# Single versus Double Blind Reviewing at WSDM 2017

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# ABSTRACT

In this paper we study the implications for conference program committees of using single-blind reviewing, in which committee members are aware of the names and affiliations of paper authors, versus double-blind reviewing, in which this information is not visible to committee members. WSDM 2017, the 10th ACM International ACM Conference on Web Search and Data Mining, performed a controlled experiment in which each paper was reviewed by four committee members. Two of these four reviewers were chosen from a pool of committee members who had access to author information; the other two were chosen from a disjoint pool who did not have access to this information. This information asymmetry persisted through the process of bidding for papers, reviewing papers, and entering scores. Reviewers in the single-blind condition typically bid for 22% fewer papers, and preferentially bid for papers from top institutions. Once papers were allocated to reviewers, single-blind reviewers were significantly more likely than their double-blind counterparts to recommend for acceptance papers from famous authors and top institutions. The estimated odds multipliers are 1.63 for famous authors and 1.58 and 2.10 for top universities and companies respectively, so the result is tangible. For female authors, the associated odds multiplier of 0.78 is not statistically significant in our study. However, a meta-analysis places this value in line with that of other experiments, and in the context of this larger aggregate the gender effect is also statistically significant.

# **1 INTRODUCTION**

The scientific peer-review process dates back to the 1600's, and is generally regarded as a cornerstone of the scientific method. The details of its implementation have been scrutinized and explored across many academic disciplines.

Peer review has many dimensions. At the present time, there is a conversation underway throughout the scientific community regarding *open peer review*, which covers a range of practices ranging from revealing reviewer names to authors to making peer reviews available to the general public, with or without the reviewer's name attached. In the last 2–3 decades there have been numerous trials of open peer review. Perhaps most visible is a long-running experiment by the journal *Nature*. After lukewarm initial experiences [14], a decade later *Nature* now reports 60% of reviewers are comfortable with their reviews becoming public, given the right of the reviewer to withhold his or her name [3]. While this important trend continues to generate lively discussion, we do not discuss open peer review further in this paper.

Rather, our focus is on the question of availability to reviewers of information about the authors. This question remains an active area of debate, with many significant conferences and journals on each side of the question. Terminology is not completely uniform across the sciences, but following common usage in computer science, we refer to *single-blind reviewing* as the practice of making reviewers aware of author identity but not the other way around. In *double-blind reviewing*, neither party is aware of the identity of the other.

Numerous anecdotal studies argue for one form or the other of peer review, often based on observations of findings before and after switching models. A much smaller number of researchers have performed controlled studies of the effects of the two models. Notable among these is the work of Rebecca Blank from 1991 [1], who performed a beautiful controlled study in reviewing papers submitted to the American Economic Review over a two-year period from 1987 to 1989. We discuss this and other related work in some detail below.

The current work came about when two of the authors of this paper were asked to co-chair the program of WSDM 2017, the 10th International ACM Conference on Web Search and Data Mining. WSDM has for its entire history employed single-blind reviewing. We were asked to consider switching to double-blind this year. Upon a review of the literature, we discovered that earlier controlled experiments in the journal setting missed many key aspects of the standard WSDM reviewing process, while many discussions of conferences switching between reviewing methods were uncontrolled experiments in the sense that the switch took place from one year to the next, introducing an analytically intractable set of possible confounding factors. Hence, we decided to perform an experiment in order to make an informed recommendation to the chairs of WSDM 2018, and to offer our findings to the rest of the community.

We now summarize some differences between conference and journal reviewing processes. As a backdrop, we observe that the accelerated pace of computer science in recent decades has led to the ascendance of academic conferences as a primary means for dissemination of new results. The level of formal methodological scrutiny applied to the conference paper acceptance process is therefore lower than it is for peer-reviewed journals. Some elements that are common in the process of conference reviewing are less common in a journal review setting, for instance:

- Conference review processes often run on an annual cycle, which results in large number of papers being reviewed by a large pool of reviewers on a single operating schedule.
- As a result, many conferences operate at a scale that makes it difficult for each paper to be matched by an expert to expert reviewers.
- The assignment of reviewers to papers is therefore performed using other mechanisms. In many cases, reviewers are asked to indicate ability or interest in reviewing each

paper as input to the assignment process. This process is referred to as *bidding*.

- Each reviewer typically reviews a batch of papers, with a single deadline for completing all reviews.
- Final decisions are often made with constraints on the overall number of slots, rather than on a notional quality standard.
- Decisions are accept or reject; there is typically no option for re-review after revision.<sup>1</sup>

These differences are not hard and fast rules, but the conference setting does raise different questions about best practices.

In the WSDM setting, we find significant differences between single-blind and double-blind reviewing. First, we find that single-blind reviewers enter about 22% fewer bids on average, a highly significant decrease (Mann-Whitney U, p = .0002). We show that, given these fewer bids, there is a significant preference to bid on papers from top universities and companies, compared to double-blind reviewers (p = 0.011 and p = 0.010 respectively).

Once the bids have been received, papers are allocated to reviewers, and we may study the resulting review scores. We find that the likelihood for single-blind reviewers to enter a positive review is significantly higher for papers with a famous author (p = 0.027) and for papers from a top university (p = 0.012) or a top company (p = 0.002) compared to double-blind reviewers. The estimated odds multipliers are 1.63, 1.58 and 2.10 respectively, equivalent to increases in underlying quality of 0.57 to 0.92 standard deviations. The effect is strong enough to warrant serious discussion on the appropriate reviewing policy.

Our findings with respect to bidding imply that reviewers bid less under single-blind reviewing. This reduced bid landscape may result in a lower-quality allocation of papers to knowledgeable reviewers. It may also be disadvantageous if it results in an "unfair" bidding pool, in favor of papers from top institutions. It is an ethics and policy question to determine whether a reviewer who (let us imagine) implicitly uses information about the quality of the paper's institution to estimate that the paper is more interesting, and hence enters a more positive bid on that paper, is acting in a manner that should be discouraged.

Our findings with respect to reviewing raise similar questions. A reviewer who knows that a particular paper is from a top school, or has a famous author, is significantly more likely to recommend acceptance than a reviewer who does not know this information. There are at least two points for consideration here. The first is that the two reviewers are not identical: reviewers that bid on a paper are more likely to be assigned to review the paper, and as we have already discussed, the bidding dynamics of the two reviewers are different. Hence, it is possible that the single-blind reviewer of a particular paper may have bid on the paper due to knowledge of the author's prior work, while the double-blind reviewer may have bid due to the topic of the paper implied by the title. In other words, paper assignment in not random, and this should be taken into account in interpreting our findings.

Our second point with respect to reviewing is that, whatever the process that resulted in the reviewers being assigned the paper, the single-blind reviewers with knowledge of the authors and affiliations are much more positive regarding papers from famous authors and top institutions. Again the implications are not cut and dried, but it is reasonable to raise the concern that authors who are not famous and not from a top institution may see lower likelihood for acceptance of *exactly the same work*.

In Section 6, we perform a meta-analysis of our study along with six other experimental studies from the literature. Our findings in this meta-analysis are as follows. First, with respect to famous authors, our effect is in fact smaller than the aggregate. For top 50 institutions, only one study covered this effect, and showed a smaller effect than ours. With respect to female authors, our effect ranks 7th out of 11 measurements, but is not qualitatively different than that observed by other authors. By the standards of meta-analysis, in aggregate, the effect against female authors can be considered statistically significant.

We therefore recommend for upcoming WSDM conferences that the program chairs strongly consider moving to an overall policy of double-blind reviewing.

#### 2 RELATED WORK

There is extensive literature on scientific peer reviewing overall, and on single-blind versus double-blind reviewing in particular. A survey of Snodgrass [21] reviews over 600 separate pieces of literature on reviewing.

For detailed information, we refer to reader to the excellent survey of Snodgrass [21] and additional survey material referenced there. For editorial perspective, see Snodgrass [22], McKinley [11, 12], or for an argument that the benefits of double-blind reviewing are small compared to the costs, see Schulzrinne [20].

Regarding the peer reviewing landscape, Walker and Rocha da Silva [26] argue that the soft sciences more commonly apply doubleblind review, while in the natural sciences single-blind review is more common. Multiple journals and conferences are moving to double-blind review (see below for some results studying the changeover in those venues). In some cases the movement is in the other direction, for example the American Economic Association announced in 2011 that it will end double-blind review, citing difficulty of maintaining anonymity and decreased information for reviewers (for example, to assess authors' possible conflicts of interest) [6].

#### 2.1 Specific biases described in the literature

A number of specific biases are described in the literature. We will focus here on literature related to three biases we consider in our study: gender, prestige, and institution of the authors.

Knobloch-Westerwick *et al.* [7] propose the *Matilda effect*, in which papers from male first authors are evaluated to have greater scientific merit than papers from female first authors, particularly in male-dominated fields. The authors study this effect by randomly assigning names to conference abstracts, and then asking study participants for assessments of merit. Studies disagree on

<sup>&</sup>lt;sup>1</sup>Some conferences add a "rebuttal" or "author feedback" round after reviewing is complete to allow authors to respond to reviewer comments or describe changes that will appear in the final revision. Additionally, if a strong paper has an addressable flaw, some conferences will "accept with shepherding" appointing a knowledgeable party to verify that the flaw has been addressed. WSDM does not use rebuttal, and very rarely uses shepherding.

the presence of gender bias in reviewing: many studies find effects, but many of these are retrospective studies of venues that have moved to double-blind reviewing, and hence cannot rule out the possibility that the findings are due to improving gender equality rather than the reviewing model itself. Our study does not find a statistically significant gender effect. However, in our field there are no fixed conventions for "first authors" so we simply study the presence of a female author on the paper, which may weaken the effect. Blank's study [1] shows a small difference depending on first author gender, but the data volume is low and the difference is not statistically significant.

Work by Robert Merton [13] in 1968 proposed the *Matthew effect*, in which already-famous researchers receive the lion's share of recognition for new work. The paper provides an enlightening survey of this effect through contemporary and historical science, and cites various psychological processes that may be at work. There has been significant follow-on work in this area; see for instance the discussion of reviewing at the ACM SIGMOD conference below.

Finally, Blank's study [1] spends significant time discussing biases resulting from the fame or quality of the authors' institution(s).

# 2.2 Retrospective studies

In 2001, the journal *Behavioral Ecology* switched from single-blind to double-blind review. Budden *et al.* [2] describe their findings analyzing data before and after the switch. They found an increase in female first-authored papers after the change. Webb *et al.* [27], however, argue that comparable journals that did not switch reviewing model also showed such an increase over a similar time period.

Roberts and Verhoef [18] study double-blind reviewing at the Evolution of Language conference series, comparing the results in 2016, which used double-blind reviewing, to the results of 2012 and 2014, which used single-blind reviewing. The authors showed a significant effect for gender, in which papers with female first authors and male first authors were accepted with similar likelihood under single-blind reviewing, but female first-author papers were accepted with higher likelihood under double-blind reviewing.

In 2001, the ACM SIGMOD conference on management of data moved to double-blind reviewing. After five years in the new model, Madden and DeWitt [10] asked whether double-blind reviewing helped junior researchers who might have been disadvantaged under single-blind reviewing. They studied the acceptance rate of more senior authors before and after the reviewing change. Their study showed no difference on acceptances before and after the reviewing change. However, a follow-on study by Tung [24] analyzing the same data using a more standard statistical test showed the opposite result.

# 2.3 Experimental studies

Peters and Ceci [16] performed a notorious study of reproducibility of peer review results. The authors of the study asked for and received permission from the authors of twelve prestigious papers to re-submit these papers to the journal in which they appeared, introducing false author names and referencing manufactured lowprestige institutions (*e.g.*, *the "Northern Plains Center for Research"*). 3 of 38 editors and reviewers detected the re-submission, so only 9 of the papers were reviewed fully. Of those, 8 were rejected, often citing serious methodological flaws. In addition to raising concerns about the ethics of peer reviewing practices, the study itself gained additional notoriety in part because an ethical debate arose regarding the propriety of the methodology; the authors provide an insightful discussion of the history [17].

The study of Peters and Ceci was published with significant commentary from many fields, and is frequently referenced in policy discussions. In addition to the authors' original intent of understanding the importance of reputation in acceptance decisions, the findings also raised questions about the overall reproducibility of acceptance decisions. Rothwell and Martyn [19] went on to study this question, and found in their setting that reviewers did not agree with one another regarding a manuscript better than random chance would indicate. In Computer Science, the Neural Information Processing Systems (NIPS) conference subsequently ran an experiment in which a subset of papers were sent through two parallel review processes. Their findings [8, 9] show that, if the committee were to re-select papers again, 38–64% of the papers would have been accepted again. We discuss this question in Section 5.3.3.

Perhaps the best known experimental study of single-blind versus double-blind reviewing behavior, and to our knowledge the only controlled experiment in this area other than our own, is the study of Rebecca Blank [1]. Over several years, 1498 papers were randomly assigned to single-blind versus double-blind reviewing condition. While Blank performs detailed analyses of many facets of the data, we may summarize part of the high-level findings as follows. First, authors at top or bottom institutions do not see significant differences in acceptance decisions based on reviewing model, but authors at mid-tier institutions perform better in a single-blind setting, as do foreign authors and those outside academia. Second, there is a mild indication, not statistically significant, that women do slightly better in double-blind review.

Recently, Okike *et al.* [15] performed an ingenious study constructing an artificial submission proposing a study of the efficacy of training to improve communication in the operating room. The fabricated study was submitted to an Orthopaedics journal, and listed as authors two past presidents of the American Academy of Orthopaedic Surgeons. With the involvement of the journal, the study was sent to 256 reviewers, of whom 119 completed the review, split between single-blind and double-blind conditions. The results showed that single-blind reviewers were significantly more favorable toward the paper.

# 2.4 Difficulties implementing double-blind reviewing

Hill and Provost [5] study the problem of automatically identifying the authors of a double-blind paper. They show fully automated techniques to identify authors with 40–50% accuracy, and 80% accuracy for highly prolific authors with 100 or more prior publications. Section 5.4.1 discusses this issue in more detail.

#### **3 EXPERIMENT**

In this section we describe the design of our experiment. We begin with an overview of the reviewing process WSDM has typically employed in the past:

- Program chairs invite program committee (PC) and senior program committee (SPC) members while authors submit papers.
- (2) PC and SPC members bid on each paper, specifying which are of interest.
- (3) Program chairs perform an assignment of 3–4 PC members and one SPC member to each paper, typically resulting in 6–10 papers assigned to each PC member.
- (4) PC members complete reviews of assigned papers.
- (5) For each paper, the assigned SPC member conducts a discussion with the PC members reviewing the paper and makes a recommendation for or against acceptance.
- (6) Based on all this information, the program chairs make final decisions.

# 3.1 Ethical Considerations in Designing the Experiment

We spent significant time in discussion about the most appropriate design for our experiment, given the many ethical considerations, and we were fortunate to receive valuable input and discussions from the conference general chairs, the WSDM steering committee, and the Ethics Committee for Information Sciences (ECIS) at the University of Amsterdam and the VU University Amsterdam.

Through this discussion, we adopted two ethical principles in our design of the experiment:

PRINCIPLE 1. **No-Bias Condition** A paper's likelihood of acceptance should not change based on its experimental condition.

PRINCIPLE 2. Veracity Condition We will not lie to any participant in the experiment.

The first principle in particular put significant constraints on possible experimental designs, as described in Section 3.2.

Our Call for Papers [23] asks authors to submit PDF documents that have been anonymized by removing references to the authors and their institutions. The CFP does not commit to a particular reviewing model. The relevant section reads as follows: "As an experiment this year, WSDM 2017 will use a combination of singleblind reviewing and double-blind reviewing. Please contact the PC chairs at the address below for any questions on the submission or review process."

# 3.2 Design of Experiment

We did not see an experimental design that tested the end-to-end decision process in a way that is consistent with the two ethical principles above. Hence, we ran the experiment through the end of the PC reviewing phase, and terminated the experiment before beginning the discussion or final decision phases. The experiment considered only the behavior of the PC, not the SPC. Our findings therefore relate just to bidding, reviewing, and scoring by PC members. The experimental design is described in Figure 1.

- Program committee is split randomly into two groups of equal size: single-blind PC (SBPC) and double-blind PC (DBPC).
- (2) During bidding, SBPC see author names and affiliations, while DBPC do not. Both groups see paper titles and abstracts. Otherwise, the bidding interface is the same.
- (3) A separate assignment is computed for SBPC and DBPC using the standard assignment algorithm provided by the EasyChair conference management system. The overall assignment allocates 4 PC members to each paper with exactly 2 from SBPC and 2 from DBPC.
- (4) The assigned papers are sent for reviewing. SBPC and DBPC again receive the same reviewing form, except that SBPC members see author names and affiliations in the reviewing form. PDF documents do not include author names or affiliations.
- (5) After reviews are received, the experiment is closed, and the data is set aside for analysis. From this point forward, all PC members operate in a singleblind condition. Discussions are managed by the SPC member assigned to each paper, in which all 4 PC members are now able to see the author names and affiliations for the paper.

#### **Figure 1: Experiment Design**

Note that our goal is not to determine whether a particular paper is more likely to be accepted in single-blind or double-blind reviewing. The variance in any single decision is too large to measure this directly (see Section 5.3.3 for some elaboration on this point). Instead, we wish to measure statistical differences in the overall behavior of SBPC and DBPC. These differences may be measured in the context of particular classes of papers (papers from top-tier institutions, papers with female authors, etc) or particular classes of paper/reviewer pairs (reviewer from the same country as the paper, etc).

Due to the design, we may study the impact of single-blind versus double-blind reviewing on the bidding process, and on how reviewers score papers. We can show whether papers written by a particular gender are more likely to receive bids and more likely to receive higher review scores in the single-blind or double-blind condition. We cannot see how the reviewing model impacts SPC recommendations or final paper acceptances. However, we felt that if significant behavioral differences exist, we should observe this in the experiment.

We considered and rejected a number of alternative approaches to the experiment, including the following:

- Splitting papers between a single-blind and a double-blind condition. We rejected this approach because authors could reasonably argue that being placed in a particular condition could have reduced their likelihood of acceptance.
- (2) Splitting each reviewer into some single-blind and some double-blind reviews. We rejected this approach because

it is not well-defined how to perform bidding in this setting, and also because it would implicitly force reviewers to compare their behavior with respect to the two groups of paper, which might introduce biases.

- (3) Removing reference to the experiment from the CFP and our communications with reviewers. We rejected this approach because we felt it would entail at some level lying to both authors and reviewers about the process.
- (4) Sending a small number of papers through both a singleblind and double-blind condition in parallel. We performed rough calculations to infer that we would not have sufficient statistical strength in this approach to make clean statements about the outcomes. We also were concerned that any reasonable scheme to fuse the results of the two decision processes would be inconsistent with our no-bias principle.

# 4 DATA

In this section, we describe the data available from our experiment. Each reviewer in the experiment performed two tasks: bidding for papers, and then reviewing a set of assigned papers.

During bidding, each reviewer considered the submitted papers and entered a bid for each. Three bids are possible: yes, maybe, no.<sup>2</sup> If a reviewer takes no action with respect to a paper, the default bid is no.

We used the EasyChair conference management tool. A reviewer in the bidding process is presented with EasyChair's standard bidding page. This shows the title of each paper on a separate row. Single-blind reviewers also see the authors before the paper title, with hyperlinks to each author's homepage if available. Institutions are not shown at this stage. There is a link to see details of the paper, and another link to download the full paper itself. The details page provides some additional information, such as keywords, the abstract for the paper, and for single-blind reviewers, the list of authors with affiliations. The PDF document itself does not list authors or their affiliations.

The distribution of bids per reviewer is shown in Table 1. The table shows that 60% of reviewers have at least 20 bids, which is a reasonable number to perform an effective allocation of papers. We will discuss below (in Section 5.2) the observation that single-blind reviewers appear to enter more reviews.

Per the experiment design in Section 3, we then use EasyChair's standard tools to allocate exactly two double-blind reviewers and two single-blind reviewers to each paper. Once these paper assignments are complete, each reviewer is directed to a page listing his/her assigned papers. This page lists the title of the paper, with links to download the paper and see additional information. Single-blind reviewers see the authors here, and may see the affiliations on the additional information page.

The submitted papers themselves are all anonymized, so author and affiliation information is not available in the PDF document.

Due to some mid-stream withdrawls, the number of papers in consideration at the end of the experiment was exactly 500. Of these, 453 have four reviews and 47 have three reviews.

Num bids	Single blind reviewers		Double blind reviewers		Common 1-CDF
	Count CDF		Count	CDF	
0-4	6	5%	4	3.3%	100%
5-9	9	12.4%	7	9.1%	96%
10 - 14	24	23.2%	13	19.8%	89%
15-19	21	49.6%	13	30.6%	74%
20-24	21	66.9%	15	43.0%	60%
25-29	25	87.6%	44	79.3%	45%
30-34	9	95%	11	88.4%	17%
>= 40	6	100%	14	100%	8%

Table 1: Distribution of number of bids for single-blind and double-blind reviewers. 1-CDF is computed over the union of single-blind and double-blind bids.

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Value	Score	Description
Strong accept	6	I think this paper is well above the bar and will fight for it
Accept	3	I think this paper should be accepted
Borderline	-2	I think this paper is below the bar, but am open to accept if there is strong support
Reject	-4	I think this paper should be rejected
Strong reject	-6	I think this paper is well below the bar and will fight against it

 Table 2: Reviewers selected a score for each paper from these options.

# 4.1 Score and Rank information from reviewers

Reviewers used a standard form to enter reviews. This form includes various fields for textual information, but also includes two fields to which we pay special attention in this study: *score* and *rank*. Score represents an overall recommendation for the paper, while rank represents a relative judgment of the paper compared to others reviewed by the same reviewer.

WSDM 2017 used asymmetric scoring, so the reviewers select one of the score values shown in Table 2. Likewise, reviewers select one of values in Table 3 for the rank of the paper. The rank values are not checked for consistency—it is for instance possible to rank all papers as the top paper, although we did not see such anomalies.

#### 4.2 Metadata for Implicit Bias Analysis

For our analysis, we generate some additional metadata as part of our exploration of the behavior of single-blind versus double-blind reviewers. First, we attempt to compute a country for each paper as the plurality value of this property across the authors of the paper.

 $<sup>^2 {\</sup>rm There}$  is a fourth value to indicate a conflict of interest, but we do not consider these bids here; we consider them separately in Section 5.3.5.

Value	Description
4	Top paper in my batch
3	Top 25% in my batch
2	Top 50% in my batch
1	Bottom 50% in my batch

1

Table 3: Reviewers selected a rank for each paper from these options.

That is, if there is a single country with strictly more authors than any other country (even if this is not a majority), we declare this to be the country of the paper.

For each (reviewer, paper) pair, we compute the following six boolean covariates:

- (1) Academic paper. We hand-wrote a set of rules to determine whether an author's institution is academic or not (corporate, governmental, non-profit, unaffiliated, are all considered non-academic institutions). If a strict majority of the authors are from an academic institution, we consider the paper to be an academic paper.
- (2) Female author. We attempt to determine if at least one of the paper's authors is female. Earlier work typically considered papers whose first author was female, but submissions to WSDM do not always follow the same conventions for first authors, so we did not have a reliable way to determine if one author contributed more than another. Hence, we consider papers with a female author versus papers with no female author.<sup>3</sup> To make this determination, we manually annotated the gender of the 1491 authors. We found 1197 male authors, 246 female authors, and 48 authors for whom we could not determine gender from online searches.
- (3) Paper from USA. This feature is true if the country of the paper as defined above is the USA.
- (4) Famous author. We define a *famous author* to be an author with at least 3 accepted papers at earlier WSDM conferences [28], and at least 100 papers according to dblp records. There are 57 such authors. This property is true if the paper has at least one famous author.
- (5) Same country as reviewer. We wished to study whether knowledge of the authors would allow a reviewer from the same country to treat the paper preferentially. This feature is true if the country of the paper as defined above is the same as the country of the reviewer as provided during the EasyChair registration process.
- (6) Top university. We define top universities as the top 50 global computer science universities.<sup>4</sup> While this choice is imperfect, the universities align reasonably well with our expectations for top universities.
- (7) Top companies. We define top companies as Google, Microsoft, Yahoo!, and Facebook. This property is true if any author is from a top company.

Factor	Feature Number of		Fraction of	
Factor	name	papers	papers	
Paper from USA	usa	176	35%	
Same country	same	146	29%	
as reviewer				
Female author	wom	219	44%	
Famous author	fam	81	16%	
Academic	aca	370	74%	
Top university	uni	135	27%	
Top company	com	90	18%	

Table 4: Summary of features and prevalence.

Table 4 gives information on the distribution for each of these features.

# 4.3 Blinded Paper Quality Score

For our analysis, we need a proxy measure for the intrinsic quality of each paper. The rationale for this is twofold: (a) The primary task of the reviewers is to rate paper quality and we want to represent this null hypothesis in the feature set. In this sense, implicit biases would be those effects that are present above and beyond that accounted for by the quality of the paper itself. (b) Almost by definition, implicit biases are second-order effects. By directly measuring intrinsic quality, we can reduce the background noise and more easily detect the presence of any second-order effects.

We construct this paper quality score from the blinded raters by combining linearly their scores and ranks, here standardized to have zero mean and unit variance. Among the blinded reviewers, the correlation between these two measures is 0.75, and principal components would combine these with equal weights. However, we choose to maximize the correlation between the pairs of blinded reviewers of the same paper. For a given score *s* and rank *r*, this between-reviewer correlation is maximized by a quality score *q* = *s*+0.111*r*. The achieved correlation between the two blinded raters is 0.38, a point to which we return in Section 5.3.3.

We take the quality score of a paper to be the average quality score of the double-blind reviews for that paper, referred to below as bpqs, for blinded paper quality score. We normalize bqps to have unit standard deviation.

# 4.4 Bid Attractiveness Scores: Bids by Reviewer and Bids by Paper

By analogy with bpqs, for modeling bid behavior we develop two first-order scores. To encode the willingness of a particular reviewer to bid, we calculate the total bids of that reviewer; we refer to this score as bbr, the bids by reviewer. In order to score the intrinsic bid-attractiveness of the paper, we calculate the total number of bids on this paper by the double-blind reviewers; we refer to this score as bbp, the bids by paper. In modeling bids, we will employ both these scores as covariates.

# 5 ANALYSIS

We now present our analysis of the experimental data described in Section 4.

<sup>&</sup>lt;sup>3</sup>In Section 5.3.1 we consider other alternatives to this approach. <sup>4</sup>Per topuniversities.com

Nomo	Nama Cooff		Conf.	n voluo	Odds	bpqs
Ivanie Coeli.		Stuerr	interval	p-value	mult.	equiv.
const	-1.83	0.24	[-2.31,-1.36]	0.000	0.16	-
bpqs	0.80	0.08	[0.64, 0.97]	0.000	2.23	1.00
com	0.74	0.24	[0.27, 1.21]	0.002	2.10	0.92
fam	0.49	0.22	[0.05,0.93]	0.027	1.63	0.61
uni	0.46	0.18	[0.09,0.83]	0.012	1.58	0.57
wom	-0.25	0.18	[-0.60,0.10]	0.160	0.78	-0.31
same	0.14	0.24	[-0.34,0.62]	0.564	1.15	0.17
aca	0.06	0.22	[-0.38,0.51]	0.775	1.07	0.08
usa	0.01	0.21	[-0.42,0.44]	0.964	1.01	0.01

 Table 5: Learned coefficients and significance for review score prediction.

# 5.1 Modeling reviews

Our modeling approach is to predict the likelihood that a singleblind reviewer will give a positive (accept) score to a paper, using the following multinomial logistic regression model:

$$\frac{\Pr[\text{score} > 0]}{\Pr[\text{score} <= 0]} = e^{\langle \Theta, \upsilon \rangle}$$

where  $\Theta$  is a set of learned parameters, and v is a vector of features consisting of a constant offset feature, the overall paper quality score bpqs defined in Section 4.3 (a first-order feature), and the six implicit bias booleans in Table 4 (second-order features).

We present the results of the logistic regression in Table 5. There are significant non-zero weights for the fam (p = .027), uni (p = .012) and com (p = 0.002) features. The corresponding odds multipliers are 1.63 for fam, 1.58 for uni, and 2.10 for com. The other features do not show significant effects.

Our hypothesis in undertaking the work was that it would be very difficult to see any effects on review behavior given the scale of the data, and the difficulty other studies have encountered in finding significant biases for single-blind reviewing. Thus, we were surprised to encounter three significant effects with substantial odds multipliers.

The ratio of these coefficients can also be compared to the 0.80 coefficient of bpqs; the result measures effect size relative to the underlying quality of bpqs. The ratio for fam, uni and com correspond to shifts of 0.61, 0.57, and 0.92 standard deviations respectively. For wom, the odds multiplier of 0.78, equivalent to -0.31 bpqs standard deviations, is not statistically significant (p = 0.16).

#### 5.2 Modeling bids

We take a similar approach to modeling bids, but some changes are required, as a reviewer may bid for an arbitrary number of papers.

As Table 1 suggests, the first question we should reasonably ask is whether single-blind and double-blind reviewers bid for the same number of papers. We test this using a Mann-Whitney test, and find that single-blind reviewers bid for more papers (p=0.0002). On average, single-blind reviewers bid for 19.9 papers compared to 24.9 for double-blind reviewers, a decrease of 22%.

Thus, the difference in behavior between the two reviewer classes is quite significant. We now ask a follow-on question: given that single-blind reviewers bid more, do they bid more for particular

Name	Coeff.	Stderr	Conf. interval	p-value	Odds mult.
const	-4.87	0.08	[-5.04,-4.71]	0.000	0.01
bbr	0.05	0.00	[0.04, 0.05]	0.000	1.05
bbp	0.08	0.00	[0.07, 0.09]	0.000	1.09
com	0.16	0.06	[0.04, 0.28]	0.010	1.17
uni	0.12	0.05	[0.03, 0.22]	0.011	1.13
fam	0.07	0.06	[-0.06,0.19]	0.287	1.07
wom	0.05	0.04	[-0.04, 0.14]	0.268	1.05
usa	0.02	0.05	[-0.07,0.11]	0.681	1.02
aca	0.01	0.06	[-0.10, 0.12]	0.881	1.01

 
 Table 6: Learned coefficients and significance for bid prediction.

types of papers? To answer this question, we pursue a similar analysis to our regression study of review scores. However, rather than including an overall paper quality score (bpqs) into the regression, we instead include covariates for the bid-appetite of the reviewer (bbr) and the bid-attractiveness of the paper (bbp) as described in Section 4.4. We retain the constant offset term.

The results are shown in Table 6. In addition to the difference in likelihood to bid, we also see that the uni feature is significant (p = 0.011), as is the com feature (p = 0.010), indicating that the bids entered by single-blind reviewers tend to favor top universities and companies, with modest odds multipliers of 1.13 and 1.17 respectively.

#### 5.3 Additional analysis

5.3.1 The Matilda effect. As described in Section 2, there is significant work regarding the importance of author gender in reviewing. Some of this work clearly points to lower assessments of scientific merit for work purportedly authored by women. For both bidding and reviewing, we do not see a behavior difference between single-blind and double-blind reviewers for papers with a female author.

We re-ran the same logistic regression analysis from two additional perspectives: papers whose first author is female (16.4% of papers), and papers written by a strict majority of female authors (3.8% of papers). In both cases, we do not see a significant *p*-value for the wom feature. We therefore do not see evidence that gender of authors influences bidding or reviewing behavior. However, Section 6 shows meta-analysis studying our results in the context of other results from the literature, and in this setting we do find an overall significant gender effect.

5.3.2 Aggregate review statistics. We checked the lengths of reviews along with the distribution of scores and ranks across the single-blind and double-blind conditions. The results are shown in Table 7. Average review length for single-blind reviewers is 2073 characters versus 2061 for double-blind, not significantly longer for either condition by Mann-Whitney test (p=0.81). Scores and ranks show a similar pattern, with no significant difference in either score or rank distribution.

Measure	Single blind	Double blind	Mann-Whitney	
	average	average	<i>p</i> -value	
Review length	2073	2061	0.81	
Reviewer score	-2.07	-1.90	0.51	
Reviewer rank	1.89	1.87	0.52	

Table 7: Aggregate comparison of review statistics.

5.3.3 *Reviewer agreement.* A standard argument suggests that single-blind reviewers would correlate slightly better than doubleblind reviewers, for instance because they would tend to share a preference for papers by famous authors.

Although our study has focused on implicit biases of reviewers, the lack of agreement among reviewers is also notable. In part, this can be mitigated by using more than one reviewer. The inter-rater reliability associated with an average of *n* raters sharing correlation  $\rho$  has correlation  $\sqrt{nR/(1 + nR)}$  where  $R = \rho^2/(1 - \rho^2)$  is the ratio of explained to unexplained variance.

For example, the inter-reviewer correlation for bpqs is 0.38, which corresponds to having benefit and inaccuracy of n = 1 reviewer per paper. Under our current protocol we have n = 2 blinded reviewers, and the operative correlation is 0.5. Were WSDM to enact double-blinded review, we would have at our disposal n = 4 reviewers and the operative correlation would be 0.63, while n = 5 and 6 achieve correlations of 0.68 and 0.71 respectively. Correlations of 0.6 characterize imperfect human-based measurement systems, and are common enough in contexts where the low-value material has been excluded from human assessment.

In summary, we recommend that conference organizers be cognizant of the inter-reviewer agreement that their review process provides, and choose appropriately the number of reviews that each paper receives.

5.3.4 Changes during discussion. Finally, we may ask what happens after the experiment concludes and the discussion phase begins. During this phase is it common to see some changes in review scores. We analyzed these scores, and saw 32 changes to scores entered by single-blind reviewers compared to 41 changes to scores entered by double-blind reviewers. This difference is not significant (Fisher-Exact, p=0.28). We compared the changes in scores to determine whether double-blind reviewers tend to have changes of larger magnitude than single-blind reviewers. The distributions of score changes are not significantly different (Mann-Whitney, p=0.58). We then checked whether double-blind reviewers tend to move more in the direction of the initial mean score than single-blind reviewers after discovering the authors of the paper. Here also, we find no difference in the magnitude of shifts towards the mean (Mann-Whitney, p=0.58). Hence, during the discussion phase, after the authors have been revealed, we cannot conclude that the initially double-blind reviewers behave differently from single-blind reviewers.

5.3.5 Conflicts of interest. It is natural to hypothesize that in a double-blind setting there will be fewer declared conflicts of interest, as reviewers will not recognize possible conflicts. In WSDM 2017, the EasyChair tool automatically (but imperfectly) detects

conflicts based on the email domains of authors and reviewers. Reviewers may specify additional conflicts as they bid for papers. It is possible to configure the system to allow authors to specify conflicts with PC members at submission time, but we did not enable this configuration.

We consider the overall set of conflicts generated both automatically by EasyChair and by reviewer specification. We find that the total number of reviewers expressing a conflict (59/121 in the single-blind setting versus 47/121 in the double-blind setting) is not significantly different (Fisher-Exact, p=0.35). Likewise, the number of conflicts expressed by those reviewers who express a conflict is not significant (Mann-Whitney, p=0.63). Hence, in the settings we adopted, we do not see that double-blind reviewing introduces a significant difference in expression of conflicts of interest.

#### 5.4 Discussion

There are several questions one may raise with respect to our experiment. First is the issue that we study the behavior of the PC with respect to bidding and scoring papers only. After these steps are complete, the SPC member conducts some discussion among the reviewers, and the program chairs make a final decision. While Section 5.3.4 suggests there may not be significant changes specifically in how reviewers modify their scores during discussion, it is nonetheless possible that during these stages, the final acceptance decision may show unexpected behaviors. This is clearly an area for further work. However, we have observed that the critical inputs to this final decision stage (score and rank of reviewers) are impacted significantly by the reviewing model.

It is possible also that PC members behaved differently in our setting than they would in a "pure" reviewing situation involving only a single type of reviewing. For instance, single-blind reviewers in our experiment were nonetheless presented with papers that do not include author names and affiliations. We also mentioned briefly in the call for papers that we would experiment with doubleblind reviewing this year. We do not have a rigorous methodology to estimate the nature of these biases, but we observe that at least in the case of presenting anonymized PDFs to both types of reviewers, it is plausible that this would cause us to under-estimate rather than over-estimate the effects.

Having stated those caveats, we now discuss some issues with respect to the practical implementation of double-blind reviewing.

5.4.1 Practical issues with double-blind reviewing. There is a longstanding question whether it is practical to anonymize a submission. This question depends on the nature of the field (for instance, it would be impossible to anonymize work in a large and wellknown systems project). Hill *et al.* [5] argue that it is possible to automatically identify authors in many cases based on the text of the paper alone. However, other studies have observed that reviewers' guesses about authorship are often wrong [21].

A second issue in the practical difficulty of retaining anonymity in double-blind reviewing is the increasingly common practice of publishing early versions of work on arXiv.org. For example, this paper appeared on arXiv before being submitted to any peerreviewed venue. This practice was a significant contributor to the decision of the Journal of the American Economic Association to abandon double-blind reviewing [6]. WSDM 2017 did not state a policy with regard to publishing pre-prints on arXiv, but when asked, we discouraged but did not forbid such publication. In its 2016 call for papers [25], the NIPS machine learning conference, which performs double-blind reviewing, informed authors that prior submissions on arXiv are allowed, but reviewers are asked "not to actively look for such submissions." If reviewers happened to be aware of the work, NIPS nonetheless allows the reviewing to proceed.

These practical issues appear to be significant and unresolved.

#### 6 META-ANALYSIS

In this section, we compare the effect sizes reported in Table 5 to those reviewed in Section 2. We focus on 6 empirical studies: Tung [24], Knoblock-Westerwick *et al.* [7], Budden *et al.* [2], Blank [1], Okike *et al.* [15] and Roberts and Verhoef [18]. By including our work above, we have 7 studies total.

We report all effect sizes as log-odds multipliers. This choice allows direct use of Table 5's logistic regression coefficients, involves modest recalculations for 3 of the other 6 studies, and is reasonably interpretable. Two studies, Knoblock-Westerwick *et al.* and Roberts and Verhoef, report *t*-statistics. For Tung, we have the annual aggregates, so we can recover the *t*-statistic relative to the binomial distribution. The method of Hasselblad and Hedges [4] allows us to transform *t*-statistics into location shifts of a continuous logistic distribution, The result is interpretable on the log-odds scale.

Table 8 presents all effects and their ranks. For famous authors and top 50 institutions, the number of studies is small enough that no study can be called an outlier. That said, for famous authors, our value of 0.51 is actually smaller than that reported elsewhere, while for top 50 institutions, our value of 0.46 is larger.

For the effect of female authors, the pattern is almost uniformly negative. The -0.25 effect reported in Table 5 ranks 7 out of 11, on the small side, albeit this value is not qualitatively different from the -0.246 combined effect of Budden *et al.* and the -0.229 effect of Blank. By the standards of meta-analysis, in aggregate, the effect against females authors can be considered statistically significant, albeit with continuing caveats regarding the observational nature of some of these studies.

In summary, the famous author effect we report is reported by others as even larger. For the effect of female authors, we report a value that is in line but somewhat smaller. Two interpretations suggest themselves: First, we may be observing the natural variation among such studies. Alternately, relative to journal reviews, the conference review process may operate with slightly different biases, and social affiliation (famous authors, top 50 institutions, and top companies) may play an enhanced role. Future research should clarify this.

#### 7 CONCLUSION

In conclusion, the heart of our findings is that single-blind reviewers make use of information about authors and institutions. Specifically, single-blind reviewers bid less yet are differentially more likely to bid on papers from top institutions, and more likely to

0	Study	N (1 1	Effect	Effect			
Source	context	ontext		rank			
Famous author							
Tung	SIGMOD	$t \rightarrow \log odds$	1.619	1			
	VLDB	$t \rightarrow \log odds$	1.306	2			
Okike et al.	CORR	log OR	1.136	3			
Tomkins et al.	WSDM	logistic reg	0.506	4			
	Femal	e author					
Budden et al.	BE	log OR	-0.426	2			
	BES	log OR	-0.119	10			
	AB	log OR	-0.224	8			
	BC	log OR	-0.398	4			
	JB	log OR	-0.048	11			
	LE	log OR	-0.370	5			
	all 6	log OP	0.246	6			
	journals	log OK	-0.240	0			
Knoblock-							
Westerwick	2010 ICA	$t \rightarrow \log odds$	-0.410	3			
et al.							
Blank	AER	log OR	-0.229	9			
Roberts							
and	EvoLang 11	$t \rightarrow \log odds$	-1.186	1			
Verhoef							
Tomkins et al.	WSDM	logistic reg	-0.25	7			
Top 50 institutes							
Blank	AER	log OR	0.020	2			
Tomkins et al.	WSDM	logistic reg	0.46	1			

Table 8: Across seven studies and 14 contexts, 17 effects as log-odds multipliers.

recommend for acceptance papers from famous authors or top institutions, compared to their double-blind counterparts. Regarding the gender effect the situation is more nuanced. Our results do not show a statistically significant effect for gender, but our metaanalysis places our findings in line with other experiments, which in aggregate warrant a conclusion that the gender effect is significant.

The primary ethical question is whether this behavior is okay. In one interpretation, single-blind reviewers make use of prior information that may allow them to make better overall judgments. As a consequence, however, it may be that other work is disadvantaged, in the sense that two contributions of roughly equal merit might be scored differently by single-blind reviewers, in favor of the one from a top school, while double-blind reviewers may not show this bias as strongly.

Clearly, our understanding of the implications of reviewing methodologies remains nascent. We feel that program and general chairs of conferences should seriously consider the advantages of employing double-blind reviewing. Furthermore, we recommend that conferences quantify and remain cognizant of inter-reviewer agreement.

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# A APPENDIX

### A.1 Mechanism of Running the Experiment

Our experiment was performed using capabilities that already exist in EasyChair, plus a few last-minute changes provided by the EasyChair team. The workflow within the EasyChair system to perform the experiment relies on the use of a little-used reviewing model known as "External Review Committee," and runs as follows:

- (1) Disable subreviewers.
- (2) Change reviewing model to ERC.
- (3) Configure PC to see author names and ERC as doubleblind.
- (4) Configure access to reviews for both PC and ERC as "see only their own reviews."
- (5) Invite randomly split half of reviewers into PC and other half into ERC.
- (6) Invite or add senior as standard PC members
- (7) Receive papers, perform do paper bidding.
- (8) For Senior PC members and program chairs, configure at most 0 papers assigned.
- (9) Configure 2 papers per member for regular PC and ERC members.
- (10) Run automatic paper assignment separately for PC and ERC.
- (11) Assign papers to senior using interactive paper assignment.
- (12) Run standard reviewing period for both PC and ERC.
- (13) When reviewing is over, change all ERC members to standard PC members
- (14) Change reviewing model from ERC to Senior PC.
- (15) Change all SPC members from regular PC to SPC in the new reviewing model.
- (16) Change review access to PC members can see all reviews for their papers.
- (17) From now on, run discussion and decision process using standard flows.