Submissions related to editors' research are more likely to succeed: Evidence from economics journals

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March 3, 2026

Abstract

Examining the editorial process at four leading economics journals, we find that editors were less likely to desk reject manuscripts related to their own research interests. This result is robust to controls for research trends, journal missions and time-varying journal characteristics. We use information on latent manuscript quality revealed by referee reports to ascertain the mechanism—whether editorial favoritism or strategic submissions by authors. Structural estimates point to the latter. Consistent with this interpretation, more productive scholars were disproportionately likely to submit related manuscripts. Finally, editors' research interests did not affect the downstream decision to invite revisions.

Keywords: Economics, research, journals, gatekeeping, curation

JEL codes: A11, A14, D82, L31, O31

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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.

Here, we investigate how research is evaluated when decision makers are endowed with significant discretion and judgments may be more subjective. By contrast with natural sciences, the social sciences are less disciplined by empirical testing, introducing randomness in the evaluation of quality. 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 (Card and DellaVigna, 2013), we find robust evidence that editors' research interests mattered in the editorial process. At the initial screening, manuscripts in fields related to the editors' research were 7.5 percentage points more likely to be sent for review (rather than desk rejected), or 13.8 percent of the 54.4 percentage points baseline for unrelated manuscripts (Figure 1). 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). Importantly, the advantage of related over unrelated manuscripts persisted through to the invitation to revise-and-resubmit (R&R), the last stage observed in the data.

– Figure 1. Sent for review (not desk rejected): Effect of specializing editor –

Why did the research interests of journal editors affect their decision to send manuscripts for review? One possible mechanism is that authors, attuned to editors' research interests, submitted related manuscripts which were more likely to pass the quality threshold

[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.

to be sent for review ("author clientele") (Kim and Koh, 2014; Heckman and Moktan, 2020). Another is that editors deliberately favored manuscripts of personal interest and were willing to lowered the threshold for review ("editor favoritism") (Ductor and Visser, 2022). The main empirical challenge is that when examining the effect of editors' research interests on the outcome of manuscript submissions, these two explanations are observationally equivalent.

We overcome this constraint by exploiting the information on latent manuscript quality inherent in referee reports. Our identification argument is simple. If editors indeed practiced favoritism at the initial screening to send for review, then manuscripts in fields related to journal editors' interests should have been of lower average quality than unrelated manuscripts. This produces an empirically testable implication: conditional on being sent for review, manuscripts handled by a specializing editor should have been less likely to receive a positive referee report than manuscripts handled by a non-specializing editor. We find no evidence of this.[2]

Next, using a model of editorial screening to structure our empirical strategy, we separately recover estimates of author clientele and editorial favoritism. Empirically, at initial screening, the author clientele effect was large and precisely estimated whereas editor favoritism was small and not significant. We also do not find evidence of editorial favoritism at the R&R stage.

Exploring the author clientele effect further, we find an increase in submissions of related manuscripts. After controlling for this increase, we still find that related manuscripts were more likely to be sent for review, indicating that the presence of a specializing editor might also alter the quality distribution of manuscripts. Moreover, 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.

This paper contributes to the literature on the production of knowledge and how science advances. Previous studies, in the context of biomedical sciences, yielded mixed findings on whether research is directed by an elite. Members of National Institutes of Health

[2]We checked and found evidence suggesting that editors did not select referees for related manuscripts differently from unrelated manuscripts.

funding panels favored proposals related to their own research, but the research produced better cited work (Li, 2017). Journals tended to publish more papers related to their editors' own research, but the observed effect of journal editors diminished substantially after accounting for journal missions and research trends (Krieger et al., 2025).

Our findings also contribute to understanding the institutions of curation. Wine critics' personal judgments shape consumer choices (Taplin, 2006) and news media and algorithmic platforms select content to publish (Gentzkow and Shapiro, 2010; Corniere and Taylor, 2014; Qian and Jain, 2024). Here, in the context of economics, we show that manuscripts related to the research of journal editors were more likely to pass the review process.

Finally, we add to a finer understanding of the performance of economics journals (Cherkashin et al., 2009; Card et al., 2020b; Brodeur et al., 2023; Ham et al., 2026; 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; 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, who attract submissions in their field. 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).

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

2 Model of Screening

Our framework models the three outcomes observed in the data—the probability that a manuscript is sent for review, the probability it receives a favorable referee recommendation, and the probability it is invited for R&R—as functions of the characteristics of the manuscript, handling editor, and referee. Consider a submitted manuscript m evaluated by editor i. We assume that the goal of each stage in the review process is to determine whether the manuscript crosses the quality threshold for publication, $\bar{q}$.

2.1 Initial Screening

Editor i evaluates manuscript m based on its characteristics and their own preferences. Suppose that the editor evaluates the quality to be

$$q_{mi} = \underbrace{\xi_m}_{\text{true quality}} + \underbrace{\alpha d_{mi} + \kappa_i + \varepsilon_{mi}}_{\text{editor-specific evaluation}}, \tag{1}$$

and sends the manuscript for review if $q_{mi} \geq \bar{q}$. In equation (1), ξ_m is the true quality of the manuscript, $d_{mi} = 1$ if the manuscript fits the editor's field of specialization and $d_{mi} = 0$ otherwise, κ_i represents editor-specific characteristics, and ε_{mi} is a random shock. This shock takes the intuitive interpretation as a noisy signal in the initial screening process. The parameter α characterizes the editor's favoritism toward manuscripts in their own field.

The challenge to identification is that the editor observes the characteristics of the manuscript which the econometrician does not. For simplicity, suppose that the true quality ξ_m is unobservable. In particular, if authors submit manuscripts of higher quality to editors in their field (an author clientele effect), then the true quality ξ_m would be correlated with the editor-field match d_{mi}. To allow explicitly for this possibility, let

$$\xi_m = \breve{\xi}_m + \gamma d_{mi}. \tag{2}$$

Then, by (1), the editor's evaluation $q_{mi} \geq \bar{q}$ if and only if

$$\varepsilon_{mi} + \breve{\xi}_m \geq \bar{q} - [\alpha + \gamma] d_{mi} - \kappa_i. \tag{3}$$

We stipulate that ε_{mi} and $\breve{\xi}_m$ are independent and follow normal distributions $\mathcal{N}(0, \frac{1}{2})$. Then, the probability of manuscript m being sent for review, conditional on observables, is

$$\mathbb{P}(\text{SFR}_m = 1 \mid d_{mi}, i) = 1 - \Phi\Big(\bar{q} - [\alpha + \gamma] d_{mi} - \kappa_i\Big). \tag{4}$$

A naive estimate of the probability of being sent for review would yield the effect of editor-field match as $-[\alpha + \gamma]$. This estimate combines the author clientele effect and editorial favoritism. In order to distinguish the two mechanisms, we exploit data on referee recommendations.

2.2 Referee Recommendation

Suppose that $q_{mi} \geq \bar{q}$ and the editor sends manuscript m to referee r, and the referee evaluates the quality of the manuscript as

$$q_{mr} = \xi_m + \eta d_{mr} + \kappa_r + \varepsilon_{mr}, \tag{5}$$

and gives a positive recommendation, $\text{RefPositive}_m = 1$, if $q_{mr} \geq \bar{q}$. In equation (5), $d_{mr} = 1$ if the manuscript fits the referee's field of specialization and $d_{mr} = 0$ otherwise, η is the referee's preference for manuscripts in their field, κ_r represents referee-specific characteristics, and ε_{mr} is the shock in the signal the referee receives.

It is reasonable to assume that the referee specializes in the field, $d_{mr} = 1$, and so the evaluation simplifies to

$$q_{mr} = \xi_m + \eta + \kappa_r + \varepsilon_{mr}. \tag{6}$$

Recall that the referee received the manuscript only because the editor decided that $\text{SFR}_m = 1$, i.e., $q_{mi} \geq \bar{q}$. Substituting from (1) for ξ_m in (6),

$$q_{mr} = \Big[q_{mi} - [\alpha d_{mi} + \kappa_i + \varepsilon_{mi}]\Big] + \eta + \kappa_r + \varepsilon_{mr} \geq \bar{q} - [\alpha d_{mi} + \kappa_i + \varepsilon_{mi}] + \eta + \kappa_r + \varepsilon_{mr}.$$

Thus, $q_{mr} \geq \bar{q}$ if $-[\alpha d_{mi} + \kappa_i + \varepsilon_{mi}] + \eta + \kappa_r + \varepsilon_{mr} \geq 0$, i.e.,

$$\varepsilon_{mr} - \varepsilon_{mi} \geq \alpha d_{mi} + \kappa_i - \eta - \kappa_r. \tag{7}$$

Stipulate that ε_{mr} is independent from ε_{mi}, and $\varepsilon_{mr} \sim \mathcal{N}(0, \frac{1}{2})$, and so, the distribution of $\varepsilon_{mr} - \varepsilon_{mi}$ is standard normal. Then the probability that the referee submits a positive recommendation,

$$\mathbb{P}(\text{RefPositive}_m = 1 \mid \text{SFR}_m = 1) = 1 - \Phi(\alpha d_{mi} + \kappa_i - \eta - \kappa_r). \tag{8}$$

Thus, in the estimate of the probability of a favorable referee recommendation in the sample of manuscripts sent for review, the effect of a manuscript fitting the editor's field, d_{mi}, is proportional to editorial favoritism, α.

The essence of the identification strategy is that the referee only receives manuscripts

that meet the editor's minimum quality threshold. This abstracts the referee evaluation from the unobserved quality of the manuscript and so identifies editorial favoritism. This identification strategy depends on the assumption that the error in the referee's evaluation is uncorrelated with whether the manuscript is in the editor's field, i.e. $\mathbb{E}[\varepsilon_{mr}|d_{mi}] = \mathbb{E}[\varepsilon_{mr}]$. We justify this assumption in Section 6 below.

2.3 R&R

We further examine possible editorial favoritism at the R&R stage. At this stage, the editor i would have the report of the referee r. Accordingly, we specify the editor's evaluation of quality to be a function of the characteristics of the manuscript, referee's report, and editor's own preference,

$$q_{mi}^{R\&R} = \xi_m + \alpha^{R\&R} d_{mi} + \zeta q_{mr} + \varepsilon_{mi}^{R\&R}. \tag{9}$$

In equation (9), ζ characterizes the editor's responsiveness to the referee report and $\varepsilon_{mi}^{R\&R}$ is random error. The editor might exercise a different degree of favoritism at R&R than at initial screening, $\alpha^{R\&R} \neq \alpha$.

The challenge in estimating (9) is that the data reveal only whether the referee recommendation was positive, RefPositive_m, whereas the editor had access to the referee's report, which would contain more information than the recommendation as such which is what the data reveal. The part of the referee's report beyond that characterized by RefPositive_m might be correlated with d_{mi} through the author-clientele mechanism described above, biasing any estimate of $\alpha^{R\&R}$.

To overcome this challenge, we build a control function λ_m for ξ_m using the referee's recommendation. This motivates the following estimating equation:

$$q_{mi}^{R\&R} = \alpha^{R\&R} d_{mi} + \zeta \cdot \text{RefPositive}_m + \lambda_m + \varepsilon_{mi}^{R\&R}, \tag{10}$$

where

$$\lambda_m = \begin{cases} \dfrac{\phi(\alpha d_{mi} + \kappa_i - \eta - \kappa_r)}{1 - \Phi(\alpha d_{mi} + \kappa_i - \eta - \kappa_r)} & \text{if } \text{RefPositive}_m = 1, \\ \dfrac{-\phi(\alpha d_{mi} + \kappa_i - \eta - \kappa_r)}{\Phi(\alpha d_{mi} + \kappa_i - \eta - \kappa_r)} & \text{if } \text{RefPositive}_m = 0, \end{cases} \tag{11}$$

$\varepsilon_{mi}^{R\&R}$ is screening noise at the R&R stage, and $\Phi(\cdot)$ is the cumulative standard normal

distribution and $\phi(\cdot)$ is the probability density function.

The identifying assumption is that $\mathbb{E}[\xi_m|\lambda_m, d_{mi}] = \mathbb{E}[\xi_m|\lambda_m]$, which means that after controlling for the information revealed by the referee report about the latent quality of the manuscript, λ_m, any remaining variation in quality is orthogonal to whether the manuscript was in the editor's field. Under this assumption, $\alpha^{R\&R}$ characterizes editorial favoritism at the R&R stage rather than residual differences in quality.

3 Estimation Strategy

We seek to estimate the parameters characterizing author clientele at submission, γ, editor favoritism at the initial screening, α, and editor favoritism at the R&R stage, $\alpha^{R\&R}$. We jointly estimate equations (4) and (8) by maximum likelihood to recover editorial favoritism, α, and the combined effect of editorial favoritism and author clientele, $\alpha + \gamma$, respectively. Then, we derive the model-implied estimate of the author clientele effect, γ. As we do not observe the identity of the handling editor for each manuscript, we stipulate that manuscripts submitted in editors' field of interest are always handled by those editors, and otherwise are randomly distributed among editors with unrelated research interests.

Then, the estimating equations, for manuscript m and journal j, are

$$\mathbb{P}(\text{SFR}_{mij} = 1) = \Phi\Big([\alpha + \gamma] \cdot \text{Specializing editor}_{mj} + Z'_m\beta_1 + Z_{mij}\Big) \tag{12}$$

and

$$\mathbb{P}(\text{RefPositive}_{mij}|\text{SFR}_{mij} = 1) = \Phi\Big(\alpha \cdot \text{Specializing editor}_{mj} + Z'_m\beta_2 + Z_{mij}\Big), \tag{13}$$

In the system (12) and (13), the key explanatory variable is the indicator of whether the manuscript is related to the research interests of the journal editors, $\text{Specializing editor}_{mj}$, and the controls, Z_m, include observable manuscript characteristics which proxy for quality (publications of the most published coauthor and number of coauthors) (Card and DellaVigna, 2020a). The parameters, β_1 and β_2 are coefficients on these controls. We further include a matrix of fixed effects Z_{mij}, which includes editor-journal fixed effects to control for editor-specific preferences as well as fixed effects explained next.

One possible threat to identification is the omission of factors that affect both the research interests of journal editors and the publishing outcomes for manuscripts submitted

to the journal. Appendix A Figure A1 shows substantial variation in the decision to send manuscripts for review across field-year, field-journal, and journal-year dimensions, which may also be correlated with editorial appointments and editors' research interests.

We therefore also control for these dimensions to isolate the variation relevant for our empirical strategy in the fixed effects Z_{mij}. Specifically, we include journal-year fixed effects to allow for temporal heterogeneity in the quality threshold owing to journal-specific publishing trends. Following Krieger et al. (2025), we also include field-year and field-journal fixed effects, which allow the threshold to depend on trends in research and journal-specific missions.

Finally, to estimate editorial favoritism at the R&R stage, we use a two-step control-function approach. In the first step, we estimate equation (13) and use the fitted model to construct the conditional expectation of latent manuscript quality, given the referee recommendation, $\hat{\lambda}_{mij}$. In the second step, we include this estimated control function in a probit estimate of the R&R decision

$$\begin{aligned}&\mathbb{P}(\text{R\&R}_{mij} = 1 \mid \text{SFR}_{mij} = 1)\\&= \Phi\Big(\alpha^{RR} \cdot \text{Specializing editor}_{mj} + Z_m'\beta_3 + Z_{mij} + \zeta \cdot \text{RefPositive}_{mij} + \hat{\lambda}_{mij}\Big). \qquad (14)\end{aligned}$$

4 Data

Our main 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., 2025), we exploit the periodic rotation of journal editors to identify their effect, drawing on data from two sources.

The first 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' recommen-

dations, 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) as declared by the manuscript authors (Card and DellaVigna, 2013).[3]

The second is a novel dataset on the research interests of editors at the four journals over the period of 2005-2013. 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 manually collected information on their start and end years of appointment and then scraped their publications from the IDEAS/RePEc service, obtaining 2,844 publications in total. We classified editors' publications into the same 14 fields by JEL codes as the manuscript dataset and defined the editor's specialization by year as the field(s) in which they published the most number of articles in the preceding 10 years. A robustness check defines an editor's specialization by their entire publication history (Krieger et al., 2025).

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 reveal the editor responsible for each manuscript. Accordingly, we focused 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 the fields of the manuscript. The indicator is specific to a manuscript and journal. This definition of Specializing editor$_{mj}$ implicitly stipulates that manuscripts in fields of journal editors' specializations are always assigned to a specializing editor, whereas manuscripts in other fields were assigned at random to

[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.

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

editors who did not specialize in the fields of the manuscript.

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. Of the manuscripts that were sent for review, an average of 0.323 received one or more positive referee reports (revise and resubmit (R&R), strong R&R, or accept) and 0.134 was invited for R&R.

— Table 1. Summary statistics —

5 Results

We begin by examining whether editorial outcomes differed for manuscripts submitted to journals with editors specializing in the field(s) of the manuscript. Table 2 reports the maximum likelihood probit estimates. Standard errors are clustered at the journal-editor level, the level at which the outcome variables may be correlated (Abadie et al., 2023). Table 2 column (a) presents the estimate of equation (12) for the editor decision at initial screening whether to send the manuscript for review (not desk reject).

– Table 2. Editorial process: Effect of specializing editor –

The coefficient of specializing editor, which represents the combination of author clientele and editor favoritism, 0.141 (s.e. 0.031), is positive and significant. It 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 estimated effect without controls (Figure 1). Relative to the baseline 56.0 percent probability of manuscripts with no specializing editor being sent for review, the effect is economically meaningful.[5] Appendix A Table A1 presents estimates that explore the effects of controls for author and editor characteristics, research trends, and journal missions and publishing trends.

Table 2 column (b) reports the estimate of equation (13) of the indicator of one or more positive referee recommendations, which identifies editor favoritism. The coefficient of specializing editor, -0.009 (s.e. 0.033), is negative, small in magnitude, and not significantly different from zero.

[5]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.

Table 2 column (c) reports the estimate of equation (14) for the editor's decision to invite an R&R. The coefficient of specializing editor, $\alpha_i^{R\&R} = -0.014$ (s.e. 0.048), is negative, small in magnitude, and not statistically significant.

By calculating the rates at which manuscripts proceeded through each stage of the review process—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)—-we can compute the overall likelihood of related vis-a-vis unrelated manuscripts being invited to R&R. Referring to Figure 3, the unconditional likelihood that an unrelated manuscript was invited to R&R is 0.068 whereas that for a related manuscript is 0.071 or 4.4 percent larger. By a t-test, the null hypothesis that the mean R&R rates are equal for unrelated and related manuscripts across bootstrap replications is rejected ($p < 0.001$).

– Figure 3. Invitation to revise-and-resubmit: Effect of specializing editor –

5.1 Mechanism

Table 3 reports the structural estimates of the author clientele effect, γ, and editor favoritism, α. Standard errors of the author clientele effect are computed using the delta method. Editor favoritism at the R&R stage, α^{RR}, is estimated via a two-step procedure. Because standard errors in the second step do not account for first-stage sampling variation, we report bootstrap standard errors. Moreover, we also apply a bootstrap procedure to correct for possible bias due to incidental parameters (Higgins and Jochmans, 2024).

— Table 3. Editorial process: Mechanisms —

Across the two sets of estimates, editor favoritism in initial manuscript screening is slightly negative and not significant. Author clientele is statistically significant and between 3 and 6 times the absolute magnitude of editor favoritism. A back-of-the-envelope calculation suggests the latent quality improvement for a manuscript submission in the editor's field translates to a 1.82% increase in the likelihood of being sent for review, relative to the baseline. As for the R&R stage, there is no evidence of editor favoritism.

To further examine the effect of editorial changes on submissions and the editorial process, we construct a panel dataset by consolidating the data of manuscripts to a panel of 490 observations by journal j, field f, and year t. Then, we estimate the following

specification:

$$Y_{jft} = \text{Specializing editor}_{jft} + W'_{jft}\theta + \varepsilon_{jft}. \tag{15}$$

In equation (15), Y_{jft} is the number of submissions, number of papers sent for review, or number invited to R&R, Specializing editor$_{jft} = 1$ if the journal had one or more editors in the relevant field whereas Specializing editor$_{jft} = 0$ otherwise, and W_{jft} comprises fixed effects to control for research trends and journal mission and trends. The outcomes of interest are counts, and so, we apply Poisson Quasi Maximum Likelihood (Silva and Tenreyro, 2011). Appendix B Table B1 reports the estimates.

In the estimate of submissions (Table B1 column (a)), the coefficient of specializing editor is positive and significant, implying that appointing one or more editors who specialized in a field attracted $4.745 \div 36.953 = 12.84\%$ more submissions in that field. This provides suggestive evidence that authors responded to changes in editorial appointments by submitting their manuscripts to journals with editors specializing in their fields.

Moreover, a specializing editor increased the number of manuscripts sent for review (Table B1 column (b)). Yet, this may be a purely mechanical effect given that a specializing editor attracted more submissions. Accordingly, referring to Table B1 column (c)), we control for the number of submissions and find that the effect, although smaller by about one-third, remains positive and significant. Combined with the evidence for the author clientele effect (Table 3), these results suggests both an increase in the number of submissions and a change in the composition of submissions.

Finally, consistent with the previous estimates, the presence of a specializing editor had no significant effect on the number of R&R invitations (Table B1 columns (d) and (e)). We interpret this as evidence that while a specializing editor attracted a higher average quality of submissions in the relevant field, they did not affect the number of submissions in the upper tail of the quality distribution—those that received an R&R.

To investigate heterogeneity in the author clientele effect, Table 4 reports estimates of whether authors differed by productivity in their probability of submitting 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 35 leading journals (Card and DellaVigna, 2020a). 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.

– Table 4. Manuscript submitted to journal with specializing editor –

Of note, the measured effect of author productivity more than doubled with controls for team size, 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.

Finally, a proviso to our findings is that we do not find differences in the quality of related vis-a-vis unrelated manuscripts as measured by Google Scholar and Web of Science citations. Referring to Appendix B Figure B1, the distributions of citations are very similar. In addition, Table B2 presents regression estimates of the citations across the samples of all manuscripts, those sent for review, and those invited to R&R, accounting for selection through control functions based on the editor leniency. The coefficients of specializing editor are positive in the estimates of Google Scholar citations but negative in Web of Science citations, and none are statistically significant. These estimates should be interpreted with caution as citations measure quality imperfectly (Hamermesh, 2018; D'Ippoliti, 2021; Koffi, 2021; Rubin and Rubin, 2021).

6 Discussion

Our reduced form estimates (Table 2) reveal that manuscripts related to editors' research interests were more likely to be sent for review. This result is robust to various sets of controls (Appendix A Table A1). In particular, 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. 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., 2025).

To identify the mechanism underlying the advantage of related manuscripts, we applied structural estimation to data on the latent quality of manuscripts revealed by referee reports (Table 3). Appendix C Table C1 shows that the structural estimates are robust to alternative measures of journal editors' interests (defined over their entire publica-

tion history rather then previous 10 years) and whether referees reviewed the manuscript positively (two or more positive referee reports rather than one or more). Still, we acknowledge that the identification strategy relied on an assumption that the error in the referee's evaluation was uncorrelated with whether the manuscript lies in the editor's research field. Appendix C Tables C2 and C3 reports tests of the two most plausible violations of this assumption—that editors exhibited favoritism by selecting lenient referees and that referees tailored their reports to the editor's research interests. We find no evidence of either.

Referring to the panel estimates (Appendix B Table B1), total submissions increased with editor specialization. In the estimates of manuscripts sent for review, the coefficient of specializing editor was about one-third smaller with control for submissions than without. Collectively, these results (Table 3 and Appendix B Table B1) suggest that the author clientele mechanism both changed the quantity and composition of submissions towards related submissions that were more likely to cross the threshold for review.

The estimates of manuscript submissions (Table 4) reveal 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. 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, suggesting 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.

While more productive scholars increased submissions of related manuscripts, the editor's decision to send for review did not vary with author characteristics (Appendix A Table A1). Apparently, in deciding whether to send a manuscript for review, editors considered only the content of the submitted manuscript and ignored the authors' background. Indeed, Card and DellaVigna (2020a) found that editors favored less established authors.

From a broader perspective, the author clientele mechanism might seem puzzling. Given that our estimates show no significant editor favoritism, why did more productive authors prefer to submit such manuscripts to the journal? One possible reason is to benefit from editorial feedback (Luo, 2024). Editors who specialize in the topic would be better able

to critique and advise on a manuscript than other editors. Another possible explanation is that editors are better able to search for and encourage the submission of high-quality papers in their own specializations, thus improving the average quality of manuscript submissions in their fields. However, subject to the imperfection of citations as a measure of quality, our analysis of citations does not support this explanation. This leaves open the possibility that the quality which editors and referees assess might be a subjective matter of taste rather than objectively measurable.

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 sent for review and proceed through to be invited to revise and resubmit. The higher success rate was due to an author clientele effect (increase in the submissions of related manuscripts and an improvement in their quality), rather than editor favoritism. More productive scholars were more likely to submit manuscripts related to the research interests of journal editors.

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 may be reinforced by social networks in the profession (Goyal et al., 2006; Fafchamps et al., 2010; Ductor and Visser, 2023), potentially contributing to the Matthew effects previously documented in the sciences (Merton, 1968; Fisman et al., 2018; Hager et al., 2024).

Relatedly, curatorial practices can also shape production itself. Our finding that editors attracted submissions of manuscripts related to their interests begs the question of whether authors adapted only their submission practices or actually tailored their research. Publication in prominent venues—especially in the "top five" journals, two of which studied here—confers substantial career benefits. 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). Future research should examine the process

by which journals select and appoint editors and the consequent effect on the direction of research.

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.

How do our results generalize to 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.

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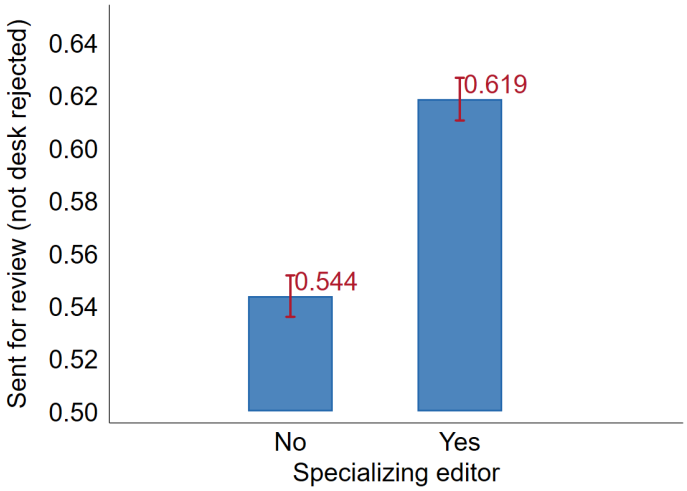
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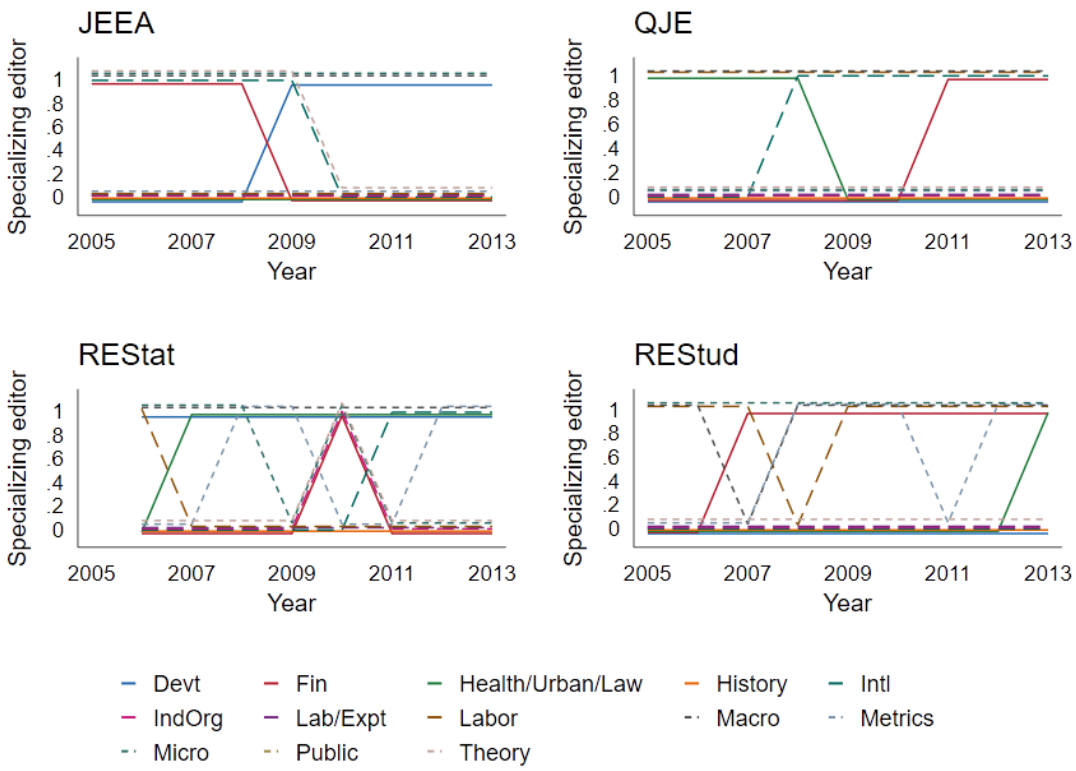
Figures and Tables

Figure 1: Sent for review (not desk rejected): Effect of specializing editor



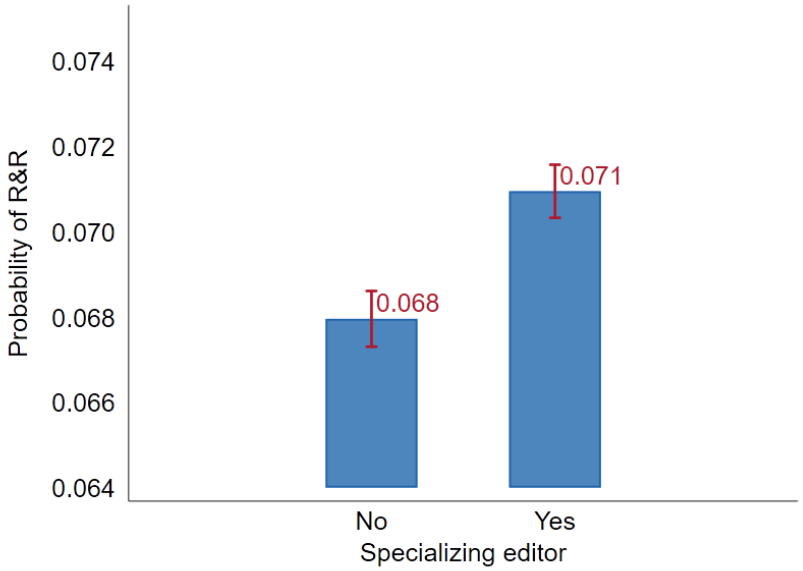
Notes: Main sample: 29,184 manuscripts. Figure depicts mean rate at which manuscripts were sent to review (not desk rejected) divided between those submitted to journals without any editor who specialized in the fields of the manuscript (no specializing editor) and one or more editors specializing in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

Figure 2: Journals: Specializing editors



Notes: Figures based on editors' publications consolidated to a panel comprising 455 observations by field, journal, and year. Editors' publications 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).

Figure 3: Invited to revise-and-resubmit: Effect of specializing editor



Notes: Sample sent for review: 16,901 manuscripts. Figure depicts mean rate at which manuscripts were invited to R&R 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). Standard errors calculated from 1000 bootstrap replications; Red bar represents 95 percent confidence interval.

Table 1: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Specializing coeditor (Specializing editor$_{mij}$)	29,184	0.47	0.50	0	1
Sent for review (SFR$_{mij}$)	29,184	0.58	0.49	0	1
One or more positive referees (RefPositive$_{mij}$)	16,901	0.32	0.47	0	1
Revise and resubmit (R&R$_{mij}$)	16,901	0.13	0.34	0	1
Google Scholar citations	29,184	20.58	50.36	0	500
WOS citations	29,184	2.20	8.36	0	100

Notes: Data compiled between April and September 2015 (Card and DellaVigna, 2020a). One or more positive referees (RefPositive$_{mij}$) and Revise and resubmit (R&R$_{mij}$) 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: Effect of specializing editor

	(a) Sent for review	(b) One or more positive referees	(c) Revise & resubmit
Specializing editor	0.141^{***}	-0.009	-0.014
	(0.031)	(0.033)	(0.048)
Author controls	Yes	Yes	Yes
Editor × FE	Yes	Yes	Yes
Field × journal FE	Yes	Yes	Yes
Field × year FE	Yes	Yes	Yes
Journal × year FE	Yes	Yes	Yes
Editor × journal clusters	49	49	49
Observations	29,202	16,901	16,901
$\ln L$	-14742.53	-9822.585	-5863.426
Baseline outcome	0.0560	0.325	0.136
Average marginal effect	0.04	-0.003	-0.003

Notes: Fields defined by Card and Dellavigna (2013); Estimated by probit. Column (a): Dependent variable is whether editors sent manuscript for review, estimated on entire sample; Column (b): Dependent variable is whether at least one referee recommended positively (revise-and-resubmit, strong revise-and-resubmit, or accept), estimated on sample of manuscripts sent for review and receiving at least two referee reports; Column (c): Dependent variable is whether invited to revise and resubmit, estimated on sample of manuscripts sent for review and receiving at least two referee reports. Robust standard errors clustered at editor-journal level (49 clusters) $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.1$.

Table 3: Author clientele and editorial favoritism: Structural estimates

Parameter	(a) Maximum likelihood estimates	(b) Estimates corrected for incidental parameters bias
Effect of specializing editor at initial screening, $\alpha + \gamma$	0.139^{***}	0.133^{***}
	(0.031)	(0.033)
Editorial favoritism at initial screening, α	-0.026	-0.064
	(0.034)	(0.035)
Author clientele, γ	0.166^{***}	0.197^{***}
	(0.049)	(0.050)
Editorial favoritism at R&R stage, $\alpha_{R\&R}$	-0.017	-0.011
	(0.056)	(0.080)
Author controls	Yes	Yes
Editor FE	Yes	Yes
Field × journal FE	Yes	Yes
Field × year FE	Yes	Yes
Journal × year FE	Yes	Yes
Observations	29,202	16,901

Notes: Column (a): $\alpha + \gamma$ and α estimated by joint maximum likelihood, standard errors clustered at journal-editor level (49 clusters). Standard errors for γ computed by delta method. $\alpha_{R\&R}$ estimated by two-step control function approach, standard errors clustered at journal-editor level (49 clusters), uncorrected for two-step approach. Column (b): Bias-correction procedure follows Higgins and Jochmans (2024), 1000 bootstrap replications. γ estimated using two-step approach within each replication due to slow convergence of joint maximum likelihood $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.1$.

Table 4: Manuscript submitted to journal with specializing editor

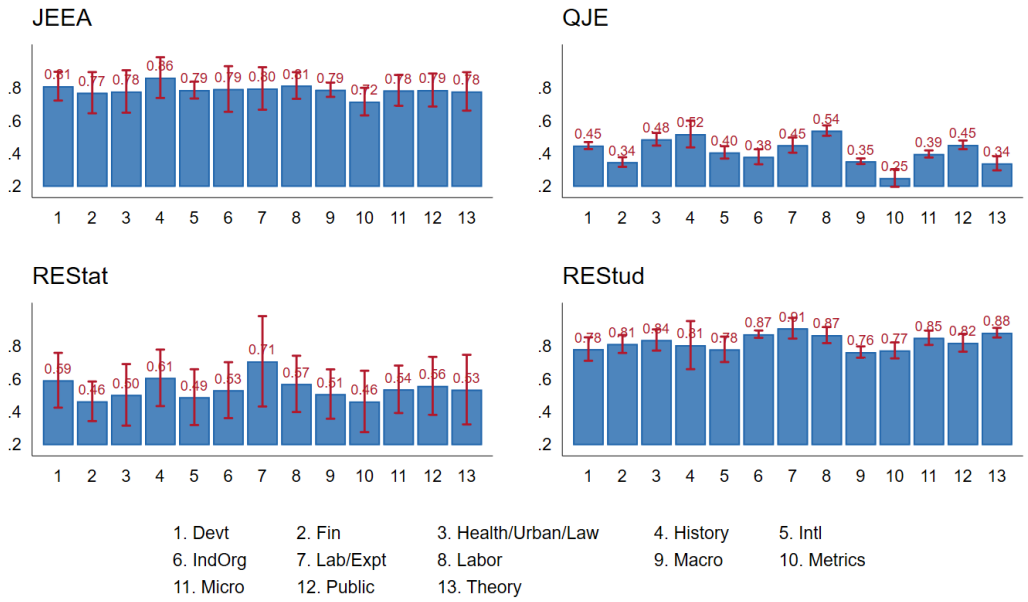
	(a) Baseline	(b) Controlling for team size	(c) All fixed effects
Specializing editor	0.067^{***}	0.092^{***}	0.147^{***}
	(0.024)	(0.026)	(0.048)
Log likelihood	$-20{,}181$	$-20{,}171$	$-6{,}428$
Marginal effect (1 publication)	0.067	0.092	0.147
Baseline publication rate	0.464	0.460	0.467
Team size controls		Yes	Yes
Topic × journal FE			Yes
Topic × year FE			Yes
Journal × year FE			Yes
Observations	29,184	29,184	29,184

Notes: Estimated by logit on dataset of all 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 $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.1$.

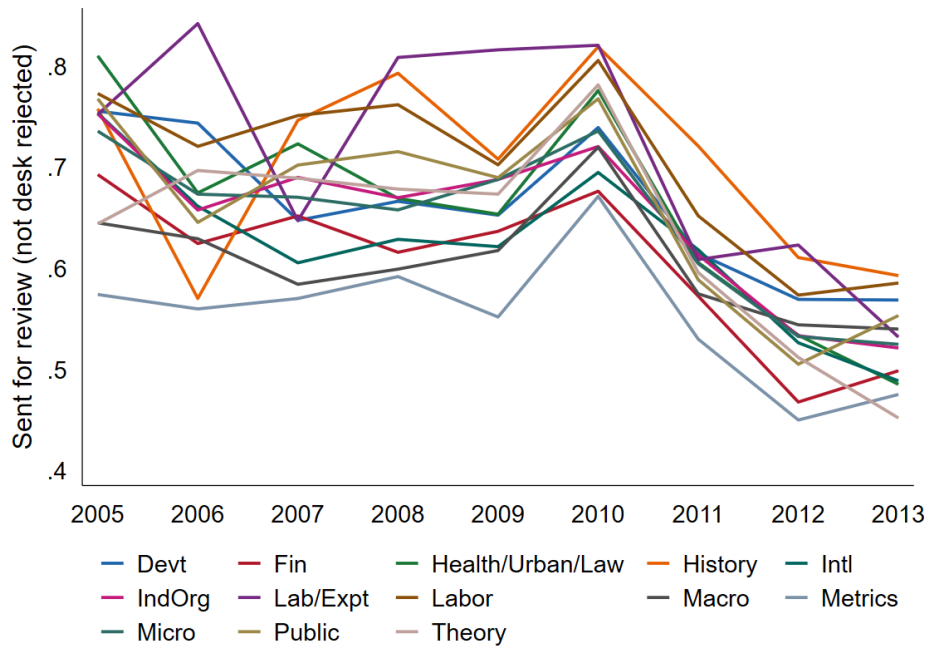
A Manuscript sent for review: Maximum likelihood probit estimates

Figure A1: Sent for review (not desk rejected): Effect of specializing editor

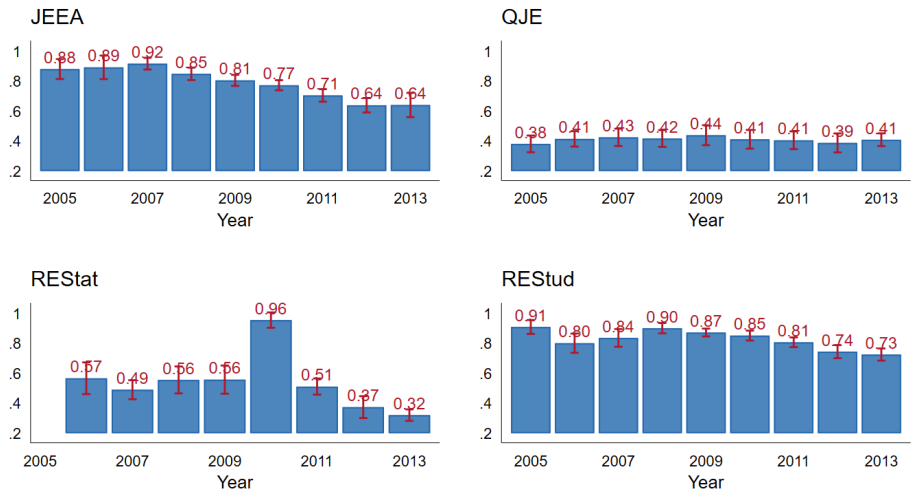
(a) By field × journal



(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 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, 0.192 (s.e. 0.057), 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 half. 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, 0.082 (s.e. 0.036), is slightly smaller than that with controls for only editor fixed effects.

Table A1: Sent for review: Editor, author, journal characteristics

	(a) Baseline	(b) Author characteristics	(c) Editor leniency	(d) Editor FE	(e) Author, editor	(f) Field-year FE	(g) Field-journal FE	(h) Journal--year FE	(i) Complete specification
Specializing editor	0.192***	0.185***	0.087***	0.094***	0.082**	0.093***	0.117***	0.082**	0.139***
	(0.057)	(0.061)	(0.031)	(0.034)	(0.036)	(0.025)	(0.035)	(0.035)	(0.032)
Recent pubs: 1		0.388***			0.448***	0.439***	0.435***	0.450***	0.438***
		(0.049)			(0.049)	(0.048)	(0.047)	(0.049)	(0.048)
Recent pubs: 2		0.569***			0.650***	0.637***	0.635***	0.652***	0.641***
		(0.051)			(0.050)	(0.048)	(0.047)	(0.049)	(0.047)
Recent pubs: 3		0.802***			0.894***	0.883***	0.886***	0.897***	0.886***
		(0.061)			(0.055)	(0.053)	(0.053)	(0.056)	(0.054)
Recent pubs: 4–5		1.011***			1.147***	1.139***	1.145***	1.151***	1.154***
		(0.081)			(0.082)	(0.081)	(0.083)	(0.082)	(0.082)
Recent pubs: 6+		1.213***			1.400***	1.400***	1.407***	1.405***	1.417***
		(0.104)			(0.100)	(0.098)	(0.096)	(0.100)	(0.096)
Authors: 2		−0.007			0.059***	0.073***	0.065***	0.060***	0.069***
		(0.037)			(0.021)	(0.020)	(0.019)	(0.021)	(0.019)
Authors: 3		−0.096			−0.021	0.008	−0.007	−0.014	0.004
		(0.059)			(0.032)	(0.028)	(0.030)	(0.031)	(0.028)
Authors: 4		−0.152*			−0.019	0.039	0.003	−0.002	0.025
		(0.087)			(0.059)	(0.055)	(0.058)	(0.057)	(0.054)
Editor leniency			2.886***						
			(0.091)						
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

Log likelihood	−19,778	−18,370	−16,988	−16,877	−15,245	−14,920	−14,937	−15,111	−14,715
Author controls	No	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Editor FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Field × jnl FE					No	No	Yes	No	Yes
Field × year FE				No	Yes	No	No	Yes	
Jnl × year FE				No	No	No	Yes	Yes	
Marginal effect	0.075	0.067	0.029	0.031	0.024	0.027	0.034	0.024	0.040
Baseline prob. sent for review	0.544	0.548	0.566	0.565	0.568	0.567	0.563	0.568	0.561

Notes: Estimated by probit. 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 × year; Column (i): Complete specification including author characteristics and fixed effects for editor, field × journal, field × year, and journal × 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 at editor-journal level (49 clusters) $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.1$.

B Mechanism

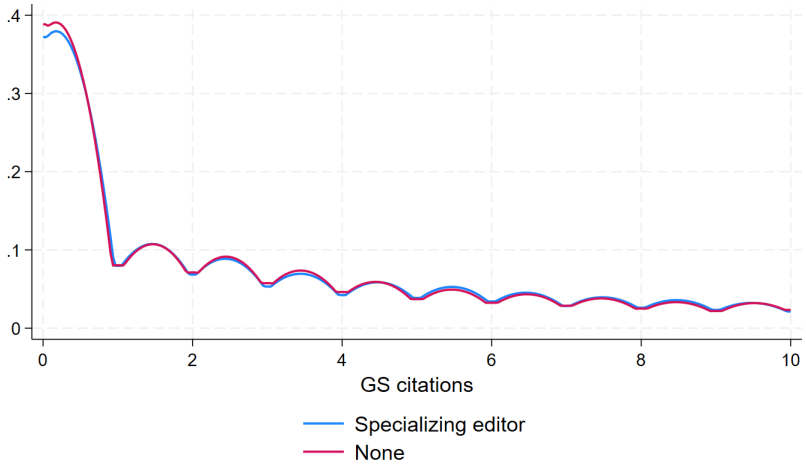
Table B1: Panel data estimates: Submissions, editorial process

	(a) Submissions	(b) Sent for review	(c) Sent for review	(d) Invited to R&R	(e) Invited to R&R
Specializing editor	0.042***	0.091***	0.059**	0.069	0.021
	(0.016)	(0.024)	(0.024)	(0.058)	(0.058)
Number of submissions			0.004***		−0.001
			(0.000)		(0.001)
Number sent for review				0.006***	
				(0.002)	
Field × journal FE	Yes	Yes	Yes	Yes	Yes
Field × year FE	Yes	Yes	Yes	Yes	Yes
Observations	490	490	490	490	490
Log likelihood	−1,668	−1,557	−1,529	−1,027	−1,022
Marginal effect	4.745	6.104	3.957	0.560	0.166
Baseline submissions	36.953				
Baseline sent for review		33.011	65.026		
Baseline R&R				2.992	7.940

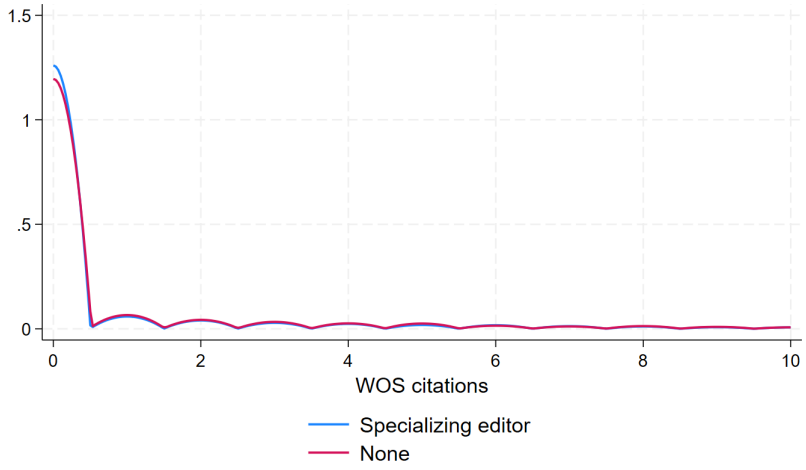
Notes: Estimated by Poisson Quasi Maximum Likelihood on manuscript data consolidated to a panel comprising 455 observations by field, journal, and year. Manuscripts with multiple fields represented multiple times, once in each field; manuscripts submitted to multiple journals represented once in each 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 (35 clusters) $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.1$.

Figure B1: 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 B2: Citations

VARIABLES	Google Scholar			Web of Science		
	(a)	(b)	(c)	(d)	(e)	(f)
	All	Sent for review	R&R	All	Sent for review	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 review	0.199			0.072		
	(0.171)			(0.225)		
Revise and resubmit (extended to desk rejected)	0.657***	0.815***		1.247***	1.672***	
	(0.144)	(0.195)		(0.193)	(0.273)	
Control function R&R (extended to desk rejected)	0.124*	−0.158	0.233***	0.019	−0.411***	0.383***
	(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
Log likelihood	−525,466	−345,594	−306,093	−93,241	−61,885	−54,214
Author controls	Yes			Yes		
Editor FE	Yes			Yes		
Field × journal FE	Yes			Yes		
Field × year FE	Yes			Yes		
Journal × year FE	Yes			Yes		
Marginal effect	0.39	0.09	0.77	−0.16	−0.16	−0.02
Baseline mean	20.4	28.4	31.0	2.3	3.1	3.4
Baseline median	11.8	17.2	19.5	0.9	1.1	1.3

Notes: Estimated by Poisson Quasi Maximum Likelihood. Dependent variable: Citations (Google Scholar (GS) or Web of Science (WoS) 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 receiving two or more referee reports. Marginal effect is proportionate effect of specializing editor on outcome. Robust standard errors clustered by journal interacted with year. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.1$.

C Additional analyses

Table C1 reports tests of the robustness of the structural estiates of author clientele and editor favoritism to alternative definitions of the editor specialization and positive referee report.

Table C1: Structural estimates: Robustness tests

	(a) Alternative definition of editor specialization	(b) Alternative definition of editor specialization	(c) Alternative definition of positive referee report	(d) Alternative definition of positive referee report
Parameter	MLE estimates	Bias-corrected estimates	MLE estimates	Bias-corrected estimates
Effect of specializing editor at initial screening, $\alpha + \gamma$	0.129^{***} (0.032)	0.125^{***} (0.030)	0.141^{***} (0.032)	0.137^{***} (0.033)
Editorial favoritism at initial screening, α	-0.027 (0.033)	-0.064 (0.032)	-0.019 0.046	-0.026 0.050
Author clientele, γ	0.155^{***} (0.046)	0.190^{***} (0.046)	0.160^{**} (0.068)	0.165^{**} (0.068)
Editorial favoritism at R&R stage, $\alpha_{R\&R}$	0.032 (0.057)	0.036 (0.077)	-0.028 (0.053)	-0.023 (0.063)
Author controls	Yes	Yes	Yes	Yes
Editor FE	Yes	Yes	Yes	Yes
Field × journal FE	Yes	Yes	Yes	Yes
Field × year FE	Yes	Yes	Yes	Yes
Journal × year FE	Yes	Yes	Yes	Yes
Observations	29,202	16,901	29,202	16,901

Notes: Columns (a) and (b) use editor specializations defined over editors' publication histories. Column (a) reports joint maximum likelihood estimates of $\alpha + \gamma$ and α, with standard errors clustered at the journal-editor level (49 clusters); the standard error for γ is computed using the delta method. Column (c) reports two-step probit estimates of $\alpha + \gamma$, as joint maximum likelihood estimation is numerically unstable due to the small number of manuscripts receiving two positive referee reports; standard errors are clustered at the journal-editor level and the standard error for γ is obtained by bootstrap. Columns (a) and (c) estimate $\alpha_{R\&R}$ using a two-step control-function approach, with clustered standard errors uncorrected for the two-step procedure. Columns (b) and (d) apply the bias-correction procedure of Higgins and Jochmans (2024), based on 1,000 bootstrap replications; within each replication, γ is estimated using the two-step approach due to slow convergence of joint maximum likelihood. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.1$.

Table C2 reports effects of a specializing editor handling the manuscript on, in column (a), the share of referees invited to review the manuscript with at least three publications; in column (b), the number of referee reports for the manuscript; and in column (c), the number of referees who declined a request to review. The objective of the empirical

exercise in column (a) is to detect editorial selection of referees through testing whether the attributes and number of referees for manuscripts handled by specializing editors was different. We find no evidence of this.

In column (c), we test for referee deference based on an editor-manuscript match based on the assumption that, if invited referees for manuscripts handled by specializing editors are attuned to the editor's research interests and therefore treat the paper differently, this may also be reflected in their willingness to provide a referee report. We again find no evidence of this.

Table C2: Referee characteristics and responses by specializing editor

	(a) Referee publications	(b) Referee reports	(c) Referee declines
Specializing editor	−0.005	0.032	−0.058
	(0.47)	(1.58)	(1.97)
R^2	0.08	0.26	0.13
Observations	16,901	16,901	16,901
Author controls	Yes	Yes	Yes
Editor FE	Yes	Yes	Yes
Field × journal FE	Yes	Yes	Yes
Field × year FE	Yes	Yes	Yes
Journal × year FE	Yes	Yes	Yes
Marginal effect	0.00	0.00	0.00
Baseline mean	0.4	2.3	0.8
Baseline median	0.4	2.3	0.8

Notes: Fixed effects linear regression on dataset of manuscripts. Dependent variable: Column (a): Share of referees with at least three publications; Column (b) Number of referee reports; Column (c) Number of referees declining request to review. Robust standard errors clustered at editor-journal level (49 clusters) $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.1$.

Table C3 further test for heterogeneous effects of an editor-manuscript match on the positivity of referee reports, based on the referee's characteristics. This test is based on the reasoning that, if referees are indeed taking editor-manuscript matches into account in their referee reports, the extent to which they take such matches may differ by their characteristics. Intuitively, referees who have completed more referee reports for the editor may be more attuned to the editor's personal interests and disposition towards related manuscripts, while referees with stronger publication records may be less prone to taking the editor's research interests into account in their evaluation of the manuscript.

Therefore, if our structural estimates are confounded by referee behavior, we may also expect heterogeneous effects in the extent to which referees respond to editor-manuscript matches.

Table C3: Heterogeneity in editor-manuscript match on positive referee report

	(a) Referee reports for editor	(b) Referee publication record
Referee reports for editor	-0.008^{**}	
	(6.68)	
Specializing editor ×	0.001	
Referee reports for editor	(0.83)	
Number of top publications		-0.015^{**}
		(7.20)
Specializing editor ×		-0.000
Number of top publications		(0.12)
R^2	0.48	0.48
Observations	34,785	34,785
Manuscript FE	Yes	Yes
Marginal effect	0.00	-0.00
Baseline mean	0.3	0.3
Baseline median	0.3	0.3

Notes: Fixed effects linear regression on dataset at referee-manuscript level. Dependent variable: Binary indicator for positive referee report. Explanatory variable interacted with editor-manuscript match: Column (a): Number of reports for the editor so far; Column (b) Number of publications in prominent journals in past 5 years (top-coded at 6). Standard errors clustered at the manuscript level (13,345 clusters) $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.1$.

Through this series of tests, we find no evidence that editor-manuscript matches alter referee reports through an alternative mechanism than changing which manuscripts are sent for review. While we emphasize that our results are suggestive—since we cannot directly observe editors' selection of referees or referee deference—they do support the interpretation that our estimate of editorial favoritism α is not confounded by these channels.