions. The comparison is now mainly in the interaction between R_i and T_t . The earlier findings turn out to hold for both journal groups, and no difference is found between the two groups.

Table 8: Robustness III: Pure-economics Journals vs. B-school Journals

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable: average page share within journal-year duplets						
	Pure-economics journals			B-school journals		
Ranking value§	0.0255** (0.0127)	0.0274** (0.0129)	0.0310** (0.0130)	0.0642*** (0.00808)	0.0660*** (0.00896)	0.0690*** (0.00976)
Time index A	0.000112 (0.000129)			-0.000531 (0.000556)		
Time index A × Ranking value	-0.000907** (0.000436)			-0.000967 (0.000617)		
Time index B	0.000377 (0.000379)			-0.00187 (0.00156)		
Time index B × Ranking value	-0.00274** (0.00123)			-0.00287* (0.00172)		
Time index C	0.000935 (0.000870)			-0.00728* (0.00381)		
Time index C × Ranking value	-0.00726*** (0.00257)			-0.00723* (0.00413)		
Fee	-0.000696 (0.00178)	-0.000696 (0.00178)	-0.000697 (0.00179)	0.00970*** (0.00130)	0.00970*** (0.00129)	0.00970*** (0.00126)
Year fixed effects	Y	Y	Y	Y	Y	Y
Publisher fixed effects	Y	Y	Y	Y	Y	Y
Observations	726	726	726	105	105	105
R-squared	0.595	0.595	0.595	0.731	0.731	0.732

§ A larger ranking value means a weaker ranking. Standard errors are reported in parentheses, allowing for arbitrary clustering across journals and years. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3 Page Limits and Field-specific Specialization

The linchpin of the model in Section 2 is the expertise loss rate γ within a journal’s scope. In the above empirical study, γ is linked to journal type (G or F) and ranking value R_i through equation (5). Below, we examine two other journal characteristics related to γ .

Page Limits on Initial Submissions. Some journals impose page limits on initial submissions, which indirectly reflect an expertise cost concern: longer submissions do not contribute proportionally more insights (recall Dixit’s example in the introduction). As found by [Card and DellaVigna \(2014\)](#), setting page limits on initial submissions risks losing high-quality but long submissions. Their reasoning is that shortening an article incurs a cost for authors, so that only authors that have no better alternative outlets choose to observe the limits and shorten their submissions. This reflects the “revealed preferences” of authors. Following their reasoning, journals would not impose page limits on initial submissions unless they believed that expertise costs were a significant concern for them, because imposing page limits risks losing high-quality, long submissions. Thus, we

hypothesize that the earlier results related to G_i , R_i , or both will become weaker for journals that do not impose page limits.

For journals that impose page limits on initial submissions, the earlier results are expected to remain. The page limits on initial submissions would not exhaust the variations in S_{it} for two reasons. First, page limits are not always binding. Submissions that are initially shorter than the page limits are unaffected by the page limits. Second, page limits are different across journals.²³

We divide journals into two groups according to whether they impose page limits on initial submissions, and rerun regression (11) using each of the two groups. The results are reported in **Table 9**. Columns (1)-(4) in the table, which correspond to journals with page limits, show results that resemble the earlier ones. The results in columns (5)-(8) correspond to journals without page limits, where the coefficient of the interaction between G_i and T_t remains as before, but the coefficient of the interaction between R_i and T_t becomes statistically insignificant. This weaker pattern is consistent with the revealed preferences that we expect. It also indicates that journals' perception of expertise loss differs mainly by journal rankings rather than between journal types (G or F) — among journals that do not impose page limits, field journals still have a sharper shrinkage in S_{it} .

Field-specific Specialization. Ellison (2002a) reports (in its Table 9) a specialization index for seven fields of economics in the 1990s.²⁴ We run regression (11), with G_i replaced by the Ellison specialization index, and with a sample that includes only field journals corresponding to the seven fields. We hypothesize that a higher specialization level is associated with a smaller γ , so that field journals corresponding to more specialized fields have a sharper decrease in S_i . The results are reported in **Table 10**. The journals in more specialized fields display a sharper decrease in S_{it} . The results related to the ranking value R_i remain the same as before.

²³We observe only the current page limits (if applicable) imposed by journals. They are found in journals' guidelines for authors. It would be nice if the page limit could be tracked over time for each journal, similar to what Card and DellaVigna (2014) did for AER and JEEA. However, in our context, there is no way to track page limits except to interview a journal's every on-duty editor during the sample period.

²⁴The specialization index was constructed in the following way: treat JEL codes as subfields into which the field is divided, and compute Ellison-Glaeser indexes on the set of economists who have two or more publications in the top-five journals in the field. Every Ellison-Glaeser index is an adjusted concentration measure that compares those authors' publication distribution across subfields with the distribution of all publications across subfields. Ellison (2002a) restricted the analysis to seven fields for which the relevant sample of economists exceeded 10 in the 1990s and for which the JEL codes provide a reasonably fine field division. The seven fields are microeconomic theory, macroeconomics, labor economics, industrial organization, international economics, public finance, and finance.

Table 9: Page Limits on Initial Submissions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Variable: average page share within journal-year duplets								
	Journals with page limits				Journals without page limits			
General-interest dummy	0.00200 (0.00220)	-0.00233 (0.00314)	-0.00324 (0.00354)	-0.00405 (0.00391)	-0.0108*** (0.00416)	-0.0149*** (0.00380)	-0.0156*** (0.00387)	-0.0169*** (0.00380)
Ranking value§	0.0166*** (0.00381)	0.0306*** (0.00561)	0.0333*** (0.00611)	0.0376*** (0.00642)	0.0173 (0.0138)	0.0208 (0.0129)	0.0217* (0.0130)	0.0239* (0.0127)
Time index A	-0.000175 (0.000166)	-3.87e-05 (0.000189)					-0.000191 (0.000237)	
Time index A × General-interest dummy		0.000434* (0.000231)					0.000406* (0.000214)	
Time index A × Ranking value		-0.00143*** (0.000314)					-0.000357 (0.000630)	
Time index B			-0.000372 (0.000569)				-0.000492 (0.000703)	
Time index B × General-interest dummy			0.00131* (0.000684)				0.00120* (0.000624)	
Time index B × Ranking value			-0.00425*** (0.000906)				-0.00112 (0.00177)	
Time index C				-0.00120 (0.00141)				
Time index C × General-interest dummy				0.00303* (0.00157)				0.00302** (0.00142)
Time index C × Ranking value				-0.0106*** (0.00206)				-0.00331 (0.00389)
Fee	-0.00247*** (0.000680)	-0.00248*** (0.000692)	-0.00248*** (0.000690)	-0.00248*** (0.000674)	0.00250 (0.00164)	0.00249 (0.00165)	0.00249 (0.00166)	0.00249 (0.00168)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Publisher fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	258	258	258	258	573	573	573	573
R-squared	0.640	0.742	0.740	0.739	0.602	0.608	0.607	0.608

§ A larger ranking value means a weaker ranking. Standard errors are reported in parentheses, allowing for arbitrary multi-way clustering across journals and years. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Field-specific Specialization

	(1)	(2)	(3)	(4)
Dep. Variable: average wage share within journal-year duplets				
Ellison specialization index	-0.0769*** (0.0223)	-0.0433** (0.0207)	-0.0365* (0.0208)	-0.0302 (0.0222)
Ranking value§	0.0311 (0.0218)	0.0407* (0.0217)	0.0425* (0.0217)	0.0459** (0.0218)
Time index A	-0.000363*** (0.000110)	0.000777*** (0.000261)		
Time index A × Ellison specialization index		-0.00335*** (0.000901)		
Time index A × Ranking value		-0.000928** (0.000391)		
Time index B			0.00232*** (0.000778)	
Time index B × Ellison specialization index			-0.0101*** (0.00262)	
Time index B × Ranking value			-0.00276** (0.00112)	
Time index C				0.00482*** (0.00175)
Time index C × Ellison specialization index				-0.0233*** (0.00660)
Time index C × Ranking value				-0.00725*** (0.00264)
Fee	0.00597*** (0.00208)	0.00597*** (0.00208)	0.00597*** (0.00209)	0.00597*** (0.00208)
Year fixed effects	Y	Y	Y	Y
Publisher fixed effects	Y	Y	Y	Y
Observations	502	502	502	502
R-squared	0.658	0.684	0.684	0.683

§ A larger ranking value means a weaker ranking. General interests journals are excluded. Standard errors are reported in parentheses, allowing for arbitrary clustering across journals and years. *** p<0.01, ** p<0.05, * p<0.1.

It should be noted that the more specialized fields may also have a tendency that raises rather than reduces γ . That is, research topics could be more likely to fall into the specialized domains of the corresponding researchers, which raises the probability of overstretching expertise. We cannot rule out this possibility. But this possibility works against finding results that support our hypothesis — without this opposing effect, the page-share shrinking in more specialized fields would be even sharper. In this regard, our findings in Table 10 should be interpreted as a net effect.

It should also be noted that the Ellison specialization index, despite being a field-specific measure, was constructed using publications in top-five journals. In contrast, the sample used in Table 10 includes only field journals. On the one hand, this is a measurement issue in our context, because the specialization level in a field’s top-five journal publications is not equivalent to that

field's specialization level in field journals. On the other, this is a strength of the index in our context, because it means that the specialization index constructed for those fields has no direct correlation with the S_{it} of field journals. If the specialization index were constructed using field journals, we would have to worry about whether those prolific authors of the field journals directly impact the S_{it} of those journals.

5 Extensions: Journal Market and Job Market

The theory and empirics in the previous sections provide a lens through which several other recent changes in the economics profession can be linked to its increasing specialization in knowledge production. In this section, we analyze the journal market of economics and the job market of economists as two examples.

5.1 Journal Market

In the journal market of economics, our primary interest is in the prices charged by publishers. Recall that in our theory, the *per-page* price is p and the journal length is y . The journal publishes n articles, such that the *per-article* price is py/n .

Our theory has an unambiguous prediction on the per-page price p over time. As the attention paid by readers to each published page declines, their willingness to pay for each page will decline, leading to a decrease in the per-page price p . This change is graphically illustrated in **Figure 2**, where one can see that the per-page price decrease Δp is greater in magnitude than the attention shock itself, because the journal length y rises at the same time (i.e., $\Delta y > 0$) and thus reduces the marginal cost per page $dC(y)/dy$.

Our theory has an ambiguous prediction on the per-article price py/n . The percentage change in py/n is

$$\Delta \left(\frac{py}{n} \right) / \left(\frac{py}{n} \right) = \underbrace{\frac{\Delta p}{p}}_{<0} + \underbrace{\frac{\Delta y}{y}}_{>0}. \quad (15)$$

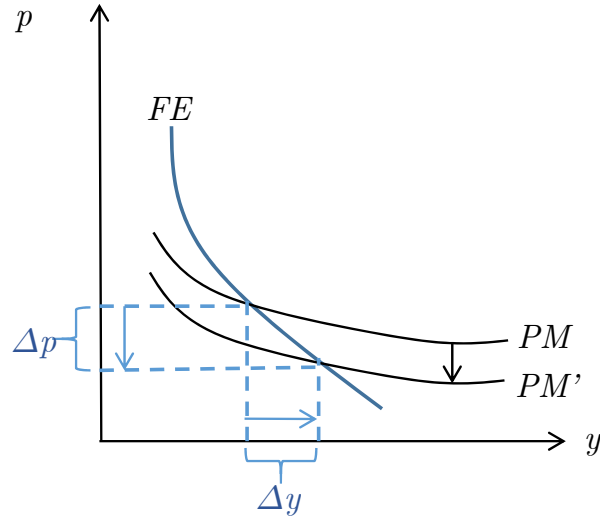
Remember the $\Delta p < 0$ analyzed above, then we know the first term in equation (15) is negative. To find out the sign of the second term in equation (15), notice the $\Delta y > 0$ analyzed above. Then, by equation (2), it is easy to derive the article length

$$\frac{y}{n} = f^{\frac{1}{\gamma+2}} y^{\frac{\gamma+1}{\gamma+2}}, \quad (16)$$

which demonstrates that the article length increases with journal length, at a rate of $0 < \frac{\gamma+1}{\gamma+2} < 1$. Thus, the second term in equation (15) must be positive.²⁵ So, according to equation (16),

²⁵The magnitude of $\frac{\Delta y}{y}$ is smaller than that of $\frac{\Delta y}{y}$ owing to the fact that the power of y in equation (16), namely $\frac{\gamma+1}{\gamma+2}$, is smaller than 1.

Figure 2: Prices of Pages and Length of Articles in Theory



Notes: Δp represents a change in the per-page price charged by a journal, while Δy represents a length (total pages) change of the journal.

$\Delta \left(\frac{py}{n} \right) / \left(\frac{py}{n} \right)$ could be either positive or negative, depending on the curvature of the demand curve that changes from point to point along the curve. Intuitively, an article with a larger number of cheaper pages could be either cheaper or more expensive.

We found journal price data from the *Journal Cost-Effectiveness 2013* (hereafter, JCE13) database, collected and maintained by Theodore C. Bergstrom.²⁶ The JCE13 database reports per-article prices for 10,100 journal-year combinations (not limited to economics). We extracted the per-article prices corresponding to the journals in our own data from the JCE13 database, which are available for the years 2004, 2006, 2008, 2009, 2010, 2011, and 2013. We examined the latest four available years among them (2009, 2010, 2011, and 2013) because these years are almost consecutive, all occurred after the Great Recession of 2008, and most importantly, all occurred after the 2009 typeset change of the Dutch publisher Elsevier.²⁷ The average per-article price is plotted across years as a line connected by hollow diamonds in the upper panel of **Figure 3**. The

²⁶The database is accessible at <https://journalprices.com>. We accessed it in March 2019.

²⁷Starting from 2009, most journals published by Elsevier use a uniform proprietary typesetting style, with two columns, compact line spaces, small font sizes, narrow page margins, and a simplistic bibliographic style. This change affects 12 journals in our sample. Notice that this change is consistent with our thesis in Section 2 as it mechanically results in more and shorter papers published in a given issue.

JCE13 database does not report the average article lengths of journals. We merge its per-article price with the average article lengths in our own data to calculate per-page price. The per-page price is plotted across years as a line connected by solid diamonds in the same panel.²⁸

Evidently, the per-page price declined, as predicted earlier; meanwhile, the per-article price rose, which is possible according to our theory. Also, such patterns indicate that the decline in per-page price should come from continually rising article length. Indeed, we plotted the average length of articles (with one standard deviation marked) across years in the lower panel of **Figure 3**. Some back-of-envelope calculation can quickly illustrate the machinery underpinning equation (15). The per-article price rose from \$14.1 to \$15.4 (9.2 percent), and the per-page price declined from \$0.815 to \$0.775 (4.9 percent). The gap between these figures, 14.1 percent, is fairly close to the number-of-pages increase, which rose from 20.9 to 23.5 (12.4 percent).²⁹ In addition, in Appendix ??, we provide an estimation-based counterpart of Figure 3, which has accounted for different profit statuses of the journals (for-profit journals charge greater prices than non-profit journals, as found by Bergstrom (2001)) and interpolated the missing year 2012. The results are highly similar.

5.2 Job Market

The economics profession has been steadily expanding in the last two decades. **Figure 4** displays the number of new jobs (and its growth rate) posted by the American Economic Association (AEA) during our sample period.³⁰ The job market of economists is known to be highly competitive, where each position has a large number of competing applicants (Cawley, 2018). Since job candidates might end up with jobs other than those posted by the AEA, the actual growth in the number of economists should be even faster than what the figure shows. Our previous framework is concerned with how journals organize their article production. It is now extended to account for two stylized facts related to the expansion of the profession: (1) newly minted economists have been trained to be familiar with all topics in their fields, and (2) the rising number of newly minted economists deepens specialization in research.

To account for the two facts, we find it sufficient to revise our previous parameterization (5) of γ now as

$$\gamma = \omega - \tau R - m, \tag{17}$$

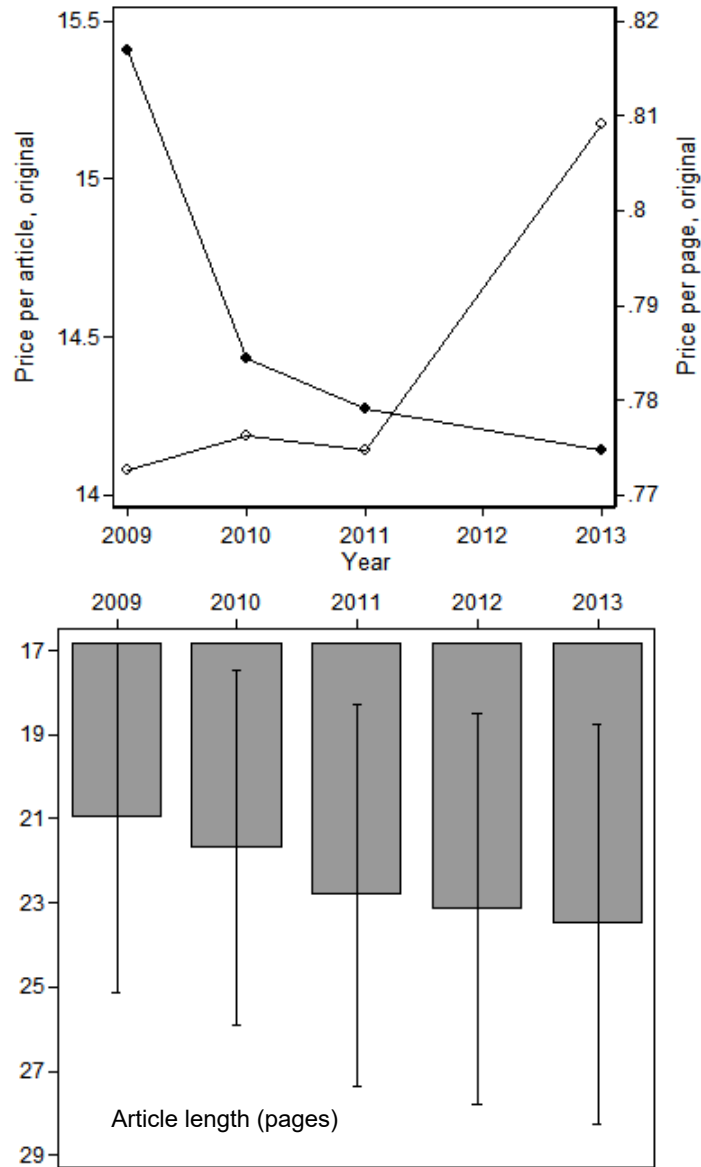
where m represents the impact of newly minted economists on the expertise costs in the journal

²⁸Price values in the plot are in 2001 US dollars. We use the *Producer Price Index by Industry: Book Publishers: Primary Services* published by the Federal Reserve Bank of St. Louis to deflate prices. The index is available at <https://fred.stlouisfed.org/series/PCU511130511130P>.

²⁹The two percentages, 14.1 percent and 12.4 percent, are not precisely equal because the back-of-envelope calculation is based on year averages, while equation (15) characterizes a theoretical marginal impact on a representative journal.

³⁰The data were extracted from the “Report: Job Openings for Economists” in the AEA Papers and Proceedings (previously titled AER Papers and Proceedings) published annually by the AEA.

Figure 3: Prices of Journal Articles and Pages in the Data

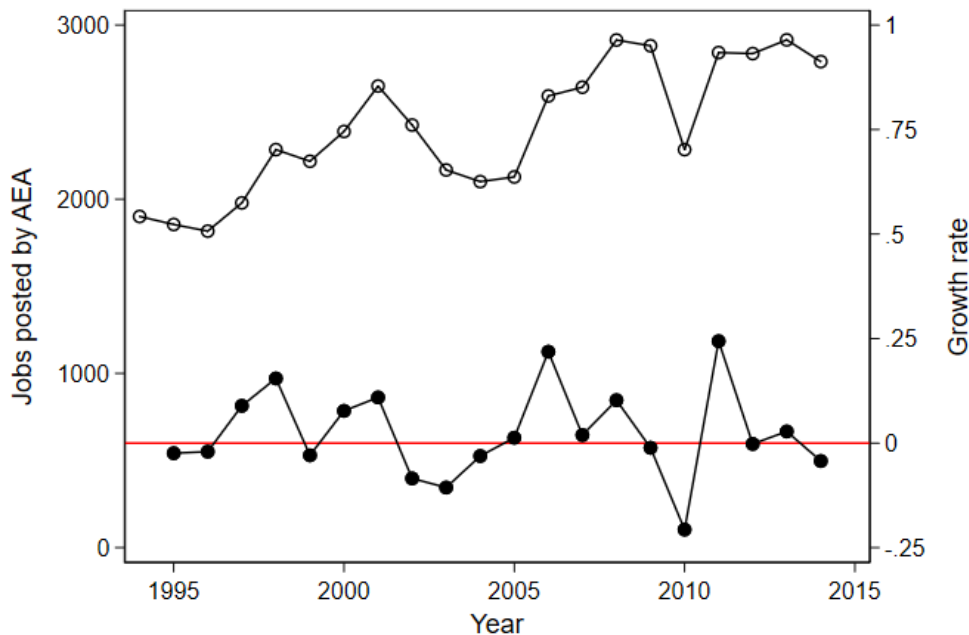


Notes: In the upper panel, the year 2012 is absent because the data for that year are not reported in the JCE13 database. In the lower panel, one standard deviation is marked along with the average article length.

represented by $\{\omega, R\}$.³¹ The previous cost structure (1) of journals implicitly assumes that each research topic in the journal's scope $[0, 1]$ has one unit of authors working on it. Newly minted economists have been trained to be familiar with all existing topics in their fields — as reflected

³¹The new economists are assumed to follow the distribution of the existing economists across fields (journals).

Figure 4: The Increasing Number of Economists



in any graduate course syllabus — such that their addition to the existing authors will reduce the expertise costs across topics. This connects with fact (1). With this new γ parameterization, the shrinkage in S is expedited through the number of articles $n = (y/f)^{\frac{1}{\gamma+2}}$ (i.e., equation (2)). That is, the increasing number of economists deepens the specialization in the profession. This delivers fact (2).

We test the new parameterization by adding an interaction between the number of new economist jobs and each of the three time trend variables. The results are reported in **Table 11**. As expected, the interaction term has a negative and statistically significant coefficient. That is, the availability of newly minted experts further shrinks the page shares of individual articles in the journals where they are published.

It should be noted that this extension remains to focus on knowledge production even though it brings a job-market force into the analysis. Treating newly minted economists as part of parameter γ is a simplistic approach to keeping our focus on knowledge production. A comprehensive modeling of the specialization in this profession would involve the interplay among knowledge production, teaching responsibilities, and human-capital formation. Integrating all these aspects of the profession into one model is challenging. [Besancenot, Faria, and Vranceanu \(2009\)](#) successfully unify the roles of researcher and teacher played by economists in higher education through a signaling mechanism. Our extension above, despite being simplistic, provides a possible channel through which production and human capital can be linked.

Table 11: Number of New Economists

	(1)	(2)	(3)
Dep. Variable: average wage share within journal-year duplets			
General-interest dummy	-0.0116*** (0.00291)	-0.0123*** (0.00306)	-0.0133*** (0.00304)
Ranking value§	0.0296*** (0.0107)	0.0315*** (0.0109)	0.0348*** (0.0110)
Time index A	0.000246 (0.000223)		
Time index A × General-interest dummy	0.000378** (0.000168)		
Time index A × Ranking value	-0.000967** (0.000476)		
Time index A × Number of new economists	-0.000171*** (6.31e-05)		
Time index B		0.000834 (0.000654)	
Time index B × General-interest dummy		0.00113** (0.000499)	
Time index B × Ranking value		-0.00291** (0.00134)	
Time index B × Number of new economists		-0.000540*** (0.000150)	
Time index C			0.00139 (0.00139)
Time index C × General-interest dummy			0.00274** (0.00111)
Time index C × Ranking value			-0.00746** (0.00300)
Time index C × Number of new economists			-0.000967*** (0.000302)
Fee	0.00208 (0.00151)	0.00208 (0.00151)	0.00208 (0.00145)
Year fixed effects	Y	Y	Y
Publisher fixed effects	Y	Y	Y
Observations	831	831	831
R-squared	0.594	0.593	0.594

§ A larger ranking value means a weaker ranking. Standard errors are reported in parentheses, allowing for arbitrary clustering across journals and years. *** p<0.01, ** p<0.05, * p<0.1.

6 Concluding Remarks

We find economics journals to be a good subject for studying the economics of economics. Journals produce articles, sell them and produce a profit. Economists are, in some sense, employed by journals because their journal publications usually determine their salaries, promotions, reputations, fundings, and what (and how much) to teach. Most importantly, recent economic knowledge has been provided mainly in the form of journal articles. Journals are economic goods. By analyzing

journals, the production of economics can be rationalized using existing production models, without resorting to a production model specifically built for economics itself.

We borrow a monopolistic competition model from the literature to model the behavior of economics journals, and use data from 41 journals over the last two decades to test the model. Every journal covers a range of topics and decides its length and the number of articles to publish. Every new article incurs a fixed cost, but extending given articles to cover more topics incurs increasing expertise costs. As a tradeoff, journals divide their length among a limited number of articles with limited length. The rise of the World Wide Web and online search engines in the last two decades were a negative shock to readers' attention on journal issues and their willingness to pay. The model predicts that journals will produce longer journal issues, longer articles, and more articles, but as a net effect, the page share of an average article in a journal shrinks over time. This prediction receives support from the data. Moreover, as predicted by the model, general-interest journals and better ranked journals, where expertise costs rise faster across topics within a journal, turn out to shrink less. This unique prediction is also supported by the data.

A limitation of this study is its abstraction away from the personnel of economics journals. We intentionally refrain from modeling the labor (author) market in order to keep our model a partial equilibrium one. Using real economists to replace the objectified "expertise" in our model will be a fruitful direction for future research because authors in the journal data can be linked to voluminous online vitae. There have been established theories on the production cycles of researchers, such as [Jones \(2010\)](#) and especially [Faria and McAdam \(2015\)](#) on the life cycles of economists. Combining fluctuations in the journal market with those in the author market will shed light on the long-term dynamics of our profession.

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