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Leadership in Scholarship: Editors' Appointments and the Profession's Narrative*

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Abstract

Academic journals disseminate new knowledge, and therefore can influence the direction and composition of ongoing research by choosing what to publish. We study the change in the topic structure of papers published in the *American Economic Review (AER)* after the appointments of editors and coeditors of the *AER* between 1985 and 2011 using a textual analysis of accepted publications. We compare *AER*'s topic structure to that of the other top general interest journals. The appointment of new *AER* editors, while accompanied by a minor co-movement of *AER* topics towards topics of editors' post-appointment publications, is not an indicator of editors' personal taste in topics, but rather indicates the desire of those who appoint editors to premediate trends in other Top 5 journals.

JEL classification: A11, A14, O3

Keywords: Academia; Knowledge Dissemination; Journals; Editors; Publications; Latent Dirichlet Allocation; Topic Analysis.

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1 Introduction

Publishing in top economics journals is 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 the journal prominence and publication counts (Heckman and Moktan, 2018). This creates a tradeoff between publishing what one thinks is important and what one thinks is likely to be published.[1] A new editor taking office in an influential journal may motivate researchers who seek recognition to steer knowledge generation towards the topics preferred by this editor. How strongly is the topic structure of a journal driven by editors' preferences in their own research?

To answer this question, we study the appointment of editors and coeditors of the *American Economic Review* (*AER*) taking office between 1985 and 2011.[2] We employ a high-detail textual analysis on the full texts of individual articles to identify the topics that emerge in the *AER* and the other leading general interest journals.[3] We analyze how topic frequencies in the published research of a newly appointed editor co-move with topic frequencies observed in the *AER* before and after that editor's appointment. The other Top 5 constitute our control group.

We establish that, from the beginning, editors appointed to the *AER* tend to be more topically aligned with the other Top 5 journals. We find that topics that are observed in the *AER* align with those observed in editors' own publications while being an editor, but are not much driven by editors' publications before becoming an editor. Although editors create a diversion of topics from the other Top 5 at first, when the time window of our analysis is increased, we obtain greater point estimates for the correlation between editors' topics and topics published in the other Top 5. We remain agnostic about cause and effect: editors

[1] Ruhm (2018) argues methodological requirements might avert scholars away from important topics.

[2] Editors and coeditors wield equal decision-making power in the *AER*, whereas associate editors do not. We thank Dan Hamermesh for pointing this out, and past editors of the *AER* for confirmation. In the rest of this paper, we refer to editors as well as coeditors as *editors*.

[3] Namely, the *Quarterly Journal of Economics* (*QJE*), the *Journal of Political Economy* (*JPE*), *Econometrica*, and the *Review of Economic Studies* (*REStud*). These 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 with. (cf. Heckman and Moktan, 2018). In what follows, we refer to the above four leading general interest journals (Top 5 excluding the *AER*) as the *other Top 5*.

could be appointed to lead the way to develop a research profile that keeps the *AER* aligned with the other Top 5, or the authors could have anticipated changes in topical interests of journals and submitted strategically.

2 Literature Review

We contribute to the empirical literature on knowledge dissemination by showing that editors can affect the profession, not only through their professional networks and their ties (Brogaard et al., 2014, Card and DellaVigna, 2017, Colussi, 2018, Medoff, 2003), but also through their influence on the topics and the narrative structures that appear in journals.

In our preliminary analysis in Section 3.2, we investigate the dynamics of topics covered by papers published in the *AER*. Using topics suggested by machine learning, we obtain patterns similar to those documented in Figure 7 of Card and DellaVigna (2013) and in Figure 2 of Angrist et al. (2017), who both use JEL codes. While the JEL codes are quite generic, there is little clarity about their persistence: it is not clear, for instance, if 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 1970s and in the 2010s. When new topics arise or old topics fade away, the pre-defined JEL classifications are hardly ever adapted accordingly. Thus, new topics may be disguised under either very generic or rather odd JEL codes. Over time, this can lead to the overcrowding of some classes and the 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).

Fontana et al. (2019) make the argument that textual topic analysis is a stable and reliable approach to avoid issues implied by the JEL classification system such as the authors' strategic self-attribution of codes and changes of the classification system. Accordingly, our approach 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. Glandon et al. (2018) avoid using JEL codes in their analysis and classify macroeconomic papers manually, because JEL codes struggle to capture the nuances of different research areas within macroeconomics. For instance, they document that DSGE methodology became more prominent. So, what constitutes macroeconomics changed in time, while the proportion of macroeconomic papers, according to Angrist et al. (2017), remained the same.

An overview of the methodology and research applications of textual analysis is provided in Gentzkow et al. (2017). Analysis of the similarity between different text data has been used in various settings. For instance, Li (2017) investigates the quality of NIH grant applications by using a similarity measure between texts of NIH grant applications and publications, to link publications to specific NIH grants. We use a similar text analysis that quantifies the vectors of topic frequencies of all publications in the *AER*, in the other Top 5, and in editors' own publications, in order to measure topic similarity.

Several studies applied topical analysis to study the development of literature in different research fields. Mela et al. (2013) and Huber et al. (2014) employ a related methodology to study publication patterns in the marketing literature. While they show that editors throughout their tenure feature different mixes of topics, they do not speculate as to why the topics of the text corpus moved in a certain direction. In economics, 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 or not the frequencies of topics of the journal co-move with the topic frequencies of the editors' own work. Kosnik (2015) uses topical analysis to study the corpus of seven journals in economics[4] published between 1960 and 2010. While this study finds suggestive evidence that research in macroeconomics diminishes, complemented by an increase in research in the microfoundations of macroeconomics, it does not concern editors' appointment, and does not compare trends across different journals. Ambrosino et al. (2018) use all economics journals in JStor, but do not inquire into the editor's influence. Kosnik (2018) asks whether or not JEL codes are informative, and applies textual analysis to papers that share the same JEL code (using about 10 topics per JEL code), but does not study the dynamics of topics.

[4]The usual Top 5 (as we use in this paper as well) plus the Journal of Economic Literature and Journal of Economic Perspectives, both of which are by invitation only and therefore have significantly different incentive structures in the author-editor relationship.

3 Data and Methodology

We study the corpus of texts in the *AER*, *QJE*, *JPE*, *REStud*, and *Econometrica*, and all articles written by *AER*'s editors between 1979 and 2014 which are available at the 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[5]. We compare trends in topic frequencies in articles published by newly appointed editors of the *AER* who took office between 1985 and 2011 against topic frequencies observed in articles published in the *AER* and also those published in the other Top 5.

A topic in our context is not necessarily 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.

3.1 Topic Analysis

We elicit the thematic structure of the text corpus using Latent Dirichlet Allocation (LDA) on full texts (Blei et al., 2003). The methodology of this 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 narrative purpose.

We preprocess our data through several technical steps. In the first step, common words are removed (such as "a", "above", "across", etc.; full list of stop words is 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 multiple-word collocations (such as "United States of America") are replaced by tokens. For the tokenizing, we employ the Python package `textmining`

[5] Word count data for individual papers are provided by ITHAKA for research purposes upon request via `http://dfr.jstor.org/`, accessed 1 June 2017; we supplemented the—at that time—missing two years of QJE papers by downloading manuscripts and counting words.

(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 the LDA model.[6] Simply put, each document can be represented as a probability distribution over words: some documents have a relatively higher probability of mentioning `inflation`, others mention `exchange rate` relatively more frequently, etc:

$$\text{Probabilistic model: each manuscript is represented by } \{p_i\}_{i\in 1..I} : \sum_{i=1..I} p_i = 1.$$

p_i is the probability that the manuscript is using the word i; words are coming out of the whole corpus, so some of the p_i can empirically be zero. The dimensionality of this model of text generation is in hundreds of thousands of parameters for each manuscript. To lower this dimensionality, the LDA model assumes a relatively small fixed amount of topics, $J << I$, and

$$\text{Topic model:} \quad \begin{array}{c} \text{each topic } j \text{ is represented by } \{p_{i,j}\}_{i\in 1..I} : \sum_{i=1..I} p_{i,j} = 1, \\ \text{each manuscript is represented by } \{\theta_j\}_{j\in 1..J} : \sum_{j=1..J} \theta_j = 1. \end{array}$$

Then the probability of the word i in the manuscript is obtained from $\sum_{j=1..J} \theta_j p_{i,j}$.

LDA returns both a list of topics $p_{i,j}$ and a list of estimated mixing proportions θ_j: each document is modelled as a mixture distribution over topics, and therefore over words, and different documents have different topic loadings. An advantage of this methodology is that it is not driven by hand-picked sets of words. It is, in this sense, “unsupervised”. 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 based on 200 topics. Results remain qualitatively similar if the number of topics is increased (in which case additional topics become more specific, potentially containing more uninformative artifacts) or decreased (which makes topics more general, potentially concealing changes in time). We used the UMass Amherst's Machine Learning for Language Toolkit (MALLET) (McCallum, 2002) in

[6] See Blei et al. (2003) for elaboration of the LDA machinery, and Ambrosino et al. (2018) on the interpretation of the topic loadings; Schwarz (2018) provides a deeper overview of the specifics of the estimation.

version 2.0.8 to carry out the estimation.[7] Model fitting was performed over 1,000 iterations of Gibbs sampling, which required multiple hours of training for each model configuration on a quad-core 2.4 GHz Intel Xeon CPU used for this purpose.

To help readers explore the topics in our analysis, we host a topic content visualizer at http://electronic-appendix.info/topics/. It is based upon the package `pyldavis`, which is a Python implementation of the package developed by Sievert and Shirley (2014). Topic 0 in the visualizer corresponds to averages across all manuscripts in the corpus; Topics 1-200 are as described in the Online Appendix.

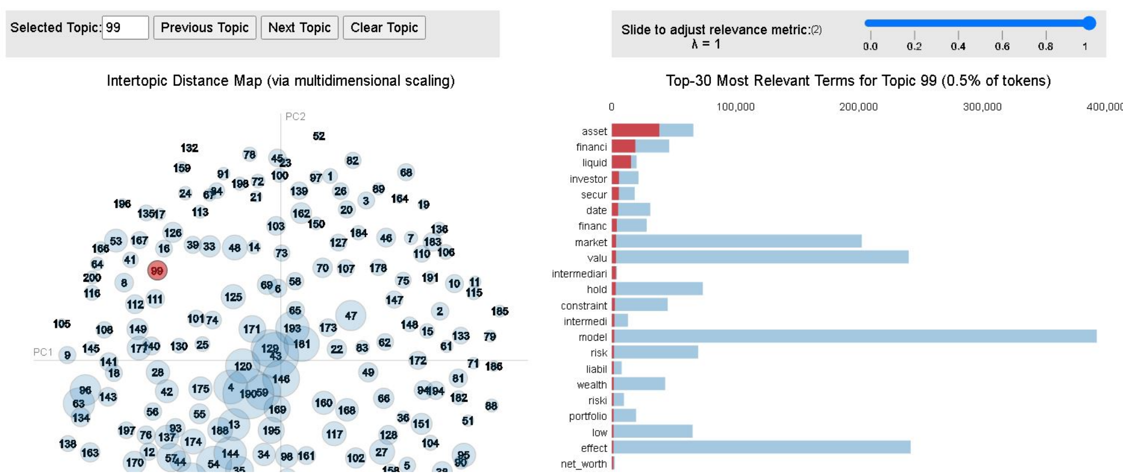


Figure 1: Visualizer displaying words in Topic 99

The left-hand side shows the locations of topics across two main components of their space. An important visual cue is given by the size of the ball which shows the proportion of that topic in the corpus. The bar plot on the right-hand side shows the top 30 most relevant words of the given topic: red colour represents the frequency of the word in the topic, blue colour represents the relevance of the word in the whole corpus. Thus, the higher the proportion of the overall bar coloured in red, the more relevant is the occurrence of a word for a given topic compared to other topics. The relevance is a function of λ: it is equal to the log of probability of encountering the word in that topic minus $1 - \lambda$ times log probability of observing the word in the corpus. This definition allows to adjust how specific a word has to be to be deemed relevant for a topic. If $\lambda = 1$, the most relevant words for the

[7] Available at https://mallet.cs.umass.edu, accessed 1 June 2017.

topics are the ones which are more likely in the corpus overall; if $\lambda = 0$, the most relevant words are likely to occur only in the specific topic.

When using the online topic content visualizer, clicking on words on the right-hand side changes the sizes of topic balls to correspond to the relative relevance of the selected word in each topics, and allows readers to find topics relevant to specific words.

3.2 Trends in Topics of the AER

After a manual consistency check, we conducted the analysis with 195 autonomous topics and omitted 5 topics that were not related to the article contents.[8] The most popular topic overall constitutes around 4.5% of the *AER* corpus; 39 topics cover around 50%.

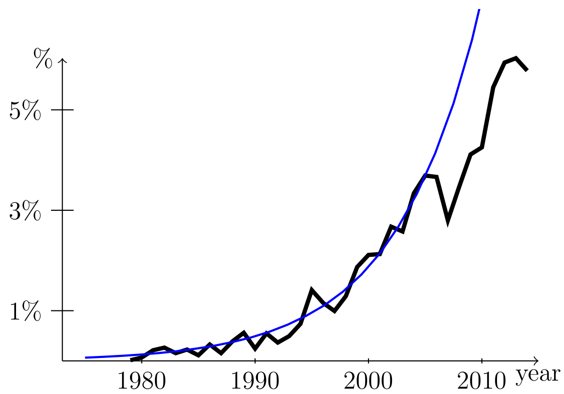
Over time, trends may change: some topics can proliferate, while other topics may wither. To test for time trends in topics, we ran a time series regression for each topic, regressing a log of share of each topic on time and time-squared, with topic-specific coefficients. Then, we conducted 195 F-tests to see whether the 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 less than 0.021, and 84.6% of topics have a $p-$value less than 0.01. A similar result is obtained if one attempts a panel regression with individual time trends: the F statistic is 9836, which with degrees of freedom of 195×2 and 195×33 yields a numerically zero $p-$value. Implementing corrections (such as adjusting for non-normality, etc) could obviously increase the $p-$value.

Among individual topics, topic 43's linear slope coefficient is highest, at 0.1342. This topic includes stems such as

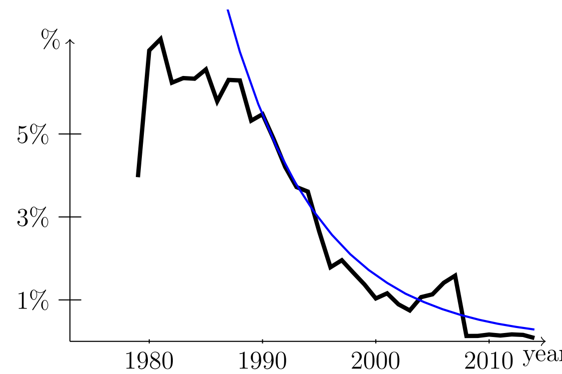
```
effect estim year result column us tabl control specif data sampl regress
includ panel level coeffici fix-effect differ measur report
```

and its share in *AER* publications increases in time, going from 0.14% of the text corpus in the late 1970s to 5.5% in the early 2010s. Meanwhile, topic 63's linear slope coefficient is lowest, at -0.1229; it includes stems such as

[8] The omission of technical topics has been applied by previous studies such as Fontana et al. (2019) who omitted 2 of 20 topics that do not pertain to the scientific content.



(a) Topic 43



(b) Topic 63

Figure 2: Topics change over time

`tion re ing ment con ex vol de behavior com di iti paper exampl creas econom chang analysi eco-nomic robert`

and it accounts for 6.2% 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 authors used the word `example` 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. Both trends are plotted in Figure 2.

The nature of our topic data 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 which changes cause which other changes. We apply the Benjamini-Hochberg-Yekutieli algorithm[9] to choose a critical value to limit our false discovery rate from above by 1%, and still there are 165 topics that seem to exhibit a quadratic trend, and these topics cover about 89% of the corpus (if we just went with 1% significance, that would be 93% of the corpus). Therefore, it is safe to say that over 1979–2014 at least some changes in topics occurred in the papers covered by our corpus. Because our topics are narrower than the subfields of economics, we detect some changes in the narrative that could not be captured by a coarser grouping methodology à la Angrist et al. (2017).

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

3.3 Assigning Documents To Editors

We employ the topic frequencies of journals and editors based on three, four, and five year windows before and after an editor's tenure in our main analysis.[10] 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 compare results for one and two year lags as well. This means that with a three year window and one year lag, the editor appointed in 2000 is relevant for papers published in 2001, 2002, and 2003 (plus maybe additional years, but we deliberately do not include further years to study the effect of the appointment only); and we compare the topic loadings of these papers to topic loadings of papers published in 1998, 1999, and 2000.

The document sets and their notations are as follows: AER, $Top5$, and $Editor_i$ denote the AER, the other Top 5, and a specific editor i, respectively. $AER^c_{i,pre}$ and $AER^c_{i,post}$ 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, $Top5^c_{i,pre}$ and $Top5^c_{i,post}$ denote the average frequency of topic c in articles published in the other Top 5 before and during tenure, respectively, of editor i at the AER. The average frequency of topic c in articles written by editor i before and after her/his appointment at the AER is denoted by $Editor^c_{i,pre}$ and $Editor^c_{i,post}$, respectively. We take logarithms of all variables so that outliers are tamed and regression coefficients can be interpreted as respective elasticities. The difference between topic frequencies of the AER and the other Top 5 during the tenure of editor i is denoted $(AER - Top5)^c_{i,post}$.

3.4 Estimation

The unit of observation in our regression analysis is an editor-topic pair. Table 1 shows the correlation coefficients of main variables we obtain from the textual analysis using a three year window and a one year lag.

We use OLS and two step LS (2SLS) estimations to investigate correlations between editors' and journals' topic frequencies. We regress topic frequencies observed in the AER

[10] A complete list of the AER's editors and coeditors covered in our analysis can be found in Table A.1 in the Appendix.

Table 1: Pairwise Correlations of Editors' and Journals' Topics

	$Editor^c_{i,post}$	$Editor^c_{i,pre}$	$AER^c_{i,post}$	$AER^c_{i,pre}$	$Top5^c_{i,post}$
$Editor^c_{i,pre}$	0.544***				
$AER^c_{i,post}$	0.617***	0.653***			
$AER^c_{i,pre}$	0.620***	0.656***	0.984***		
$Top5^c_{i,post}$	0.611***	0.640***	0.964***	0.961***	
$Top5^c_{i,pre}$	0.615***	0.644***	0.962***	0.962***	0.982***

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

and the other Top 5 during the tenure of an editor on her/his preference for topics and journals' topic frequencies which are observed prior to that editor's tenure. We not only control topic frequencies of the *AER* and the other Top 5 during editor i's tenure for editor's preferences 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 the 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. In particular we estimate:

$$AER^c_{i,post} = F_A(\textbf{Editor Preference}^c_i, AER^c_{i,pre}, Top5^c_{i,pre})$$

$$Top5^c_{i,post} = F_T(\textbf{Editor Preference}^c_i, AER^c_{i,pre}, Top5^c_{i,pre})$$

$$(AER - Top5)^c_{i,post} = H(\textbf{Editor Preference}^c_i, AER^c_{i,pre}, Top5^c_{i,pre})$$

where **Editor Preference**^c_i is captured either by an editor's topic frequencies prior to taking office (denoted by $Editor^c_{i,pre}$) or during her/his tenure at the *AER* (denoted by $Editor^c_{i,post}$).

Editors' topic frequencies during their tenure, however, might be influenced by topic frequencies observed in the *AER* or at the other Top 5 during that time. For instance, just by looking at an editor's topics during her/his tenure ($Editor^c_{i,post}$) and the AER's published topics during that time ($AER^c_{i,post}$) might be problematic because one cannot tell whether the editor had a research agenda and shaped her/his own papers' topics as well as the *AER*'s topics accordingly, or whether the editor observes which submissions are deemed a hot topic (based on referees' overly enthusiastic reviews), so that the editor reshapes the topics of her/his papers accordingly. A similar argument can be made for editors' topics and topics getting published in the other Top 5 at the same time. This poses a potential problem of simultaneity. In order to address this problem, we use a 2SLS estimation in addition to the simple OLS when investigating relations between topic frequencies of an editor and journals during that editor's tenure.

The 2SLS allows us to isolate variations in topic frequencies of an editor's own research during her/his tenure to what can be explained by variations in topic frequencies observed before her/his tenure in her/his own research or in journal publications. Consider an extreme case such as the Covid-19 pandemic in 2020. Although Covid has certainly not been a great topic of research in economics until then, there may be many Covid-related publications in top journals for a while starting in 2020. Suppose that an editor who took office at the *AER* early in 2020 finds Covid a fertile subject all of a sudden (either because of incoming submissions or due to the editor's own observations) and starts writing papers on Covid, so that we observe a high correlation between topic frequencies of this editor and top journals during her/his tenure. OLS would capture the positive association between this editor's topics and top journals' topics. However, 2SLS will only indicate such an association to the extent that the editor's Covid-loaded topics during tenure are explained by top journals' topics and the editor's own topics before 2020, that is, if they were predictable at the moment of the appointment. In particular, we estimate

$$Editor^c_{i,post} = \beta_0 + \beta_1 Editor^c_{i,pre} + \beta_2 AER^c_{i,pre} + \beta_3 Top5^c_{i,pre} + \psi^c_i$$

and we obtain fitted values for editor i's topic frequencies during his/her tenure, denoted by $Editor^{c,fitted}_{i,post}$ which we refer to as the fitted topic frequency or the *fitted preference* of editor i. In the second stage, we use editor i's fitted preference as an independent variable in the estimation of topic frequencies in the *AER* and in the other Top 5 during editor i's tenure.

Simultaneity is a specific kind of endogeneity so that the timing of events helps us to eliminate possible scenarios about the flow of cause and effect. We use editors' topic frequencies before taking office ($Editor^c_{i,pre}$) and after taking office ($Editor^c_{i,post}$) to capture editors' preferences. There is no simultaneity problem when $Editor^c_{i,pre}$ is used but there is when $Editor^c_{i,post}$ is used. Hence, we report 2SLS estimates for $Editor^c_{i,post}$ and use $Editor^c_{i,pre}$ as an instrument, which clearly satisfies exclusion restrictions as there is no other way how an editor's pre-tenure topic frequencies can affect a journal's later topic frequencies by any other way than via the editor's current preferences. It must be noted that editors are not appointed randomly and our 2SLS estimates do not solve that endogeneity.

4 Results

We present estimations focusing on topic frequencies obtained from the textual analysis of a three year window in this section. We restrict this analysis to editors who have been in office at least for three years and have sufficient text data for the textual analysis. For the rest of this paper, *post-tenure* refers to the time window (including any lag whenever applied) after the editor took office, and *pre-tenure* refers to the time window before they took office.

Table 2 shows estimation results to assess interdependencies between topic frequencies (for brevity, referred to as *topics*) arising in editors' papers and journals' contents. We use topic fixed effects in all specifications in order to account for time-invariant differences across topics' frequencies due to their inherent nature and content.[11] The first two columns capture how editors' pre-tenure and post-tenure topics are related to the content that has been published in the *AER* and the other Top 5 journals during the pre-tenure period. Editors' pre-tenure topics significantly correlate with the *AER*'s topics, but there is no significant relation to the other Top 5's pre-tenure topics (column (1)). As shown in column (2), editors' post-tenure topics are related to the *AER*'s as well as their own pre-tenure topics, but not related to the other Top 5's topics. In columns (3) to (5), we investigate the *AER*'s post-tenure topics and observe that these are significantly correlated with editors' pre-tenure topics even after controlling for journals' pre-tenure topics. In column (5), we find that the editors' fitted preferences are significantly and positively related to the *AER*'s post-tenure topics, although we obtain no such significance when editors' post-tenure topics are used directly.

[11] Time fixed effects are not used in this setting. Often, there is only one editor in a given year starting tenure so that time and topic fixed effects together pin down invididividual editors. To control for the timing of the appointment would have been helpful in the following context: Theoretically, two coeditors who are appointed within three years of one another with their most favorable topics being perfect substitutes may cancel out each other's efforts in their pursuit to push for their most favorite topic. Although we do not have a direct way to measure the substitutability of topics, we find no negative correlation between frequencies of editors' favorite topics.

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

	$Editor^c_i$		$AER^c_{i,post}$			$Top5^c_{i,post}$			$(AER - Top5)^c_{i,post}$		
	(1)pre	(2)post	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$AER^c_{i,pre}$	0.462**	0.256+	0.257***	0.258***	0.255***	0.171***	0.171***	0.171***	0.0858	0.0868	0.0833
	(0.177)	(0.143)	(0.0365)	(0.0366)	(0.0364)	(0.0490)	(0.0491)	(0.0488)	(0.0537)	(0.0538)	(0.0536)
$Top5^c_{i,pre}$	0.213	0.142	0.201***	0.201***	0.199***	0.394***	0.394***	0.394***	-0.193***	-0.193***	-0.195***
	(0.171)	(0.138)	(0.0309)	(0.0309)	(0.0308)	(0.0383)	(0.0383)	(0.0384)	(0.0466)	(0.0465)	(0.0467)
$Editor^c_{i,pre}$		0.225***	0.00239+			0.000141			0.00225		
		(0.0201)	(0.00126)			(0.00153)			(0.00199)		
$Editor^c_{i,post}$				0.00209			0.00186			0.000230	
				(0.00131)			(0.00131)			(0.00177)	
$Editor^{c,fitted}_{i,post}$					0.0106+			0.000627			0.00998
					(0.00561)			(0.00678)			(0.00884)
Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4485	4485	4485	4485	4485	4485	4485	4485	4485	4485	4485
R^2	0.479	0.504	0.980	0.980	0.980	0.980	0.980	0.980	0.585	0.585	0.585

Standard errors in parentheses

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

As discussed in subsection 3.4 in detail, fitted preferences capture the variation in editors' post-tenure topic frequencies that is solely explained by journals' and editors' pre-tenure topics and thus avoids simultaneity problems that might occur when using editors' post-tenure topics directly as we do in column (4). This is an instrumented version of editors' post-tenure topics where the exclusion restriction[12] is editors' pre-tenure topic frequencies. Fitted preferences for post-tenure topics are significantly related to the *AER*'s post-tenure topics. We repeat the same analysis using post-tenure topics of the other Top 5 (columns (6) to (8)) and using the difference between the *AER*'s and the other Top 5's topics (columns (9) to (11)) as dependent variables. Although editors' fitted topic preferences are significantly related to topics published in the *AER* during post-tenure, they do not explain any significant variation in the other Top 5's topics and the difference of topics between the *AER* and the other Top 5.

When we keep all editors irrespective of how short they may have served and run our analysis, editors' topics preferences turn out insignificant as can be seen in Table A.2 in the Appendix. The same holds also when we use a one year as well as a two year lag to accommodate for publication bottlenecks. This emphasizes the fact that editors who served less than three years did not have time to plausibly affect topic structures (thus, their inclusion blurs our estimation results).

Since topic frequencies are highly correlated, we also check for multicollinearity. Variation inflation factors (VIF) for non-instrumented variables capturing editors' topic preferences are about 1.9 which is an acceptable range. The problem with multicollinearity is coefficients' error inflation and increased variability due to addition of additional explanatory variables. In order to demonstrate that our estimations do not exhibit such vulnerability, we show in Table A.3 in the Appendix how coefficient estimates behave as we add and remove controls or explanatory variables in various alternative specifications of Table 2.

As there are increasing publication lags in recent decades in most economics journals including top journals, we introduce a one year lag in our analysis and investigate a three year window with a one year lag in Table 3. Although editors' preferences show no significant relation to the *AER*'s topics (columns (3) to (5)), we find strong negative correlation between

[12] In this context, column (2) is the first stage of the 2SLS.

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

	$Editor_i^c$		$AER_{i,post}^c$			$Top5_{i,post}^c$			$(AER - Top5)_{i,post}^c$		
	(1)pre	(2)post	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$AER_{i,pre}^c$	0.218	0.228	0.302***	0.303***	0.301***	0.210***	0.209***	0.213***	0.0928	0.0938	0.0885
	(0.205)	(0.178)	(0.0569)	(0.0570)	(0.0570)	(0.0405)	(0.0406)	(0.0405)	(0.0689)	(0.0688)	(0.0688)
$Top5_{i,pre}^c$	0.0400	0.444*	0.177***	0.176***	0.175***	0.328***	0.327***	0.334***	-0.151*	-0.151*	-0.159*
	(0.173)	(0.189)	(0.0462)	(0.0461)	(0.0465)	(0.0581)	(0.0582)	(0.0582)	(0.0658)	(0.0659)	(0.0662)
$Editor_{i,pre}^c$		0.202***	0.00100			-0.00282*			0.00383*		
		(0.0194)	(0.00122)			(0.00139)			(0.00167)		
$Editor_{i,post}^c$				0.000689			0.00121			-0.000520	
				(0.00143)			(0.00154)			(0.00175)	
$Editor_{i,post}^{c,fitted}$					0.00496			-0.0140*			0.0189*
					(0.00604)			(0.00686)			(0.00827)
Topics FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4485	4485	4485	4485	4485	4485	4485	4485	4485	4485	4485
R^2	0.480	0.477	0.981	0.981	0.981	0.978	0.978	0.978	0.554	0.553	0.554

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the other Top 5's post-tenure topics and editors' pre-tenure as well as fitted post-tenure topics. A plausible interpretation of this finding is that editors diverge submissions from the other Top 5 so that we find editors' topics are being published less in the other Top 5. Although our estimations without publication lags in Table 2 do not obtain a significant relation between editors' topics and the difference of topics between journals (columns (9) to (11)), they do so with the inclusion of a one year publication lag in Table 3. Topics' diversion does not reveal itself in form of a topical alignment between editors and the *AER* but rather a negative alignment[13] between editors and the other Top 5. One plausible reason for the diversion effect to become visible with the inclusion of a publication lag may be longer review times that these diverted topics have been subject to for whatever reason. Nevertheless, when a three year window with two year lag is used, we find no statistically significant relation between editors' preferences and journals' post-tenure topics, most likely because a two year lag overshoots publication lags that editors in the current subsample (having served a minimum of three years) are subject to.

In the Appendix, we document results using a four year window in Table A.4 where editors' post-tenure topics are shown to be positively and significantly related to journals' post-tenure topics. Yet, we obtain no significance for editors' fitted post-tenure topics and thus one cannot be sure whether the variation in editors' topics preceed that in journal topics or not as one cannot rule out simultaneity. Estimation results using a four year window and a two year lag are shown in Table A.5 in the Appendix where we obtain a positive and significant coefficient for editors' post-tenure topics when post-tenure topics of the other Top 5 is regressed on. However, the above mentioned simultaneity remains an argument as fitted preferences obtain no statistical significance. When a five year window with a two year lag is used, results are qualitatively very similar to those obtained for a four year window with a two year lag.[14]

Our analysis so far is based on 200 topics that are constructed by the LDA model. As explained in Section 3.1 in detail, although topics are not pre-determined and they arise

[13]It is important to note that the difference between zero and one year lag is not driven by the inclusion of different editors, because exactly the same set of editors underlie results shown in Tables 2 and 3.

[14]Note that the editors in this subsample have served at least for four years and hence their editorial work may have been subject to a different lag structure than editors serving for three years.

Table 4: Journals' Topics and Editor's Preference with Three Year Window and One Year Lag using 300 Topics

	$Editor^c_i$		$AER^c_{i,post}$			$Top5^c_{i,post}$			$(AER$ - $Top5)^c_{i,post}$		
	(1)pre	(2)post	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$AER^c_{i,pre}$	0.436***	0.141	0.211***	0.210***	0.211***	0.184***	0.184***	0.182***	0.0271	0.0262	0.0285
	(0.126)	(0.114)	(0.0459)	(0.0458)	(0.0461)	(0.0452)	(0.0453)	(0.0453)	(0.0459)	(0.0460)	(0.0459)
$Top5^c_{i,pre}$	0.332**	0.118	0.194***	0.193***	0.193***	0.304***	0.304***	0.303***	-0.110	-0.111	-0.109
	(0.107)	(0.113)	(0.0517)	(0.0518)	(0.0518)	(0.0643)	(0.0642)	(0.0643)	(0.0848)	(0.0847)	(0.0850)
$Editor^c_{i,pre}$		0.199***	0.000264			0.00216+			-0.00189		
		(0.0137)	(0.00118)			(0.00130)			(0.00164)		
$Editor^c_{i,post}$				0.00272*			0.00230+			0.000420	
				(0.00108)			(0.00138)			(0.00157)	
$Editor^{c,fitted}_{i,post}$					0.00132			0.0108+			-0.00950
					(0.00595)			(0.00652)			(0.00824)
Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6785	6785	6785	6785	6785	6785	6785	6785	6785	6785	6785
R^2	0.441	0.426	0.973	0.973	0.973	0.965	0.965	0.965	0.566	0.566	0.566

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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

	$Editor_i^c$		$AER_{i,post}^c$			$Top5_{i,post}^c$			$(AER - Top5)_{i,post}^c$		
	(1)pre	(2)post	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$AER_{i,pre}^c$	0.766***	0.101	0.579***	0.516***	0.577***	0.302***	0.311***	0.301***	0.277***	0.205**	0.276***
	(0.129)	(0.139)	(0.0898)	(0.104)	(0.0896)	(0.0806)	(0.0653)	(0.0807)	(0.0527)	(0.0732)	(0.0530)
$Top5_{i,pre}^c$	0.123	0.0773	0.128	0.240	0.127	0.357**	0.443***	0.356**	-0.228**	-0.203*	-0.229**
	(0.194)	(0.144)	(0.174)	(0.172)	(0.175)	(0.106)	(0.0981)	(0.106)	(0.0787)	(0.0957)	(0.0787)
$Editor_{i,pre}^c$		0.442***	0.00847*			0.00283			0.00565*		
		(0.0337)	(0.00385)			(0.00522)			(0.00245)		
$Editor_{i,post}^c$				0.00177			-0.00501			0.00679^+	
				(0.00210)			(0.00332)			(0.00395)	
$Editor_{i,post}^{c,fitted}$					0.0192*			0.00640			0.0128*
					(0.00872)			(0.0118)			(0.00555)
Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3112	3098	3112	3116	3112	3112	3116	3112	3112	3116	3112
R^2	0.818	0.812	0.996	0.996	0.996	0.996	0.996	0.996	0.864	0.851	0.864

Standard errors in parentheses

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

as result of an optimization process, the total amount of topics (200 in this case) is pre-determined. We document in Table 4 a new set of results that arise from using 300 topics with a three year window and a one year lag. In Table A.6 in the Appendix, we report results using 300 topics with a four year window and and two year lag. We analyze topic results also when the number of topics is restricted to 100. Tables A.7 and A.8 document coefficient estimates in this case using a three year and four year window, respectively. We obtain qualitatively very similar results to those when 200 topics are used. A four year window with a two year lag using 100 as well as 300 topics shows strong alignment of the *AER*'s post-tenure topics with editors' topic preferences before and also after having taken office.

There are more ways of training topics to pitch the textual analysis, of course, and a plausible way is to take JEL codes as topics. When we run a naive textual analysis by taking the JEL codes at face value and pining topics down to JEL categories, we obtain no statistical significance for editors' preference in our estimations. This is mainly due to the adhoc and not necessarily significant separation between topics defined in that way. Kosnik (2018) demonstrates a more elegant way to take JEL categories as the main guide and yet allow topics' divisions to emerge endogenously. When we use topics arising from Kosnik's method (we obtain 138 topics) with a three year window, editors' pre-tenure topics and fitted topics turn out positively and significantly related to the *AER*'s post-tenure topics. Furthermore, editors' topic preferences are significantly related to the difference between post-tenure topics of the *AER* and the other Top 5 (see Table 5). In the Appendix we show further estimation results using Kosnik's topics with a four year window in Tables A.9 and A.10.

Topics that are obtained from the textual analysis may have very different citation patterns. As shown by Angrist et al. (2020), citations not only from within economics but also from other disciplines play a role in how economics papers accumulate citations. Citations from other disciplines may especially be important for empirical work in economics. In addition to this, perception of citations is not exogenous and editors may be fine-tuning the topical structure so as to maximize citations to the *AER*. In order to account for unequal citation patterns across topics, we control for citations of topics during the pre-tenure window of each editor and then control for citation tendencies in the post-tenure topics. In Tables A.11 and A.12 in the Appendix, we document our findings based on 200 topics using a three year window without and with a one year lag, respectively. Editors' preferences for topics have qualitatively very similar association to post-tenure topics published in journals as when post-tenure topics are not controlled for citation tendencies as in our baseline analysis.

There are some *AER* editors and coeditors who have also held office in the other Top 5 or other influential journals. In Table A.13 in the Appendix, we run our baseline analysis using a three year window and a one year lag excluding such editors and coeditors and we still observe the above discussed diversion effect (columns (6) and (8)) where editors' topics preferences are significantly and negatively related to post-tenure topics of the other Top 5.

5 Conclusion

We use textual analysis to quantify the topic frequency in the narrative of publications in the *AER* and ask if and how they align with the content of editors' individual publication portfolios. We find that topic frequencies that are observed in the *AER* align with those observed in editors' own publications while being an editor, but are not much driven by editors' publications before becoming an editor. Moreover, point estimates for editors topics when regressed on topics of other Top 5 are larger in most specifications. Our favorite interpretation of these estimates is that editors are hired to make sure that the *AER* keeps up with the topics that are trending in the other Top 5 journals.

The size of the effect is economically significant, amounting to a replacement of 1–2 *regular* papers in 100 by a paper that is devoted only to the newly appointed editor's interests. Obviously, this could also mean that the papers submitted to the *AER* now have on average 1%–2% more irrelevant verbiage targeted at the new editor. This looks large, as most editors' work is not too far from what was getting published in the *AER* before their appointment in any case. 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 sign of the average effect.

We provide estimates on multiple time horizons because shorter horizons suffer less from the supply side issues (the academia can respond to an appointment by producing more papers in related fields), while longer horizons make sure that the new appointment had enough time to influence publications. We cannot distinguish the decisions that a new editor makes from the decisions that other editors are making, either compensating for the new appointee's possible biases or embracing new trends in the profession. Our data do not allow us to look inside of the black box of the editorship of the *AER*, but it does allow us to see that innovations in that black box do not seem to change the structure of the output beyond what was predictable from the deviation of the *AER* output from the rest of the Top 5.

Publications in top general interest journals are claimed to be accessible to a broader base of academic economists and in this respect one may be tempted to assume that editorial processes in these journals may differ from those in major field journals. Nevertheless, Heckman and Moktan (2018) point out that editors of top general interest journals rely as much on experts' opinions for their decisions as do editors of field journals. As a result, we do not expect great differences between top general interest journals and field journals with regard to how their editors' topic preferences may relate to (or even affect) journal publications. Thus, we expect our findings to be generalizable across less prominent general interest journals as well as field journals in economics. As for the generalizability across different scientific fields, this mainly depends on how similar these fields are to economics regarding their research dissemination, publication, and citation patterns. For instance, Franceschet and Costantini (2010) as well as Rafols et al. (2010) show that economics and statistics are fairly similar in above mentioned traits to natural sciences and less so to humanities.

Our findings imply that editors of the AER do not typically drive radical content changes. Instead, they tend to act conservatively and incrementally. Put positively, this finding allays possible concerns that editors could be overreaching and insert their personal taste too much. If, however, unpopular reforms of content orientation should become necessary, appointing a new editor might be insufficient to warrant the desired results.

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Appendices

A Model of Unbiased Change in Topics. 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

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

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. $\blacksquare$

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 A.1: List of Editors and Coeditors of the *AER* covered in our Analysis

Name	starting	ending	included when using a Window of Three Years	Four Years	Five Years
Editors : (1985 – 2011)					
Orley Ashenfelter	1985	2001	✓	✓	✓
Ben S. Bernanke	2001	2004	✓	✗	✗
Robert A. Moffitt	2004	2010	✓	✓	✓
Pinelopi K. Goldberg	2011	2016	**	**	**
Coeditors : (1985 – 2011)					
John B. Taylor	1985	1988	✓	✗	✗
Robert H. Haveman	1985	1991	✓	✓	✓
Hal R. Varian	1987	1989	✗	✗	✗
Bennett T. McCallum	1988	1991	✓	✗	✗
Paul R. Milgrom	1990	1993	✓	✗	✗
John Y. Campbell	1991	1993	✗	✗	✗
Roger H. Gordon	1991	1994	✓	✗	✗
Kenneth D. West	1993	1996	*	✗	✗
R. Preston McAfee	1993	2002	✓	✓	✓
Dennis N. Epple	1994	1999	*	✓	✓
Matthew D. Shapiro	1997	1999	✗	✗	✗
Valerie A. Ramey	1999	2002	*	✗	✗
Timothy J. Besley	1999	2004	✓	✓	✓
Orley Ashenfelter	2001	2002	**	**	**
David Card	2002	2004	✗	✗	✗
B. Douglas Bernheim	2002	2005	✓	✗	✗
Richard Rogerson	2003	2008	✓	✓	✓
Judith A. Chevalier	2004	2007	✓	✗	✗
Jeremy I. Bulow	2005	2008	✓	✗	✗
Vincent P. Crawford	2005	2009	✓	✓	✗
Mark Gertler	2005	2010	✓	✓	✓
Pinelopi K. Goldberg	2007	2010	✓	✓	✓
Alessandro Lizzeri	2008	2011	✓	✗	✗
Joel Sobel	2009	2010	✗	✗	✗
Dirk Krueger	2009	2011	✗	✗	✗
Larry Samuelson	2010	2016	✓	✓	✓
Martin Eichenbaum	2011	2014	✓	✓	✗
Andrzej Skrzypacz	2011	2014	✓	✗	✗
Marianne Bertrand	2011	2017	*	✓	✓
Hilary Hoynes	2011	2017	✓	✓	✓
Luigi Pistaferri	2011	2017	✓	✓	✓

(*)Editors who did not publish articles that meet our selection criteria for the duration of a window are not included in the analysis of that window.

(**)P.Goldberg and O.Ashenfelter have served as editor as well as coeditor. They enter our analysis only once at the starting date of either editorship or coeditorship whichever comes first.

Table A.2: Journals' Topics and Editor's Preference with Three Year Window (including all editors and co-editors)

	$Editor^c_i$		$AER^c_{i,post}$			$Top5^c_{i,post}$			$(AER$ - $Top5)^c_{i,post}$		
	(1)pre	(2)post	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$AER^c_{i,pre}$	0.427**	0.210+	0.249***	0.249***	0.247***	0.172***	0.172***	0.171***	0.0769	0.0773	0.0757
	(0.162)	(0.124)	(0.0365)	(0.0365)	(0.0364)	(0.0460)	(0.0461)	(0.0457)	(0.0508)	(0.0509)	(0.0507)
$Top5^c_{i,pre}$	0.366*	0.0457	0.207***	0.208***	0.207***	0.368***	0.368***	0.368***	-0.161***	-0.160***	-0.161***
	(0.155)	(0.129)	(0.0304)	(0.0305)	(0.0304)	(0.0335)	(0.0334)	(0.0335)	(0.0440)	(0.0440)	(0.0440)
$Editor^c_{i,pre}$		0.211***	0.00175			0.000558			0.00119		
		(0.0177)	(0.00119)			(0.00130)			(0.00173)		
$Editor^c_{i,post}$				0.00175			0.00143			0.000317	
				(0.00124)			(0.00126)			(0.00163)	
$Editor^{c,fitted}_{i,post}$					0.00831			0.00265			0.00567
					(0.00564)			(0.00616)			(0.00820)
Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5460	5460	5460	5460	5460	5460	5460	5460	5460	5460	5460
R^2	0.486	0.497	0.979	0.979	0.979	0.979	0.979	0.979	0.581	0.581	0.581

Standard errors in parentheses

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

Table A.3: Journals' Topics and Editor's Preference with Four Year Window and One Year Lag (Focusing on AER's and the Other Top 5's point estimates and errors due to potential multicollinearity)

	$AER^c_{i,post}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$AER^c_{i,pre}$	0.313***		0.257***	0.313***		0.258***
	(0.0366)		(0.0365)	(0.0367)		(0.0366)
$Top5^c_{i,pre}$		0.265***	0.201***		0.265***	0.201***
		(0.0348)	(0.0309)		(0.0348)	(0.0309)
$Editor^c_{i,pre}$	0.00279*	0.00341*	0.00239+			
	(0.00131)	(0.00140)	(0.00126)			
$Editor^c_{i,post}$				0.00243+	0.00284*	0.00209
				(0.00137)	(0.00141)	(0.00131)
Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4485	4485	4485	4485	4485	4485
R^2	0.979	0.979	0.980	0.979	0.979	0.980

Standard errors in parentheses

$^+ p < 0.10$, $^* p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$

	$AER^c_{i,post}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$AER^c_{i,pre}$	0.280***		0.171***	0.280***		0.171***
	(0.0589)		(0.0490)	(0.0590)		(0.0491)
$Top5^c_{i,pre}$		0.437***	0.394***		0.436***	0.394***
		(0.0423)	(0.0383)		(0.0423)	(0.0383)
$Editor^c_{i,pre}$	0.000934	0.000819	0.000141			
	(0.00162)	(0.00162)	(0.00153)			
$Editor^c_{i,post}$				0.00253+	0.00236+	0.00186
				(0.00134)	(0.00136)	(0.00131)
Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4485	4485	4485	4485	4485	4485
R^2	0.976	0.979	0.980	0.976	0.979	0.980

Standard errors in parentheses

$^+ p < 0.10$, $^* p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$

Table A.4: Journals' Topics and Editor's Preference with Four Year Window

	$Editor_i^c$		$AER_{i,post}^c$			$Top5_{i,post}^c$			$(AER - Top5)_{i,post}^c$		
	(1)pre	(2)post	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$AER_{i,pre}^c$	0.455*	0.451*	0.154**	0.153**	0.149**	0.0777	0.0760	0.0740	0.0763	0.0767	0.0747
	(0.205)	(0.196)	(0.0538)	(0.0539)	(0.0545)	(0.0589)	(0.0589)	(0.0598)	(0.0488)	(0.0490)	(0.0490)
$Top5_{i,pre}^c$	0.634**	0.187	0.278***	0.279***	0.276***	0.408***	0.408***	0.407***	-0.130**	-0.129**	-0.131**
	(0.235)	(0.176)	(0.0816)	(0.0819)	(0.0811)	(0.0939)	(0.0936)	(0.0939)	(0.0476)	(0.0473)	(0.0480)
$Editor_{i,pre}^c$		0.249***	0.00298			0.00205			0.000930		
		(0.0226)	(0.00212)			(0.00223)			(0.00230)		
$Editor_{i,post}^c$				0.00471*			0.00461*			0.000101	
				(0.00194)			(0.00233)			(0.00219)	
$Editor_{i,post}^{c,fitted}$					0.0119			0.00822			0.00373
					(0.00849)			(0.00896)			(0.00921)
Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2925	2925	2925	2925	2925	2925	2925	2925	2925	2925	2925
R^2	0.559	0.572	0.983	0.983	0.983	0.979	0.979	0.979	0.669	0.669	0.669

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.5: Journals' Topics and Editor's Preference with Four Year Window and Two Year Lag

	$Editor^c_i$		$AER^c_{i,post}$			$Top5^c_{i,post}$			$(AER$ - $Top5)^c_{i,post}$		
	(1)pre	(2)post	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$AER^c_{i,pre}$	0.394$^+$	0.271	0.238***	0.238***	0.237***	0.176**	0.175**	0.173**	0.0620	0.0631	0.0642
	(0.200)	(0.198)	(0.0525)	(0.0524)	(0.0525)	(0.0535)	(0.0535)	(0.0541)	(0.0637)	(0.0636)	(0.0640)
$Top5^c_{i,pre}$	0.422$^+$	-0.0580	0.225***	0.225***	0.225***	0.333***	0.334***	0.333***	-0.108	-0.108	-0.108
	(0.224)	(0.197)	(0.0481)	(0.0482)	(0.0482)	(0.0705)	(0.0705)	(0.0705)	(0.0758)	(0.0758)	(0.0758)
$Editor^c_{i,pre}$		0.235***	0.00108			0.00298			-0.00191		
		(0.0273)	(0.00224)			(0.00289)			(0.00360)		
$Editor^c_{i,post}$				0.00142			0.00625**			-0.00483$^+$	
				(0.00164)			(0.00216)			(0.00249)	
$Editor^{c,fitted}_{i,post}$					0.00458			0.0127			-0.00810
					(0.00954)			(0.0123)			(0.0153)
Topics FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2925	2925	2925	2925	2925	2925	2925	2925	2925	2925	2925
R^2	0.560	0.541	0.985	0.985	0.985	0.976	0.976	0.976	0.571	0.571	0.571

Standard errors in parentheses

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

Table A.6: Journals' Topics and Editor's Preference with Four Year Window and Two Year Lag using 300 Topics

	$Editor_i^c$		$AER_{i,post}^c$			$Top5_{i,post}^c$			$(AER - Top5)_{i,post}^c$		
	(1)pre	(2)post	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$AER_{i,pre}^c$	0.284^{+}	0.333^{*}	0.216^{***}	0.215^{***}	0.211^{***}	0.158^{*}	0.157^{*}	0.154^{*}	0.0583	0.0588	0.0563
	(0.146)	(0.153)	(0.0397)	(0.0398)	(0.0398)	(0.0618)	(0.0618)	(0.0615)	(0.0621)	(0.0623)	(0.0622)
$Top5_{i,pre}^c$	0.0822	0.0363	0.181^{***}	0.181^{***}	0.180^{***}	0.319^{***}	0.319^{***}	0.319^{***}	-0.139^{*}	-0.139^{*}	-0.139^{*}
	(0.136)	(0.149)	(0.0495)	(0.0497)	(0.0495)	(0.0568)	(0.0565)	(0.0568)	(0.0667)	(0.0667)	(0.0668)
$Editor_{i,pre}^c$		0.204^{***}	0.00341^{*}			0.00220			0.00120		
		(0.0188)	(0.00149)			(0.00156)			(0.00196)		
$Editor_{i,post}^c$				0.00459^{**}			0.00502^{*}			-0.000434	
				(0.00154)			(0.00197)			(0.00223)	
$Editor_{i,post}^{c,fitted}$					0.0167^{*}			0.0108			0.00590
					(0.00730)			(0.00766)			(0.00961)
Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4425	4425	4425	4425	4425	4425	4425	4425	4425	4425	4425
R^2	0.495	0.504	0.975	0.975	0.975	0.968	0.968	0.968	0.601	0.601	0.60

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.7: Journals' Topics and Editor's Preference with Three Year Window using 100 Topics

	$Editor^c_i$		$AER^c_{i,post}$			$Top5^c_{i,post}$			$(AER\text{ - }Top5)^c_{i,post}$		
	(1)pre	(2)post	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$AER^c_{i,pre}$	0.797*	0.443	0.307***	0.307***	0.303***	0.173**	0.168**	0.180**	0.135	0.139	0.124
	(0.314)	(0.291)	(0.0636)	(0.0638)	(0.0631)	(0.0548)	(0.0552)	(0.0561)	(0.0977)	(0.0986)	(0.0982)
$Top5^c_{i,pre}$	-0.0693	-0.109	0.169+	0.169+	0.170+	0.416***	0.417***	0.414***	-0.247*	-0.248*	-0.245*
	(0.382)	(0.189)	(0.0865)	(0.0868)	(0.0861)	(0.0366)	(0.0372)	(0.0366)	(0.0979)	(0.0999)	(0.0971)
$Editor^c_{i,pre}$		0.218***	0.00203			-0.00347			0.00550+		
		(0.0263)	(0.00171)			(0.00247)			(0.00297)		
$Editor^c_{i,post}$				0.00307+			0.00314			-0.0000666	
				(0.00177)			(0.00276)			(0.00253)	
$Editor^{c,fitted}_{i,post}$					0.00928			-0.0159			0.0252+
					(0.00784)			(0.0113)			(0.0136)
Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2254	2254	2254	2254	2254	2254	2254	2254	2254	2254	2254
R^2	0.510	0.541	0.990	0.990	0.990	0.981	0.981	0.981	0.590	0.590	0.590

Standard errors in parentheses

$^+ p < 0.10$, $^* p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$

Table A.8: Journals' Topics and Editor's Preference with Four Year Window using 100 Topics

	$Editor_i^c$		$AER_{i,post}^c$			$Top5_{i,post}^c$			$(AER - Top5)_{i,post}^c$		
	(1)pre	(2)post	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$AER_{i,pre}^c$	0.437	1.105***	0.258*	0.253*	0.229*	0.125+	0.120+	0.0994	0.133	0.132	0.130
	(0.354)	(0.316)	(0.102)	(0.101)	(0.101)	(0.0691)	(0.0688)	(0.0703)	(0.0863)	(0.0861)	(0.0872)
$Top5_{i,pre}^c$	-0.349	0.182	0.143*	0.140*	0.138*	0.441***	0.438***	0.437***	-0.298***	-0.298***	-0.298***
	(0.423)	(0.340)	(0.0683)	(0.0684)	(0.0683)	(0.0623)	(0.0621)	(0.0618)	(0.0687)	(0.0685)	(0.0683)
$Editor_{i,pre}^c$		0.292***	0.00752**			0.00667*			0.000842		
		(0.0432)	(0.00246)			(0.00280)			(0.00358)		
$Editor_{i,post}^c$				0.00665*			0.00577*			0.000881	
				(0.00316)			(0.00267)			(0.00363)	
$Editor_{i,post}^{c,fitted}$					0.0258**			0.0229*			0.00289
					(0.00842)			(0.00961)			(0.0123)
Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1470	1470	1470	1470	1470	1470	1470	1470	1470	1470	1470
R^2	0.575	0.639	0.988	0.988	0.988	0.990	0.990	0.990	0.700	0.700	0.700

Standard errors in parentheses

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

Table A.9: Journals' Topics and Editor's Preference with Four Year Window using Kosnik's Topics

	$Editor^c_i$		$AER^c_{i,post}$			$Top5^c_{i,post}$			$(AER - Top5)^c_{i,post}$		
	(1)pre	(2)post	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$AER^c_{i,pre}$	0.837**	-0.393	0.553***	0.481***	0.557***	0.320***	0.337***	0.317***	0.233**	0.144+	0.240**
	(0.277)	(0.364)	(0.0859)	(0.0858)	(0.0857)	(0.0493)	(0.0458)	(0.0494)	(0.0754)	(0.0839)	(0.0746)
$Top5^c_{i,pre}$	0.179	0.396	0.105	0.226	0.101	0.379***	0.420***	0.382***	-0.274*	-0.195	-0.281*
	(0.200)	(0.267)	(0.175)	(0.181)	(0.174)	(0.0653)	(0.0718)	(0.0646)	(0.128)	(0.134)	(0.127)
$Editor^c_{i,pre}$		0.522***	0.00554			-0.00341			0.00895**		
		(0.0391)	(0.00391)			(0.00346)			(0.00298)		
$Editor^c_{i,post}$				0.00142			-0.00185			0.00327	
				(0.00402)			(0.00387)			(0.00555)	
$Editor^{c,fitted}_{i,post}$					0.0106			-0.00653			0.0171**
					(0.00749)			(0.00663)			(0.00570)
Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2030	2026	2030	2036	2030	2030	2036	2030	2030	2036	2030
R^2	0.846	0.873	0.996	0.996	0.996	0.996	0.996	0.996	0.844	0.840	0.844

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.10: Journals' Topics and Editor's Preference with Four Year Window and Two Year Lag using Kosnik's Topics

	$Editor_i^c$		$AER_{i,post}^c$			$Top5_{i,post}^c$			$(AER - Top5)_{i,post}^c$		
	(1)pre	(2)post	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$AER_{i,pre}^c$	0.628^{***}	-0.267	0.508^{***}	0.457^{***}	0.505^{***}	0.0930	0.119	0.0956	0.415^{**}	0.338^{**}	0.409^{**}
	(0.159)	(0.227)	(0.128)	(0.124)	(0.126)	(0.157)	(0.137)	(0.157)	(0.130)	(0.104)	(0.130)
$Top5_{i,pre}^c$	-0.279^{+}	1.026^{***}	0.307	0.356^{+}	0.319	0.317^{***}	0.332^{***}	0.307^{***}	-0.00965	0.0244	0.0121
	(0.142)	(0.302)	(0.203)	(0.194)	(0.197)	(0.0801)	(0.0896)	(0.0829)	(0.178)	(0.198)	(0.172)
$Editor_{i,pre}^c$		0.574^{***}	-0.00668			0.00548			-0.0122^{+}		
		(0.0434)	(0.00649)			(0.00374)			(0.00643)		
$Editor_{i,post}^c$				0.000300			-0.00144			0.00174	
				(0.00609)			(0.00412)			(0.00637)	
$Editor_{i,post}^{c,fitted}$					-0.0116			0.00953			-0.0212^{+}
					(0.0113)			(0.00651)			(0.0112)
Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2034	2026	2034	2032	2034	2034	2032	2034	2034	2032	2034
R^2	0.848	0.871	0.996	0.996	0.996	0.993	0.993	0.993	0.740	0.744	0.740

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.11: Journals' Topics and Editor's Preference with Three Year Window (Controlling for Topics' Citations)

	$Editor_i^c$		$AER_{i,post}^c$			$Top5_{i,post}^c$			$(AER - Top5)_{i,post}^c$		
	(1)pre	(2)post	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$AER_{i,pre}^c$	0.511**	0.257+	0.258***	0.259***	0.255***	0.176***	0.175***	0.176***	0.0818	0.0832	0.0784
	(0.171)	(0.144)	(0.0368)	(0.0369)	(0.0368)	(0.0486)	(0.0487)	(0.0484)	(0.0536)	(0.0537)	(0.0535)
$Top5_{i,pre}^c$	0.179	0.156	0.199***	0.199***	0.197***	0.390***	0.389***	0.390***	-0.191***	-0.190***	-0.193***
	(0.160)	(0.139)	(0.0311)	(0.0311)	(0.0310)	(0.0385)	(0.0384)	(0.0385)	(0.0468)	(0.0468)	(0.0468)
$CitesAER_{i,pre}^c$	0.131	0.0534	-0.0136	-0.0134	-0.0143	-0.0150	-0.0152	-0.0149	0.00137	0.00173	0.000660
	(0.132)	(0.125)	(0.0223)	(0.0223)	(0.0223)	(0.0229)	(0.0229)	(0.0229)	(0.0276)	(0.0275)	(0.0275)
$CitesTop5_{i,pre}^c$	-0.660***	-0.0284	0.0211	0.0196	0.0215	-0.00957	-0.00912	-0.00960	0.0307	0.0288	0.0311
	(0.131)	(0.125)	(0.0216)	(0.0216)	(0.0216)	(0.0225)	(0.0224)	(0.0226)	(0.0271)	(0.0270)	(0.0272)
$Editor_{i,pre}^c$		0.226***	0.00280*			-0.000185			0.00299		
		(0.0205)	(0.00124)			(0.00155)			(0.00201)		
$Editor_{i,post}^c$				0.00220+			0.00187			0.000338	
				(0.00132)			(0.00131)			(0.00176)	
$Editor_{i,post}^{c,fitted}$					0.0124*			-0.000821			0.0133
					(0.00550)			(0.00686)			(0.00890)
Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4462	4462	4462	4462	4462	4462	4462	4462	4462	4462	4462
R^2	0.487	0.505	0.980	0.980	0.980	0.980	0.980	0.980	0.583	0.583	0.583

Standard errors in parentheses

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

Table A.12: Journals' Topics and Editor's Preference with Three Year Window and One Year Lag (Controlling for Topics' Citations)

	$Editor_i^c$		$AER_{i,post}^c$			$Top5_{i,post}^c$			$(AER - Top5)_{i,post}^c$		
	(1)pre	(2)post	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$AER_{i,pre}^c$	0.320	0.291	0.292***	0.292***	0.290***	0.214***	0.213***	0.219***	0.0772	0.0786	0.0707
	(0.203)	(0.178)	(0.0557)	(0.0558)	(0.0558)	(0.0413)	(0.0413)	(0.0413)	(0.0692)	(0.0691)	(0.0691)
$Top5_{i,pre}^c$	0.0601	0.471*	0.174***	0.174***	0.171***	0.330***	0.330***	0.337***	-0.156*	-0.156*	-0.167*
	(0.169)	(0.186)	(0.0461)	(0.0459)	(0.0465)	(0.0579)	(0.0580)	(0.0580)	(0.0648)	(0.0650)	(0.0653)
$CitesAER_{i,pre}^c$	0.116	0.103	0.0265	0.0265	0.0258	-0.0270	-0.0275	-0.0255	0.0535+	0.0541+	0.0512+
	(0.126)	(0.127)	(0.0189)	(0.0189)	(0.0189)	(0.0305)	(0.0305)	(0.0307)	(0.0302)	(0.0303)	(0.0302)
$CitesTop5_{i,pre}^c$	-0.394**	-0.308*	0.0129	0.0128	0.0152	0.00629	0.00789	0.00168	0.00663	0.00488	0.0135
	(0.130)	(0.126)	(0.0207)	(0.0207)	(0.0206)	(0.0334)	(0.0332)	(0.0339)	(0.0350)	(0.0350)	(0.0349)
$Editor_{i,pre}^c$		0.199***	0.00147			-0.00298*			0.00445**		
		(0.0194)	(0.00120)			(0.00141)			(0.00164)		
$Editor_{i,post}^c$				0.00110			0.00109			0.0000127	
				(0.00140)			(0.00153)			(0.00170)	
$Editor_{i,post}^{c,fitted}$					0.00736			-0.0150*			0.0223**
					(0.00605)			(0.00710)			(0.00824)
Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4462	4462	4462	4462	4462	4462	4462	4462	4462	4462	4462
R^2	0.484	0.480	0.981	0.981	0.981	0.978	0.978	0.978	0.559	0.559	0.559

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.13: Journals' Topics and Editor's Preference with Three Year Window and One Year Lag (No Editors Elsewhere)[a]

	$Editor_i^c$		$AER_{i,post}^c$			$Top5_{i,post}^c$			$(AER - Top5)_{i,post}^c$		
	(1)pre	(2)post	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$AER_{i,pre}^c$	0.328	0.104	0.304***	0.304***	0.304***	0.223***	0.222***	0.225***	0.0807	0.0819	0.0782
	(0.265)	(0.286)	(0.0569)	(0.0571)	(0.0567)	(0.0543)	(0.0541)	(0.0543)	(0.0801)	(0.0800)	(0.0800)
$Top5_{i,pre}^c$	0.365	0.615*	0.168**	0.167**	0.166**	0.324***	0.323***	0.337***	-0.156*	-0.156*	-0.170*
	(0.278)	(0.291)	(0.0541)	(0.0537)	(0.0560)	(0.0725)	(0.0729)	(0.0740)	(0.0761)	(0.0761)	(0.0785)
$Editor_{i,pre}^c$		0.222***	0.000816			-0.00448+			0.00530		
		(0.0301)	(0.00226)			(0.00258)			(0.00323)		
$Editor_{i,post}^c$				0.00240			-0.000863			0.00326	
				(0.00207)			(0.00248)			(0.00275)	
$Editor_{i,post}^{c,fitted}$					0.00367			-0.0202+			0.0238
					(0.0102)			(0.0116)			(0.0145)
Topic.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1950	1950	1950	1950	1950	1950	1950	1950	1950	1950	1950
R^2	0.512	0.533	0.983	0.983	0.983	0.978	0.978	0.978	0.576	0.576	0.576

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] We drop the following AER editors/coeditors who have served as editor/coeditor/assoc editor in other major journals: Taylor, Milgrom, Gordon, West, Card, Bernheim, Crawford, Samuelson (Econometrica), Chevalier, Bertrand (QJE), Goldberg (REStud), Hoynes (JEP), Haveman (JEL)