Northwestern | INSTITUTE FOR POLICY RESEARCH

IPR Working Paper Series

WP-22-05

Clubs and Networks in Economics Reviewing

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Version: January 10, 2022

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Abstract

The network of economists who publish in leading journals is generally perceived as small, exclusive, and tightly knit. Carrell, Figlio, and Lusher study how author-editor and author-reviewer network connectivity and “match” influences editor decisions and reviewer recommendations of economic research at the Journal of Human Resources (JHR). Their empirical strategy employs several dimensions of fixed effects to overcome concerns of endogenous assignment of papers to editors and reviewers in order to identify causal impacts. Results show that clubs and networks play a large role in influencing both editor and reviewer decisions. Authors who attended the same PhD program, were ever colleagues with, are affiliates of the same NBER program(s), or are more closely linked via co-authorship networks as the handling editor are significantly more likely to avoid a desk rejection. Likewise, authors from the same PhD program or who previously worked with the reviewer are significantly more likely to receive a positive evaluation. The researchers also find that sharing “signals” of ability, such as publishing in “top five,” attending a high-ranked PhD program, or being employed by a similarly ranked economics department significantly influences editor decisions and/or reviewer recommendations.

The authors thank Adrian Amaya, Devon Baldwin, Adina Barg, Salma Barhoumeh, Brianna Bonsack, Yili Chen, Siyuan Ding, Tyler Eguchi, Saori Fuji, Kendall Gail, Nick Halliwell, Tanya Henne, Kayla Hoang, Jesse Luu, Connor McKenney, Michael McKenney, Brooklynn Miller, Hengbo Tong, Markus Tran, Shannon Tran, Qian Yang, and Zhiyuan Zhu for providing excellent research assistance.

1 Introduction

Corporations, governments, and academic organizations have increasingly placed diversity of individuals and ideas at the forefront of decision-making (Bilimoria et al., 2008; Østergaard et al., 2011; Riccucci, 2018), including in hiring decisions (Fernandez and Fernandez-Mateo, 2006), promotions (Castilla and Benard, 2010), and resource allocation (Boudreau et al., 2016). Beyond equity considerations, a robust literature has shown that diversity in gender (Woolley et al., 2010; Hoogendoorn et al., 2013; Kamas et al., 2008) and ethnicity/nationality (Phillips et al., 2006; Sommers, 2006; Levine et al., 2014; Leung et al., 2008; Orazbayev et al., 2017) lead to improved outcomes and higher levels of productivity. Still, in the economics profession, representation is disproportionately low for women and ethnic minorities relative to the overall population and other academic disciplines (Ceci et al., 2014; West et al., 2013; Price, 2009). A lack of inclusion and diversity is concerning since it could constrain the range of economic issues discussed and reduce capacity to approach questions with novel and innovative methods (Bayer and Rouse, 2016).

A dense and growing literature has investigated the causes of underrepresentation, including differences in preferences for competition (Niederle and Vesterlund, 2010; Reuben et al., 2017), preferences for time allocation (Goldin, 2014), the presence of role models (Carrell et al., 2010; Fairlie et al., 2014; Lusher et al., 2018), and institutional policies (Lopez, 2000). Perhaps most pressing, a large literature suggests that issues like stereotyping biases (Greenwald and Banaji, 1995; Greenwald and Krieger, 2006) and other forms of discrimination may be contributing to a suppressing and undervaluation of minorities (see Bayer and Rouse, 2016, and studies therein). Such implicit discrimination may extend beyond gender and race as well, where evaluators may be biased toward individuals of similar educational background or toward those who are closely linked via social and professional networks. The implications for these concerns are perhaps magnified in economics, where a vast majority of senior faculty, journal editors and reviewers are generally perceived to be male, white, from a small set of elite schools, and belong to a tightly knit network (Ginther and Kahn, 2004; Goyal et al., 2006; Bayer and Rouse, 2016; Hsieh et al., 2018).

In this study, we investigate the role of potential biases in the evaluation of economics research for papers submitted for journal publication at the *Journal of Human Resources* (JHR). The JHR is a highly ranked applied microeconomics field journal with approximately 800 papers submitted for publication consideration annually. The journal has a large corps of editors who tend to have comparatively strong substantive expertise in the papers they handle, relative to “top five” editors whose editorial billets are necessarily much broader. As such, we would expect that this journal’s editors would be relatively likely to select reviewers with very close substantive knowledge about the papers they are asked to review.

Using journal submission data over a 12-year period, we focus on how author-editor and author-reviewer network connectivity and "matches" influence editor decisions and reviewer recommendations. The existing evidence on match effects has largely focused on gender match and has found mixed results. Using data from the *American Economic Review*, Blank (1991) finds no gender differential impacts to masked versus unmasked review processes. Using data on National Science Foundation reviews, Broder (1993) finds that female reviewers give lower ratings to female-authored papers. Dillingham et al. (1994) find that female voters were more likely to vote for female candidates for officer positions at a professional society. Using matched author-reviewer data from economics journals, Abrevaya and Hamermesh (2012) and Card et al. (2020) find no significant gender match effect.[1]

A few papers have documented correlations on characteristics other than gender. Using data on papers published in six economics journals, Medoff (2003) finds that authors who served on the journal's editorial board experienced increased citations. Also utilizing published articles, Brogaard et al. (2014) and Colussi (2018) document connections based on academic history between published authors and journal editorial boards. For instance, PhD students and faculty colleagues of a head editor are more likely to publish in the editor's journal.[2]

But these types of matches do not get to the question of whether economics publishing is affected by "club" membership. To do so, we explore several new margins of "matching" between reviewers and manuscript authors. First, after constructing a network of coauthors based on published and working papers, we analyze how "degrees of separation" between the author and editor/reviewer impacts editor decisions and reviewer recommendations. For example, all else equal, do authors receive beneficial evaluations from editors/reviewers who were previously a coauthor's coauthor (two degrees of separation) relative to editors/reviewers who were a coauthor's coauthor's coauthor (three degrees of separation)? Then, by visiting every author's/editor's/reviewer's personal website and/or curriculum vitae, we construct a comprehensive panel data set tracking all individuals starting from their PhD in order to investigate other potential matches of interest. These include whether the author-editor or author-reviewer pair attended the same PhD institution (or a similarly ranked PhD program), whether a pair were ever colleagues together (or currently employed by similar ranked institution), whether a pair are both affiliates of the same NBER program(s),

[1] Though not directly investigating gender match, Donald and Hamermesh (2006) find that the predominately male American Economic Association exhibit a *positive* bias toward electing female candidates for the Association's executive board. A similar finding from a working paper from Bransch et al. (2017) finds that the gender composition of the editorial board from the top-five economics journals is *negatively* associated with the gender composition of published papers.

[2] Because Medoff (2003), Brogaard et al. (2014), and Colussi (2018) only observe journal publications, one cannot be certain whether these results are driven by matching effects between authors and reviewers/editors, or driven by increased selection (i.e., submissions) to the journal. In other words, it may be that there is no editor/reviewer bias toward authors who are connected, but that authors connected to the editor decide to submit more manuscripts to the editor's journal.

and whether a pair had both published in one of the "top five" economics journals.

Our empirical strategy employs several dimensions of fixed effects to overcome concerns of endogenous assignment of papers to editors and reviewers in order to identify the causal impact of network connectivity and match. First, when evaluating desk rejection decisions, editor fixed effects account for differential sorting of paper types across editors. With editor fixed effects, we estimate differences in editor decisions across papers written by authors with varying network connectivity and match to the same editor. In other words, editor fixed effects allow us to look at how the same editor evaluates papers written by authors with different academic histories (and thus across different "club" matches) and by authors of differing network connectivity. Similarly, when evaluating reviewer recommendations, since reviewers often review more than one manuscript, our data allow us to control for any sorting of papers across reviewers by estimating reviewer fixed effects. Finally, in reviewer recommendation models, paper fixed effects can be estimated by using variation in network connectivity and "club" match across author-reviewer pairs. These are estimated for any paper that has multiple reviewers, of whom have varying network connectivity or match with the paper's author(s). Paper fixed effects control for anything related to the paper-specific probability of getting reviewed positively or negatively, such as the paper's quality, subfields, or team of authors.[3]

Our results suggest that clubs and networks play a large role in influencing editor and reviewer decisions. Authors who attended the same PhD, were ever colleagues with, or are both affiliates of the same NBER program(s) as the handling editor are significantly more likely to avoid a desk rejection (5.2pp, 4.6pp, and 12.2pp, respectively). Authors more closely linked to the editor via coauthorship networks are also more likely to pass the desk. When estimating all these effects simultaneously in one model, we find that NBER program affiliation and coauthor networks play the strongest role in constituting the "club" effect. These club effects stack as well—authors with multiple matches do better than those with fewer. We find evidence that "top five" matching also matters for desk rejection decisions, while match based on the PhD rank or institution of employment rank does not influence editor desk rejection decisions.

Turning to reviewers, we similarly find that reviewers are persuaded by authors who they share a match with. Authors from the same PhD as and who previously worked with the reviewer are significantly more likely to receive a positive evaluation (6.2pp and 3.7pp, respectively). NBER program affiliation match is also positively associated with reviewer recommendations, but is imprecisely estimated. Degrees of separation seems to matter less for reviewer decisions, with the lone exception coming from the rare instances

[3]Though some survey evidence suggests that editors note observable characteristics such as author gender (Card et al., 2020), our data allow us to control for all unobservable characteristics that relate to editor/reviewer and paper quality. Investigating whether editor assignment is based on author-reviewer match, Hamermesh (1994) provides evidence that with the exception of a few superstar authors, editor assignment of papers to reviewers is orthogonal to the author and reviewer quality, as proxied by citations from prior papers.

of one degree of separation: Reviewers reviewing a direct co-author are nearly 10pp more likely to give a positive recommendation on a paper relative to an author of four or more degrees of separation. Similar to editors, the match effects stack—having more connections further bolsters the average positive evaluation rate. Finally, we also find that sharing "signals" of ability significantly influences reviewer recommendations—reviewers who published in a "top five" are 2.9pp more likely to give a positive evaluation to an author who also published in a "top five." Reviewers also give positive reviews to authors who attended a similarly ranked PhD program or were employed by a similarly ranked economics department. This rank-match effect is driven almost exclusively by higher ranked schools—that is, reviewers from higher ranked PhD programs and economics departments favorably review authors from higher ranked PhD programs and economics departments, while reviewers from lower ranked PhD programs and economics departments appear to be more ambivalent toward their lower ranked author counterparts.[4]

Finally, we illustrate how these match effects ultimately capitalize into publication decisions. Unsurprisingly, editorial decisions are very strongly correlated with reviewer recommendations: Papers where all reviewer recommendations are positive are over 54pp more likely to be published than papers with all negative reviews. But network effects do not end with differential reviewer recommendations: Conditional on getting passed the desk *and* controlling for reviewer recommendations, separate author-editor matching effects arise, particularly for NBER program affiliation. Networks apparently matter at all stages of the editorial process.

Our paper contributes to the literature in at least three important ways. First, our rich data and identification strategy allow us to rule out many potential concerns for endogeneity (e.g., paper quality and assignment to editors and reviewers).[5] Second, to our knowledge, this is the first paper to directly examine how the network of coauthorships affects editor and reviewer decisions. Finally, our study is the first to take a comprehensive examination of author and editor/reviewer matches by direct "club" participation (such as attending the same PhD, working together as colleagues, and shared NBER program affiliations) and outward signals of quality (such as rank of PhD, rank of institution of employment, and prior publication in a "top five").

Relying on external signals of quality is a potentially rational response taken by editors and reviewers who may be looking for shortcuts to lessen the evaluation burden, and not one limited to the economics

[4]A series of additional explorations and robustness checks further suggest strong club and network effects. While our primary analysis weights each author equally, we also consider models with a "hierarchy" of each paper's coauthors: these include models where we identify the "closest" connection across authors for each editor/reviewer, and models where we strictly consider the most "prominent" author. Results are also robust when estimating with logit models.

[5]To our knowledge, the only studies to employ similarly rich data include Abrevaya and Hamermesh (2012), who estimate reviewer fixed effects, and Card et al. (2020), who estimate paper fixed effects.

profession; for instance, English (2008) posits this as an explanation for the concentration of winners of cultural prizes. Doing so, however, comes at a potentially major cost: Our results indicate that these biases likely contribute to the lack of diversity within the economics profession, since publication success is the primary factor in promotion and tenure decisions. Our findings suggest that the "tyranny of the top five" documented by Heckman and Moktan (2020), in which top five publications play an outsized role in determining promotion and tenure at major economics departments, has an even longer reach still, as the signal of a "top five" publication apparently substantively influences publication potential in journals ranked just below. And since the purview of editors at top five journals is likely more expansive than that of editors at top field journals, there is reason to believe (though we obviously cannot demonstrate this) that top five reviewers might rely even more on signals than do reviewers at top field journals, suggesting that the "club" findings we uncover might be even greater in top five journals, possibly even further amplifying the "tyranny of the top five" uncovered by Heckman and Moktan (2020). Within economics, a field arguably obsessed by rankings and stature, external evaluation is often required for hiring, promotion and tenure decisions as well as for prestigious awards for teaching, research, and service. Though we can only speculate, it is likely that similar biases may also exist in these evaluations, thereby further exacerbating the lack of diversity within the profession.

2 Data Sources and Background

Our data consist of three parts. First we collected data on nearly 8,000 paper submissions to the JHR from 2007 to 2018. For each submission, we know the paper's author(s), the handling editor, and the assigned reviewers (if sent for review). The review process at this journal is single-blind: Reviewers can observe the identity of the authors, but the authors do not know the identity of the reviewers. Our analyses uses these data to consider three outcomes of interest: whether the paper passed the editor's desk, whether the assigned reviewer(s) evaluated the paper positively, and whether the editor ultimately accepted the article for publication.

The second part of our data consists of manually-collected information on authors, editors, and reviewers. Our primary data set was collected by visiting each individual's website(s), including the full history of an individual's academic employment, starting with their PhD. NBER program affiliation was also collected by visiting the NBER webpage. Rankings for the prestige of each individual's PhD program were collected from the 2019 US News rankings[6] and department of employment productivity rankings on ideas.repec.org.[7]

[6] https://www.usnews.com/best-graduate-schools/top-humanities-schools/economics-rankings

[7] IDEAS rankings retrieved in May 2019 from https://ideas.repec.org/top/top.econdept.html.

Our third set of data come from RePEc (Research Papers in Economics). We use RePEc for two purposes. First, we collected time-series information on each individual's yearly publication history, including total number of publications, publications in "top five" journals, number of unique coauthors, and number of unique coauthor's coauthors. Secondly, we use RePEc in order to generate networks between authors and editors/reviewers across years. To start, using the EconPapers (econpapers.repec.org) service, we compiled a list of all publications from nearly 100 related economics journals and four popular working paper series (NBER, IZA, arXiv, and CEPR).[8] Then, for each author who appeared on this list of papers, we created an "author account" that consisted of all the author's papers.[9] Finally, for each year of our sample, an author network was generated based on coauthorships from the author accounts.

2.1 The *Journal of Human Resources*

The JHR is widely considered a "top field journal" in economics, with an overall acceptance rate of 6.2% and just over two-thirds of manuscripts desk rejected.[10] Journal rankings confirm this perception. For instance, when examining the 2020 Scimago Journal Rankings[11] by impact factor, the JHR ranks 23$^{\text{rd}}$ among journals listed in the "Economics and Econometrics" category, ahead of the Journal of Public Economics (JPubE) and behind the Journal of Labor Economics (JoLE), both which are also widely considered "top field journals".[12] Recent research by Heckman and Moktan (2020) also highlights the importance of the JHR in tenure and promotion decisions at the Top 35 economics departments. Using Combes and Linnemer (2019) journal categorizations, which includes the JHR in their list of "Tier A Field Journals," Heckman and Moktan (2020) find that tenured faculty accumulate significantly more "Tier A Field Journals" by year eight compared to their untenured counterparts, with this relationship growing stronger as one moves from the Top 10 departments to those ranked 16-35. Additionally, using various metrics, Heckman and Moktan (2020) ranks the JHR anywhere between 11th (residual log citations) and 15th (5-year impact factor) among economics journals.

To further examine the relative importance of publishing in the JHR in the economics discipline, we collected data on journal publications, at the time of tenure, for all tenured applied microeconomists at the

[8] The full list of journals can be found in Table A1.

[9] We coded two individuals as being the same if they shared a first name and a last name. Manual checks were included in case authors used different first names across papers (e.g. Ben vs. Benjamin) and in case an author's last name changed. We also used registered RePEc author profiles to verify and adjust matches across papers.

[10] Based on authors calculations.

[11] See *https://www.scimagojr.com/journalrank.php*.

[12] Oddly, SJR has two economics categories,"Economics and Econometrics" and "Economics, Econometrics, and Finance (miscellaneous)", which do not overlap in their list of journals. In later analysis, we match impact factors to all (400+) published-in journals from tenured applied micro economists currently employed at the top 100 ranked economics departments. Among these matched journals, the JHR ranks 26$^{\text{th}}$ according to the SJR impact factor.

top 100 economics departments in the United States. Importantly, we also recorded the department in which the author originally received tenure. We then matched journal publications to the 2020 SJR journal rankings to examine where the JHR fits within the distribution of publications among faculty who *received* tenure at a top 100 US economics department in our sample. Analyses of these data reveal several interesting findings. First, the JHR is the fifth most commonly published-in journal behind the AER, REStat, JPubE, and QJE. In total, 20.2% (101 of 499) of authors in our sample published at least one article in the JHR, compared to 21.0% in the JPubE and 11.0% in JoLE. Second, for each tenured author, we calculated their median ranked journal article at the time of tenure. Across the entire sample of top 100 departments, the average author's median ranked publication is 90.7, with the 25$^{\text{th}}$, 50$^{\text{th}}$ and 75$^{\text{th}}$ percentiles of 26, 57, and 131.5. Only 23% (115 of 499) of tenured authors' median ranked publications were ranked better than the JHR.

Not surprisingly, there is a strong positive relationship between publication ranks and department ranks in our sample. Figure 1 shows distributions of the median ranked publication for the median ranked author in each department, separately for departments ranked 1-35 (Figure 1a) and departments ranked 36-100 (Figure 1b). Vertical lines represent the ranks of several commonly published-in journals in our sample, including the JHR.

Next, Figure 1c plots each top-100 department's median ranked author's median ranked publication in percentiles against department rank,[13] with a horizontal line depicting the JHR's percentile rank. Notably, the median ranked publication of the median author for all departments outside the top 20 is at or below JHR's rank. In Figure 1d, we plot the fraction of all publications that are published in journals ranked higher (e.g., better ranked) than the JHR against department rank. The figures shows a strong negative relationship between these two variables. For instance, 44% of all publications among economists tenured in the top 35 departments are in journals ranked higher than the JHR, while only 15% of publications are ranked higher than the JHR among economists tenured in departments ranked 36-100.

Finally, to examine author journal submission behavior at the JHR, as detailed in Brodeur et al. (2021), in early 2021 we conducted a survey across a broad sample of applied microeconomists. Specifically, we collected contact information for all authors who had published at least one article with an empirical identification strategy (IV, DID, RD, or RCT) in 2018 within a top 25-ranked economics journal. This produced 561 email invitations, with 143 authors fully completing the survey. The survey first asked the authors to list all the journals they had submitted to in the previous five years. For a random subset of journal submissions, authors were then asked which journals they had submitted to prior to the specified journal submission. In Figure 1 of Brodeur et al. (2021), we plot the distributions of these prior submissions, sorted

[13] We include only departments with at least four applied microeconomists who received tenure in that department.

by journal rank, for several journals of interest. When examining the JHR, the most common journal authors submit to prior to a JHR submission is the American Economic Journal: Applied Economics (AEJ:AE), with a significant share also submitting to the JHR after receiving rejections from a top five journal. Notably, the JHR submission patterns closely resemble that for the JPubE. Likewise, the most common journals published-in after rejection from the JHR were the Economics of Education Review, Journal of Health Economics, Health Economics, Journal of Economic Behavior and Organization, Economic Development and Cultural Change, and Labour Economics.

2.2 Summary Statistics

Table 1 presents summary statistics for our sample at the author and reviewer level (in the top panel) and at the author-paper and reviewer-paper level (in the bottom panel). In the middle section, we consider the subsample of authors and author-papers that passed the desk (i.e., the sample of authors and author-papers who constitute our sample when analyzing reviewer recommendations). Our full sample includes 8,369 authors and 2,006 reviewers. Unsurprisingly, authors of papers which pass the desk tend to have received their PhDs from higher ranked institutions, have more "top five" publications, are twice as likely to be a NBER affiliate, and are employed at higher ranked economics departments. Reviewers also tend to be "more qualified" than authors—reviewers come from higher ranked PhD programs, have published more articles, published more in the "top five," are more likely to be an NBER affiliate, and are employed by higher ranked economics departments.[14]

Table 2 presents summary statistics at the units of observation for our analyses. First, we will analyze editor decisions to desk reject a paper by utilizing data at the author-editor-paper level. Roughly 37% of observations constitute "passing the desk." The second set of columns describe the data at the author-reviewer-paper level, where we will analyze whether the reviewer gave a positive recommendation ("positive evaluation"). At the JHR, reviewers are given five different options for recommendations ranging from outright rejection to publish as is. Approximately 45% of these observations came with a positive recommendation (i.e. recommend against outright rejection).

From the RePEc data, we see that over 10 percent of author-editors and author-reviewers are connected within three degrees of separation. We also observe a non-zero probability that a direct coauthor served as an editor or a reviewer. Approximately 13% of author-editor-papers and 11% of author-reviewer-papers do not appear in our constructed RePEc network. Unreported in Table 2, unmatched authors and reviewers

[14] Later analyses involving paper and reviewer fixed effects will involve dropping certain papers and reviewers. In Table A2 we characterize differences across author(-papers) and reviewer(-papers) between those kept in our estimation sample and those who are dropped when investigating reviewer decisions.

tend to have graduated more recently, which is unsurprising: younger authors are less likely to have released a working paper or to have published. Between 2-3% of observations include author-editor and author-reviewer pairs that attended the exact same PhD program. Using bins of top 10 vs. 11-30 vs. 31-50 vs. >51 or missing, we find that roughly 20% of author-editor pairs and 36% of author-reviewer pairs attended similarly ranked PhD programs. Between 4-5% of observations include author-editor and author-reviewer pairs that were formerly or currently colleagues. Similarly, the match rate for publishing in the "top five" is between 7-9%. Between 2-3% of author-editor and author-reviewer pairs are affiliates in the same NBER program(s).

3 Econometric Specifications

We start with our primary specification for analyzing editor desk rejection decisions:

$$\text{PassedTheDesk}_{aep} = \alpha + \beta[\text{Match}]_{aep} + \lambda_e + X_{ap} + \epsilon_{aep} \tag{1}$$

where each observation is an author-editor pair ae for a specific paper p submitted to the JHR. For instance, a manuscript that has three authors will have three observations in this data set. $\text{PassedTheDesk}_{aep}$ is an indicator for whether the editor did not desk reject the manuscript. $[\text{Match}]_{aep}$ includes various measurements of interest that reflect the connectivity between an author-editor pair. For example, we consider whether both the author and editor attended the same PhD institution, in which case $[\text{Match}]_{aep}$ is an indicator for the author-editor pair coming from the same PhD. Other indicators considered include whether the author-editor pair were ever colleagues, were in the same NBER program(s), both published in a "top five" journal, attended similarly ranked PhD, and were employed by a similarly ranked university.[15] We also consider "degrees of separation" between the author-editor pair as constituted by our constructed network of coauthorships, where one degree of separation reflects a direct coauthorship between an author-editor pair, two degrees reflects an author and editor sharing a common coauthor (but not directly coauthors), etc. Overall, a positive estimate for β reflects a positive relationship between author-editor matching and the probability the paper passes the desk.

Importantly, editor fixed effects λ_e control for potential issues of endogenous assignment to editors. That is, these models compare how the same editor handles different papers written by authors with varying levels of match to the editor. Naturally, $[\text{Match}]_{aep}$ may still be correlated with paper quality, particularly since

[15] Note that "top five," NBER affiliation, and employment statuses are time-varying, and thus vary at the author-paper and reviewer-paper level.

editors tend to come from "stronger" backgrounds, and so papers written by "stronger" authors who write (unobserved) "better" papers may also simultaneously be more likely to "match" to an editor. Thus, we also include a rich set of author-paper level controls in X_{ap} to proxy for paper quality. These include the author's number of publications up to year of submission, publications in the "top 5" economics journals, number of unique coauthors from published manuscripts, number of unique coauthors' coauthors from published manuscripts, NBER program affiliations, gender, binned rankings of institution of PhD (according to US News), and binned rankings for their institution of employment (according to IDEAS).

Turning to reviewer recommendations, we estimate a similar model:

$$\text{PositiveEvaluation}_{arp} = \alpha + \beta[\text{Match}]_{arp} + \lambda_r + \lambda_p + \epsilon_{arp} \tag{2}$$

where observations are unique at the author-reviewer-paper level. The outcome variable is an indicator for the reviewer giving a positive evaluation on the paper, while our various considerations for $[\text{Match}]_{arp}$ remain the same.

The key addition to this model comes from our inclusion of paper fixed effects λ_p, which rely on variation in $[\text{Match}]_{arp}$ across author-reviewer pairs. Thus, our β coefficients are identified using papers that had two or more reviewers with varying match to the paper's author(s). Hence, paper fixed effects control for anything related to paper-specific probability of getting reviewed differentially, such as paper quality, subfields, or team of authors. Moreover, paper fixed effects absorb editor fixed effects, which control for the possibility that different editors handle different types of papers, or may make different types of reviewer assignment decisions. Similar to the editor fixed effects from (1), reviewer fixed effects λ_r look at how the same reviewer rates different papers written by authors with varying levels of match. Since both paper and reviewer fixed effects can be estimated simultaneously, we can account for endogenous sorting of papers to reviewers. For instance, if reviewer A is systemically assigned "low quality" papers while reviewer B is assigned "high quality" papers, our inclusion of paper fixed effects will account for the quality difference in papers assigned across reviewers. Likewise, if paper C is given "harsh" reviewers while paper D is given "easy" reviewers, our inclusion of reviewer fixed effects will account for the differences in reviewer propensity to suggest rejections. Altogether, our fully specified models can be estimated so long as there exists variation in "match" within papers and within referees (i.e. papers which have multiple referees who have reviewed multiple manuscripts).

Since editor/reviewer decisions are made at the paper level, we weight observations at the editor-paper or reviewer-paper level. Hence, we assume an equal weighting across the paper's authors. Therefore, our specifications implicitly assume that match effects are additive across authors (e.g. a solo-authored paper with a "matched" editor-author will carry as much weight as a two-authored paper having two matched editor-authors). Additional robustness checks will loosen this assumption by checking whether multiple "matches" matter, or if a singular match across any of the paper's authors suffices to influence editor/reviewer decisions. We also consider specifications where authors are weighted deferentially by their connectivity to the editor/reviewer and by author "prominence."

4 Main results

4.1 Editor desk rejection decisions

We begin by examining editor desk rejection decisions by estimating (1) via OLS. Our first set of results are presented in Table 3. Each column comes from a separate regression. Standard errors are clustered at the paper level, and observations are weighted at the paper-editor level (i.e. each observation is weighted by the inverse of the number of coauthors on the paper).

Starting in column (1), we see that an author is 5.2pp more likely to pass the desk when they attended the same PhD institution as the handling editor (significant at the 90% level). Similarly, in column (2) authors who were ever colleagues with the editor by the time the paper was submitted experience a 4.6pp increase in likelihood of passing the desk (significant at the 95% level). Next, In column (3) we estimate a large and robust effect for NBER program affiliation—editors are 12.2pp more likely to send a paper out for review if the author is affiliated with the same NBER program(s) as the editor at the time of the paper submission (significant at the 99% level). In column (4) we estimate degrees of separation as a series of dummies, omitting any author-editor connections of four (an author who is the editor's coauthor's coauthor's coauthor's coauthor) or greater. We first see that direct coauthorship leads to a huge boost in avoiding desk rejection relative to all connections of four or greater. The connectivity effects decrease as the degree of separation increases, from 26.5pp to 13.7pp to 7.4pp when moving from one to three degrees of separation, respectively. In column (5), we estimate each of these match effects simultaneously in one regression: we find that NBER affiliation and coauthor networks are the strongest drivers of matching effects for editor decisions.

Finally, in column (6), we consider a specification where we count the number of "matches" for each author-editor pair, where a match occurs if the author-editor pair attended the same PhD institution, were ever colleagues, affiliated with the same NBER program(s), or were direct coauthors (for a max of four). We estimate dummies for just a single match versus multiple (two+), omitting cases with no matches. This specification suggests that the matching effects "stack"—having one connection boosts the probability of passing the desk by 5.6pp, while having multiple connections boosts the probability by 8.9pp.

Our next set of author-editor match results are presented in Table 4. In this table, we consider matches based on observable characteristics of the author of which do not necessarily constitute a "direct" connection between the author and editor. For instance, in column (1), we consider match based on whether the author-editor pair had both published in a "top five." Here, we estimate a positive and statistically significant effect of 4.5pp. Thus, it appears that "top five" publication may also constitute a "club."

In the next set of columns, we consider matches based on the ranking of the author and editor PhD programs and institutions of employment.[16] We'd expect to see effects here if, for example, editors who graduated from lower ranked PhD programs or are employed at comparatively lower rank institutions show preference for authors who are also from relatively "weaker" backgrounds (compared to editors/authors from relatively "stronger" backgrounds). As shown in columns (2) and (4), we find little evidence that editors are biased toward authors who come from similarly ranked education or employment institutions.

4.2 Reviewer evaluations

In this section, we move to reviewer evaluations by estimating equation (2) via OLS. We present results in Table 5 and Table 6 in similar fashion to the two tables in the previous section. Standard errors are clustered at the paper level, and observations are weighted at the paper-reviewer level. Recall that in these models, we simultaneously estimate both paper fixed effects and reviewer fixed effects, which rely on papers with multiple reviewers, each of whom have reviewed multiple papers for the JHR during our sample period.

In Table 5, we first consider an indicator for whether the author and reviewer attended the exact same PhD institution. We find that reviewers are 6.2pp more likely to positively review an author from the same graduate program (significant at the 90% level). Reviewers who were ever colleagues with the author are 3.7pp more likely to give a positive review (significant at the 90% level). We also observe a positive relationship for NBER program matching (2.3pp), though the coefficient is imprecisely estimated. Turning to degrees of separation in column (4), we only find evidence of match effects for direct coauthors (when the reviewer is one degree from the author). When estimating all match effects simultaneously in column (5), PhD matching and one degree of separation display the strongest effects, though they are imprecisely estimated. Finally, in column (6), we again find that the matching effects "stack"—authors with multiple matches to the reviewer experience a 6.7pp increase in the probability of receiving a positive evaluation

[16] Graduate student authors (and later, reviewers) are included in this analysis and were coded using their current institution of graduate enrollment.

relative to authors with no matches to the reviewer (95% significant).

Turning to Table 6, we find strong evidence of match effects based on signaling characteristics of "quality". Reviewers who published in a "top five" are 2.9pp more likely to positively review an author who also published in a "top five" (significant at the 95% level). Reviewers also favor authors who attended a similar ranked PhD (significant at the 95% level). This positive "PhD rank match" effect could also be interpreted as a negative "rank mismatch" effect; therefore, in column (3), we investigate whether the negative rank mismatch effect is driven by lower (higher) ranked reviewers punishing higher (lower) ranked authors. To do so, we generate indicators for whether the author and reviewer did not attend a similarly ranked PhD program and whether the author rank is higher vs. lower than the reviewer. These results suggest that the negative rank mismatch effect is driven by lower ranked reviewers being less likely to give a positive evaluation to higher ranked authors. We repeat this same exercise in columns (4) and (5) for the author's and reviewer's institution of employment rank (at the time of the paper submission). Again we find that reviewers positively favor authors of a similar rank. Interestingly, when decomposing by rank mismatch in column (5), we find this effect is largely driven by reviewers from higher ranked institutions punishing authors from lower ranked institutions.

In Figure A1 and Figure A2, we test for the sensitivity of these rank match results by considering an indicator for whether the author and reviewer both attended a top x PhD program or were employed by a top x economics department, respectively. For instance, the first point above "5" in Figure A1 estimates the impact of both the author and reviewer having attended a top five PhD program. We find that as we include more lower ranked schools to define PhD rank match (moving right in the figure), the effects slowly decrease and become statistically insignificant around rank 23. A similar pattern, albeit more noisily, can be observed for employment rank match. These results show that the author-reviewer rank match effects are strongest for higher ranked schools, and imply that more "prominent" reviewers favor authors from similarly high ranked backgrounds, whereas lower ranked reviewers appear to be more apathetic toward lower ranked authors.

4.3 Publication decisions

In this section, we consider a model to investigate (a) how reviewer evaluations influence editor publication decisions, and (b) whether author-editor matching effects still manifest conditional on the reviewer recommendations. This analysis is carried out at the author-editor-paper level for the subset of papers that passed the desk. We then re-estimate specification (1) but include a control for the fraction of the reviewers' recommendations that were positive. These results are presented in Table 7. We first find that editors typically closely follow the recommendations of the reviewers: Going from all rejection recommendations to all positive evaluations increases the probability the paper publishes by over 54 percentage points. We then find that some author-editor matching effects still manifest conditional on reviewer recommendations, particularly for column (3) where NBER program affiliation match leads to an additional 15.1pp increase in the probability of publication acceptance.

5 Alternative specifications and robustness checks

In this section, we consider a series of alternative specifications and robustness checks. In our primary analysis, all authors on a paper are given equal weight. However, it is plausible that instead of all authors mattering equally, an editor or reviewer may be swayed by "matching" to at least one of the paper's authors. To investigate this possibility, we collapse our data to the editor-paper and reviewer-paper levels and redefine our PhD institution, formerly/currently colleagues, and NBER program(s) "match" variables as equal to one if the editor/reviewer matched to *any* of the paper's authors. Furthermore, we redefine degrees of separation as the shortest path across all author-editor and author-reviewer pairs for the paper. In our final specification, we total the number of "matches" across all authors. For editor-paper models, our author controls are collapsed into averages (note that author controls are irrelevant in reviewer models due to paper fixed effects). The results from this exercise are presented in Table A3 (for editors passing the desk) and Table A4 (for positive reviewer recommendations). Overall, the pattern of our results do not change, with some notable coefficients increasing in magnitude (NBER program(s) match and degrees of separation). This suggests that (perhaps unsurprisingly) match to the closest author is what appears to matter most in influencing editor and reviewer behavior.

As another alternative specification, we seek to identify the most "prominent" author of the paper. Many times, there exists a clear hierarchy among the authors, and it may be that match to the most prominent author matters more than the average match across authors. To consider this, we first flag an author as the most "prominent" if they've published the most "top fives." To break ties, we then consider the rank of the department of the author's employment, followed by which author has the most publications, then PhD rank, then whoever is oldest (years since PhD). Remaining ties (typically two graduate student coauthors from the same cohort) are then broken randomly. This analysis is presented in Table A5 and Table A6. Once again we observe a similar pattern overall as our primary results. Some estimates lose statistical significance for both editor and reviewer decisions (exact same PhD institution and former/current colleagues), while coefficients for NBER program(s) match attain greater precision and statistical significance. These results suggest that the most prominent author on a paper carries a substantial proportion of the weight in influencing editor and reviewer decisions.

Next, in Table A7 and Table A8 we test the sensitivity of our reviewer model results to replacing paper fixed effects with editor fixed effects and author controls. We do this as a proxy to test for how well our author controls explain unobserved paper characteristics, particularly since we are unable to include paper fixed effects in our editor models. Reassuringly, our results are largely consistent with our previously reported results when including paper fixed effects. With the exception of top five match, the magnitude the effects (e.g., PhD institution, current/former colleagues, degrees of separation, etc) are of equal or larger magnitude, while standard errors tend to increase as well.

Finally, in Table A9 through Table A12 we estimate our primary specifications using logit models.[17] Again, we find results consistent with our primary specifications. Both editors and reviewers are positively influenced by "match" to the author.

6 Discussion and conclusion

In this study, we examine how author-editor and author-reviewer network connectivity and "match" influence editor decisions and reviewer recommendations when evaluating papers submitted to the JHR, a leading applied microeconomics field journal. Our empirical strategy employs several dimensions of fixed effects to overcome concerns of endogenous assignment of papers to editors and reviewers in order to identify the causal effects. Importantly, our editor models include editor fixed effects, while our reviewer models employ reviewer and paper fixed effects. As such, these latter models focus on papers that received at least two reviewers, and on reviewers who completed at least two reviews.

Our results show strong and robust evidence that network connectivity and match significantly influence editor decisions and reviewer recommendations in publishing. For editors, we find significant positive match effects for PhD institution of attendance, employment, NBER program affiliation, coauthor network degrees of separation, and publishing in a "top five" economics journal. Importantly, we find that these effects are additive, with an increased number of matches further influencing editor decisions. For reviewers, we similarly find that reviewers are swayed by authors with whom they have shared attributes. Specifically, we find significant positive match effects for authors and reviewers who attended the same (and similarly ranked) PhD institution, were previous colleagues (and are employed at similarly ranked departments), and have published in a "top five".

[17] Due to the high dimensionality of the paper fixed effects in our reviewer models, we were unable to estimate paper fixed effect logit models. Instead, we estimate our logit models while including editor fixed effect and author controls as in Table A7 and Table A8.

It is important to note that these observed match effects can be driven by both a conscious and unconscious bias by the reviewer. A conscious bias is straightforward—the editor/reviewer may simply prefer or trust papers written by authors for whom they share the same observable attributes. An unconscious bias would arise if the editor/reviewer has an underlying bias or preference for papers of certain characteristics for which "matched" authors are more likely to write. For example, Lusher et al. (2018) find positive racial matching effects between Asian students and teaching assistants in settings where TAs graded essay-style exams, suggesting (non-)Asian TAs preferred writing styles of (non-)Asian students. In the publishing context, it may be that authors of certain educational backgrounds write papers in a certain style, or adopt certain methodologies or utilize certain data sets, that are preferred by editors/reviewers of the same or similar educational background. Since the identity of the authors are not hidden from the editors/reviewers, differentiating between conscious and unconscious biases is difficult.[18] However, given our results tend to be strongest for indicators signaling "club" or "elite" status, this suggests at least partially a conscious bias.

Regardless of whether the observed match effects are driven by conscious biases or not, our results suggest that there are important determinants in both the editor's and reviewer's evaluation process that extend beyond the paper's suitability for publication. On a basic level, we find that part of what drives decisions across papers is simply whether the author(s) of the paper share a characteristic with the editor/reviewer. However, if the objective is to publish the "best" research, then there is no reason an author sharing a characteristic with the editor/reviewer should be indicative of the paper's publication prospects, conditional on paper quality. Thus, our results imply at least one major inefficiency in the current system of paper evaluation. We suspect that this tendency among editors/reviewers to upweight authors in the "club" or who have achieved some "elite" status further exacerbates the "tyranny of the top five" illuminated by Heckman and Moktan (2020).

Still, the potential policy implications for the current reviewing process are complicated. Editors are largely selected on expertise and stature in the profession, which are highly correlated with our measures of "club" membership. Likewise, the primary factor for selecting a reviewer is the reviewers' expertise on the paper's topic. Therefore, if certain topics attract researchers from, for example, the same PhD program, then it may be more efficient to have increased "PhD match" for the sake of having more highly qualified reviewers. That is, the editor may face a reviewer capability-impartiality trade-off: picking reviewers who are capable of evaluating the paper's topic, while recognizing that (even conditional on paper quality) the reviewer may be positively biased toward authors of similar background characteristics.

[18] A recent example of biases arising in a double blind-review setting comes from Kolev et al. (2019), who find gender biases in the reviews of grant proposals submitted to the Gates Foundation.

A potential remedy would be for editors to discount recommendations to account for matching biases. This could be done by either (a) "down-grading" recommendations with positive match (e.g. "strong R&Rs" are treated more like "weak R&Rs"), and/or (b) the editor giving less weight to reviews with positive match in making their final decision. However, an obvious shortcoming is that what we observe is the average bias across matches, with (unobserved) variation in how these biases manifest. Hence, in some instances the review should not be discounted because of author-reviewer match, while others should perhaps be heavily discounted.

Lastly, it is important to note that the match effects we estimate are relative to the editor's/reviewer's own background characteristic. That is, our study does not identify whether, for example, authors from top PhD programs directly face easier publication prospects compared to authors from lower PhD programs. Still, our study does suggest that authors who better match the editor/reviewer pool on background characteristics are indirectly gaining an advantage, assuming it is more likely that they draw a reviewer who matches with them. In our setting, the population of editors/reviewers tend to be of a higher "status" compared to the author population, implying that the "rich" do, in fact, "get richer".

Hence, in an environment where the prospect of publishing is increasingly difficult and journals face capacity constraints, our results imply that authors who attain "club" or "elite status" will see continued publication success, conditional on paper quality, at the expense of those who do not possess such signals. That is, being part of the "club" boosts an author's publication prospects when being evaluated by editors/reviewers of the same club in a system where editors/reviewers are relatively more likely to be part of said club.

Our results provide evidence that biases in the publication process likely contribute directly to the lack of diversity in the economics profession, since publications are the primary factor in tenure decisions. Likewise, these same biases may also exist in the tenure review process, even over and above the strong positive weight placed on top five publications (Heckman and Moktan, 2020), as the promotion process relies heavily upon further external evaluation. Overburdened reviewers, who often rely on external signals (just as English (2008) suggests, leads to a concentration of "winners" in cultural prizes), clearly look upon these signals in the promotion and tenure process–and, apparently, along the way (at the paper publication recommendation level) as well.

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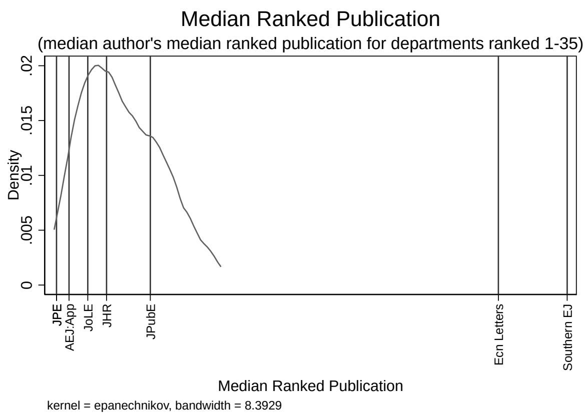
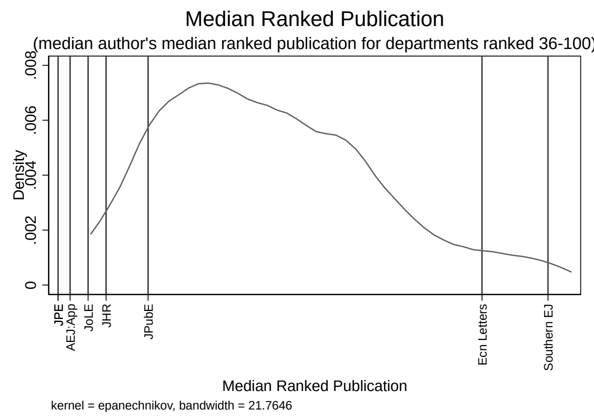
7 Tables and Figures

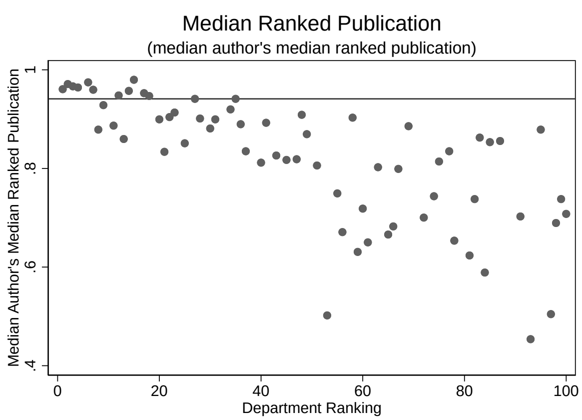
Figure 1: Publication Ranks by Department Ranks



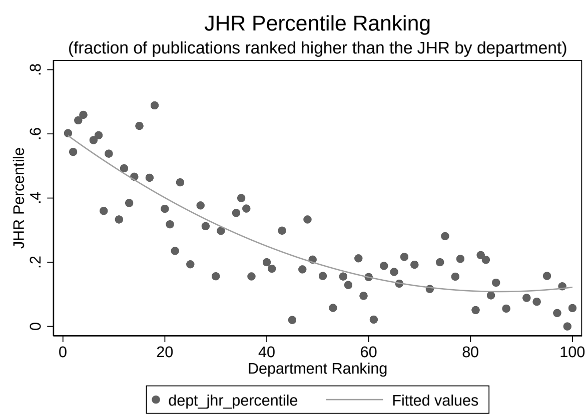
(a) Distribution of Median Ranks - Departments 1-35



(b) Distribution of Median Ranks - Departments 36-100



(c) Median author's median ranked publication



(d) Fraction of publications ranked higher than the JHR

Notes: Data consist of journal publications, at the time of tenure, for the population of currently (Fall 2021) tenured applied microeconomists at the top 100-ranked economics departments according to IDEAS. Journal rankings are from the 2020 SJR journal rankings. "Median author's median ranked publication" is found by calculating each author's median ranked publication, then finding the median across authors within each department.

Table 1: Summary statistics - Author and reviewer characteristics

	All authors		Passed the desk authors		All reviewers	
	Mean	SD	Mean	SD	Mean	SD
Female	0.36	0.48	0.37	0.48	0.35	0.48
Gender missing	0.02	0.15	0.01	0.08	0.00	0.04
Institution of PhD (US News):						
-Ranked top 10	0.16	0.36	0.24	0.43	0.41	0.49
-Ranked 11-30	0.18	0.39	0.23	0.42	0.26	0.44
-Ranked 31-50	0.06	0.23	0.07	0.25	0.05	0.21
-Ranked 51+ / missing	0.60	0.49	0.47	0.50	0.28	0.45
Institution of PhD (IDEAS):						
-Ranked top 10	0.14	0.35	0.21	0.41	0.36	0.48
-Ranked 11-30	0.15	0.36	0.21	0.40	0.25	0.44
-Ranked 31-50	0.08	0.27	0.10	0.30	0.09	0.29
-Ranked 51+ / missing	0.62	0.48	0.48	0.50	0.30	0.46
Year receive PhD	2005.45	10.67	2005.38	10.50	2004.22	9.57
Unknown PhD year	0.16	0.37	0.09	0.28	0.04	0.20
Observations	8369		3344		2006	
	Author-papers		Passed the desk author-papers		Reviewer-papers	
	Mean	SD	Mean	SD	Mean	SD
# prior publications	3.32	7.12	4.50	8.58	4.79	6.23
# prior top fives	0.28	1.39	0.50	1.90	0.72	1.58
NBER affiliated	0.05	0.21	0.10	0.30	0.27	0.45
# of unique coauthors	8.19	27.41	9.77	27.63	8.14	16.23
# of coauthors' coauthors	115.51	476.32	143.80	519.86	113.82	271.47
Department rank (IDEAS):						
-Ranked top 10	0.05	0.22	0.08	0.27	0.13	0.34
-Ranked 11-30	0.06	0.24	0.10	0.30	0.17	0.38
-Ranked 31-100	0.16	0.36	0.20	0.40	0.25	0.43
-Ranked 101-250	0.15	0.36	0.17	0.38	0.18	0.38
-251+ / missing / non-academic	0.58	0.49	0.45	0.50	0.26	0.44
Observations	11275		4134		4523	

Notes: Sample collected from the population of submissions made to the *Journal of Human Resources* from 2007 to 2018. "Passed the desk" focuses on the sample of submissions that were not desk rejected by the handling editor.

Table 2: Summary statistics - Units of observation

	Author-editor-papers		Author-reviewer-papers	
	Mean	SD	Mean	SD
Outcome: Passed the desk (editor), positive evaluation (reviewer)	0.37	0.48	0.45	0.50
Degrees of separation (RePEc):				
-One (direct coauthors)	0.00	0.04	0.00	0.07
-Two (coauthor's coauthor)	0.02	0.13	0.03	0.16
-Three	0.10	0.31	0.10	0.31
-Four	0.27	0.44	0.25	0.43
-Five	0.20	0.40	0.21	0.41
-Six+ or no path	0.27	0.44	0.29	0.45
-Author and/or reviewer missing	0.13	0.34	0.11	0.32
Author-editor/reviewer PhD (US News):				
-Exact same PhD	0.02	0.14	0.03	0.16
-Both ranked top 10	0.11	0.31	0.13	0.33
-Both ranked 11-30	0.07	0.25	0.07	0.26
-Both ranked 31-50	0.00	0.00	0.00	0.05
-Both ranked 51+ / missing	0.01	0.12	0.13	0.33
Author-editor/reviewer employment:				
-Former/current colleagues	0.04	0.21	0.05	0.21
-Both top 10 department	0.01	0.10	0.01	0.12
-Both 11-30 department	0.03	0.16	0.02	0.13
-Both 31-100 department	0.06	0.23	0.05	0.22
-Both 101-250 department	0.02	0.12	0.03	0.17
-251+ / missing / non-academic	0.00	0.01	0.12	0.33
Author and editor/reviewer both:				
-Female	0.13	0.34	0.13	0.34
-Published in top five	0.09	0.29	0.07	0.25
-NBER affiliated	0.04	0.20	0.04	0.18
-Same NBER program(s)	0.03	0.16	0.02	0.15
Observations	11275		8954	

Notes: "Passed the desk" is an indicator for the editor not desk rejecting the submission. "Positive evaluation" is an indicator for the reviewer recommending the possibility of a revision (i.e. not suggesting outright rejection). Degrees of separation calculated from a constructed network of coauthorships based on a set of journal publications and working papers series housed on RePEc.

Table 3: Author-editor matching by PhD, employment history, NBER affiliation, and coauthor networks

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome: Passed the desk						
Exact same PhD institution	0.052*				0.034	
	(0.031)				(0.035)	
Former/current colleagues		0.046**			0.026	
		(0.022)			(0.025)	
Same NBER program(s)			0.122***		0.093**	
			(0.046)		(0.046)	
Degrees of separation: 1				0.265***	0.241***	
				(0.064)	(0.067)	
Degrees of separation: 2				0.137***	0.129***	
				(0.034)	(0.034)	
Degrees of separation: 3				0.074***	0.072***	
				(0.017)	(0.017)	
# of direct matches:						
- One match						0.056**
						(0.023)
- Two+ matches						0.089***
						(0.033)
Author-editor-papers	11062	11062	11062	11062	11062	11062
Editor FE	X	X	X	X	X	X
Author controls	X	X	X	X	X	X

Notes: Observations are unique at the author-editor-paper level. Each column presents results from a single regression, with observations weighted by the inverse of the number of coauthors on the paper. "Passed the desk" is an indicator for the editor not desk rejecting the paper. Degrees of separation in (4) and (5) are calculated from a constructed network of coauthorships based on a set of journal publications and working papers series housed on RePEc. A direct match in (6) between an author and editor occurs when they are direct coauthors, went to the same PhD, were ever colleagues, or affiliated with the same NBER program(s) (max of four per author-editor pair). Author controls include number of publications up to year of submission, publications in the "top 5" economics journals, number of unique coauthors from published manuscripts, number of unique coauthors' coauthors from published manuscripts, NBER program affiliations, gender, binned rankings of institution of PhD (according to US News), and binned rankings for their institution of employment (according to IDEAS). Standard errors clustered at the paper level. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Table 4: Author-editor matching by publication in top five and department rankings

	(1)	(2)	(3)	(4)	(5)
<u>Outcome: Passed the desk</u>					
Author-editor both T5	0.045**				
	(0.021)				
Both from similar rank PhD (US News)		-0.004			
		(0.015)			
-Not similar rank (editor higher)			-0.018		
			(0.023)		
-Not similar rank (editor lower)			0.029		
			(0.027)		
Both employed at similar rank department (IDEAS)				-0.027	
				(0.018)	
-Not similar rank (editor higher)					0.052**
					(0.022)
-Not similar rank (editor lower)					-0.014
					(0.027)
Author-editor-papers	11062	11062	11062	11062	11062
Editor FE	X	X	X	X	X
Author controls	X	X	X	X	X

Notes: Observations are unique at the author-editor-paper level. Each column presents results from a single regression, with observations weighted by the inverse of the number of coauthors on the paper. "Passed the desk" is an indicator for the editor not desk rejecting the paper. Each reported covariate is an indicator for whether both the author and the editor share a particular characteristic. Author controls include number of publications up to year of submission, publications in the "top 5" economics journals, number of unique coauthors from published manuscripts, number of unique coauthors' coauthors from published manuscripts, NBER program affiliations, gender, binned rankings of institution of PhD (according to US News), and binned rankings for their institution of employment (according to IDEAS). Standard errors clustered at the paper level. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Table 5: Author-reviewer matching by PhD, employment history, NBER program affiliation, and coauthor networks

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome: Positive evaluation						
Exact same PhD institution	0.062*				0.050	
	(0.033)				(0.033)	
Former/current colleagues		0.037*			0.013	
		(0.022)			(0.022)	
Same NBER program(s)			0.023		0.022	
			(0.032)		(0.033)	
Degrees of separation: 1				0.096*	0.079	
				(0.052)	(0.052)	
Degrees of separation: 2				-0.020	-0.027	
				(0.026)	(0.027)	
Degrees of separation: 3				0.005	0.003	
				(0.012)	(0.013)	
# of direct matches:						
- One match						0.021
						(0.020)
- Two+ matches						0.067**
						(0.032)
Author-reviewer-papers	8164	8164	8164	8164	8164	8164
Reviewer FE	X	X	X	X	X	X
Paper FE	X	X	X	X	X	X

Notes: Observations are unique at the author-reviewer-paper level. Each column presents results from a single regression, with observations weighted by the inverse of the number of coauthors on the paper. "Positive evaluation" is an indicator for the reviewer recommending the possibility of a revision (i.e. not suggesting outright rejection). Degrees of separation in (4) and (5) are calculated from a constructed network of coauthorships based on a set of journal publications and working papers series housed on RePEc. A direct match in (6) between an author and reviewer occurs when they are direct coauthors, went to the same PhD, were ever colleagues, or affiliated to the same NBER program(s) (max of four per author-reviewer pair). Standard errors clustered at the paper level. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Table 6: Author-reviewer matching by publication in top five and department rankings

	(1)	(2)	(3)	(4)	(5)
<u>Outcome: Positive evaluation</u>					
Author-reviewer both T5	0.029**				
	(0.014)				
Both from similar rank PhD (US News)		0.022**			
		(0.010)			
-Not similar rank (reviewer higher)			-0.009		
			(0.009)		
-Not similar rank (reviewer lower)			-0.040***		
			(0.014)		
Both employed at similar rank department (IDEAS)				0.019*	
				(0.011)	
-Not similar rank (reviewer higher)					-0.034**
					(0.013)
-Not similar rank (reviewer lower)					-0.005
					(0.011)
Author-reviewer-papers	8164	8164	8164	8164	8164
Reviewer FE	X	X	X	X	X
Paper FE	X	X	X	X	X

Notes: Observations are unique at the author-reviewer-paper level. Each column presents results from a single regression, with observations weighted by the inverse of the number of coauthors on the paper. "Positive evaluation" is an indicator for the reviewer recommending the possibility of a revision (i.e. not suggesting outright rejection). Each reported covariate is an indicator for whether both the author and the reviewer share a particular characteristic. Standard errors clustered at the paper level. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

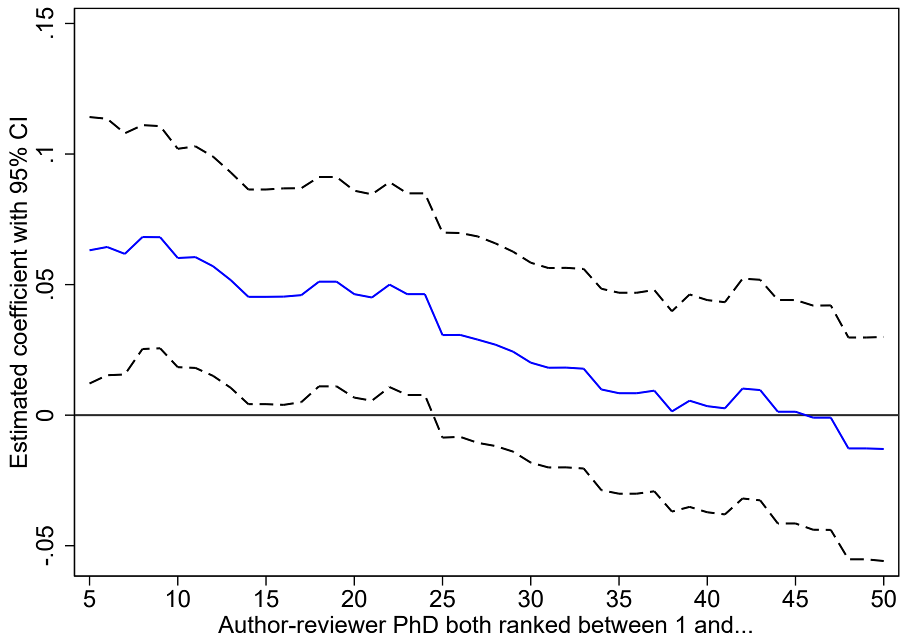
Table 7: Publication conditional on reviewer recommendation - Author-editor matching by PhD, employment history, NBER affiliation, and coauthor networks

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome: Published						
Fraction positive review	0.543***	0.543***	0.542***	0.541***	0.541***	0.542***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Exact same PhD institution	0.029				0.003	
	(0.039)				(0.044)	
Former/current colleagues		0.044			0.034	
		(0.029)			(0.033)	
Same NBER program(s)			0.151***		0.134***	
			(0.050)		(0.050)	
Degrees of separation: 1				0.179*	0.150	
				(0.101)	(0.103)	
Degrees of separation: 2				0.078*	0.062	
				(0.044)	(0.044)	
Degrees of separation: 3				0.042**	0.039*	
				(0.021)	(0.021)	
# of direct matches:						
- One match						0.069**
						(0.029)
- Two+ matches						0.068*
						(0.040)
Author-editor-papers	4114	4114	4114	4114	4114	4114
Editor FE	X	X	X	X	X	X
Author controls	X	X	X	X	X	X

Notes: Observations are unique at the author-editor-paper level. Each column presents results from a single regression, with observations weighted by the inverse of the number of coauthors on the paper. "Published" is an indicator for whether the paper ultimately published. "Fraction positive review" is the share of the reviewer evaluations that were positive. Degrees of separation in (4) and (5) are calculated from a constructed network of coauthorships based on a set of journal publications and working papers series housed on RePEc. A direct match in (6) between an author and editor occurs when they are direct coauthors, went to the same PhD, were ever colleagues, or affiliated to the same NBER program(s) (max of four per author-editor pair). Author controls include number of publications up to year of submission, publications in the "top 5" economics journals, number of unique coauthors from published manuscripts, number of unique coauthors' coauthors from published manuscripts, NBER program affiliations, gender, binned rankings of institution of PhD (according to US News), and binned rankings for their institution of employment (according to IDEAS). Standard errors clustered at the paper level. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

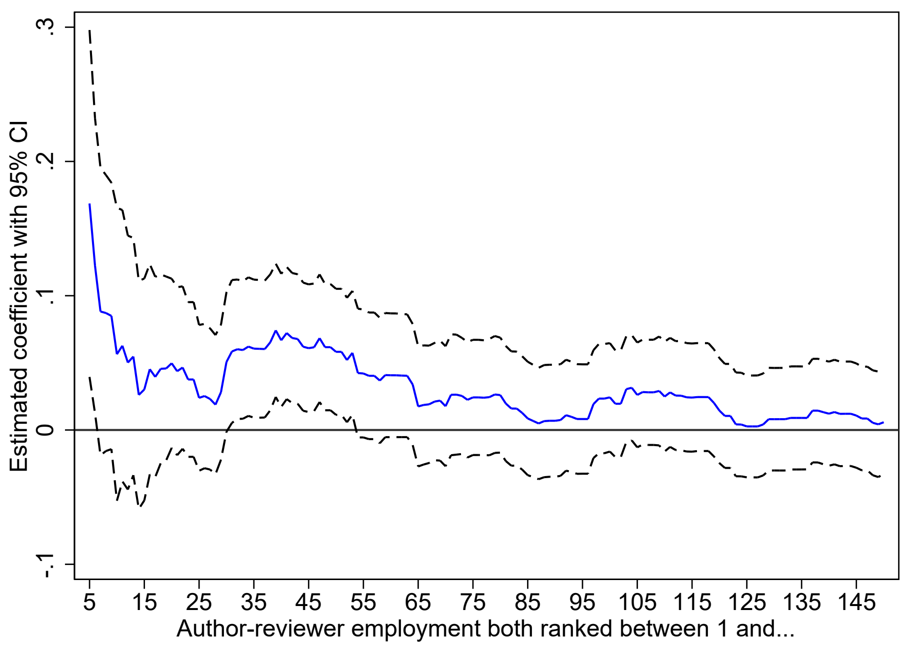
Appendix 1: Additional Tables and Figures

Figure A1: Author-reviewer PhD rank match on positive evaluation by different rank cutoffs



Notes: Each point reports a single estimate and its 95% confidence internal from a regression of receiving a positive evaluation on PhD rank match from our fully specified model (reviewer and paper fixed effects with author controls). For instance, the first point reports the estimated coefficient on an indicator for both the author and reviewer receiving their PhD from a top five department (as ranked by IDEAS). The point for "10" reports the estimated coefficient on an indicator for both the author and reviewer receiving their PhD from a top 10 department.

Figure A2: Author-reviewer employment rank match on positive evaluation by different rank cutoffs



Notes: Each point reports a single estimate and its 95% confidence internal from a regression of receiving a positive evaluation on employment rank match from our fully specified model (reviewer and paper fixed effects with author controls). For instance, the first point reports the estimated coefficient on an indicator for both the author and reviewer being employed by a top five department (as ranked by IDEAS). The point for "10" reports the estimated coefficient on an indicator for both the author and reviewer being employed by a top 10 department.

Table A1: List of journals from RePEc used for covariate and network calculations

American Economic Journal: Applied Economics	Journal of Economic Perspectives
American Economic Journal: Economic Policy	Journal of Economic Surveys
American Economic Journal: Macroeconomics	Journal of Economic Theory
American Economic Journal: Microeconomics	Journal of Environmental Economics and Management
Annual Review of Economics	Journal of Finance
Annual Review of Financial Economics	Journal of Financial and Quantitative Analysis
Applied Economics	Journal of Financial Economics
Applied Energy	Journal of Financial Intermediation
Brookings Papers on Economic Activity	Journal of Financial Stability
Canadian Journal of Economics	Journal of Health Economics
Demography	Journal of Human Capital
Ecological Economics	Journal of Human Resources
Econometric Theory	Journal of International Business Studies
Econometrica	Journal of International Economics
Econometrics Journal	Journal of International Money and Finance
Economia	Journal of Labor Economics
Economic Development and Cultural Change	Journal of Monetary Economics
Economic Inquiry	Journal of Money, Credit and Banking
Economic Journal	Journal of Policy Analysis and Management
Economic Modelling	Journal of Political Economy
Economic Policy	Journal of Population Economics
Economica	Journal of Public Economics
Economics Letters	Journal of the European Economic Association
Economics of Education Review	Journal of Urban Economics
Energy	Labour Economics
Energy Economics	Management Science
Energy Policy	National Tax Journal
European Economic Review	Ovidius University Annals, Economic Sciences Series
European Journal of Operational Research	Oxford Bulletin of Economics and Statistics
European Journal of Political Economy	Quantitative Economics
Experimental Economics	RAND Journal of Economics
Games and Economic Behavior	Regional Science and Urban Economics
Health Economics	Renewable and Sustainable Energy Reviews
ILR Review	Renewable Energy
IMF Economic Review	Research Policy
International Economic Review	Review of Economic Dynamics
Journal of Accounting and Economics	Review of Economic Studies
Journal of Applied Econometrics	Review of Finance
Journal of Banking & Finance	Review of Financial Studies
Journal of Business & Economic Statistics	Scandinavian Journal of Economics
Journal of Business Research	Small Business Economics
Journal of Comparative Economics	Stata Journal
Journal of Development Economics	Sustainability
Journal of Econometrics	The Quarterly Journal of Economics
Journal of Economic Behavior & Organization	The Review of Economics and Statistics
Journal of Economic Dynamics and Control	World Bank Economic Review
Journal of Economic Geography	World Bank Research Observer
Journal of Economic Growth	World Development
Journal of Economic Literature	

Notes: All papers from journals listed above were collected from RePEc (Research Papers in Economics) in order to calculate author covariates (e.g. number of publications) and network connectivity (e.g. degrees of separation between a author-editors and author-reviewers. Network calculations additionally use working papers from the NBER, IZA, arXiv, and CEPR.

Table A2: Summary statistics by whether author or reviewer dropped from sample due to paper and reviewer fixed effects

	Kept authors		Dropped authors		Kept reviewers		Dropped reviewers	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Female	0.36	0.48	0.38	0.49	0.36	0.48	0.32	0.47
Gender missing	0.01	0.08	0.01	0.07	0.00	0.03	0.01	0.08
Institution of PhD (US News):								
-Ranked top 10	0.24	0.43	0.24	0.43	0.41	0.49	0.41	0.49
-Ranked 11-30	0.22	0.41	0.26	0.44	0.25	0.44	0.27	0.44
-Ranked 31-50	0.06	0.25	0.09	0.28	0.04	0.20	0.06	0.24
-Ranked 51+ / missing	0.48	0.50	0.40	0.49	0.29	0.45	0.26	0.44
Institution of PhD (IDEAS):								
-Ranked top 10	0.21	0.41	0.19	0.39	0.37	0.48	0.34	0.48
-Ranked 11-30	0.20	0.40	0.26	0.44	0.25	0.43	0.27	0.44
-Ranked 31-50	0.10	0.30	0.11	0.32	0.09	0.29	0.08	0.27
-Ranked 51+ / missing	0.49	0.50	0.44	0.50	0.29	0.45	0.31	0.46
Year receive PhD	2005.25	10.57	2006.32	9.93	2004.80	9.45	2002.53	9.73
Unknown PhD year	0.09	0.29	0.07	0.25	0.04	0.19	0.06	0.23
Observations	2955		389		1491		515	
	Kept author-papers		Dropped author-papers		Kept reviewer-papers		Dropped reviewer-papers	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
# prior publications	4.71	8.75	2.96	6.99	4.88	6.28	4.34	5.98
# prior top fives	0.52	1.92	0.34	1.74	0.71	1.56	0.74	1.66
NBER affiliated	0.10	0.30	0.09	0.29	0.29	0.45	0.22	0.41
# of unique coauthors	10.03	27.56	7.83	28.08	8.27	16.19	7.53	16.43
# of coauthors' coauthors	144.56	499.41	137.99	654.66	115.50	271.88	106.21	269.66
Department rank (IDEAS):								
-Ranked top 10	0.08	0.27	0.09	0.29	0.14	0.34	0.13	0.33
-Ranked 11-30	0.10	0.29	0.12	0.32	0.17	0.38	0.17	0.38
-Ranked 31-100	0.21	0.40	0.18	0.39	0.26	0.44	0.22	0.41
-Ranked 101-250	0.17	0.37	0.19	0.39	0.18	0.39	0.16	0.36
-251+ / missing / non-academic	0.45	0.50	0.42	0.49	0.25	0.43	0.33	0.47
Observations	3651		483		3705		818	

Notes: Sample collected from the population of submissions made to the *Journal of Human Resources* from 2007 to 2018.

Table A3: Results by “closest” connection between editor-authors

	Passed the desk					
	(1)	(2)	(3)	(4)	(5)	(6)
At least one author & editor:						
-Exact same PhD institution	0.051*				0.034	
	(0.030)				(0.033)	
-Former/current colleagues		0.038*			0.013	
		(0.022)			(0.025)	
-Same NBER program(s)			0.165***		0.123***	
			(0.040)		(0.041)	
Shortest coauthor connection:						
Degrees of separation: 1				0.269***	0.238***	
				(0.067)	(0.071)	
Degrees of separation: 2				0.159***	0.138***	
				(0.034)	(0.035)	
Degrees of separation: 3				0.066***	0.062***	
				(0.018)	(0.018)	
Total # of direct matches:						
- One match						0.076***
						(0.023)
- Two+ matches						0.079**
						(0.031)
Editor-papers	6107	6107	6107	6107	6107	6107
Editor FE	X	X	X	X	X	X
Author controls (averages)	X	X	X	X	X	X

Notes: Observations are unique at the editor-paper level. Each column presents results from a single regression. “Passed the desk” is an indicator for the editor not desk rejecting the paper. Degrees of separation in (4) and (5) are calculated from a constructed network of coauthorships based on a set of journal publications and working papers series housed on RePEc. A direct match in (6) between an author and editor occurs when they are direct coauthors, went to the same PhD, were ever colleagues, or affiliated to the same NBER program(s) (max of four per author-editor pair). Author controls include number of publications up to year of submission, publications in the “top 5” economics journals, number of unique coauthors from published manuscripts, number of unique coauthors’ coauthors from published manuscripts, NBER program affiliations, gender, binned rankings of institution of PhD (according to US News), and binned rankings for their institution of employment (according to IDEAS). Standard errors clustered at the paper level. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Table A4: Results by "closest" connection between reviewer-authors

	Positive evaluation					
	(1)	(2)	(3)	(4)	(5)	(6)
At least one author & reviewer:						
-Exact same PhD institution	0.070				0.054	
	(0.070)				(0.086)	
-Former/current colleagues		0.048			0.009	
		(0.053)			(0.065)	
-Same NBER program(s)			0.106		0.123	
			(0.084)		(0.086)	
Shortest coauthor connection:						
Degrees of separation: 1				0.230*	0.220*	
				(0.120)	(0.121)	
Degrees of separation: 2				-0.127*	-0.148*	
				(0.075)	(0.076)	
Degrees of separation: 3				0.041	0.040	
				(0.044)	(0.045)	
Total # of direct matches:						
- One match						0.040
						(0.061)
- Two+ matches						0.126**
						(0.063)
Reviewer-papers	2321	2321	2321	2321	2321	2321
Editor FE	X	X	X	X	X	X
Paper FE	X	X	X	X	X	X

Notes: Observations are unique at the reviewer-paper level. Each column presents results from a single regression. "Positive evaluation" is an indicator for the reviewer recommending the possibility of a revision (i.e. not suggesting outright rejection). Degrees of separation in (4) and (5) are calculated from a constructed network of coauthorships based on a set of journal publications and working papers series housed on RePEc. A direct match in (6) between an author and editor occurs when they are direct coauthors, went to the same PhD, were ever colleagues, or affiliated to the same NBER program(s) (max of four per author-editor pair). Standard errors clustered at the paper level. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Table A5: Editor match to the most "prominent" author

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome: Passed the desk						
Exact same PhD institution	0.032				0.015	
	(0.034)				(0.038)	
Former/current colleagues		0.038			0.023	
		(0.025)			(0.027)	
Same NBER program(s)			0.139***		0.115**	
			(0.048)		(0.048)	
Degrees of separation: 1				0.356***	0.332***	
				(0.073)	(0.077)	
Degrees of separation: 2				0.142***	0.131***	
				(0.039)	(0.039)	
Degrees of separation: 3				0.070***	0.069***	
				(0.019)	(0.019)	
# of direct matches:						
- One match						0.068***
						(0.025)
- Two+ matches						0.072*
						(0.037)
Editor-papers	6085	6085	6085	6085	6085	6085
Editor FE	X	X	X	X	X	X
Author controls	X	X	X	X	X	X

Notes: Observations are unique at the editor-paper level. Each column presents results from a single regression. "Passed the desk" is an indicator for the editor not desk rejecting the paper. Degrees of separation in (4) and (5) are calculated from a constructed network of coauthorships based on a set of journal publications and working papers series housed on RePEc. A direct match in (6) between an author and editor occurs when they are direct coauthors, went to the same PhD, were ever colleagues, or affiliated to the same NBER program(s) (max of four per author-editor pair). Author "prominence" is first determined by the author with the most top five publications, followed by rank of department of employment, then whoever has the most publications overall, then PhD rank, then whoever is oldest (years since PhD); remaining ties (typically two graduate student coauthors) are broken randomly. Author controls include number of publications up to year of submission, publications in the "top 5" economics journals, number of unique coauthors from published manuscripts, number of unique coauthors' coauthors from published manuscripts, NBER program affiliations, gender, binned rankings of institution of PhD (according to US News), and binned rankings for their institution of employment (according to IDEAS). Standard errors clustered at the paper level. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Table A6: Reviewer match to the most "prominent" author

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome: Positive evaluation						
Exact same PhD institution	0.091				0.128	
	(0.080)				(0.101)	
Former/current colleagues		0.003			-0.077	
		(0.059)			(0.074)	
Same NBER program(s)			0.173*		0.185**	
			(0.090)		(0.089)	
Degrees of separation: 1				0.194	0.235	
				(0.180)	(0.179)	
Degrees of separation: 2				-0.020	-0.052	
				(0.080)	(0.082)	
Degrees of separation: 3				0.054	0.060	
				(0.049)	(0.049)	
# of direct matches:						
- One match						0.052
						(0.066)
- Two+ matches						0.097
						(0.078)
Reviewer-papers	2321	2321	2321	2321	2321	2321
Reviewer FE	X	X	X	X	X	X
Paper FE	X	X	X	X	X	X

Notes: Observations are unique at the reviewer-paper level. Each column presents results from a single regression. "Positive evaluation" is an indicator for the reviewer recommending the possibility of a revision (i.e. not suggesting outright rejection). Degrees of separation in (4) and (5) are calculated from a constructed network of coauthorships based on a set of journal publications and working papers series housed on RePEc. A direct match in (6) between an author and editor occurs when they are direct coauthors, went to the same PhD, were ever colleagues, or affiliated to the same NBER program(s) (max of four per author-editor pair). Author "prominent" is first determined by the author with the most top five publications, followed by rank of department of employment, then whoever has the most publications overall, then PhD rank, then whoever is oldest (years since PhD); remaining ties (typically two graduate student coauthors) are broken randomly. Standard errors clustered at the paper level. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Table A7: Author-reviewer matching by PhD, employment history, NBER affiliation, and coauthor networks - Robustness to editor fixed effects and author controls instead of paper fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome: Positive evaluation						
Exact same PhD institution	0.114**				0.103**	
	(0.046)				(0.051)	
Former/current colleagues		0.056*			0.008	
		(0.033)			(0.036)	
Same NBER program(s)			0.004		0.001	
			(0.046)		(0.045)	
Degrees of separation: 1				0.138*	0.106	
				(0.083)	(0.081)	
Degrees of separation: 2				-0.002	-0.010	
				(0.042)	(0.042)	
Degrees of separation: 3				-0.017	-0.018	
				(0.022)	(0.022)	
# of direct matches:						
- One match						0.010
						(0.030)
- Two+ matches						0.108**
						(0.046)
Author-reviewer-papers	8164	8164	8164	8164	8164	8164
Reviewer FE	X	X	X	X	X	X
Editor FE	X	X	X	X	X	X
Author controls	X	X	X	X	X	X

Notes: Observations are unique at the author-reviewer-paper level. Each column presents results from a single regression, with observations weighted by the inverse of the number of coauthors on the paper. “Positive evaluation” is an indicator for the reviewer recommending the possibility of a revision (i.e. not suggesting outright rejection). Degrees of separation in (4) and (5) are calculated from a constructed network of coauthorships based on a set of journal publications and working papers series housed on RePEc. A direct match in (6) between an author and reviewer occurs when they are direct coauthors, went to the same PhD, were ever colleagues, or affiliated to the same NBER program(s) (max of four per author-reviewer pair). Standard errors clustered at the paper level. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Table A8: Author-reviewer matching by publication in top five and department rankings - Robustness to editor fixed effects and author controls instead of paper fixed effects

	(1)	(2)	(3)	(4)	(5)
Outcome: Positive evaluation					
Author-reviewer both T5	-0.036				
	(0.026)				
Both from similar rank PhD (US News)		0.018			
		(0.016)			
-Not similar rank (reviewer higher)			0.006		
			(0.019)		
-Not similar rank (reviewer lower)			-0.055**		
			(0.022)		
Both employed at similar rank department (IDEAS)				0.018	
				(0.017)	
-Not similar rank (reviewer higher)					-0.030
					(0.020)
-Not similar rank (reviewer lower)					0.001
					(0.019)
Author-reviewer-papers	8164	8164	8164	8164	8164
Reviewer FE	X	X	X	X	X
Editor FE	X	X	X	X	X
Author controls	X	X	X	X	X

Notes: Observations are unique at the author-reviewer-paper level. Each column presents results from a single regression, with observations weighted by the inverse of the number of coauthors on the paper. "Positive evaluation" is an indicator for the reviewer recommending the possibility of a revision (i.e. not suggesting outright rejection). Each reported covariate is an indicator for whether both the author and the reviewer share a particular characteristic. Standard errors clustered at the paper level. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Table A9: Author-editor matching by PhD, employment history, NBER program affiliation, and coauthor networks - Robustness to logit model

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome: Passed the desk						
Exact same PhD institution	0.365*				0.263	
	(0.202)				(0.228)	
Former/current colleagues		0.323**			0.204	
		(0.140)			(0.157)	
Same NBER program(s)			0.854**		0.650*	
			(0.374)		(0.366)	
Degrees of separation: 1				—	—	
Degrees of separation: 2				0.880***	0.835***	
				(0.227)	(0.228)	
Degrees of separation: 3				0.422***	0.414***	
				(0.096)	(0.096)	
# of direct matches:						
- One match						0.259*
						(0.144)
- Two+ matches						0.660***
						(0.231)
Author-editor-papers	11051	11051	11051	11034	11034	11051
Editor FE	X	X	X	X	X	X
Author controls	X	X	X	X	X	X

Notes: Observations are unique at the author-editor-paper level. Each column presents results from a single logit regression, with observations weighted by the inverse of the number of coauthors on the paper. "Passed the desk" is an indicator for the editor not desk rejecting the paper. Degrees of separation in (4) and (5) are calculated from a constructed network of coauthorships based on a set of journal publications and working papers series housed on RePEc. A direct match in (6) between an author and editor occurs when they are direct coauthors, went to the same PhD, were ever colleagues, or affiliated with the same NBER program(s) (max of four per author-editor pair). Author controls include number of publications up to year of submission, publications in the "top 5" economics journals, number of unique coauthors from published manuscripts, number of unique coauthors' coauthors from published manuscripts, NBER program affiliations, gender, binned rankings of institution of PhD (according to US News), and binned rankings for their institution of employment (according to IDEAS). Standard errors clustered at the paper level. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Table A10: Author-editor matching by publication in top five and department rankings - Robustness to logit model

	(1)	(2)	(3)	(4)	(5)
<u>Outcome: Passed the desk</u>					
Author-editor both T5	0.209				
	(0.128)				
Both from similar rank PhD (US News)		0.017			
		(0.088)			
-Not similar rank (editor higher)			-0.311**		
			(0.141)		
-Not similar rank (editor lower)			0.292*		
			(0.155)		
Both employed at similar rank department (IDEAS)				-0.109	
				(0.099)	
-Not similar rank (editor higher)					0.241**
					(0.123)
-Not similar rank (editor lower)					-0.089
					(0.145)
Author-editor-papers	11051	11051	11051	11051	11051
Editor FE	X	X	X	X	X
Author controls	X	X	X	X	X

Notes: Observations are unique at the paper-editor-author level. Each column presents results from a single logit regression, with observations weighted by the inverse of the number of coauthors on the paper. "Passed the desk" is an indicator for the editor not desk rejecting the paper. Each reported covariate is an indicator for whether both the author and the editor share a particular characteristic. Author controls include number of publications up to year of submission, publications in the "top 5" economics journals, number of unique coauthors from published manuscripts, number of unique coauthors' coauthors from published manuscripts, NBER program affiliations, gender, binned rankings of institution of PhD (according to US News), and binned rankings for their institution of employment (according to IDEAS). Standard errors clustered at the paper level. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Table A11: Author-reviewer matching by PhD, employment history, NBER program affiliation, and coauthor networks - Robustness to logit model

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome: Positive evaluation						
Exact same PhD institution	0.511**				0.250	
	(0.250)				(0.289)	
Former/current colleagues		0.444**			0.279	
		(0.185)			(0.217)	
Same NBER program(s)			0.405		0.340	
			(0.304)		(0.310)	
Degrees of separation: 1				0.859	0.642	
				(0.524)	(0.528)	
Degrees of separation: 2				0.430*	0.381	
				(0.239)	(0.241)	
Degrees of separation: 3				0.215*	0.188	
				(0.126)	(0.127)	
# of direct matches:						
- One match						0.228
						(0.193)
- Two+ matches						0.649***
						(0.248)
Author-reviewer-papers	4934	4934	4934	4934	4934	4934
Reviewer FE	X	X	X	X	X	X
Editor FE	X	X	X	X	X	X
Author controls	X	X	X	X	X	X

Notes: Observations are unique at the paper-reviewer-author level. Each column presents results from a single logit regression, with observations weighted by the inverse of the number of coauthors on the paper. "Positive evaluation" is an indicator for the reviewer recommending the possibility of a revision (i.e. not suggesting outright rejection). Degrees of separation in (4) and (5) are calculated from a constructed network of coauthorships based on a set of journal publications and working papers series housed on RePEc. A direct match in (6) between an author and reviewer occurs when they are direct coauthors, went to the same PhD, were ever colleagues, or affiliated to the same NBER program(s) (max of four per author-reviewer pair). Standard errors clustered at the paper level. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Table A12: Author-reviewer matching by publication in top five and department rankings - Robustness to logit model

	(1)	(2)	(3)	(4)	(5)
Outcome: Positive evaluation					
Author-reviewer both T5	0.153				
	(0.177)				
Both from similar rank PhD (US News)		0.139			
		(0.095)			
-Not similar rank (reviewer higher)			-0.201		
			(0.182)		
-Not similar rank (reviewer lower)			-0.076		
			(0.183)		
Both employed at similar rank department (IDEAS)				0.017	
				(0.107)	
-Not similar rank (reviewer higher)					-0.240
					(0.147)
-Not similar rank (reviewer lower)					0.243
					(0.151)
Author-reviewer-papers	4934	4934	4934	4934	4934
Reviewer FE	X	X	X	X	X
Editor FE	X	X	X	X	X
Author controls	X	X	X	X	X

Notes: Observations are unique at the paper-reviewer-author level. Each column presents results from a single logit regression, with observations weighted by the inverse of the number of coauthors on the paper. "Positive evaluation" is an indicator for the reviewer recommending the possibility of a revision (i.e. not suggesting outright rejection). Each reported covariate is an indicator for whether both the author and the reviewer share a particular characteristic. Standard errors clustered at the paper level. One, two, and three asterisks indicate statistical significance at the 10, 5, and 1 percent levels, respectively.