Research in economics: Journal editors influence the agenda

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Abstract

We study the editorial process from initial screening to invitations to revise (R&R) at four top economics journals and find that editors were less likely to desk reject manuscripts related to their own research interests. This finding is robust to controls for research trends, and journal missions and trends. Structural estimates reveal the mechanism to be increased submission of related manuscripts which cross the threshold for publication instead of editorial favoritism. We find that related manuscripts were not more cited than unrelated manuscripts, suggesting the threshold may pertain to research style rather than absolute quality. Finally, we find more productive scholars were more likely to submit related manuscripts.

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1 Introduction

How do the frontiers of knowledge in natural and social sciences move forward? Ideally, knowledge advances as superior ideas prevail over weaker ones through fair competition in the marketplace of ideas.[1] A less sanguine possibility, famously proposed by Merton (1968), is that an elite of established scholars sets the agenda through control over resources and publication outlets.

Research in the context of biomedical sciences has yielded mixed findings. The deaths of star scientists made room for the rise of research on new topics, which turned out to yield higher citations (Azoulay et al., 2019). Members of National Institutes of Health funding panels favored proposals on topics related to their own research, but the research produced better cited work (Li, 2017). Journals tended to publish more papers on topics related to their editors' own research, but the observed effect of journal editors diminished substantially when accounting for journal missions and research trends (Krieger et al., Forthcoming).

By contrast with natural sciences, the social sciences are less disciplined by empirical testing. Further, the scope of social sciences can range across a very broad canvas: For instance, an economics journal may publish research on climate change, healthcare, and politics. The inherent softness and broad scope yields decision-makers great latitude. Which paradigm—the marketplace of ideas or elite domination—does the social sciences fit?

In a dataset of over 29,100 manuscripts submitted to four leading economics journals during the years 2005-2013 (Card and DellaVigna, 2013),[2] we find robust evidence that editors matter. Referring to Figure 1, at the initial screening, manuscripts in fields related to the editors' research were 5.1 percentage points more likely to be sent for review (rather than desk rejected), 9.2 percent of the 55 percentage points baseline for unrelated manuscripts. This difference is robust to controls for author and editor characteristics, trends in research (fixed effects for field interacted with year), differences in journal mission (fixed effects for field interacted with journal), and trends in journal policies (fixed effects for journal interacted with year).

[1] Although Justice Oliver Wendell Holmes articulated this in the context of political speech (Abrams v United States, 250 U.S. 630), it applies equally to research in natural and social sciences.

[2] Journal of the European Economic Association, Quarterly Journal of Economics, Review of Economics and Statistics, and the Review of Economic Studies.

– Figure 1. Specializing editors: Sent for review (not desk rejected) –

Why did the research interests of journal editors affect their decision to send manuscripts for review? One possible mechanism is that authors catered to editors' research interests by submitting manuscripts that were more likely to pass some threshold for publication ("author clientele") (Kim and Koh, 2014; Heckman and Moktan, 2020). Another is that editors deliberately favored manuscripts that interested them personally ("editor favoritism") (Ductor and Visser, 2022), and were willing to lower the threshold for publication.

We use a structural model to identify the mechanism. Empirically, at initial screening, editor favoritism was small and not significant. Related manuscripts were more likely to be sent for review because of the author clientele effect. Considering the entire editorial process, a related manuscript was 4.4 percent more likely to be invited for R&R. Apparently, the initial advantage in favor of related manuscripts persisted through the editorial process. At all stages of the process (submission, review, and R&R), related manuscripts did not exhibit higher impact (measured by citations) than unrelated manuscripts.

Regarding the author clientele mechanism, the threshold for publication could pertain to research approach, methodology, or style (Angrist et al., 2017; Heckman and Moktan, 2020) or absolute quality. The evidence leans against a quality threshold: The likelihood that manuscripts were sent for review did not vary with author characteristics, and related manuscripts were not more highly cited than unrelated manuscripts.

Of note, the editors did not attract an overall increase in submissions of related manuscripts, but rather a shift in submissions towards those more likely to meet the threshold. In particular, more productive scholars (with recent publications in leading journals) were more likely to submit related manuscripts. Apparently, they were more attuned to the personal research interests of journal editors.

Gauging the impact of research by citations is fraught with challenges (Hamermesh, 2018; Koffi, 2021; Rubin and Rubin, 2021). Subject to that proviso, the finding that related manuscripts were not more highly cited than unrelated manuscripts suggests that the higher success rate of related manuscripts does not indicate that they were of higher absolute quality.

Our findings contribute to research into the institutions of curation including Internet search engines, recommendation systems, educational curricula, news media, and fashion

and wine appraisal. Fashion and wine critics hold forth personal judgments to shape consumer choices (Cillo et al., 2020; Taplin, 2006). Educational curricula veer between religion and science (Arold, 2024) and the news media are subject to slant (Gentzkow and Shapiro, 2010). Indeed, it may be optimal for search engines and recommendation systems to bias their content (Corniere and Taylor, 2014; Qian and Jain, 2024).

Curatorial practices influence production. Publishers of science textbooks downplayed mention of evolution to safeguard sales in fundamentalist Christian communities (Woodward and Elliott, 1987). Military operations were timed to coincide with major events that would crowd out publicity about civilian casualties (Durante and Zhuravskaya, 2018). Here, we show that leading economics journals selectively attracted submissions of manuscripts that were related to their editors' research. Moreover, related manuscripts were not more highly cited than unrelated manuscripts.

We also contribute to research on the direction of scientific research (Merton, 1968; Kuhn, 1970; Okike et al., 2016; Fisman et al., 2018; Azoulay et al., 2019; Hager et al., 2024; Shi et al., 2023). In the context of biomedical sciences, previous studies yielded mixed results on the role of scientific leaders. Top scholars and funding panels set the agenda (Azoulay et al., 2010, 2019; Li, 2017). However, in journal publications, the measured effect of editors was very sensitive to controls for research trends and journal missions (Krieger et al., Forthcoming). By contrast, we find that, in economics, journal editors did matter and the measured effect is robust to controls for research trends and journal mission and trends.

More specifically, we add to a finer understanding of the performance of economics journals (Blank, 1991; Gans and Shepherd, 1994; Stigler et al., 1995; Cherkashin et al., 2009; Card et al., 2020b; Brodeur et al., 2023; Hadavand et al., 2024; Ham et al., 2023; Altonji et al., 2025). Economics and finance journals published relatively more papers written by scholars personally connected to the editors (Laband and Piette, 1994; Medoff, 2003; Brogaard et al., 2014; Colussi, 2018; Heckman and Moktan, 2020; Ductor and Visser, 2022; Carrell et al., 2024). Our findings provide an intuitive explanation of why personal connections might matter—the research of connected scholars is likely close to the interests of journal editors. Of note, based on data of submitted manuscripts rather than published articles, our results provide the first direct evidence for the author clientele hypothesis (Kim and Koh, 2014; Heckman and Moktan, 2020) and reject editor favoritism (Ductor and Visser, 2022).

We also contribute to research into the effect of publications on scientific careers (Berenbaum, 2019; Hager et al., 2024). In economics, the alphabetical norm of author ordering (Ray and Robson, 2018) hinders the careers of scholars with surnames behind in the alphabet (Einav and Yariv, 2006). In particular, it shifts them towards careers outside academia and beyond the United States (Li and Yi, 2021; Liu, 2024). Here, we show that more productive scholars were more likely to tailor submissions to the research interests of journal editors, gaining an advantage in the editorial process, which may produce career benefits.

In the remainder of the paper, Section 2 presents a model of the editorial process and Section 3 presents the empirical strategy. Section 4 explains the compilation of the data and Section 5 presents the estimates. Section 6 discusses the findings and Section 7 concludes with policy implications and directions for future research.

2 Data

Our objective is to examine how the research interests of journal editors affected editorial decisions and outcomes. Following previous research (Colussi, 2018; Card and DellaVigna, 2020a; Card et al., 2020b; Ductor and Visser, 2022; Krieger et al., Forthcoming), we exploit the periodic rotation of journal editors to identify their effect, drawing on data from two sources. One is the Card and DellaVigna (2020a) dataset of 29,202 submissions to four leading economics journals (Journal of the European Economic Association (JEEA), Quarterly Journal of Economics (QJE), Review of Economics and Statistics (REStat), and the Review of Economic Studies (REStud)) over the years 2005-2013.

For each manuscript, the dataset includes information on the journal (a manuscript might be submitted to multiple journals), initial disposition of submissions (desk rejected or sent for review), the number of referees approached, the number of reports received, the referees' recommendations, and the editors' decision whether to invite a revision or reject with reviews.

Manuscripts were classified into 14 fields based on the Journal of Economic Literature (JEL) code(s) declared by the manuscript authors (Card and DellaVigna, 2013).[3] A

[3]Development economics, finance, health/urban/law economics, economic history, industrial organization, international economics, laboratory and experimental economics, labor economics, macroeconomics, econometrics, microeconomics, public economics, theory, and other fields.

manuscript might span multiple fields, in which case the field variable is a fraction (one divided by the number of fields).

To compile data on the research interests of the editors of the journals, we referred to the IDEAS/RePEc service. Following Ductor and Visser (2022), anyone who had final decision rights on acceptance of submissions for publication was stipulated to be an "editor", regardless of their actual title. For each of the 45 unique editors, we compiled their start and end years of appointment at the journal, and collated and then classified their 2,844 publications into the 14 fields. We then defined the editor's specialization by year as the field(s) in which they published the most number of articles in the past 10 years. We also consider defining an editor's specialization according to their entire publication history and report estimates based on this specification in Appendix Figure D1. The results are robust to this specification.

As discussed below, our empirical strategy depends on the research interests of editors differing between journals and changing over time. Figure 2 depicts the specializations of the journal editors.[4] For each journal and field, the colored graph denotes the presence of one or more editors at the journal who specialized in the field (= 1) or otherwise (= 0). Evidently, the research interests of the editors did differ between journals and did evolve over time.

– Figure 2. Journals: Specializing editors –

Finally, we merged the data on manuscripts and editors by journal and year. The manuscript dataset did not disclose the identity of the editor responsible for each manuscript. Accordingly, we had to focus the analysis on the collective of editors at a journal. For each manuscript submitted to a journal, we constructed the indicator, Specializing editor$_{mj}$ = 1, if editors at the journal specialized in at least half of the fields implicated by the manuscript. The indicator is specific to a manuscript and journal.

Referring to Table 1, the combined dataset comprises observations of 29,184 manuscripts. On average, manuscripts were sent to review with probability 0.579 and had one or more editors at the journal who specialized in the field(s) of the manuscript with probability 0.473.

— Table 1. Summary statistics —

On average, representing the referee recommendation by receiving one or more positive

[4]The graphs are based on a dataset of the manuscripts consolidated to a panel comprising 455 observations by field, journal, and year. Manuscripts with multiple fields are represented multiple times, once in each field.

referee report (revise and resubmit (R&R), strong R&R, or accept), the average was 0.323 for the sample of manuscripts which were sent for review. On the same sample, following the referee reports, an average of 0.134 manuscripts were invited for R&R.

3 Model

This section describes the model and estimation of the model parameters. This framework models the three main outcomes we observe in the data—the probability that a manuscript is sent for review, the probability it receives a favorable referee report, and the probability it receives an R&R decision—as functions of the characteristics of the manuscript, handling editor, and referee.

3.1 Initial Screening

Consider a manuscript m submitted to a journal and evaluated by editor i at the initial screening. We stipulate that the editor's evaluation of the quality of the manuscript, q_{mi}, is an additively separable function of characteristics of the manuscript, the editor's preferences over the manuscript, and editor's characteristics, given by

$$q_{mi} = \mu_X X_m + \mu_\xi \xi_m + \alpha_i r_{mi} + \kappa_i. \tag{1}$$

In equation (1), X_m denotes characteristics of the manuscript that both the editor and econometrician observe, ξ_m denotes characteristics that only the editor observes, r_{mi} is an indicator of whether the manuscript fits the editor's field of specialization, and κ_i denotes the editor's characteristics. The parameters μ_X and μ_ξ then are respectively the coefficients of the observable and unobservable characteristics of the manuscript, and the parameter α_i characterizes the editor's preference in favor of manuscripts in their own field.

We use the term "quality" here in a very broad sense that encompasses both absolute quality as well as approach, methodology, or style (Angrist et al., 2017; Heckman and Moktan, 2020). The editor must evaluate whether the manuscript meets some threshold for publication, $\bar{q} + \phi_m$, and if so, send it for review. The parameter ϕ_m is some manuscript-specific factor. Then the editor's decision to send a manuscript for review

may be described by

$$\mathbb{1}\{q_{mi} \geq \bar{q} + \phi_m\} = \mathbb{1}\{\mu_X X_m + \mu_\xi \xi_m + \alpha_i r_{mi} + \kappa_i \geq \bar{q} + \phi_m\} \tag{2}$$

Hence, empirically, in the data, the probability that a manuscript is sent for review would be

$$\mathbb{P}(\text{NDR}_m = 1) = \mathbb{P}(\phi_m - \kappa_i \leq \mu_X X_m + \mu_\xi \xi_m + \alpha_i r_{mi} - \bar{q}). \tag{3}$$

Stipulating that κ_i and ϕ_m follow independent type-1 extreme value distributions, the preceding analysis motivates a logistic estimating equation

$$\mathbb{P}(\text{NDR}_m = 1) = \frac{1}{1 + \exp(\bar{q} - \mu_X X_m - \mu_\xi \xi_m - \alpha_i r_{mi})}. \tag{4}$$

The challenge to identification is that the econometrician cannot observe ξ_m, but these unobservable characteristics are plausibly correlated with whether the manuscript fits the editor's field of specialization, r_{mi}. For instance, authors might selectively submit manuscripts with better unobservable characteristics to journals with an editor specializing in the field.

Accordingly, to explicitly consider such a correlation, we generalize the unobservable characteristics of manuscript to $\xi_m = \underline{\xi}_m + \sigma_{\xi r} r_{mi}$ and the estimating equation becomes

$$\mathbb{P}(\text{NDR}_m = 1) = \frac{1}{1 + \exp\left\{\bar{q} - \mu_X X_m - \mu_\xi \underline{\xi}_m - (\alpha_i + \mu_\xi \sigma_{\xi r}) r_{mi}\right\}}. \tag{5}$$

In equation (5), the parameter $\gamma = \mu_\xi \sigma_{\xi r}$ characterizes the differential effect of the unobservable characteristics of related manuscripts on quality—an author clientele effect. Yet, given that we only observe r_{mi} and not $\underline{\xi}_m$, we cannot distinguish between editor favoritism, α_i, and author clientele, γ. As discussed next, we exploit data on the referee report to identify editor favoritism and hence infer author clientele.

3.2 Referee Report

Suppose that the editor sends the manuscript to referee f for review. Let the referee evaluate the quality of the manuscript as

$$q_{mf} = \mu_X X_m + \mu_\xi \xi_m + \alpha_f r_{mf} + \kappa_f, \tag{6}$$

where α_f characterizes the referee's preference in favor of the manuscript and κ_f represents referee characteristics. Stipulate that κ_f and κ_i are independently and identically distributed.

It is reasonable to stipulate that the referee specializes in the relevant field, $r_{mf} = 1$. Hence the observed quality simplifies to

$$q_{mf} = \mu_X X_m + \mu_\xi \xi_m + \alpha_f + \kappa_f. \tag{7}$$

The referee recommends the manuscript for publication if it meets the quality threshold, $q_{mf} \geq \bar{q} + \phi_m$. Now, by equation (2), for the editor to have sent the manuscript for review, it must be that $q_{mi} = \mu_X X_m + \mu_\xi \xi_m + \alpha_i r_{mi} + \kappa_i \geq \bar{q} + \phi_m$. Hence, by equation (7), $q_{mf} = q_{mi} - \alpha_i r_{mi} - \kappa_i + \alpha_f + \kappa_f \geq \bar{q} + \phi_m - \alpha_i r_{mi} - \kappa_i + \alpha_f + \kappa_f$. Thus $q_{mf} \geq \bar{q} + \phi_m$ if and only if

$$\alpha_f + \kappa_f \geq \alpha_i r_{mi} + \kappa_i. \tag{8}$$

Thus, conditional on the manuscript having been sent for review, the probability that the referee evaluates it positively is

$$\begin{aligned} \mathbb{P}(\text{RefPositive}_m = 1 \mid \text{NDR}_m = 1) &= \mathbb{P}(\kappa_i - \kappa_f \leq \alpha_f - \alpha_i r_{mi}) \\ &= \frac{1}{1 + \exp(\alpha_i r_{mi} - \alpha_f)}. \end{aligned} \tag{9}$$

3.3 R&R decision

At the stage of screening for R&R, having received the referee report, the editor again evaluates the manuscript for publication. The editor chooses whether to invite an R&R based on their own assessment and the referee's recommendation. Formally, stipulate

that the editor's decision to invite an R&R is

$$\mu_X X_m + \mu_\xi \xi_m + \alpha_i^{R\&R} r_{mi} + \kappa_i \geq \bar{q}^{R\&R} + \phi_m. \tag{10}$$

At the R&R stage, the editor might exercise a different degree of favoritism and apply a different threshold of quality than at initial screening. Accordingly, we represent editorial favoritism by $\alpha_i^{R\&R}$ and the threshold by $\bar{q}^{R\&R} + \phi_m$. By (7), the referee recommendation is positive if $q_{mf} = \mu_X X_m + \mu_\xi \xi_m + \alpha_f + \kappa_f \geq \bar{q} + \phi_m$. Conditional on the referee report being positive, the probability that an editor invites an R&R is then

$$\begin{aligned} \mathbb{P}(\text{R\&R}_m = 1 | \text{RefPositive}_m = 1) =& \mathbb{P}(\kappa_f - \kappa_i \leq -\bar{q}^{R\&R} + \bar{q} + \alpha_i^{R\&R} r_{mi} - \alpha_f) \\ =& \frac{1}{1 + \exp(\bar{q}^{R\&R} - \bar{q} - \alpha_i^{R\&R} r_{mi} + \alpha_f)}. \end{aligned} \tag{11}$$

4 Empirical Strategy

We seek to estimate the parameters characterizing editor favoritism at the initial screening, α_i, author clientele at submission, γ, and editor favoritism at the R&R stage, $\alpha_i^{R\&R}$. As elaborated below, maximum likelihood estimation of equations (9) and (2) yield α_i and $\alpha_i + \gamma$, from which γ can be inferred. Similarly, maximum likelihood estimation of equation (11) yields $\alpha_i^{R\&R}$.

The main outcomes of interest are whether a manuscript was sent for review (not desk rejected), one or more positive referee reports,[5] and whether the editor invited the authors to R&R. As derived above, we model these decisions by logistic regression. Specifically, regarding manuscript m submitted to journal j and evaluated by editor i, the probability of the outcome is

$$\Pr(Y_{mij}) = \frac{1}{1 + \exp(X_{mij})}. \tag{12}$$

The indicator $Y_{mij} = 1$ if the manuscript was sent for review (not desk rejected), received a positive referee report, or invited to R&R, and the explanatory variables,

$$\begin{aligned} X_{mij} = G(&\text{Specializing editor}_{mj} + \text{Author characteristics}_m + \text{Editor}_i + \\ &+ [\text{Field}_f \times \text{Journal}_j] + [\text{Field}_f \times \text{Year}_y] + [\text{Journal}_j \times \text{Year}_y] + \xi_{mij}). \end{aligned} \tag{13}$$

[5] We also consider specifying the variable $RefPos$ as two or more positive referee reports and report results from a robustness check based on this specification in Appendix Figure D1. Results are qualitatively similar.

In equation (13), the key explanatory variable is the indicator Specializing editor$_{mij}$ of whether the manuscript is related to the research interests of the journal editors. The equation controls for author characteristics (indicators of the number of publications of the most published coauthor in 35 leading journals within the previous 5 years and indicators of the numbers of coauthors) (Card and DellaVigna, 2020a). Including editor and journal-year fixed effects allows for heterogeneity in $\bar{q}$ by the handling editor and journal-specific publishing trends (such as increases in page count). Following Krieger et al. (Forthcoming), we include field-year and field-journal fixed effects, which allow $\bar{q}$ to depend on trends in research and journal missions. ξ_{mij} represents the structural error.

Appendix A Figure A1 shows that the decision to send for review varied substantially by field-year, field-journal and journal-year dimensions, which might affect the estimated relation between the decision to send for review and editor specialization. This justifies our choice to control for these variables to abstract from possible confounds in the empirical strategy. However, the inclusion of these fixed effects complicates non-linear estimation (Neyman and Scott, 1948) and so we apply a bootstrap procedure to correct for possible bias due to incidental parameters (Higgins and Jochmans, 2024). Standard errors are clustered by editor, the level at which outcomes of interest might be correlated (Abadie et al., 2023).

Our estimates rely on the rotation of journal editors to identify the effect of editors' research interests on the editorial process. We acknowledge that editors were not randomly assigned to journals, and so the empirical results might possibly be interpreted in other ways. Reverse causality is unlikely as we characterize the editors' research interests by their past publications, which would have been the product of research several years earlier.

A more serious threat to identification is the omission of factors that affect both the research interests of journal editors and the outcomes for manuscripts submitted to the journal. Our estimates do control for editor characteristics through fixed effects and also control for research trends, and journal mission and trends. The rich set of controls would ameliorate concern about omitted factors.

5 Estimates

Table 2 reports the maximum likelihood logit estimates. Table 2 column (a) presents the estimate of equation (5) for the editor decision at initial screening whether to send the manuscript for review (not desk reject). The coefficient of specializing editor, which represents the combination of editor favoritism and author clientele, $\alpha_i + \gamma = 0.237$ (s.e. 0.054), is positive and significant.

– Table 2. Editorial process: Maximum likelihood logit estimates –

The coefficient implies that the presence of a specializing editor increased the probability of a manuscript being sent for review by 4.0 percentage points, or more than half of the raw effect without controls (Figure 1). Relative to the baseline 56.1 percent probability of manuscripts with no specializing editor being sent for review, the effect is economically meaningful.[6]

Next, Table 2 column (b) reports the logit estimate of equation (9) of the indicator of one or more positive referee recommendations, which identifies editor favoritism. The coefficient of specializing editor, $-\alpha_i = -0.016$ (s.e. 0.054), is negative and not significantly different from zero.

The author clientele mechanism, γ, is identified by sum of the estimate of editor favoritism, $-\alpha_i$ (equation (9)) and the estimate of editor favoritism combined with author clientele, $\alpha_i + \gamma$ (equation (5)). We bootstrap the standard error estimate for γ. Table 3 column (a) reports the maximum likelihood logit estimates of $\alpha_i + \gamma$ and α_i from Table 2 columns (a) and (b), and the corresponding estimate of γ. We apply the bootstrap procedure for incidental-parameter bias correction in Higgins and Jochmans (2024) and report results in Table 3 column (b).

— Table 3. Editorial process: Mechanisms —

Across the two sets of estimates, editorial favoritism is positive but not significant. Author clientele is statistically significant and approximately 15 times the magnitude of editorial favoritism.

Finally, Table 2 column (c) reports the logit estimate of equation (11) for the edi-

[6]The baseline probability reported here is based on the regression sample (which excludes observations that predict success or failure perfectly) and so differs from the baseline probability in the raw data.

tor decision whether to invite an R&R. The coefficient of specializing editor, $\alpha_i^{R\&R} = -0.030$ (s.e. 0.095), is negative, small in magnitude, and not statistically significant.

5.1 Specification

Appendix A Table A1 reports estimates of equation (5) for the editor decision to send a manuscript for review with alternative sets of controls. Referring to column (a), in the basic estimate without any controls, the coefficient of editor specialization, 0.308 (s.e. 0.092), is positive and significant.

With the addition of controls for author characteristics (column (b)), the coefficient of editor specialization is very slightly smaller. Apparently, the effect of editor specialization at initial screening did not vary much by the characteristics of the authors. So, the estimated effect of editor specialization did not vary much with or without controls for author characteristics.

Referring to Table A1 column (c), the inclusion of editor fixed effects reduced the coefficient of editor specialization by more than one-third. A key way in which editors differ is their overall leniency (Cherkashin et al., 2009; Card and DellaVigna, 2020a). Table A1 column (d) therefore reports an estimate that controls for editor leniency, characterized by the rate at which manuscript an editor sent other manuscripts (besides the one at hand) for review (Card and DellaVigna, 2020a). The coefficient of editor specialization is slightly larger than that with controls for editor fixed effects. The similarity of the estimates suggests that the main way by which individual editor characteristics possibly confounded the estimated effect of editor specialization was differences in leniency.

Further, the inclusion of editor fixed effects should abstract the analysis from the individual editor's specialization. Hence, the estimated coefficient of editor specialization (which characterizes the overlap between the manuscript fields with the research interests of all of the journal editors) yields a conservative estimate of the effect of editor specialization.

Table A1 column (e) reports an estimate that controls for both author characteristics and editor fixed effects. The coefficient of editor specialization, 0.139 (s.e. 0.061), is one-tenth smaller than that with controls for only editor fixed effects.

Referring to Appendix A Figure A1, the decision to send manuscripts for review varied substantially in multiple ways—by journal, field, and year, and also within journals by

field and year, and within fields by year. Table A1 columns (f)-(h) report estimates that variously control for research trends (fixed effects for field interacted with year), journal mission (fixed effects for field interacted with journal), and journal trends (fixed effects for journal interacted with year). Relative to the estimate that controls for only author characteristics and editor fixed effects, the estimates including the additional fixed effects yield coefficients of editor specialization that are larger or the same.

Finally, Table A1 column (i) reports the estimate including the full set of controls—for author characteristics, editor fixed effects, research trends, journal missions, and journal trends. The estimated coefficient, 0.237 (s.e. 0.054), is half again as large as the estimate with controls only for author characteristics and editor fixed effects. This specification is preferred as it controls for all possible confounds.

5.2 Mechanism

Referring to Table 2, manuscripts related to editors' research interests were more likely to be sent for review than unrelated manuscripts. Further, referring to Table 3, the higher likelihood was due to author clientele rather than editor favoritism.

To further examine the mechanism, Appendix B Table B1 reports estimates of submissions and editor decisions in a panel dataset constructed by consolidating the data of manuscripts to a panel comprising 455 observations by field, journal, and year. In the panel dataset, a manuscript spanning several fields would be represented multiple times, once in each field. Similarly, a manuscript submitted to multiple journals would be represented once in each journal.

The outcomes of interest—numbers of submissions, sent for review, and R&R—are counts, and so, the estimation applied Poisson Quasi Maximum Likelihood (Silva and Tenreyro, 2011). The key explanatory variable is the indicator Specializing editor$_{kjy}$ which represents whether there was one or more editors specializing in field k at journal j in year y. As with the manuscript level estimation, the panel data estimates controlled for research trends and journal mission and trends through the relevant fixed effects.

In the estimate of submissions (Table B1 column (a)), the coefficient of specializing editor is positive but not statistically significant. By contrast, in an estimate of the initial screening (Table B1 column (b)), the coefficient of specializing editor is positive and very precisely estimated. Table B1 column (c) reports an estimate that controls for the number

of submissions. The coefficient of the number of submissions is positive and very precise. The coefficient of specializing editor, 0.060 (s.e. 0.021), is positive and similar to that without controlling for submissions. The estimate implies that about 6 percent more related manuscripts were sent for review.

To examine the role of author productivity in the author clientele mechanism, Table 4 reports estimates of whether the manuscript was submitted to a journal with one or more editors specializing in the fields of the manuscript. The explanatory variable is an indicator of whether the author(s) had one or more recent publications in the 35 leading journals. The estimates variously control for team size (number of coauthors) and research trends, and journal mission and trends. Across all estimates, the coefficients of author productivity are positive and significant.

Of note, the measured effect of author productivity more than doubled with controls for research trends, and journal mission and trends (Table 4, column (c)). This estimate implies that better published authors were about one-third more likely to submit related manuscripts than less well published authors. (This estimate identifies the characteristics of the authors who submitted related manuscripts. By contrast, the estimates in Appendix A Table A1 showed that the effect of editor specialization on send for review did not vary with author characteristics, i.e., among submitted manuscripts, the only information that mattered was whether the manuscript was related to the editors' research interests.)

5.3 Consequences

Next, consider the consequences of manuscripts related to journal editors' research interests being more likely to pass the initial screening and being sent for review. Two important downstream consequences are publication and research impact.

Table 2 reports the effect of editor specialization on the three stages of editorial flow—initial editor screening, referee recommendations (conditional on manuscript being sent for review), and editor review for R&R (conditional on manuscript receiving one or more positive referee recommendations). By calculating the rates at which manuscripts proceeded through each stage, we can compute the overall likelihood of related vis-a-vis unrelated manuscripts being invited to R&R. We bootstrap these rates in order to derive standard errors on the likelihoods. Referring to Appendix C Figure C1, considering the complete flow, the likelihood that an unrelated manuscript was invited to R&R is 0.068

[0.061, 0.075], whereas the likelihood for a related manuscript was 4.4% larger, 0.0710 [0.064, 0.078].

To consider research impact, we report analyses of citations in Google Scholar and the Web of Science. Google Scholar is useful as the time between manuscript submission and collection of the citation data was quite short. On the other hand, manuscripts might accumulate Google Scholar citations before being considered by journal editors. This presents the possibility of citations influencing editorial decisions. The Web of Science avoids this problem.

Appendix C Figure C2 compares the kernel densities of citations of related vis-a-vis unrelated manuscripts. A very small minority of manuscripts (0.2 percent) attracted very high citations and were top-coded for privacy. So, for clearer visualization, the graphs are limited to manuscripts with 10 or fewer citations. Apparently, related and unrelated manuscripts did not differ much in citations.

Table C1 presents regression estimates of the citations across the samples of all manuscripts, those sent for review, and those that received an R&R. (The estimates account for selection through control functions based on the leniency of editors at the relevant stage of the editorial process.) Generally, across all estimates, the coefficient of specializing editor is not statistically significant.

6 Discussion

Here, we studied the editorial process at four leading economics journals from the editors' initial screening through referee review to the editors' decision whether to invite revise-and-resubmit (R&R). We show that manuscripts related to editors' research interests were more likely to pass initial screening and go for review. The initial advantage of related manuscripts carried forward slightly through the editorial process. As a result, related manuscripts were 4 percent more likely to be invited to R&R (Appendix C Figure C1).

The estimated effect of editors' research interests on the success rate of manuscripts was more pronounced with controls for research trends and journal missions and trends (Appendix A Table A1). To the extent that journals intentionally chose editors to guide the selection of manuscripts, this result suggests that journals sought to differentiate themselves from general patterns and trends. The result contrasts with findings in the

biomedical sciences that the observed effect of editors' research interests on publications was much diminished by controls for research trends and journal missions (Krieger et al., Forthcoming).

Structural estimates (Table 3) reveal the mechanisms by which related manuscripts were more likely to be sent for review. The key finding is that the mechanism was editors attracting submissions that were more likely to pass some threshold for publication (author clientele) rather than editors deliberately favoring such submissions (editor favoritism). (There was no evidence in reduced form or structural estimate of editor favoritism at the R&R stage. This result is consistent with previous research (Welch, 2014, Section 2.5).)

Importantly, the threshold for initial screening might be cast in the sense of approach, methodology, or style (Angrist et al., 2017; Heckman and Moktan, 2020) or according to an absolute standard. The evidence points against the latter interpretation. One is that estimates of the manuscript being sent for review were not sensitive to controls for author characteristics (Appendix A Table A1, columns (a) and (b)). Supposing that more productive scholars would produce better work in an absolute sense, the estimates should vary with controls for author characteristics. Moreover, manuscripts related to the editors' research interests were not more cited (Appendix C Figure C2 and Table C1). These results are not consistent with such manuscripts being of higher absolute quality.

Referring to the panel estimates (Appendix B Table B1), total submissions did not increase with editor specialization. In the estimates of manuscripts sent for review, the coefficient of specializing editor was similar without and with controlling for submissions. Collectively, these results suggest that the author clientele mechanism (by which related manuscripts were more likely to be sent for review) did not consist of increasing the volume of related submissions. Rather, the mechanism was to change the composition of related submissions.

The estimates of manuscript submissions (Table 4) show that more productive scholars were more responsive to editor specialization. They were more likely than less productive scholars to submit manuscripts related to the editors' research interests. Of note, the effect of author productivity on submissions of related manuscripts was much more pronounced with controls for research trends and journal mission and trends than without. The latter result suggests that, in deciding where to submit their manuscripts, more productive scholars were particularly attentive to the specific interests of journal editors relative to broader patterns and trends.

How did the higher success rate of manuscripts related to editors' research interests affect social welfare? The only evidence is that the citations of related manuscripts were not higher than those of unrelated manuscripts (Appendix C Figure C1 and Table C1). Citations should be used to measure the impact of research with caution (Kim and Koh, 2014; Hamermesh, 2018; Koffi, 2021; Rubin and Rubin, 2021). Subject to this proviso, we infer that the higher success rate of related manuscripts did not increase welfare.

The data studied here were generated by the periodic rotation of editors at journals. It is possible that the higher rate at which manuscripts related to editors' research interests were more likely to succeed might be explained in other ways besides author clientele and editorial favoritism.

One alternative explanation is that within journals, manuscripts were assigned to editors with the relevant expertise. This might mechanically result in manuscripts related to editors' research being more likely to be sent for review. However, our estimates cast the treatment at the level of the journal—the presence of one or more editors specializing in the field—rather than at the editor. This abstracts from any mechanical relation between a manuscript and the expertise of the handling editor.

Another alternative explanation is that journal editors adopted a developmental approach, helping junior scholars to refine their work. Editors would be better able to guide scholars on manuscripts related to their own research, and so sent more of such manuscripts for review. However, the estimated effect of editor specialization is almost the same with and without controlling for author characteristics (Appendix A Table A1, columns (a) and (b)). These results seem inconsistent with the developmental narrative.

7 Concluding Remarks

Here, we show that, in economics, journal editors mattered substantially. Manuscripts related to the editors' research interests were more likely to be reviewed and proceed through to be invited for revision and resubmission. The higher success rate was due to an increase in the submissions of related manuscripts that would meet some threshold and not editor favoritism. More productive scholars were more likely to submit manuscripts related to the research interests of journal editors.

Of note, two of the journals studied here rank in the "top five" that exercise dispropor-

tionate influence over the academic economics profession (Card and DellaVigna, 2013; Heckman and Moktan, 2020; Koffi, 2021; Hengel and Moon, 2023). What gets published affects not only the direction of research but also the careers of academic economists. In particular, we found that more productive scholars seemed to better attune their submissions to movements in journal editors. The finding suggests that what might seem to be public information (changes in journal editors and their research interests) either was distributed asymmetrically (Singh et al., 2010) or received asymmetric attention.

The impact of journal editors would be reinforced by social networks in the profession (Goyal et al., 2006; Fafchamps et al., 2010; Ductor and Visser, 2023). They would contribute to the Matthew effects previously documented in the sciences (Merton, 1968; Fisman et al., 2018; Hager et al., 2024).

What about other social sciences? Economists are thought to agree relatively more in judging research quality than other social scientists (Lamont, 2009). To this extent, in other social sciences, editors might have more latitude to engage in deliberate favoritism. Combined with the author clientele mechanism, the result would be an even stronger effect of editor research interests on what journals publish, the direction of research, and academic careers.

A limitation of the present study is the very coarse classification of research. It cannot account for divisions within fields such as the tension between structural and atheoretic approaches in empirical research (Keane, 2010). An analysis of the editorial process with finer classification of research would provide more definitive evidence of the nature of the author clientele mechanism.

An intriguing question that we were unable to address is the rationality of the author clientele mechanism. If the editors of a journal do not deliberately favor manuscripts related to their own interests, why did authors prefer to submit such manuscripts to the journal? In a world of rational expectations, the author clientele mechanism would depend on editorial favoritism. Yet, our results show that the effect of editorial favoritism was not statistically significant.

A broader question is whether, beyond the research that is published, journal editors also influence the research that is carried out. Heckman and Moktan (2020), page 422, conjectured: "authors ... to increase their chances of publication, choose to *conduct research* that caters to the policy and/or methodology preferences of editors" [emphasis added]. Indeed, this might well be an objective of journals in selecting editors to appoint

(Colussi, 2018; Önder et al., 2020). It would be interesting to examine the process by which journals select and appoint editors and the consequent effect on scientific research.

References

Abadie, Alberto, Susan Athey, Guido W Imbens, and Jeffrey M Wooldridge, "When should you adjust standard errors for clustering?," *Quarterly Journal of Economics*, 2023, *138* (1), 1–35.

Altonji, Joseph, Guido Imbens, Kevin Lang, Erzo Luttmer, Imran Rasul, Stefanie Stantcheva, and Romain Wacziarg, "Report on Improving the Publication Process in Economics," Econometric Society 2025.

Angrist, Joshua, Pierre Azoulay, Glenn Ellison, Ryan Hill, and Susan Feng Lu, "Economic research evolves: Fields and styles," *American Economic Review*, 2017, *107* (5), 293–297.

Arold, Benjamin W, "Evolution vs. creationism in the classroom: The lasting effects of science education," *Quarterly Journal of Economics*, 2024, *139* (4), 2331–2375.

Azoulay, Pierre, Christian Fons-Rosen, and Joshua S Graff Zivin, "Does science advance one funeral at a time?," *American Economic Review*, 2019, *109* (8), 2889–2920.

_ , Joshua S Graff Zivin, and Jialan Wang, "Superstar extinction," *The Quarterly Journal of Economics*, 2010, *125* (2), 549–589.

Berenbaum, May R, "Impact factor impacts on early-career scientist careers," 2019.

Blank, Rebecca M., "The Effects of Double-Blind versus Single-Blind Reviewing: Experimental Evidence from The American Economic Review," *American Economic Review*, 1991, *81*, 1041–1067.

Brodeur, Abel, Scott Carrell, David Figlio, and Lester Lusher, "Unpacking p-hacking and publication bias," *American Economic Review*, 2023, *113* (11), 2974–3002.

Brogaard, Jonathan, Joseph Engelberg, and Christopher A. Parsons, "Economics Networks and Productivity: Causal Evidence from Editor Rotations," *Journal of Financial Economics*, 2014, *111*, 251–270.

Card, David and Stefano DellaVigna, "Nine Facts about Top Journals in Economics," *Journal of Economic Literature*, 2013, *51*, 144–161.

_ and _ , "What Do Editors Maximize? Evidence from Four Economics Journals," *Review of Economics and Statistics*, 2020a, *102*, 195–217.

_ , _ , Patricia Funk, and Nagore Iriberri, "Are Referees and Editors in Economics Gender Neutral?," *Quarterly Journal of Economics*, 2020b, *135*, 269–327.

Carrell, Scott, David Figlio, and Lester Lusher, "Clubs and Networks in Economics Reviewing," *Journal of Political Economy*, 2024, *132*, 2999–3024.

Cherkashin, Ivan, Svetlana Demidova, Susumu Imai, and Kala Krishna, "The inside scoop: Acceptance and rejection at the Journal of International Economics," *Journal of International Economics*, 2009, *77* (1), 120–132.

Cillo, Paola, Joseph C Nunes, Emanuela Prandelli, and Irene Scopelliti, "Changing Style in Style-changing Industries: The Role of Critics as Gatekeepers in High-end Fashion," in G Cattani, S Ferriani, F Godart, and S V Sgourev, eds., *Aesthetics and Style in Strategy*, Vol. 42 of *Advances in Strategic Managemen*, Emerald Publishing Limited, 2020, pp. 171–197.

Colussi, Tommaso, "Social Ties in Academia: A Friend Is a Treasure," *Review of Economics and Statistics*, 2018, *100* (1), 45–50.

de Corniere, Alexandre and Greg Taylor, "Integration and search engine bias," *RAND Journal of Economics*, 2014, *45* (3), 576–597.

Ductor, Lorenzo and Bauke Visser, "When a coauthor joins an editorial board," *Journal of Economic Behavior & Organization*, 2022, *200*, 576–595.

_ and _ , "Concentration of power at the editorial boards of economics journals," *Journal of Economic Surveys*, 2023, *37* (2), 189–238.

Durante, Ruben and Ekaterina Zhuravskaya, "Attack when the world is not watching? US news and the Israeli-Palestinian conflict," *Journal of Political Economy*, 2018, *126* (3), 1085–1133.

Einav, Liran and Leeat Yariv, "What's in a surname? The effects of surname initials on academic success," *Journal of Economic Perspectives*, 2006, *20* (1), 175–188.

Fafchamps, Marcel, Marco J Van der Leij, and Sanjeev Goyal, "Matching and network effects," *Journal of the European Economic Association*, 2010, *8* (1), 203–231.

Fisman, Raymond, Jing Shi, Yongxiang Wang, and Rong Xu, "Social ties and favoritism in Chinese science," *Journal of Political Economy*, 2018, *126* (3), 1134–1171.

Gans, Joshua S. and George B. Shepherd, "How Are the Mighty Fallen: Rejected Classic Articles by Leading Economists," *Journal of Economic Perspectives*, 1994, *8*, 165–179.

Gentzkow, Matthew and Jesse M Shapiro, "What drives media slant? Evidence from US daily newspapers," *Econometrica*, 2010, *78* (1), 35–71.

Goyal, Sanjeev, Marco J Van Der Leij, and José Luis Moraga-González, "Economics: An emerging small world," *Journal of Political Economy*, 2006, *114* (2), 403–412.

Hadavand, Aboozar, Daniel S Hamermesh, and Wesley W Wilson, "Publishing economics: How slow? Why slow? Is slow productive? How to fix slow?," *Journal of Economic Literature*, 2024, *62* (1), 269–293.

Hager, Sebastian, Carlo Schwarz, and Fabian Waldinger, "Measuring science: Performance metrics and the allocation of talent," *American Economic Review*, 2024, *114* (12), 4052–4090.

Ham, John C, Julian Wright, and Ziqiu Ye, "Documenting and Explaining the Dramatic Rise of the New Society Journals in Economics," IZA Discussion Paper 16337 2023.

Hamermesh, Daniel S, "Citations in economics: Measurement, uses, and impacts," *Journal of Economic Literature*, 2018, *56* (1), 115–156.

Heckman, James J. and Sidharth Moktan, "Publishing and Promotion in Economics: The Tyranny of the Top Five," *Journal of Economic Literature*, 2020, *58*, 419–470.

Hengel, Erin and Eunyoung Moon, "Gender and quality at top economics journals," Mimeo, Brunel University 2023.

Higgins, Ayden and Koen Jochmans, "Bootstrap inference for fixed-effect models," *Econometrica*, 2024, *92* (2), 411–427.

Keane, Michael P., "Structural vs. atheoretic approaches to econometrics," *Journal of Econometrics*, 2010, *156* (1), 3–20.

Kim, Jinyoung and Kanghyock Koh, "Incentives for Journal Editors," *Canadian Journal of Economics*, February 2014, *47* (1), 348–371.

Koffi, Marlène, "Gendered citations at top economic journals," in "AEA Papers and Proceedings," Vol. 111 American Economic Association May 2021, pp. 60–64.

Krieger, Joshua L., Kyle R. Myers, and Ariel D. Stern, "How Important is Editorial Gatekeeping? Evidence from Top Biomedical Journals," *Review of Economics and Statistics*, Forthcoming, pp. 1–33.

Kuhn, Thomas S, *The structure of scientific revolutions*, Chicago, IL: University of Chicago press Chicago, 1970.

Laband, David N. and Michael J. Piette, "Favoritism versus Search for Good Papers: Empirical Evidence Regarding the Behavior of Journal Editors," *Journal of Political Economy*, 1994, *102*, 194–203.

Lamont, Michèle, *How professors think: Inside the curious world of academic judgment*, Cambridge, MA: Harvard University Press, 2009.

Li, Danielle, "Expertise vs. Bias in Evaluation: Evidence from the NIH," *American Economic Journal: Applied Economics*, April 2017, *9*, 60–92.

Li, Wenchao and Junjian Yi, "Alphabetical author order, intellectual collaboration and high-skilled migration," *Economic Journal*, 2021, *131* (635), 1250–1268.

Liu, Liqiang, "Three Essays on Labor and Health Economics," PhD thesis, State University of New York at Buffalo 2024.

Medoff, Marshall H., "Editorial Favoritism in Economics?," *Southern Economic Journal*, 2003, *70*, 425–434.

Merton, Robert K, "The Matthew Effect in Science," *Science*, 1968, *159* (3810), 56–63.

Neyman, J. and Elizabeth L. Scott, "Consistent estimates based on partially consistent observations," *Econometrica*, 1948, *16* (1), 1–32.

Okike, Kanu, Kevin T Hug, Mininder S Kocher, and Seth S Leopold, "Single-blind vs double-blind peer review in the setting of author prestige," *JAMA*, 2016, *316* (12), 1315–1316.

Önder, Ali Sina, Sergey V. Popov, and Sascha Schweitzer, "Leadership in Scholarship: Editors' Appointments and Scientific Narrative," SSRN Working Paper 3105539 2020.

Qian, Kun and Sanjay Jain, "Digital content creation: An analysis of the impact of recommendation systems," *Management Science*, 2024, *70*, 8217–9119.

Ray, Debraj and Arthur Robson, "Certified random: A new order for coauthorship," *American Economic Review*, 2018, *108* (2), 489–520.

Rubin, Amir and Eran Rubin, "Systematic Bias in the Progress of Research," *Journal of Political Economy*, 2021, *129*, 2666–2719.

Shi, Dongbo, Weichen Liu, and Yanbo Wang, "Has China's Young Thousand Talents program been successful in recruiting and nurturing top-caliber scientists?," *Science*, 2023, *379* (6627), 62–65.

Silva, J.M.C. Santos and Silvana Tenreyro, "Further Simulation Evidence on the Performance of the Poisson Pseudo-Maximum Likelihood Estimator," *Economics Letters*, 2011, *112*, 220–222.

Singh, Jasjit, Morten T Hansen, and Joel M Podolny, "The world is not small for everyone: Inequity in searching for knowledge in organizations," *Management Science*, 2010, *56* (9), 1415–1438.

Stigler, George J, Stephen M Stigler, and Claire Friedland, "The journals of economics," *Journal of Political Economy*, 1995, *103* (2), 331–359.

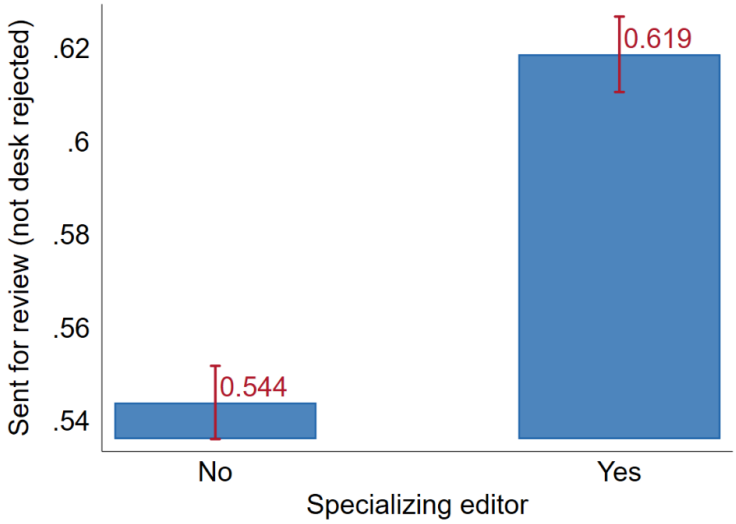
Taplin, Ian M, "Competitive pressures and strategic repositioning in the California premium wine industry," *International Journal of Wine Marketing*, 2006, *18* (1), 61–70.

Welch, Ivo, "Referee recommendations," *Review of Financial Studies*, 2014, *27* (9), 2773–2804.

Woodward, Arthur and David L Elliott, "Evolution and creationism in high school textbooks," *The American Biology Teacher*, 1987, *49* (3), 164–170.

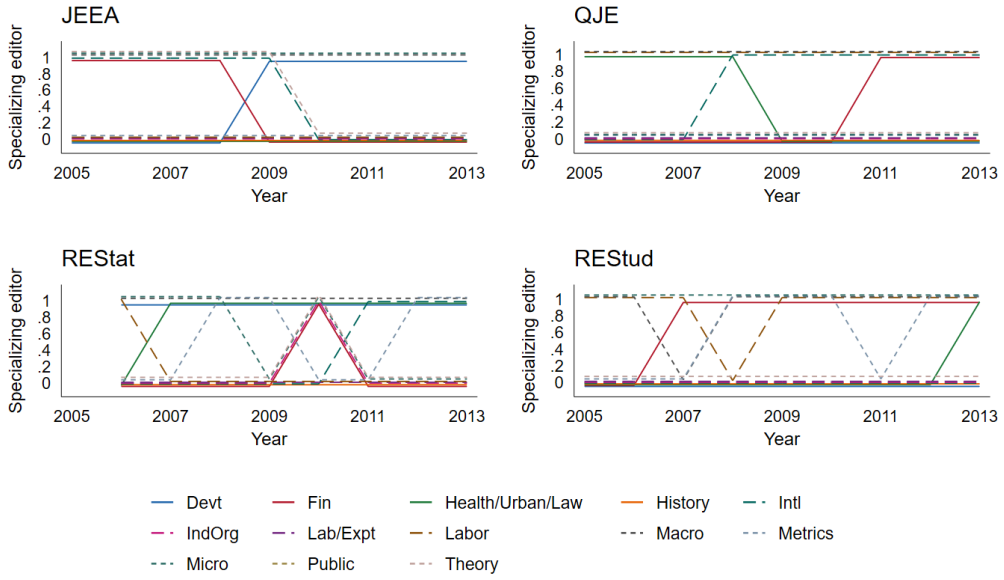
Figures and Tables

Figure 1. Specializing editor: Sent for review (not desk rejected)



Notes: Main sample: 29,184 manuscripts. Figure depicts mean rate at which manuscripts were sent to review (not desk rejected) divided between those submitted to journals without any editor who specialized in the fields of the manuscript (no specializing editor) and one or more editors specializing in the field (specializing editor). Red bar represents 95 percent confidence interval.

Figure 2. Journals: Specializing editors



Notes: Figures based on manuscript data consolidated to a panel comprising 455 observations by field, journal, and year. Manuscripts with multiple fields represented multiple times, once in each field. For each journal and field, the colored graph denotes the presence of one or more editors specializing in the field (= 1) or otherwise (= 0).

Table 1. Summary statistics

VARIABLE	Obs	Mean	Std. Dev.	Min	Max
Sent for review (not desk rejected)	29184	0.579	0.494	0	1
One or more positive referees	16901	0.323	0.468	0	1
Revise and resubmit	16901	0.134	0.341	0	1
Google Scholar citations	29184	20.58	50.36	0	500
Web of Science citations	29184	2.197	8.359	0	100
Specializing editor	29184	0.473	0.499	0	1

Notes: Data compiled between April and September 2015 (Card and Dellavigna 2020a). One or more positive referees and Revise and resubmit limited to sample of manuscripts sent for review. Google Scholar citations top-coded at 500; Web of Science citations top-coded at 100.

Table 2. Editorial process: Maximum likelihood logit estimates

VARIABLES	(a) Sent for review	(b) At least one positive review	(c) R&R
Specializing editor			
$\alpha_i + \mu_\xi \sigma_{\xi r}$	0.237***		
	(0.054)		
$-\alpha_i$		-0.016	
		(0.054)	
$\alpha_i^{R\&R}$			-0.030
			(0.095)
Author controls	Yes	Yes	Yes
Editor FE	Yes	Yes	Yes
Field x journal FE	Yes	Yes	Yes
Field x year FE	Yes	Yes	Yes
Journal x year FE	Yes	Yes	Yes
Editors	49	49	49
Observations	29,184	16,837	1,572
lnL	-14,720	-9,825	-3,196
Average marginal effect	0.040	-0.003	-0.006
Baseline outcome (no specializing editor)	0.561	0.325	0.373

Notes: Fields defined by Card and Dellavigna (2013); Estimated by logit, Stata routine logit. Column (a): Dependent variable is whether editors sent manuscript for review estimated on entire sample; Column (b): Dependent variable is whether at least two referees recommended positively (revise-and-resubmit, strong revise-and-resubmit, or accept), estimated on sample of manuscripts sent for review; Column (c): Dependent variable is whether invited to revise and resubmit, estimated on sample of manuscripts with two or more positive reviews. Robust standard errors clustered by editor in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 3. Editorial process: Mechanisms

VARIABLES	(a) Maximum likelihood estimates	(b) Estimates corrected for incidental parameters bias
Author clientele +	0.237	0.228
editor favoritism,	0.057	0.057
$\alpha_i + \mu_\xi \sigma_{\xi r}$	[0.126, 0.348]	[0.117, 0.339]
Editor favoritism, α_i	0.016	0.014
	0.058	0.058
	[-0.098, 0.130]	[-0.100, 0.128]
Author clientele,	0.221	0.217
$\gamma = \mu_\xi \sigma_{\xi r}$	0.086	0.086
	[0.052, 0.390]	[0.048, 0.386]

Notes: Column (a); Maximum likelihood logit estimates of $\alpha_i + \mu_\xi \sigma_{\xi r}$ and α_i (Table 2), and bootstrap estimates of γ and standard errors computed from 500 replications; Column (b): Bootstrap estimates of all parameters with correction for the incidental parameters problem and computed from 500 replications.

Table 4. Author submissions

VARIABLES	(a) Basic	(b) Controlling for team size	(c) All fixed effects
Recent publications ≥ 1	0.067***	0.092***	0.147***
	(0.024)	(0.026)	(0.048)
Team size FE	No	Yes	Yes
Topic x journal FE	No	No	Yes
Topic x year FE	No	No	Yes
Journal x year FE	No	No	Yes
Observations	29,184	29,184	29,184
lnL	-20,181	-20,171	-6,428
Marg effect of ≥ 1 recent pubn	0.067	0.092	0.147
Baseline outcome (no recent publications)	0.464	0.465	0.467

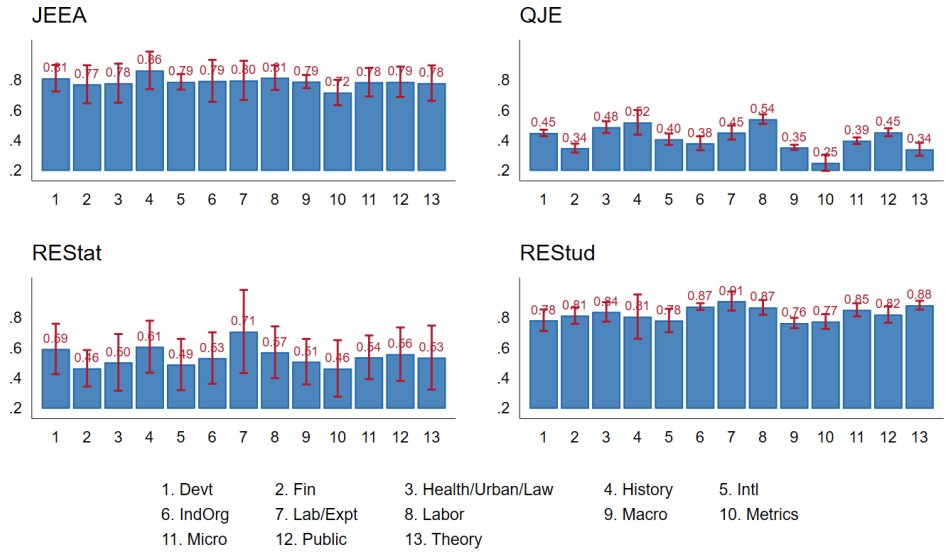
Notes: Estimated by logit, Stata routine logit, on dataset of manuscripts. Dependent variable: Indicator of whether manuscript was submitted to journal with one or more editors specializing in the fields of the manuscript. Robust standard errors (***p < 0.01 **p < 0.05 *p < 0.1).

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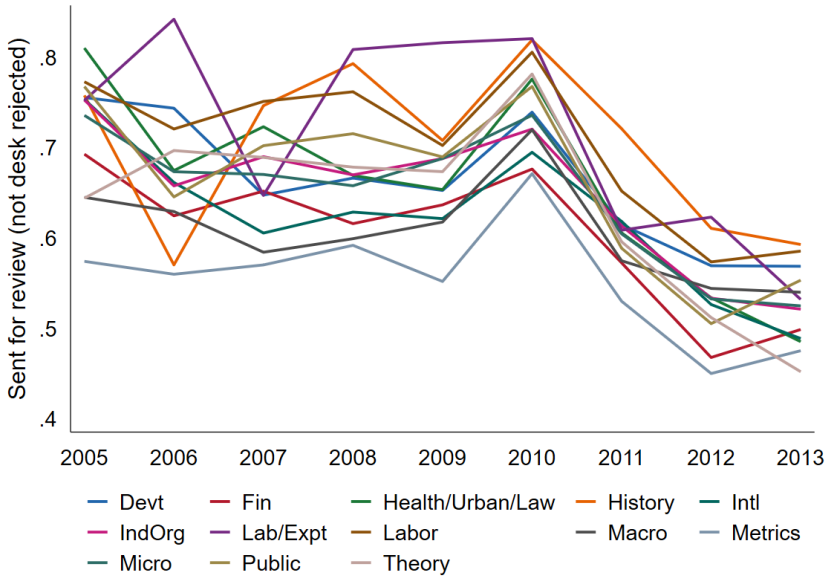
Appendix A. Manuscript analysis: Specification

Figure A1. Editor decision: Sent for review (not desk rejected)

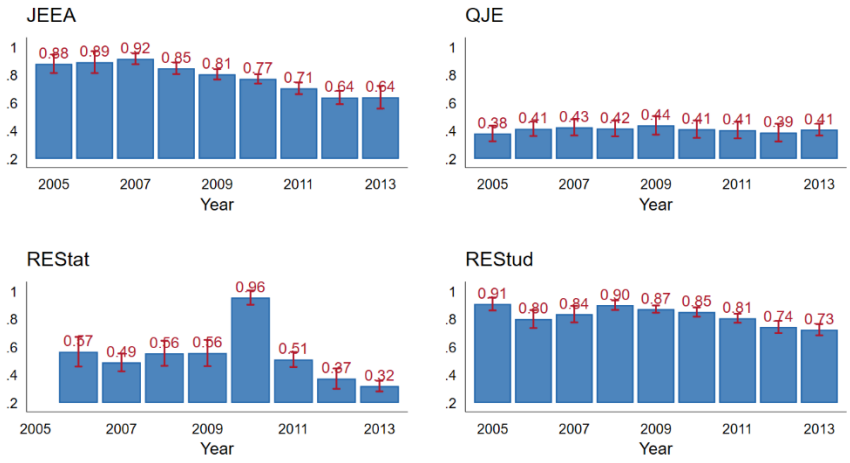
A. By field × journal



B. By field × year



C. By journal × year



Notes: Figures based on manuscript data consolidated to a panel comprising 455 observations by field, journal, and year. Manuscripts with multiple fields represented multiple times, once in each field; Manuscripts submitted to multiple journals represented once in each journal.

Table A1. Sent for review: Alternative specifications

VARIABLES	(a) Basic	(b) Author charact-eristics	(c) Editor FE	(d) Editor leniency	(e) Author, editor controls	(f) Field-year FE	(g) Field-journal FE	(h) Journal-year FE	(i) Complete specif-ication
Specializing editor	0.308***	0.302***	0.146***	0.156***	0.139**	0.159***	0.197***	0.140**	0.237***
	(0.092)	(0.100)	(0.052)	(0.056)	(0.061)	(0.043)	(0.059)	(0.059)	(0.054)
Editor leniency				4.729***					
				(0.169)					
Editors	49	49	49	49	49	49	49	49	49
Observations	29,184	29,184	29,184	29,184	29,184	29,184	29,184	29,184	29,184
lnL	-19,805	-18,396	-17,002	-16,876	-15,256	-14,935	-14,947	-15,116	-14,722
Author controls	No	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Editor FE	No	No	Yes	No	Yes	Yes	Yes	Yes	Yes
Field x year FE	No	No	No	No	No	Yes	No	No	Yes
Field x journal FE	No	No	No	No	No	No	Yes	No	Yes
Journal x year FE	No	No	No	No	No	No	No	Yes	Yes
Marginal effect	0.062	0.053	0.031	0.032	0.025	0.026	0.034	0.025	0.037
Baseline prob of review (no specializing editor)	0.550	0.554	0.564	0.564	0.567	0.567	0.563	0.568	0.562

Notes: Estimated by Logit, Stata routine logit; Dependent variable: Whether manuscript was sent for review. Column (a): Baseline specification including presence of specializing editor; Column (b): Baseline specification plus author characteristics; Column (c): Baseline specification plus fixed effects for editor; Column (d): Baseline specification plus author characteristics and fixed effects for editor; Column (e): Specification (d) plus fixed effects for field x journal; Column (f): Specification (d) plus fixed effects for field x year; Column (g): Specification (d) plus fixed effects for journal x year; Column (h): Specification (d) plus fixed effects for journal x year; Column (i): Complete specification including author characteristics and fixed effects for editor, field x journal, field x year, and journal x year. Baseline probability of review (no specializing editor) varies with estimation sample due to the logit estimator dropping observations that predict success or failure perfectly. Robust standard errors clustered by editor (***p < 0.01 **p < 0.05 *p < 0.1).

Appendix B. Mechanism

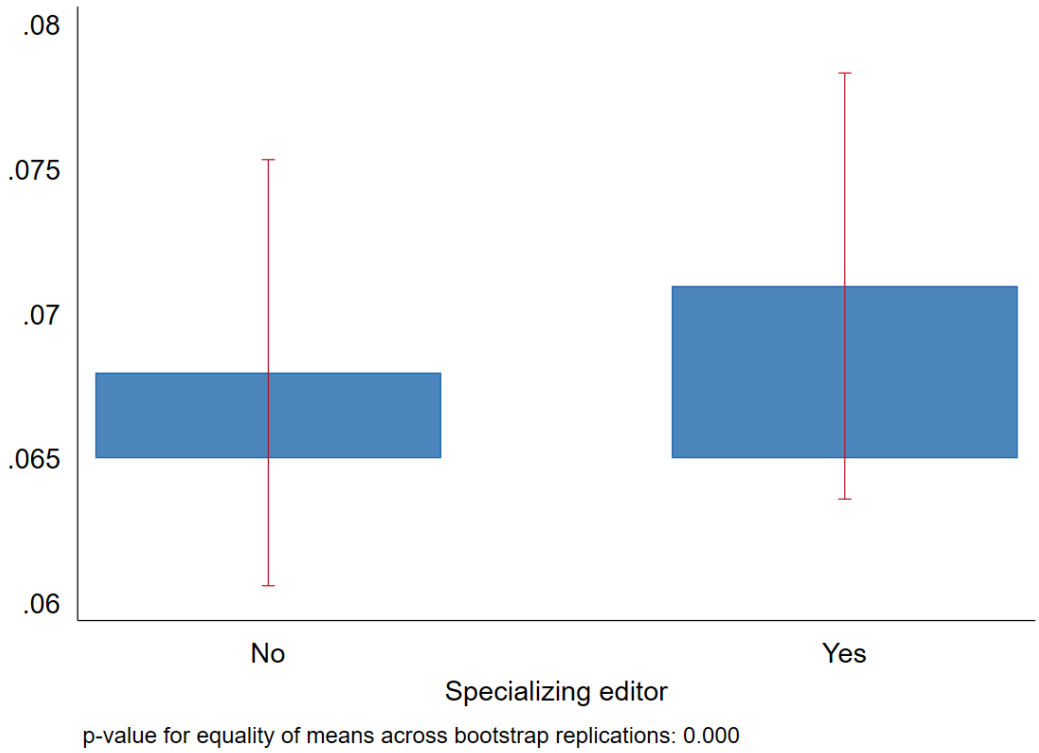
Table B1. Panel data estimates: Submissions, editor decisions

VARIABLES	(a) Submi-ssions	(b) Sent for review	(c) Sent for review	(d) Invited to revise & resubmit (R&R)	(e) Invited to revise & resubmit (R&R)
Specializing editor	0.023	0.071***	0.060***	0.060	0.022
	(0.014)	(0.020)	(0.021)	(0.056)	(0.055)
Number of submissions			0.004***		-0.001
			(0.000)		(0.001)
Number sent for review					0.006***
					(0.002)
Field x journal FE	Yes	Yes	Yes	Yes	Yes
Field x year FE	Yes	Yes	Yes	Yes	Yes
Journal x year FE	Yes	Yes	Yes	Yes	Yes
Journal-year	35	35	35	35	35
Observations	490	490	490	490	490
lnL	-1,669	-1,559	-1,528	-1,027	-1,022
Marginal effect	2.650	4.768	4.032	0.480	0.174
Baseline outcome (no specializing editor)	36.769	32.621	65.001	2.966	7.937

Notes: Estimated by Poisson Quasi Maximum Likelihood, Stata routine PPMLHDFE, on manuscript data consolidated to a panel comprising 455 observations by field, journal, and year. Manuscripts with multiple fields represented multiple times, once in each field; manuscripts submitted to multiple journals represented once in each journal. Column (a): Dependent variable: Number of manuscripts submitted; Columns (b)-(c): Dependent variable: Number of manuscripts sent for review; Columns (d)-(e): Dependent variable: Number of manuscripts invited for R&R. Marginal effect is the proportionate effect of Specializing editor on outcome. Baseline outcome (no specializing editor) varies with estimation sample due to the Poisson estimator dropping groups in which the outcome is constant. Robust standard errors clustered by journal interacted with year (***p < 0.01 **p < 0.05 *p < 0.1).

Appendix C. Consequences

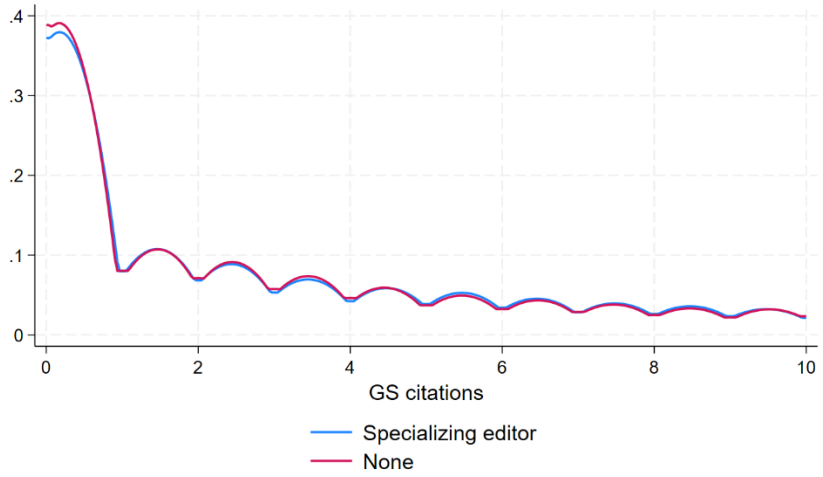
Figure C1. R&R



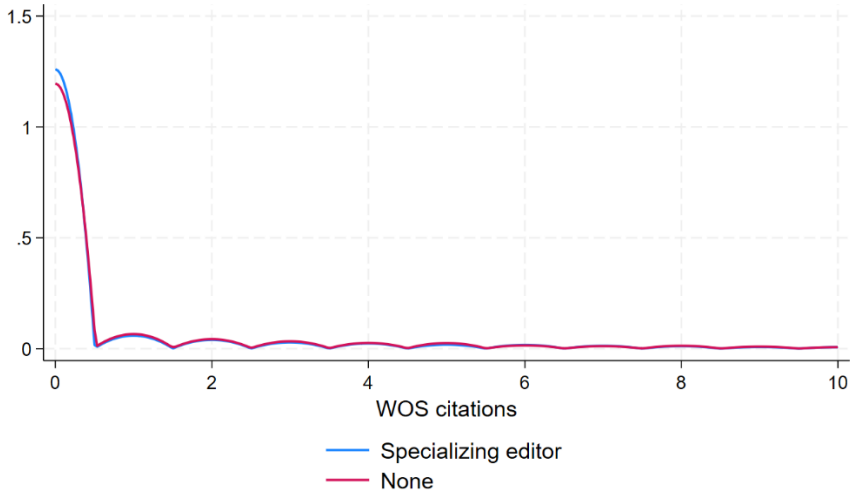
Notes: Unconditional probability of receiving a revise and resubmit computed using the probability of being sent for review multiplied by the probability of receiving a positive referee report conditional on being sent for review multiplied by the probability of receiving a revise and resubmit conditional on receiving a positive referee report.

Figure C2. Citations

A. Google Scholar



B. Web of Science



Notes: Graphs depict kernel density of citations of manuscripts. A very small minority of manuscripts attracted larger numbers of citations, so for better visibility, the graphs are limited to manuscripts with 10 or fewer citations.

Table C1. Citations

VARIABLES	(a) Google Scholar: All manuscripts	(b) Google Scholar: Sent for review	(c) Google Scholar: R&R	(d) Web of Science: All manuscripts	(e) Web of Science: Sent for review	(f) Web of Science: R&R
Specializing editor	0.019	0.003	0.024	-0.071	-0.051	-0.005
	(0.031)	(0.037)	(0.033)	(0.050)	(0.057)	(0.055)
Sent for review	0.464			0.411		
	(0.336)			(0.418)		
Control function for	0.199			0.072		
selection into review	(0.171)			(0.225)		
Revise and resubmit	0.657***	0.815***		1.247***	1.672***	
	(0.144)	(0.195)		(0.193)	(0.273)	
Control function for	0.124*	-0.158	0.233***	0.019	-0.411***	0.383***
selection into R&R	(0.072)	(0.100)	(0.025)	(0.093)	(0.141)	(0.053)
Editors	49	49	49	47	46	45
Observations	29,184	16,901	14,095	28,992	16,737	13,691
lnL	-525,466	-345,594	-306,093	-93,241	-61,885	-54,214
Author controls	Yes	Yes	Yes	Yes	Yes	Yes
Editor FE	Yes	Yes	Yes	Yes	Yes	Yes
Field x journal FE	Yes	Yes	Yes	Yes	Yes	Yes
Field x year FE	Yes	Yes	Yes	Yes	Yes	Yes
Journal x year FE	Yes	Yes	Yes	Yes	Yes	Yes
Marginal effect	0.39	0.09	0.77	-0.16	-0.16	-0.02
Baseline mean citations	20.4	28.4	31.0	2.3	3.1	3.4
Baseline median citations	11.8	17.2	19.5	0.9	1.1	1.3

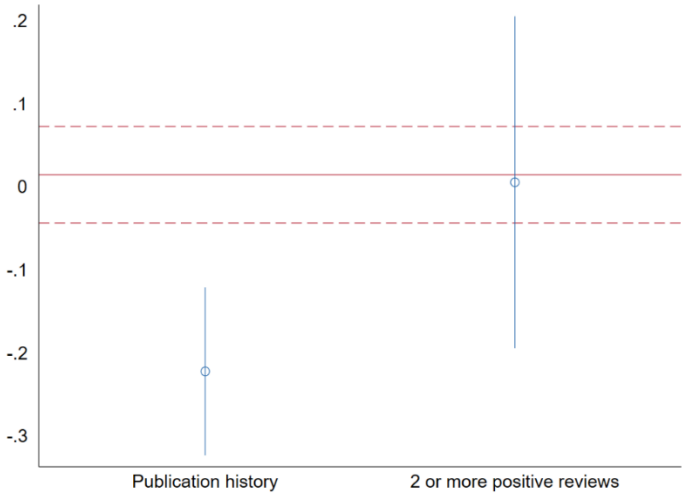
Notes: Estimated by Poisson Quasi Maximum Likelihood, Stata routine PPMLHDFE. Dependent variable: Citations (Google Scholar or Web of Science as indicated in column header). Columns (a) and (d): Including control functions for sent for review and R&R on sample of all manuscripts; Columns (b) and (e): Including control function for sent for review and R&R on sample of manuscripts that were sent for review; Columns (c) and (f): Including control function for R&R on sample of manuscripts that received two or more referee reports. Marginal effect is proportionate effect of specializing editor on

outcome. Robust standard errors clustered by journal interacted with year (***p < 0.01 **p < 0.05 *p < 0.1).

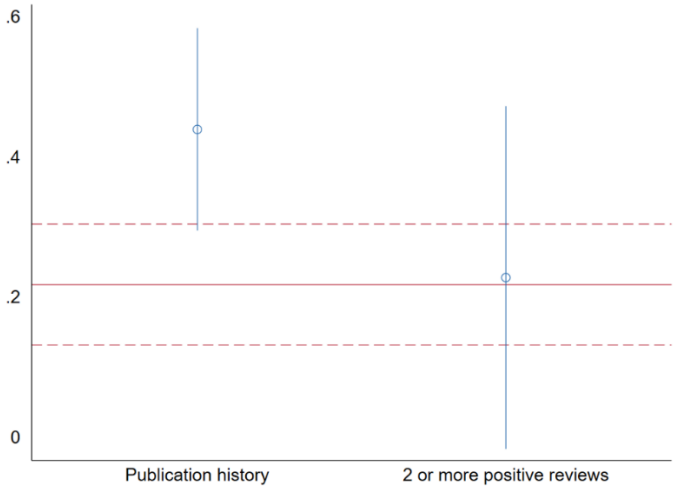
Appendix D. Robustness Tests

Figure D1. Robustness Tests

A. Bias-corrected estimates of α



B. Bias-corrected estimates of γ



Notes: Robustness checks computing bootstrap-based bias-corrected estimates of structural parameters α and γ using alternative specifications of editor specialization (r_{mi}) and favorable referee reports (RefPos). Publication history refers to specifying that an editor specializes in a topic if they have published the most papers in that topic over all years up to the year of interest. 2 or more positive reviews refers to specifying that RefPos takes the value of 1 only if two or more referees recommend that the paper be accepted. Solid red lines indicate point estimates using the main specification, while dashed red lines indicate 95% confidence intervals around these point estimates.