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Working Paper

Leadership in scholarship: A machine learning based investigation of editors' influence on textual structure

Cardiff Economics Working Papers, No. E2018/2

Provided in Cooperation with:

Cardiff Business School, Cardiff University

Suggested Citation: Önder, Ali Sina; Popov, Sergey V.; Schweitzer, Sascha (2018) : Leadership in scholarship: A machine learning based investigation of editors' influence on textual structure, Cardiff Economics Working Papers, No. E2018/2, Cardiff University, Cardiff Business School, Cardiff

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Cardiff Economics Working Papers



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January 2018

ISSN 1749-6010

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Leadership in Scholarship: A Machine Learning Based Investigation of Editors' Influence on Textual Structure*

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January 19, 2018

Abstract

Academic journals disseminate new knowledge, and editors of prominent journals are in a position to affect the direction and composition of research. Using machine learning procedures, we measure the influence of editors of the *American Economic Review* (*AER*) on the relative topic structure of papers published in the *AER* and other top general interest journals. We apply the topic analysis apparatus to the corpus of all publications in the Top 5 journals in Economics between 1976 and 2013, and also to the publications of the *AER*'s editors during the same period. This enables us to observe the changes occurring over time in the relative frequency of topics covered by the *AER* and other leading general interest journals over time. We find that the assignment of a new editor tends to coincide with a change of topics in the *AER* in favour of a new editor's topics which can not be explained away by shifts in overall research trends that may be observed in other leading general interest journals.

JEL CLASSIFICATION: A11, A14, O3

KEYWORDS: Text Search; Topical Analysis; Academia; Knowledge Dissemination; Influence; Journals; Editors.

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1 Introduction

Publishing in top Economics journals is, and has already been for some time, increasingly competitive (Hamermesh, 2013) and extremely rewarding (Attema et al., 2014). Short-term rewards, such as promotions and grant awards, are prone to depend not only on publication content, but also on publication etiquette. This creates a tradeoff between publishing what one thinks is important and what one thinks is likely to be published. A new editor taking office at a major journal may create an incentive for researchers who are yearning for promotion, tenure, or simply recognition to steer knowledge generation towards the topics preferred by this editor. Hence we ask in this paper: Are there traces of editors' preference in the topic structure of a journal that cannot be solely explained by the concurrent trends in research topics?

We calculate the topic frequencies of editors and associate editors of the *American Economic Review* (*AER*) between 1976 and 2013, and analyze how an editor's topic frequencies co-move with the topic frequencies observed in the *AER* during the same editor's tenure. The other four leading general interest journals, namely the *Quarterly Journal of Economics* (*QJE*), the *Journal of Political Economy* (*JPE*), *Econometrica*, and the *Review of Economic Studies* (*REStud*)¹, constitute our control group against which we compare changes in topic frequencies. We employ a fine-grained textual analysis on the full texts of individual articles to identify the topics and their frequencies that emerge in editors' and associate editors' own research as well as in the *AER* and the four other journals listed above. Topic frequencies are used for inferring what editors' topic preferences are and whether they drive a wedge between the topic frequencies observed in the *AER* and in the four other journals.

The sheer size of the corpus of our texts allows us to demonstrate the birth and the death of topics: the words related to matching and schools, for instance, seem more likely to feature in recent studies, whereas words related to Keynes and capitalism fade. Some changes in topics could be driven by the general trends in the field or specific historical reasons, such

¹These journals together with the *AER* make up the top group of the journal ranking documented by Combes and Linnemer (2010), moreover, these are the conventional Top 5 economics journals that most academic economists would agree on. Throughout this paper, we refer to the above four leading general interest journals (hence Top 5 excluding the *AER*) as *other Top 5*.

as the Cold War and the Great Recession. To identify such general trends and correct for them, we employ changes in other Top 5 journals as a proxy for the profession’s interests.

We establish that the appointment of a new editor affects the topics of papers published in the *AER*, namely the topic frequencies observed in the *AER* tend to align with the editor’s profile. We do not obtain such an alignment between the *AER* editors’ topic frequencies and the other Top 5 journals. These results hold when the time window of our analysis is made shorter or longer than its initial setting. In both cases, the shift towards a new editor’s topics is greater for the *AER* than for other Top 5. We remain agnostic about why topics in the *AER* tend to be part and parcel of the editor’s topics: while this may be due to bias, it could also be due to the high ability of the new editor to pick good papers on the topics that he/she is working on. Had we had data on both acceptance and rejection decisions, our data would be less noisy, and our point estimates would not be biased towards zero.

A topic in our context is not quite the same as something considered a field or a subfield in Economics research. A topic can be a field, or an aspect of a field, and it can even be a certain style of narrative that features distinct patterns that is picked up by our textual analysis. Our results therefore can be interpreted as evidence that individual members of the academic profession can change the narrative of disseminated knowledge and hence reshape the focus of the profession (at least for a while), especially if these individuals occupy a gate-keeping position such as editorship of an influential academic journal.

2 Literature Review

We contribute to the empirical literature on knowledge dissemination by showing that those who edit journals can affect the profession not only by their connectedness (Brogaard et al., 2014, Card and DellaVigna, 2017, Colussi, 2015, Medoff, 2003), but also by shifting the topics that journals cover.

In our preliminary analysis in Section 3.3 we investigate dynamics of topics covered by papers published in the *AER*, and, using topics suggested by machine learning instead of JEL codes, we obtain patterns similar to those documented in Figure 7 of Card and DellaVigna (2013) and in Figure 2 of Angrist et al. (2017). While the JEL codes are quite generic,

there is little certainty whether, for instance, a paper on job market signaling would be best categorized as a Micro paper, a Labor paper, or both, with 50-50 allocation; and whether the decision regarding the allocation of such a paper to JEL codes would be the same in the 2010s and in the 1970s. When new topics arise or old topics fade away, the pre-defined JEL classifications are hardly ever adopted. Thus, new topics may be disguised under either very generic or rather odd JEL codes. Over time, this can lead to overcrowding of some classes and depopulation of others. Even a reform of the classification system such as the one in 1990 brings inconsistencies of its own that complicate the investigation of the continuous development of topics (Cherrier, 2017). Our approach does not incur this problem: it continuously tracks changes in topics and terminology, with no sudden artificial breaks. As long as the terminology persists, topics are assigned in the same way.

An overview of the methodology and research applications of textual analysis is described in Gentzkow et al. (2017). In studying publication patterns, a methodology similar to ours was applied by Mela et al. (2013) and Huber et al. (2014) to marketing literature. While they show that editors throughout their tenure feature different mixes of topics, they do not speculate why the topics of the text corpus moved in a certain direction. Similarly, Angrist et al. (2017) study the development of economic literature over time. While finding little evidence for change in the composition of Economics fields, they demonstrate a greater propensity for publishing empirical literature. Their analysis does not extend to studying whether the frequencies of topics of the journal co-move with the topic frequencies of the editor’s own work. Kosnik (2015) uses topical analysis to study the corpus of seven journals in Economics published between 1960 and 2010. While this study finds that research in macroeconomics diminishes, complemented by an increase in research in the microfoundations of macroeconomics, it focuses on descriptive results, does not concern editors’ appointment, and does not compare trends across different journals.

Li (2017) investigates NIH grant applications and finds that evaluators assign higher scores to applications whose authors they cite. As in our analysis, text matching is an important tool used by Li (2017) for creating a measure of similarity between two sets of text data: the author measures the quality of a grant application by matching that grant to subsequent publications and their citations. If a certain group of words in the title or abstract

of a grant application matches those in published papers afterwards, then these papers are deemed to be related the grant, and their citations are used to evaluate the grant’s ex-post performance. We use a more sophisticated text analysis approach that quantifies the vector of topic frequencies of all publications in the *AER* to quantify the topic similarity; but we also go beyond this by verifying whether the direction taken by the journal is steered in the direction of the topic frequencies of the new editor.

3 Data and Methodology

3.1 Text Corpus

We collect data on the editorial office of the *AER* including chief as well as associate editors from 1980 to 2013, and we compare trends in topic frequencies in articles published in the *AER* against those in articles published by newly appointed *AER* editors as well as against topic frequencies of articles in other Top 5 general interest economics journals. We study the corpus of texts of journals of *AER*, *QJE*, *JPE*, *REStud*, and *Econometrica*, as well as all papers by the editors of *AER* from 1976 to 2013 available from JStor. We obtain our data from ITHAKA, the owners of JStor, the digital online library, which provides word and n-gram counts of academic papers for researchers.² To avoid issues with copyright, only the n-gram counts computed by ITHAKA based on the original full texts are downloaded, not the original papers.

3.2 Topic Analysis

The methodology of the analysis is based on reducing the inherently high dimensionality of textual data. This approach shares some similarities with principal components analysis: words (or combinations of words, such as “sovereign debt”) that occur together with other specific words (such as “default”) in many texts are likely to carry the same message on the same topic.

²Data are provided by ITHAKA for research purposes upon request via <http://dfr.jstor.org/>, accessed 1 June 2017.

We preprocess full texts of research articles in our data through several technical steps. In the first step, common words are removed (such as “a”, “above”, “across”, etc; full list available on request). In the second step, words are stemmed in order to abstract them from their different grammatical forms. The stemming procedure follows the standard approach described by Porter (1980). Finally, common 2-word collocations are replaced by tokens. For the tokenizing, we employ the Python package `textmining` (Peccei, 2010). All of these preprocessing steps were performed using a Python script that is available on request.

After preprocessing the text data, the topic analysis was performed using Latent Dirichlet Allocation (LDA)³ model. Each topic is a set of probabilities assigned to words that are encountered in the whole text corpus. For each document, LDA returns a list of mixing proportions: each document is a mixture of distributions over words according to topics. An advantage of this methodology is that it is not driven by hand-picked sets of words: topics are constructed to fit a model consisting of a mixture of distributions over words, subject to a pre-specified number of topics. Our ex-ante specification is that we use 200 topics; results remain qualitatively similar if the number of topics is increased to 300 (in which case additional topics become more specific, potentially containing more arbitrary artifacts) or decreased to 100 (which makes topics more general, concealing some potential changes). For carrying out the LDA estimation we used the UMass Amherst’s Machine Learning for Language Toolkit (MALLET) (McCallum, 2002).⁴

3.3 Trends in Topics of AER

Over time, trends may change: some topics can bloom, while other topics may wither. To test for this, we ran 200 time series regressions for each topic, regressing a log share of each topic in papers of *AER* on year and year-squared. Then we conducted 200 F-tests to see whether the quadratic time trend was statistically significant, and kept the p -value of this test. Under the null hypothesis of no quadratic time trend across topics, the distribution of p -values should be close to uniform. In fact, it is not: the average p -value is somewhat more than 0.096, and 65% of topics have a p -value less than 0.01. A similar result is obtained

³See Blei et al. (2003) for elaboration of the LDA machinery.

⁴Available at <https://mallet.cs.umass.edu>, accessed 1 June 2017.

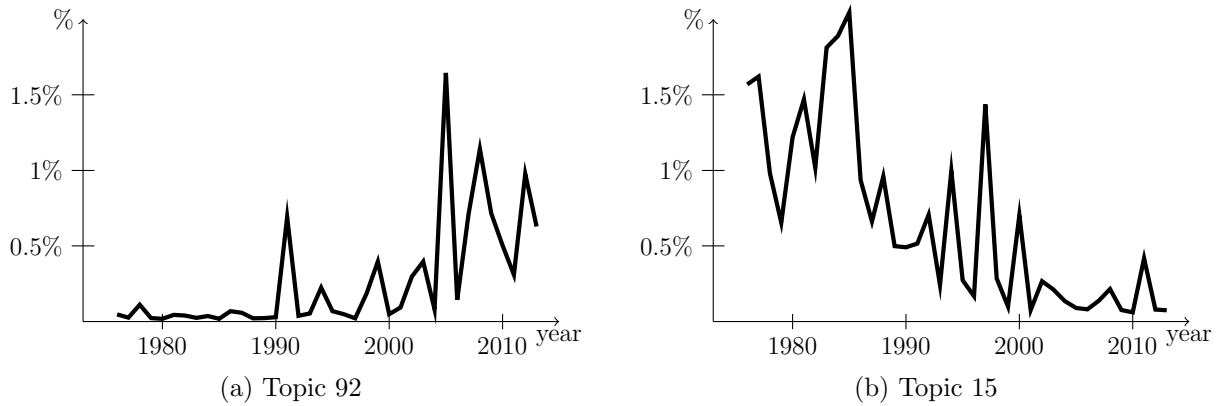


Figure 1: Topics in *AER* change over time

if one attempts a panel regression with individual time trends: the F-test value is 12.82, which with degrees of freedom of 200×2 and 200×35 yields a numerically zero p -value. Implementing some corrections (such as adjusting for non-normality, etc) could obviously increase the p -value.

Among individual topics, topic 92's linear slope coefficient is 0.0937. This topic includes stems such as

match prefer student assign pair stabl prioriti mechan two algorithm
choic applic rank roth posit set order number earli list

and its share in overall publications increases in time, going from 0.004% of the text corpus in the late 1970s to .6% in the early 2010s. Meanwhile, topic 15's linear slope coefficient is -0.0848 ; it includes stems such as

theori econom economi keyn pp polit new smith gener capitalist york
economist london work analysi journal classic econ neoclass press

and it accounts for 1.15% of the *AER* publications in late 1970s, but only for 0.1% of the text corpus in the late 2010. This does not necessarily mean that the *AER* authors used the word **theory** in 2010s less than they did before, it means that this characteristic accumulation of words tended to be part and parcel of a text more frequently before 2000 than afterwards. Figure 1 contains the plots.

The nature of our topic data, the percentages of the corpus, induces some of the trends: if there is a strong trend in one topic, there will be an opposite trend in the total loading

of other topics, which is why it is hard to say what changes caused what other changes. We apply the Benjamini-Hochberg-Yekutieli algorithm⁵ to choose a critical value to limit our false discovery rate from above by 0.01%, and still there are 75 topics that seem to exhibit a quadratic trend. Therefore, it is safe to say that over time at least some changes in topics occurred in the papers covered by our corpus. Because our topics are probably narrower than the subfields of Economics, we detect some changes in the narrative that could not be captured by a coarser grouping methodology a la [Angrist et al. \(2017\)](#).

3.4 Assigning Documents To Editors

The topic analysis yields the topic frequencies in each article as well as the distribution of words in each topic. The most popular topic overall constitutes around 4% of the corpus; 35 topics cover around 50% of the corpus.

We employed the topic frequencies of journals and editors based on a 4-year window before and after an editor’s tenure in our main analysis. As already been pointed out by [Ellison \(2002\)](#) there are significant time lags between the crafting of a research paper and its actual publication. To accommodate publication lags we build a one year lag on top the four year window. This means that the editor appointed in 2000 is relevant for papers published in 2001, 2002, 2003, and 2004 (plus maybe additional years, but we don’t include further years to study the effect of the appointment only); and we contrast the topic loadings of these papers with the topic loadings of papers published in 1997, 1998, 1999 and 2000. We conduct robustness checks, recalculating topic frequencies based on a 3-year window and 5-year window without lag and with 1-year lag each.

The document sets and their notations are as follows: AER , $Top5$, and $Edit$ denote the AER , other Top 5, and a specific editor, respectively. $AER_{i,before}^c$ and $AER_{i,during}^c$ denote the average frequency of topic c in articles published in the AER before and during tenure, respectively, of editor i in the AER . Similarly, $Top5_{i,before}^c$ and $Top5_{i,during}^c$ denote the average frequency of topic c in articles published in other Top 5 before and after the appointment, respectively, of editor i at the AER . The average frequency of topic c in articles written

⁵We use the conservative approach that allows for arbitrary dependence across outcomes of our tests, exploiting Theorem 1.3 in [Benjamini and Yekutieli \(2001\)](#).

Table 1: Pairwise Correlations of Editors' and Journals' Topics using Four Year Window One Year Lag

	$Editor_{during}$	$Editor_{before}$	AER_{during}	AER_{before}	$Top5_{during}$
$Editor_{before}$	0.583***				
AER_{during}	0.281***	0.336***			
AER_{before}	0.234***	0.357***	0.868***		
$Top5_{during}$	0.178***	0.252***	0.394***	0.400***	
$Top5_{before}$	0.160***	0.245***	0.351***	0.389***	0.936***

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

by editor i before and after his appointment at the AER is denoted by $Edit_{i,before}^c$ and $Edit_{i,during}^c$, respectively. Furthermore we denote changes in topic frequencies over time or between AER and $Top5$ as follows:

- $(AER_{i,during}^c) - (AER_{i,before}^c) = \Delta AER_i^c$
- $(Top5_{i,during}^c) - (Top5_{i,before}^c) = \Delta Top5_i^c$
- $(Edit_{i,during}^c) - (Edit_{i,before}^c) = \Delta Edit_i^c$
- $(AER_{i,during}^c) - (Top5_{i,during}^c) = \Delta AER Top5_i^c$

3.5 Estimation

The unit of observation in our regression analysis is an editor-topic pair, and there are 1,379 editor-topic pairs when the analysis is run using a 4-year window with 200 topics. Table 1 shows the correlation coefficients of the six measures we obtain from the textual analysis.

We use a two step estimation approach to isolate deviations in an editor's own research that cannot be explained away with common trends in the literature and investigate the correlations between these deviations and the topic frequencies in the journals. The topic frequencies observed in an editor's research prior to his/her tenure at the AER can well be explained by common research trends that exist at the time.

In the first step of the estimation we isolate the part of the variation in editor i 's topic frequencies before his/her tenure at the AER that is not explained by the variation in topic frequencies of articles published in top general interest journals at the time. We strip the

variation in the observed preference of an editor down to the variation in this editor's personal preference by estimating

$$Edit_{i,before}^c = \alpha_0 + \alpha_1 AER_{i,before}^c + \alpha_2 Top5_{i,before}^c + YearFE + TopicFE + \pi_i^c$$

in order to obtain residuals $\hat{\pi}_i^c = Edit_{i,before}^c - \widehat{Edit}_{i,before}^c$, which we refer to as the residual topic frequency or *the residual preference* of editor i . We regress the topic frequency in editor i 's own research during his/her tenure at the *AER* on his/her residual topic frequency and thus we obtain a projection of what can be considered an editor's own preference for topic frequencies on their observed topic frequencies during his/her tenure at the *AER*. Hence we estimate

$$Edit_{i,during}^c = \beta_0 + \beta_1 \hat{\pi}_i^c + YearFE + TopicFE + \psi_i^c$$

and we obtain fitted values for editor i 's topic frequencies during his/her tenure, denoted by $\widehat{Edit}_{i,during}^c$ which we refer to as the fitted topic frequency or *the fitted preference* of editor i .

In the second stage we use $\hat{\pi}_i^c$ and $\widehat{Edit}_{i,during}^c$ as independent variables in the estimation of topic frequencies in the *AER* and in other Top 5 during editor i 's tenure. In particular we estimate:

$$AER_{i,during}^c = F_A(\mathbf{Editor\ Preference}, AER_{i,before}^c, Top5_{i,before}^c)$$

$$Top5_{i,during}^c = F_T(\mathbf{Editor\ Preference}, AER_{i,before}^c, Top5_{i,before}^c)$$

$$\Delta AER_i^c = G_A(\mathbf{Editor\ Preference}, Top5_{i,before}^c)$$

$$\Delta Top5_i^c = G_T(\mathbf{Editor\ Preference}, AER_{i,before}^c)$$

$$\Delta AERTop5_i^c = H(\mathbf{Editor\ Preference}, AER_{i,before}^c, Top5_{i,before}^c)$$

where **Editor Preference** is captured either by the residual topic frequency $\hat{\pi}_i^c$ or by the fitted topic frequency $\widehat{Edit}_{i,during}^c$.

We not only control topic frequencies of the *AER* and other Top 5 during editor i 's tenure for editor's preferences (in the form of either residual or fitted topic frequencies) but we control also for topic frequencies observed in the *AER* and the other Top 5 before editor i 's tenure. Any discrepancy in topic frequencies of the *AER* and other Top 5 may lead to

a realignment in the next period, i.e. during editor i 's tenure, independent of editor i 's personal preferences. Since the values of topic frequencies are bounded between zero and one, we use a fractional logit estimation as proposed by [Papke and Wooldridge \(1996\)](#) when these are dependent variables. We estimate the *AER* and other Top 5 topic frequencies using a generalized linear model (GLM) with a logit link and binomial family. We estimate the changes in topic frequencies of the *AER* and other Top 5 using OLS.

4 Results

We employ topic frequency variables that are obtained from the text analysis (as described in the previous section) using a four year window. We restrict our sample to those editors who have been in office for at least four years. The coefficient estimates for the editors' residual preferences and fitted preferences are shown in panels A and B of [Table 2](#), respectively. In columns (1) to (3) we control for the topic frequencies in the *AER* as well as in the other top general interest journals before the editor's tenure. Topic frequencies in the *AER* may change in order to fall in line with prevailing topic frequencies in other top journals, or similarly, other top journals' topic frequencies may fall in line with those of the *AER*. Hence it is important to control for such alignment effects. Topic fixed effects filter out inherent and time invariant differences in the levels of different topics, and year fixed effects capture any specific changes in the level of topic frequencies in the calendar year in which an editor takes office.

The topic frequencies observed in the *AER* during the editors' tenure are positively and significantly correlated with these editors' residual preference. One standard deviation increase in an editors' residual preference for a given topic is associated with an increase in that topic's frequency in the *AER* by about 3.3% of the mean of topic frequencies. Robust standard errors are reported for the specification in column (1) of [Table 2](#) and the coefficient estimate of an editor's residual preference is statistically very significant. The bootstrapped (using 500 repeated draws) standard errors associated with editors' residual preferences that are reported in column (2) indicate that the estimated coefficient of the editors' residual preference is statistically significant at 5%. We do not obtain statistical significance when

Table 2: Journals' Topics and Editor's Preference with Four Year Window

<i>PanelA</i>	(1) <i>AER</i>	(2) <i>AER</i>	(3) <i>Top5</i>	(4) ΔAER	(5) ΔAER	(6) $\Delta Top5$	(7) $\Delta AER Top5$	(8) $\Delta AER Top5$
Editors' Residual Preference	2.443*** (0.714)	2.443* (0.997)	0.488 (0.760)	0.00715 (0.00714)	0.00715 (0.00832)	-0.00508 (0.00607)	0.0122+ (0.00661)	0.0122+ (0.00711)
Year.FE & Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1379	1379	1379	1379	1379	1379	1379	1379
<i>R</i> ²				0.244	0.244	0.473	0.843	0.843
<i>F</i>				5.606		7.717	39.62	
<i>AIC</i>	476.0	476.0	473.6					

<i>PanelB</i>	(1) <i>AER</i>	(2) <i>AER</i>	(3) <i>Top5</i>	(4) ΔAER	(5) ΔAER	(6) $\Delta Top5$	(7) $\Delta AER Top5$	(8) $\Delta AER Top5$
Editors' Fitted Preference	0.0657*** (0.0192)	0.0657* (0.0257)	0.0131 (0.0204)	0.0113 (0.0113)	0.0113 (0.0129)	-0.00805 (0.00962)	0.0194+ (0.0105)	0.0194 (0.0120)
Year.FE & Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1379	1379	1379	1379	1379	1379	1379	1379
<i>R</i> ²				0.244	0.244	0.473	0.843	0.843
<i>F</i>				5.606		7.717	39.62	
<i>AIC</i>	476.0	476.0	473.6					

Note: Additional controls are $AER_{i, before}^c$ and $Top5_{i, before}^c$ in (1), (2), (3), (7), (8); $Top5_{i, before}^c$ in (4), (5); $AER_{i, before}^c$ in (6).

Columns (1) to (3) obtained by GLM (binomial); columns (4) to (8) obtained by OLS.

Robust standard errors in parentheses. Bootstrapped (500 reps) standard errors for (2), (5), and (8).

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the topic frequencies of other Top 5 are regressed on editors' residual preference and other controls. This finding lines up with our ex post expectation that the personal topic preferences of editors of the *AER* should have no effect on the topics found in other top journals.

Dependent variables in specifications (4) to (6) in Table 2 are the change in topic frequencies in the *AER* (in columns (4) and (5)) and other Top 5 (in column (6)). Change is the difference between what is observed in topic frequencies up to four years before and after the editor takes office. It is important to note that the specifications in columns (4) to (6) are OLS equivalents of the specifications in columns (1) to (3) with a restriction that forces the coefficient of the respective journal's (*AER* or other Top 5) topics before the editor's tenure to be equal to one. Such a restriction can be interpreted as a forced persistence of patterns that would otherwise not be captured by our empirical model. Editors' residual preferences lose their statistical significance in this setting, but it is hard to tell if this is the consequence of the forced persistence mentioned above or simply due to the suboptimal nature of the OLS compared to the GLM in this specific setting.

Columns (7) and (8) in Table 2 document how the difference between topic frequencies observed in the *AER* and in other Top 5 changes during editors' tenure. We find that one standard deviation increase in an editor's residual preference is associated with an increase in the gap between the *AER* and other Top 5 corresponding to about 2.4% of one standard deviation in topic frequencies. This magnitude is statistically significant at a 10% level when standard errors are bootstrapped.

In panel B of Table 2 we use editors' fitted preference as the main explanatory variable. Editors are appointed to lead the way in which the research agenda unfolds in a given journal. This is especially important when top journals are concerned. In practice, however, it is unclear whether editors lead the way by imposing their own preferences in the publication of research or whether they are affected by submissions and update their preferences accordingly. This endogeneity problem prevents us from regressing the topic frequencies of the *AER* publications on editors' topic frequencies during their tenure. We obtain editors' fitted preference as a linear projection of their topic frequencies during their tenure on their residual preference⁶. One standard deviation increase in editors' fitted preference is associ-

⁶First stage regression results using a four year window are shown in the appendix in Table B.1.

ated with about a 4% increase in the difference between the *AER* and other Top 5 in favor of the *AER*, and this increase is statistically significant at a 5% level when robust standard errors are considered. Statistical significance is lost when bootstrapped standard errors are considered instead.

Publications lags have been growing over recent decades as documented by [Ellison \(2002\)](#), hence it may be plausible to incorporate an alternative time window to calculate the relative frequency of topics that appear in journals and in editors' published articles. We re-run our text search machinery using a four year window and one year lag, that is, we assume that any paper that is accepted in year t does not get published before year $t + 1$. Incorporating a one year lag, we revise the relative topic frequencies of journals and editors. In [Table 3](#) we provide an alternative set of regression results using the revised version of the relative topic frequencies.

Comparing coefficient estimates and their standard errors in [Tables 2 and 3](#), we observe that the magnitudes of coefficients' point estimates with a one year lag are slightly less than those obtained without lag, and standard errors throughout all specifications in [table 3](#) are greater than their counterparts in [Table 2](#). Hence with the change in lag, our estimations reveal a greater effect of editors' preference on topic frequencies, although the estimation of this effect becomes at the same time more noisy. Comparing different specifications in [Table 3](#) against each other, we observe that the point estimates for editors' residual preferences are more than ten times as great when dependent variable is the topic frequencies of other Top 5 as those when dependent variable is the topic frequencies of the *AER*. Nevertheless, standard errors associated with specifications involving *AER* topic frequencies are also large; so that we do not obtain statistical significance except for the specification in column (1) in [Table 3](#).

We verified that our results are robust to changing the number of topics that the machine learning process is forced to calculate. We create an alternative set of topics by allowing the computer to identify 300 topics instead of 200 and we calculate the relative topic frequencies of journals and editors using the values calculated for these 300 topics. We provide regression results based on a four year window and 300 topics in [Table 4](#). Here we obtain greater point estimates for the current levels of the relative topic frequencies found in the *AER* and the

Table 3: Journals' Topics and Editor's Preference with Four Year Window and One Year Lag

<i>Panel A</i>	(1) <i>AER</i>	(2) <i>AER</i>	(3) <i>Top5</i>	(4) ΔAER	(5) ΔAER	(6) $\Delta Top5$	(7) $\Delta AER Top5$	(8) $\Delta AER Top5$
Editors' Residual Preference	1.453 ⁺ (0.745)	1.453 (0.981)	0.135 (0.449)	0.00406 (0.00813)	0.00406 (0.00969)	-0.00144 (0.00419)	0.00550 (0.00663)	0.00550 (0.00738)
Year.FE & Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1379	1379	1379	1379	1379	1379	1379	1379
<i>R</i> ²				0.249	0.249	0.454	0.774	0.774
<i>F</i>				5.400		9.150	40.43	
<i>AIC</i>	476.2	476.2	474.2					

<i>Panel B</i>	(1) <i>AER</i>	(2) <i>AER</i>	(3) <i>Top5</i>	(4) ΔAER	(5) ΔAER	(6) $\Delta Top5$	(7) $\Delta AER Top5$	(8) $\Delta AER Top5$
Editors' Fitted Preference	0.181 ⁺ (0.0929)	0.181 (0.115)	0.0168 (0.0559)	0.0128 (0.0256)	0.0128 (0.0355)	-0.00451 (0.0132)	0.0173 (0.0208)	0.0173 (0.0247)
Year.FE & Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1379	1379	1379	1379	1379	1379	1379	1379
<i>R</i> ²				0.249	0.249	0.454	0.774	0.774
<i>F</i>				5.400		9.150	40.43	
<i>AIC</i>	476.2	476.2	474.2					

Note: Additional controls are $AER_{i,before}^c$ and $Top5_{i,before}^c$ in (1), (2), (3), (7), (8); $Top5_{i,before}^c$ in (4), (5); $AER_{i,before}^c$ in (6).

Columns (1) to (3) obtained by GLM (binomial); columns (4) to (8) obtained by OLS.

Robust standard errors in parentheses. Bootstrapped (500 reps) standard errors for (2), (5), and (8).

⁺ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Journals' Topics and Editor's Preference with Four Year Window- using 300 Topics

<i>PanelA</i>	(1) <i>AER</i>	(2) <i>AER</i>	(3) <i>Top5</i>	(4) ΔAER	(5) ΔAER	(6) $\Delta Top5$	(7) $\Delta AER Top5$	(8) $\Delta AER Top5$
Editors' Residual Preference	3.055*** (0.724)	3.055*** (0.948)	2.186* (0.950)	0.00310 (0.00536)	0.00310 (0.00649)	-0.00131 (0.00338)	0.00441 (0.00532)	0.00441 (0.00668)
Year.FE & Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	2072	2072	2072	2072	2072	2072	2072	2072
<i>R</i> ²				0.338	0.338	0.472	0.772	0.772
<i>F</i>				5.848		8.094	37.08	
<i>AIC</i>	676.7	676.7	675.8					

<i>PanelB</i>	(1) <i>AER</i>	(2) <i>AER</i>	(3) <i>Top5</i>	(4) ΔAER	(5) ΔAER	(6) $\Delta Top5$	(7) $\Delta AER Top5$	(8) $\Delta AER Top5$
Editors' Fitted Preference	0.0894*** (0.0212)	0.0894** (0.0284)	0.0640* (0.0278)	0.00347 (0.00599)	0.00347 (0.00769)	-0.00146 (0.00377)	0.00493 (0.00594)	0.00493 (0.00690)
Year.FE & Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	2072	2072	2072	2072	2072	2072	2072	2072
<i>R</i> ²				0.338	0.338	0.472	0.772	0.772
<i>F</i>				5.848		8.094	37.08	
<i>AIC</i>	676.7	676.7	675.8					

Note: Additional controls are $AER_{i,before}^c$ and $Top5_{i,before}^c$ in (1), (2), (3), (7), (8); $Top5_{i,before}^c$ in (4), (5); $AER_{i,before}^c$ in (6). Columns (1) to (3) obtained by GLM (binomial); columns (4) to (8) obtained by OLS.

Robust standard errors in parentheses. Bootstrapped (500 reps) standard errors for (2), (5), and (8).

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

other Top 5. Editors’ residual preferences turn out to be statistically significant when the *AER*’s topic frequencies (columns (1) and (2) in Table 4) as well as the topic frequencies of the other Top 5 ((column (3) in Table 4) are considered. Although these coefficients differ in magnitude and their level of significance, their difference does not turn out to be statistically significant from zero (columns (7) and (8) in Table 4).⁷

Next we investigate relative topic frequencies that are obtained using alternative window lengths. Tables 5 and 6, respectively, show regression results when the relative topic frequencies are calculated using a three year window and a five year window. When using a three year window, we restrict the set of editors to those who served for at least three years. Similarly, when using a five year window, we keep only those editors who served for at least five years. Coefficients’ point estimates are greater for the five year window (Table 6) than for the three year window (Table 5). Moreover, comparing these coefficients to those that we obtain using a four year window (Table 2) one should immediately note that the sizes of estimated coefficients line up so that the least magnitudes are obtained using three year window, followed by those obtained using four year window, and the largest magnitudes are obtained in case of five year window.

This pattern can be attributed to the fact that we restrict the set of editors in each analysis to those who served for at least the full length of the time window of the respective analysis. Hence the analysis using a three year window contains editors whose tenure has been shorter than those who are contained in the analysis using four year or five year window. Because the editors contained in the analysis using five year window have had the longest tenure period, we find that the greatest point estimates for editors’ preference are for this subset of editors. Three years is a short span of time and editors may not have had enough time to instill their own agenda, style, or narrative—whatever we may call it—above and beyond what is being considered as hot research in the profession in general at the time. This may be the reason why we obtain significant positive correlations between editors’ preference and the *AER*’s as well as other Top 5’s topic frequencies in an analysis based on a three year window. It is also important to note that in Tables 5 and 6 specifications using the current levels of relative topic frequencies found in the *AER* as dependent variables obtain

⁷Similar results are obtained with 100 topics, see Table B.2 in the Appendix.

Table 5: Journals' Topics and Editor's Preference with Three Year Window

<i>PanelA</i>	(1) <i>AER</i>	(2) <i>AER</i>	(3) <i>Top5</i>	(4) ΔAER	(5) ΔAER	(6) $\Delta Top5$	(7) $\Delta AER Top5$	(8) $\Delta AER Top5$
Editors' Residual Preference	0.737 ⁺ (0.380)	0.737 ⁺ (0.414)	0.107 (0.279)	0.00186 (0.00364)	0.00186 (0.00400)	-0.00247 (0.00164)	0.00433 (0.00354)	0.00433 (0.00385)
Year.FE & Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	3152	3152	3152	3152	3152	3152	3152	3152
<i>R</i> ²				0.206	0.206	0.289	0.816	0.816
<i>F</i>				3.341		5.341	51.31	
<i>AIC</i>	579.7	579.7	573.7					

<i>PanelB</i>	(1) <i>AER</i>	(2) <i>AER</i>	(3) <i>Top5</i>	(4) ΔAER	(5) ΔAER	(6) $\Delta Top5$	(7) $\Delta AER Top5$	(8) $\Delta AER Top5$
Editors' Fitted Preference	0.0605 ⁺ (0.0312)	0.0605 ⁺ (0.0354)	0.00880 (0.0229)	0.00435 (0.00851)	0.00435 (0.00939)	-0.00578 (0.00384)	0.0101 (0.00828)	0.0101 (0.00863)
Year.FE & Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	3152	3152	3152	3152	3152	3152	3152	3152
<i>R</i> ²				0.206	0.206	0.289	0.816	0.816
<i>F</i>				3.341		5.341	51.31	
<i>AIC</i>	579.7	579.7	573.7					

Note: Additional controls are $AER_{i,before}^c$ and $Top5_{i,before}^c$ in (1), (2), (3), (7), (8); $Top5_{i,before}^c$ in (4), (5); $AER_{i,before}^c$ in (6).

Columns (1) to (3) obtained by GLM (binomial); columns (4) to (8) obtained by OLS.

Robust standard errors in parentheses. Bootstrapped (500 reps) standard errors for (2), (5), and (8).

⁺ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Journals' Topics and Editor's Preference with Five Year Window

<i>PanelA</i>	(1) <i>AER</i>	(2) <i>AER</i>	(3) <i>Top5</i>	(4) ΔAER	(5) ΔAER	(6) $\Delta Top5$	(7) $\Delta AER Top5$	(8) $\Delta AER Top5$
Editors' Residual Preference	3.468** (1.192)	3.468* (1.588)	1.022 (0.763)	0.00917 (0.0137)	0.00917 (0.0155)	-0.00722 (0.00547)	0.0164 (0.0100)	0.0164 (0.0134)
Year.FE & Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	985	985	985	985	985	985	985	985
<i>R</i> ²				0.264	0.264	0.524	0.833	0.833
<i>F</i>				7.671		8.470	53.77	
<i>AIC</i>	454.7	290.7	453.2					

<i>PanelB</i>	(1) <i>AER</i>	(2) <i>AER</i>	(3) <i>Top5</i>	(4) ΔAER	(5) ΔAER	(6) $\Delta Top5$	(7) $\Delta AER Top5$	(8) $\Delta AER Top5$
Editors' Fitted Preference	0.0913** (0.0314)	0.0913* (0.0459)	0.0269 (0.0201)	0.0158 (0.0237)	0.0158 (0.0254)	-0.0124 (0.00942)	0.0282 (0.0173)	0.0282 (0.0193)
Year.FE & Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	985	985	985	985	985	985	985	985
<i>R</i> ²				0.264	0.264	0.524	0.833	0.833
<i>F</i>				7.671		8.470	53.77	
<i>AIC</i>	454.7	334.7	453.2					

Note: Additional controls are $AER_{i,before}^c$ and $Top5_{i,before}^c$ in (1), (2), (3), (7), (8); $Top5_{i,before}^c$ in (4), (5); $AER_{i,before}^c$ in (6).

Columns (1) to (3) obtained by GLM (binomial); columns (4) to (8) obtained by OLS.

Robust standard errors in parentheses. Bootstrapped (500 reps) standard errors for (2), (5), and (8).

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

statistical significance, and this significance remains robust to a bootstrapping procedure of 500 iterations.

We provide results for three year and five year windows results using a one year lag in the Appendix in Tables B.3 and B.4. Estimation results are comparable to those that we obtain when no lag is used, but the statistical significance obtained in the specification of column (1) in both Tables B.3 and B.4 is lost when bootstrapped standard errors are considered. It is also interesting to note that although point estimates of editors' preferences (residual as well fitted) are greater with a one year lag compared to without lag when a three year window is used, these are smaller in case of a five year window. It should not go unnoticed that editors' preferences turn out to be positively and significantly related to those in topic frequencies of the other Top 5 (column (3) in Panels A and B in Table B.4). A possible interpretation of this observation is that editors who have served for at least five years in the AER may have been extraordinarily influential figures in setting up the overall research agenda with the result that other top journals also pick up the tone that these editors have been setting in the *AER*.

5 Conclusion

In this paper, we use textual analysis to quantify the topic frequency in the narrative of publications in the *AER* and ask whether editors affect the published content. We find that editors seem to induce more publications that align with their own topics, as measured by the topics covered in these editors' publications. The publication patterns in other top general interest journals do not correlate significantly with the *AER* editors' topic frequencies, which means that this appointment is not widely informative for the profession regarding what is important in the profession (otherwise the coefficient would be positive and the other Top 5 journals would also see the influx of papers on the editor's topics). A new editor does not affect much the capacity of papers on his or her own topics by shifting the focus towards these topics, because that would make the Top5 coefficient in our estimations significant as well.

The size of the economic effect is quite small, amounting to a replacement of 1 ‘regular’ paper in 200 by a paper that is devoted only to an editor’s interests. Obviously, this could also mean that the papers submitted to the *AER* now have on average 0.5% more irrelevant verbiage targeted at a newcoming editor. We expected a greater effect. However, for the natural reason of the secrecy covering author-editor relationships, we know neither the editors who were handling individual papers nor what was rejected by the very same editors. While the effect of the latter is unclear, the effect of the former clearly will make our coefficients biased towards zero. Our topic assignment is data-driven, not coming from a training dataset or heuristics, though either could have provided us with a better measure of topic dynamics; again, however, this would have biased the coefficients that we obtain towards zero. Heterogeneity in editors—some editors may be more prone to impose their own agenda, and some may be less—will add noise to our estimates, making our coefficients look statistically less significant, but will not alter the average effect. Even with underestimation and noise in the estimates, our estimates are consistently positive.

There are many gatekeeping economic interactions where people or committees approve or disapprove applications (grants, promotions, hiring, PhD applications, building permits, legal pleadings, etc). Gatekeepers may influence the success rates by their decisions of approval or disapproval, which can lead to longer term changes in application institutions. This paper demonstrates how *AER* editors, rationally or subconsciously, may be steering the research coverage of *AER* publications towards their own work. Thus it is important for gatekeepers as well as those who appoint them to be aware of such steering effects that come with the very nature of the gatekeeping.

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Appendices

A A Theoretical Model of Unbiased Change in Topic Coverage

To illustrate the driving forces behind our finding, we design a simple model of editor choice. Assume there are two topics, indexed by $i \in \{1, 2\}$. Assume each paper can be either good (quality $q = 1$) or bad ($q = 0$), and the paper is good with probability π_i . Assume that at every period the representative editor obtains measure m_i of papers of topic i without knowing their true quality, and then for every paper with quality q of type i the refereeing process (an interaction of editor's specialties, editor's networks, and the profession's supply of refereeing labour) provides a signal $q + \varepsilon$, where ε is distributed with the cdf $F_i(x)$.

Assume now the editor picks papers based upon the threshold rule: if the signal is above \bar{q} , the paper is accepted, and the paper is rejected otherwise. This leads to the share of papers of topic 1 in the journal to be equal to

$$\frac{m_1 [(1 - \pi_1)F(\bar{q}) + \pi_1 F(\bar{q} - 1)]}{m_1 [(1 - \pi_1)F(\bar{q}) + \pi_1 F(\bar{q} - 1)] + m_2 [(1 - \pi_2)F(\bar{q}) + \pi_2 F(\bar{q} - 1)]}.$$

If there is a change in the proportion of topics published by the journal, does it have to be driven by the editor's leniency? No: it can be driven by the editor's specialization.

Result 1 *If the distribution of ϵ_i is uniform with support $[-b_i, b_i]$, $b_i > 1$, and $\bar{q} \in (0, 1)$, a marginal increase in b_i increases the proportion of published papers of topic i if $\pi_i < \bar{q}$, and increases otherwise.*

Proof. The probability that a paper of topic i of quality q will get published is $P(q + \varepsilon_i > \bar{q}) = \frac{b_i - (\bar{q} - q)}{2b_i}$, which leads to the calculation that the proportion of papers of topic i getting published is then

$$(1 - \pi_i) \overbrace{\frac{b_i - (\bar{q} - 0)}{2b_i}}^{\text{bad paper is published}} + \pi_i \overbrace{\frac{b_i - (\bar{q} - 1)}{2b_i}}^{\text{good paper is published}} = \frac{1}{2} + \frac{\pi_i - \bar{q}}{2b_i}.$$

Taking a derivative with respect to b_i , which is $-(\pi_i - \bar{q})/2b_i^2$, observe that it is negative when $\pi_i > \bar{q}$, and positive otherwise. The increase in the mass of papers of topic i getting accepted will lead to an increased proportion of papers of topic i in the journal. ■

This can be extended to a general setting, with general distributions, adjusting for the editor's choice of \bar{q} , having multiple thresholds \bar{q}_i (for either the reason of bias, or a tradeoff between Type I and Type II errors, or both), introducing an endogenous decision of the topic choice or effort choice by the authors, having competing journals, etc. The purpose of this model is to illustrate that even under the simplest assumptions, a change in the refereeing process (an increase in one b_i and a decrease in another) can lead to a change in the composition of accepted papers, even if the editor applies the same acceptance rule to all papers.

Table B.1: First Stage Estimations of Editors' Preferences Four Year Window)

	$Edit_{i,before}^c$		$Edit_{i,during}^c$	
	(1)	(2)	(3)	(4)
	<i>GLM</i>	<i>OLS</i>	<i>GLM</i>	<i>OLS</i>
$AER_{i,before}^c$	40.49** (12.32)	0.678*** (0.110)		
$Top5_{i,before}^c$	14.40 (25.44)	0.0327 (0.208)		
Editors' Residual Preference			37.18*** (4.073)	0.631*** (0.101)
Start.Year.FE & Topic.FE	Yes	Yes	Yes	Yes
N	1379	1379	1379	1379
R^2		0.247		0.462
F		2.747		3.647
AIC	469.9		460.4	

(corresponding to second stage results shown in Table 2 in this paper)

Robust standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B Estimation Results using Alternative Window and Lag Structures

Table B.2: Journals' Topics and Editor's Preference with Four Year Window- using 100 Topics

<i>PanelA</i>	(1) <i>AER</i>	(2) <i>AER</i>	(3) <i>Top5</i>	(4) ΔAER	(5) ΔAER	(6) $\Delta Top5$	(7) $\Delta AER Top5$	(8) $\Delta AER Top5$
Editors' Residual Preference	0.922 ⁺ (0.480)	0.922 (0.594)	0.00568 (0.347)	0.00643 (0.00712)	0.00643 (0.00790)	-0.00448 (0.00596)	0.0109 (0.00758)	0.0109 (0.00797)
Year.FE & Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	693	693	693	693	693	693	693	693
<i>R</i> ²				0.385	0.385	0.489	0.911	0.911
<i>F</i>				7.863		6.400	51.41	
<i>AIC</i>	271.4	271.4	270.2					

<i>PanelB</i>	(1) <i>AER</i>	(2) <i>AER</i>	(3) <i>Top5</i>	(4) ΔAER	(5) ΔAER	(6) $\Delta Top5$	(7) $\Delta AER Top5$	(8) $\Delta AER Top5$
Editors' Fitted Preference	0.0404 ⁺ (0.0210)	0.0404 (0.0266)	0.000249 (0.0152)	0.00850 (0.00942)	0.00850 (0.0101)	-0.00592 (0.00788)	0.0144 (0.0100)	0.0144 (0.0112)
Year.FE & Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	693	693	693	693	693	693	693	693
<i>R</i> ²				0.385	0.385	0.489	0.911	0.911
<i>F</i>				7.863		6.400	51.41	
<i>AIC</i>	271.4	271.4	270.2					

Note: Additional controls are $AER_{i,before}^c$ and $Top5_{i,before}^c$ in (1), (2), (3), (7), (8); $Top5_{i,before}^c$ in (4), (5); $AER_{i,before}^c$ in (6).

Columns (1) to (3) obtained by GLM (binomial); columns (4) to (8) obtained by OLS.

Robust standard errors in parentheses. Bootstrapped (500 reps) standard errors for (2), (5), and (8).

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.3: Journals' Topics and Editor's Preference with Three Year Window and One Year Lag

<i>PanelA</i>	(1) <i>AER</i>	(2) <i>AER</i>	(3) <i>Top5</i>	(4) ΔAER	(5) ΔAER	(6) $\Delta Top5$	(7) $\Delta AER Top5$	(8) $\Delta AER Top5$
Editors' Residual Preference	0.842 ⁺ (0.505)	0.842 (0.600)	0.315 (0.335)	0.00145 (0.00478)	0.00145 (0.00541)	0.000491 (0.00241)	0.000959 (0.00471)	0.000959 (0.00518)
Year.FE & Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	2758	2758	2758	2758	2758	2758	2758	2758
<i>R</i> ²				0.221	0.221	0.313	0.807	0.807
<i>F</i>				3.455		6.045	55.89	
<i>AIC</i>	556.3	556.3	551.2					

<i>PanelB</i>	(1) <i>AER</i>	(2) <i>AER</i>	(3) <i>Top5</i>	(4) ΔAER	(5) ΔAER	(6) $\Delta Top5$	(7) $\Delta AER Top5$	(8) $\Delta AER Top5$
Editors' Fitted Preference	0.0633 ⁺ (0.0380)	0.0633 (0.0418)	0.0237 (0.0252)	0.00324 (0.0107)	0.00324 (0.0111)	0.00110 (0.00539)	0.00214 (0.0105)	0.00214 (0.0110)
Year.FE & Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	2758	2758	2758	2758	2758	2758	2758	2758
<i>R</i> ²				0.221	0.221	0.313	0.807	0.807
<i>F</i>				3.455		6.045	55.89	
<i>AIC</i>	556.3	556.3	551.2					

Note: Additional controls are $AER_{i,before}^c$ and $Top5_{i,before}^c$ in (1), (2), (3), (7), (8); $Top5_{i,before}^c$ in (4), (5); $AER_{i,before}^c$ in (6).

Columns (1) to (3) obtained by GLM (binomial); columns (4) to (8) obtained by OLS.

Robust standard errors in parentheses. Bootstrapped (500 reps) standard errors for (2), (5), and (8).

⁺ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.4: Journals' Topics and Editor's Preference with Five Year Window and One Year Lag

<i>PanelA</i>	(1) <i>AER</i>	(2) <i>AER</i>	(3) <i>Top5</i>	(4) ΔAER	(5) ΔAER	(6) $\Delta Top5$	(7) $\Delta AER Top5$	(8) $\Delta AER Top5$
Editors' Residual Preference	2.683* (1.190)	2.683 (1.652)	1.277+ (0.744)	0.00386 (0.0127)	0.00386 (0.0148)	-0.000259 (0.00510)	0.00412 (0.00851)	0.00412 (0.00952)
Year.FE & Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	985	985	985	985	985	985	985	985
<i>R</i> ²				0.259	0.259	0.496	0.775	0.775
<i>F</i>				5.830		8.742	34.35	
<i>AIC</i>	454.8	284.8	453.5					

<i>PanelB</i>	(1) <i>AER</i>	(2) <i>AER</i>	(3) <i>Top5</i>	(4) ΔAER	(5) ΔAER	(6) $\Delta Top5$	(7) $\Delta AER Top5$	(8) $\Delta AER Top5$
Editors' Fitted Preference	0.0814* (0.0361)	0.0814 (0.0521)	0.0387+ (0.0226)	0.00815 (0.0269)	0.00815 (0.0330)	-0.000547 (0.0108)	0.00869 (0.0180)	0.00869 (0.0235)
Year.FE & Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	985	985	985	985	985	985	985	985
<i>R</i> ²				0.259	0.259	0.496	0.775	0.775
<i>F</i>				5.830		8.742	34.35	
<i>AIC</i>	454.8	292.8	453.5					

Note: Additional controls are $AER_{i,before}^c$ and $Top5_{i,before}^c$ in (1), (2), (3), (7), (8); $Top5_{i,before}^c$ in (4), (5); $AER_{i,before}^c$ in (6).

Columns (1) to (3) obtained by GLM (binomial); columns (4) to (8) obtained by OLS.

Robust standard errors in parentheses. Bootstrapped (500 reps) standard errors for (2), (5), and (8).

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$