

## ABSTRACT

Title of Document: ACCOUNTING FOR INFORMATION: CASE STUDIES IN EDITORIAL DECISIONS AND MORTGAGE MARKETS

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I demonstrate that referee comments at a scholarly journal contain information on submissions' future citation impact above and beyond information available in referee scores. I measure this signal on future citation impact and show that it does not enter into editorial decision-making directly but rather through an interaction that amplifies the information content of referee scores: the more citations predicted for a low- or mediocre-scoring paper, the less likely it is to be published. Secondly, I describe referee comments that are highly predictive of greater citations. Papers that referees say have access to unique datasets, or are written on topics of relevance to ongoing debates or government applications receive greater citations on average. Third, I show the appearance of favoritism amongst editors who accept a higher share of papers that cite themselves is partly a reflection of an ability to draw and select for papers that receive more citations. Finally, I characterize budget constraints on publication space and referee capital and provide some guidance on what types of

information editorial systems could capture to promote transparency in future analyses while protecting privacy of authors or referees.

A second chapter introduces a theoretical framework for assessing the empirical discussion of asymmetric information amongst mortgage lenders and adds the idea of lender competition into this framework.

ACCOUNTING FOR INFORMATION: CASE STUDIES IN EDITORIAL  
DECISIONS AND MORTGAGE MARKETS

By

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# Chapter 1: Editorial Decisions and Information Contents of Reviews

## *1. Introduction*

In economics, we often wish to understand decisions driven by utility functions that may have multiple inputs. For example, a consumer's choice of digital camera purchase may depend on his utility from multiple camera attributes such as megapixels per photo, storage, battery life, lens quality, and cost, plus interactions between these and other attributes. Likewise, a supervisor's choice for a promotion may depend on noisy signals received from others on any number of an employee's characteristics. Many decisions -- from an individual's choice of restaurant, a supervisor's choice for promotion, or an editor's choice of papers to publish -- share this multi-facetedness.

Since empirical analysis requires metrics or proxies for each facet of interest, economists have traditionally had to restrict empirical studies of decision-making, signaling, information and learning to those phenomena, decisions and decision-makers for which metrics on various utility inputs are available, either through careful and often expensive or difficult-to-arrange research studies or through sheer chance of existing datasets appropriate for econometric evaluation. In the absence of highly controlled experiments, many research questions such as the role of information-



sharing versus preference similarity between peers can be studied only theoretically for a lack of available data on decision-making inputs. Even studies where limited data, such as user ratings, make some empirical analysis feasible may still be plagued with questions of endogeneity due to unobserved variables, such as unrated characteristics of a good, service or employee.

Of course, empirical analysis of the role of information is simplified in cases where ratings and other summary product characteristics provide directly observable numerical data on each relevant attribute of a good or service. However, typically, decision-makers reading reviews (and the researchers who study them) have access to just one or perhaps a few summary ratings combined with unstructured information such as long bodies of text. This poses a challenge as researchers may not be able to measure some key attributes that enter individual utility functions. For example, an editor with a high aversion to publishing results that could subsequently be refuted may skim reviews for descriptions of errors that cannot be overcome with revision; however, the distinction between errors that can and cannot be ameliorated with revision may not be fully broken out in numerical ratings that accompany reviews and therefore may not be directly measurable to a researcher.

A key contribution of this paper is to present methods for building metrics on relevant attributes of goods and services from textual reviews -- here in the context of referee reviews and editorial decisions. I demonstrate not only that it is possible to build metrics from referee language that capture information about paper attributes such as eventual citations but that these metrics also capture information about ultimate editorial decisions beyond what is contained by referee scores accompanying

those referee reviews. These results suggest that decision-makers who read reviews may disambiguate and reintegrate information available in the reviews and summary ratings according to their own unique preferences rather than simply accepting referees' summary weighting of relevant signals. Therefore, researchers should not rely solely on summary ratings that accompany reviews for a complete understanding of signaling in review systems unless there is sufficient evidence of homogeneity in the weighting of factors among users and writers of reviews. By demonstrating that under certain circumstances it is possible to build metrics from raw text to measure distinct utility inputs, this work highlights the possibility of a much richer set of studies on decision-making in the presence of reviews than previously could be endeavored.

A second set of contributions come from the insights this study provides into editorial incentives, referee scoring and citation drivers at five scholarly journals that provided access to their editorial databases for the period from 1992-2010. Previous empirical literature on journals (see subsequent section for a more detailed discussion) focuses on evaluating editorial bias towards secondary characteristics of papers (i.e. authors' genders, institution rank, and age for example) and journals' effectiveness at filtering for high quality papers, with quality defined as a paper's ultimate citation impact. Rather than assuming that citation impact enters directly into an editor's decision, I use a referee-language-based predictor of citations at one journal to investigate both direct and interaction effects of citations in editorial decisions. I find that my predictor of citations does not enter editorial decisions directly as is sometimes assumed. Instead, predicted citations enters editorial

decisions principally through a negative interaction with negative referee scores (and a smaller positive interaction with positive referee scores). In other words, the more low referee scores that a paper receives the more negative the impact of its citeability on getting accepted. These results suggest that editors may care more about the risk presented by a submission's citeability than its direct potential to be cited. For excellent, consistently well-scoring papers, citeability is positively correlated with acceptance whereas for papers with mixed reviews citeability has a negative effect. Besides evaluating editorial incentives, I also provide an analysis of referee preferences, drivers of citations, and other summary information on the journals.

The remainder of this paper is organized into the following sections. Section 2 provides some background into editorial incentives and the existing literature on this topic. The editorial data that are used are described in detail in Section 3, including summary statistics on referee recommendations, editorial decisions and other aspects of the review process. In Section 4, I provide a background on natural language processing (NLP) methods used by computational linguists for evaluating document and corpus similarity in a wide range of contexts and describe how I implement these tools to evaluate submissions' fit to their journal's subject niche. In Section 5, I describe and estimate a statistical model for predicting a submission's citation impact using language from first round referee comments. The results yield a journal-specific early-stage predictor of citation impact that can be measured for published and unpublished papers alike. I discuss intermediate results from the analysis of referee terms which are interesting because of what they reveal about papers that receive particularly high or low citations and scores. I also raise a number of methodological

limitations to consider when interpreting results from this type of textual analysis. I conclude Section 5 with a discussion of other submission characteristics that are predictive of greater citations. In Section 6, I evaluate the role of various factors such as predicted citations in referee scores to help provide a clearer understanding of what referee signals communicate. Section 7 gives an in-depth econometric assessment of editorial decisions, incorporating analysis of referee reports and citation impact together with a more basic assessment of editorial decisions across all five journals. Section 8 provides a discussion of the results and Section 9 concludes.

## *2. What We Do (And Don't) Know About Editorial Incentives*

As gatekeepers who decide what new ideas in their areas of expertise are worthy of publication, journal editors may face incentives on a number of factors. For example, they may care about their journals' ranking on impact factor, which is a measure of the frequency with which the average article published in a journal receives citations over a certain period of time. Higher impact factors often mean that more researchers pay attention to the journal; in turn these may lead to greater prestige and influence for the editors as well as higher profits via institutional subscriptions. Pressure to increase profits from publication could also encourage editors to broaden the readership and niche of the journal or both; journals may be able to use larger numbers of published articles per issue to justify a higher subscription fee. On the other hand, pressure to increase profits could also push editors to spend less money on publication costs in the form of fewer articles and limited budgets to cover time and other expenses. While a broader niche may appeal

to a broader readership and bring a broader pool of articles from which to select quality publications, a more specialized niche may lower the editorial workload involved in processing large numbers of submissions and increase attention and quality of submissions from researchers within the specialized area. In addition, as trained scientists, editors will also be expected to value quality science. The peer review system also contains further built-in incentives to publish rigorous, accurate work, as editors may face potential embarrassment from colleagues if they publish research that is later refuted.

In addition to a submission's technical accuracy and merit, potential for impact, and fit within the journal's niche, editors may face personal spillovers and benefits from their decisions. Since editors are sometimes active or recent researchers in their journals' niches, they may benefit or face competition from publication of articles on topics related to their own or their colleagues' work or which cite themselves directly. Referees, too, are typically active researchers in the fields they referee and may face similar incentives; yet, their reputations may be on the line in lesser or different ways, particularly since their identities are usually kept anonymous.

While there have been a number of economic studies of outcomes and durations of the editorial review process, there is not much research evaluating editorial incentives or how editors (or referees) gather and interpret information on these or other factors. As discussed below, those studies that consider editorial incentives often use citation impact as a direct measure or proxy for quality without examining whether the two are equivalent in practice. This paper evaluates the role of citations

in editorial and referee incentives as well as the availability of information about citations in both referee scores and reviews.

The limited literature with access to data on both accepted and rejected submissions, such as Abreveya and Hamermesh (2009) and Hamermesh and Oster (1998), focuses largely on editorial bias for secondary characteristics of papers (authors' gender, institution rank, and age for example). Blank (1991) looks at which editorial practices (i.e. single- or double-blind) are more biased<sup>1</sup> on some of these secondary characteristics. One exception, Cherkashin et al (2009), evaluates how well editors are selecting quality papers by following rejected papers at one journal that were eventually published elsewhere. By tracking the number of citations received by both accepted papers and rejected papers that go on to get published elsewhere, the authors study whether editors are rejecting the “right” (i.e. low impact) papers. In drawing comparisons between the number of citations received by papers at the original journal versus other publications, they face the challenge that their data and methods are not powerful enough to break out the journal-specific component of citations, i.e. the fraction of citations due to a particular journal's ability to broadcast research and its interaction with particular niches or articles. Notably, none of this empirical literature examines whether impact is in fact a direct, let alone primary, driver of editorial decisions and what role other factors play.

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<sup>1</sup> I use the term bias broadly here in order to encapsulate both desirable and undesirable selection behavior. Obviously, editors are hired to bring certain bias for selecting high quality papers. They may also have other biases that are not desirable from the perspective of publishers or researchers working within their fields.

Ellison (2002), Laband (1990), and Laband and Piette (1994) are among the few papers that comment on editorial incentives and/or the information content of referee reviews. Ellison provides a theory of editorial incentives and referee communication as part of explaining why editorial lags may have increased over the years. He hypothesizes that editors value quality along two dimensions, i.e. those that are inherent in a paper and those that can be improved with revision. He makes the case that the balance between value placed on the two is a social norm that may change over time. In his model, authors are the only ones who act “non-mechanically;” referees and editors receive perfect signals on each of the two dimensions and select those submissions with the highest combined quality to publish. If referees’ expectations regarding the social norm thresholds for publication in their fields comes from personal experience sending their own submissions to journals, and if referees overvalue their own work, then Ellison finds referees may become tougher and demand more revisions over time, lengthening the publication process. He suggests that the most worthwhile extensions of his work would be to examine what happens if referees send/receive noisy signals and if there are editor fixed-effects reflecting more “revision-loving” editors.

Laband and Piette (1994) look at citations data on published papers to show that when editors publish work by past coauthors or graduate students, it usually though not always goes on to have higher citation impact, suggesting that editors use their networks to identify and capture better research and improve efficiency in the market for scientific knowledge.

Finally, Laband (1990) conducts a survey to gather data characterizing the role of referees in the review process. His findings describe how critical referees' letters are to helping authors revise their work and how much more information they contain than editors' letters to authors. Laband makes the case that referees provide much more than a signal to editors about which papers are most promising for publication; rather, they are active contributors to the production of "good papers," where "good" is once again implicitly defined as highly citeable. He also provides a striking quote from one of the editors in his study who laments that his job as an editor requires him to spend too much time trying to improve the quality of "marginal" papers. While this may seem a stunning admission, Laband explains that this editor is only admitting what the data show for every other journal in the study, namely that each publishes a fair number of papers that go on to receive zero citations. He argues these anecdotes reflect a shortage of high-quality paper submissions at many journals, causing editors to rely more heavily on reviewers to help improve marginal submissions to the minimum acceptable threshold for publication. Lastly, he also suggests that matching submissions to good complementary referees who can play a productive role in the development of those assigned submissions may be one of the primary roles of an editor.<sup>2</sup>

Instead of making assumptions about the relationship between citation impact and quality, or relying on surveys or controlled experiments to shed light on the role of referees and editors, I combine textual and econometric analyses to gather and

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<sup>2</sup> This observation was also made by editors participating in this study.



measure information on different attributes of submission quality from written documents then employ logit and OLS regressions to track how this information flows into and reflects on editor and referee incentives and citation outcomes.

Besides challenging the assumption in the literature that citations are directly correlated with editors' definition of submission quality, my findings provide empirical validation and significant extensions of a number of hypotheses presented by Ellison (2002), Laband (1990), Laband and Piette (1994), and others. I demonstrate that initial referee reports contain a great deal more information about potential impact than is captured by the scores referees assign. I find some direct evidence in support of Laband's postulation that referees actively contribute to the production of good papers. Conditional on getting accepted, papers for which referees make certain kinds of suggestions for improvement such as "the authors need..." or "...would be interesting" go on to receive significantly more citations. I show that referee scores decrease over time and with the number of previous reviews a referee has submitted as Ellison theorizes, although I cannot rule out that this trend is partially due to lower paper quality or the editors' selection of harsher reviewers over time. I characterize editor-specific fixed effects that support Laband's and Ellison's theories that some editors possess better abilities to match papers to referees and/or revision-loving behavior. Finally, the framework I employ overcomes a challenge faced by both Laband and Cherkashin et al. Since they cannot directly observe how many more or fewer citations a rejected submission would have received at the journal it was originally submitted to, they must rely on the number of citations received by rejected papers published at other journals as an estimate, correcting for

journal fixed effects in Laband's case but not article-journal interactions. Since my measure of citations is both article- and journal-specific, I can predict how many citations would be received at the original journal by a particular paper, even for rejected submissions.

### *3. Overview of the Editorial Process and Data*

The data used in this study come from several scientific journals that have granted permission and secure access to their editorial databases as well as from public sources of citation data online, such as REPEC. These databases include a variety of information used in the manuscript evaluation process including submissions, decisions, and correspondence between editors, referees and authors.

In order to respect the privacy of the journals, their identities and those of their editors, authors and referees are treated with strict confidentiality. Certain additional identifying data such as editor names and some referee language are suppressed in the analysis in order to respect this confidentiality. Finally, the scope of this work was reviewed and approved by the Institutional Review Board of the University of Maryland to ensure it does not fall under the use of human subject data.

#### *3.1 Timing and Scoring in the Editorial Process*

At each of the journals studied, submissions are first received by the editor-in-chief who then assigns each submission to a coeditor, typically based on coeditor interests, expertise and workload. After reviewing the submission, the coeditor will either make a summary desk rejection or select referees to distribute the submission

to for review. Each of these referees will either decline or agree to review the submission. Referees agreeing to review will provide an evaluation score together with a note to the editor and/or a written referee report outlining some combination of the submission's contributions, shortcomings, suggested changes and a suggested course of action. For submissions that did not receive an initial summary desk reject, the coeditor typically waits for all referee evaluations to arrive before reviewing them and making a decision. Editors generally attempt to obtain reports and scores from all referees in order to avoid bias towards certain reviewers, but sometimes exceptions are made to facilitate the timeliness of decisions.

After each round of review, the editor chooses one of the following decisions for each submission. Those decisions indicating acceptance or some kind of rejection are final, while others requesting revisions provide an opportunity for the author to prepare an updated draft for a subsequent round of review.

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<b>Editor Decisions</b>
Summary Reject, No Referee Input
Summary Reject, Referee Input
Reject
Returned for Revision
Conditionally Accepted (Minor Revisions)
Accept

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Even within the first round, several factors affect the number of referees an editor will ask to review a submission. An editor may seek more or less information from referees depending on his own familiarity with the submission's niche. In addition, an

editor may seek referees to validate his own point of view or may select a number of referees to comment on different facets of a paper, such as its contribution to different literatures. If a referee indicates a low familiarity with a paper's field in her evaluation or identifies additional areas where expertise is warranted, an editor may solicit reviews from additional referees before making his first round decision.

Referees can also decline to review a submission. If they agree to complete a review, they choose from amongst the following evaluation scores to assign to each manuscript revision:

<b>Referee Scores</b>
Definite Reject
Reject
Weak Revise & Resubmit
Revise & Resubmit
Strong Revise & Resubmit
Accept with Revisions
Accept

### *3.2 Summary of Available Data*

Altogether five journals provided access to data on a total of 16,817 submissions from 1992-2010 for which final editorial decisions had been assigned. 3,189 of these were at Journal 4, where more extensive analysis was carried out. Tables A.a. and A.b. show the breakdown of these submissions by journal together with their ultimate fates, including the share that were accepted, desk rejected initially, summarily

rejected by the assigned editor before completing the review process, rejected after completing full review, and withdrawn by the author.

The data show a great deal of variability between journals. Between 11-33% of first round submissions at each journal were desk rejected without any referee review. Another 0-5% were summarily rejected by the assigned editor before completing the review process. In each database, between 15-70% of submissions were eventually accepted. Table A.b. shows the same summary measures restricted to the period between 2006-2010, which reflects greater annual submission volumes at each journal as well as greater selectivity. During this time, desk rejects are higher at 16-47% of submissions and acceptance rates are lower at 9-58%, depending on the journal.

Although editorial decisions are available for all of these submissions, due to slow adoption of editorial databases, only a subset of articles, primarily from 2006 onward (2004 at Journal 4), underwent electronically documented referee review and can therefore be analyzed to understand the information content of referee scoring, review-writing, and their role in the editorial process. Table B shows additional detail on the subset of submissions (21-78% depending on the journal) that were sent for review. A total of 8,934 first round referee evaluations were available for 4,107 submissions that underwent full review. Of these, 3,040 evaluations correspond to 1,452 submissions at Journal 4, where more extensive analysis was carried out. The data here show both the fraction of referees that agreed to review their assigned manuscripts together with the distribution of scores they assigned by journal and review round for the first through third revisions.

These data reflect a slightly different picture at each journal. While Journal 4 appears to be the most selective of the five journals, it also subjects the largest number of submissions to first, second and third round reviews. The larger sample size of initial reviews makes it ideal for more extensive analysis of information content of reviews and their role in the editorial process. Here, the majority (56%) of referee scores in the first round were reject or definite reject while very few (6%) recommended acceptance or acceptance with additional revisions. However, this tendency to recommend rejection in the first round was reversed in the second round where 65% of referee scores recommended acceptance with or without additional revisions and only 13% recommend rejection or definite rejection. Referee scores tend to be even more positive in the third round, with 84% recommending acceptance with or without additional revisions and just 4% recommending rejection or definite rejection. Not only do referee scores become more positive with further revisions at Journal 4 but, conversely from other journals, they also become more definitive with firm accept/reject recommendations making up an increasing fraction of referee scores and revise and resubmit recommendations a decreasing share of scores in subsequent rounds. The greater number of review rounds and increasing definitiveness of referee scores at Journal 4 may suggest that the review process plays a more intensive and important role there, both in improving the quality of submissions and in weighing into editorial decisions.

Table C shows the distribution of the number of reviews received by submissions in the first round across all journals. Most reviewed submissions ( $\geq 94\%$ ) receive between one and three reviews with two reviews being the median and the most

frequently received number (46-62% of reviewed submissions) at all journals. No submission received more than five reviews.

The figures in Appendix D depict how final editorial decisions vary with first round referee evaluations at Journal 4. For all papers receiving two referee evaluations in the first round, the top panel shows how many received zero, one and two positive referee recommendations (i.e. revise/resubmit or acceptance) and how many of these were eventually accepted by editors (red) or rejected (blue). The lower two panels show the same distributions for papers receiving three and four total referee evaluations, respectively. Not surprisingly, holding the total number of reviews a paper receives constant, the higher the number of positive referee recommendations (i.e. some type of recommended revise and resubmit or acceptance), the more likely an editor is to eventually accept the submission rather than reject it. This trend could reflect some combination of two factors: first, editors' own views of a paper are likely to be correlated with referees' opinions and second, editors weigh the recommendations of referees in their own final decisions.

To conduct the textual analysis of manuscripts and referee comments described in Section 4, I have extracted full texts of 6,759 manuscripts across all five journals,<sup>3</sup> primarily from 2002 onwards. This includes 2,633 of 3,189 manuscripts at Journal 4 and earliest versions of 2,173 of those. In addition, I processed full texts of 2,930 referee reviews (i.e. combined referee reports and referee remarks to the editors) at

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<sup>3</sup> Due to gradual onset of electronic submissions, some manuscripts (particularly older ones) were not stored in editorial databases. Of those that are available electronically, some could not be converted to plain text due to their formatting settings.

Journal 4 corresponding to 1,310 manuscripts. Of those referee comments, 458 correspond to initial reviews of 220 submissions that were eventually published. I have been able to identify citation counts for 187 of these publications.

Citations data was collected by hand through REPEC over the course of a week in order to ensure that there was no significant date bias in the number of citations each published paper received. Appendix E shows the distribution of citation counts for this sample.

#### *4. Textual Analysis*

The last two decades have seen significant advances in algorithms for analyzing and building meaningful numeric metrics from unstructured textual content. While these computer science-based algorithms have long been iterated on and have ultimately facilitated powerful, practical tools including search engines, electronic record-management, and even image classification technologies, they are still rarely employed by economists in the study of decision-making. My hope is that this work will serve as an example of how, when it comes to analyzing decisions, text-based and machine learning models are at their most powerful when combined with appropriate economic models. These tools often require econometric analysis to elucidate the meaning of metrics, to disambiguate between causation and correlation, and to identify the mechanisms through which measurable information is driving outcomes.

One of several reasons for the dearth of natural language processing and machine learning methods applied in economics is that these models often function as a black



box. Simply building a machine learning algorithm that can successfully predict an editor's decision does not necessarily convey the researcher an inherent understanding of the decision process or even the material factors that influence it. The approach taken in this paper is unique in that I first build metrics using textual analysis and machine-learning-based model selection tools that capture information about journal submissions. Then, I rely on simple, traditional, econometric tools (in this case, binary and ordered logits) to measure and interpret the role played by those and other factors in referee and editorial decisions.

The family of text-based models and algorithms employed in this analysis are valuable tools for economists because they open up much richer sources of data about individuals and the information sets available to decisionmakers for use with traditional economic models. Both the measures of cosine similarity described in this section and Least Angle Regression, which is described in the subsequent section, are also easier to interpret than many other tools from computational linguistics.

This section gives some background and description of the algorithm used in this paper for measuring similarity between submissions and journals' corpora of published papers. The subsequent section describes additional methods for building a predictor of the number of citations a paper will receive based on first-round referee comments.

#### *4.1 Measuring Textual Similarity*

Measures of textual similarity have been widely used by computer scientists for a variety of purposes, from search-engine algorithms to image recognition. Hoberg and

Phillips (2010) measure cosine similarity between the texts of thousands of 10-K filings to show that firms with higher similarities are not only more likely to merge but also show higher post-merger increases in revenue. Here, I use cosine similarity to measure how closely related each submission is to past accepted work at the journal, which I will employ as a proxy for fit.

In order to evaluate textual similarity between papers, I first store a term frequency vector,  $\vec{t}_k$ , for each submission,  $k$ , containing the frequencies,  $t_{ki}$ , of all terms  $i$  appearing in the submission. I store frequencies of all three-word terms of at least twelve characters occurring in at least two submissions:

$$\vec{t}_k = \begin{pmatrix} t_{k1} \\ t_{k2} \\ \vdots \\ t_{k(n-1)} \\ t_{kn} \end{pmatrix}$$

To measure textual similarity between any two papers, I use the cosine similarity between their term-frequency vectors (Salton and McGill, 1983) which is defined as the angle between the term frequency vectors representing the documents. This can be measured using the length normalized dot-product of their term frequency vectors,  $t_k$  and  $t_l$ :

$$similarity_{kl} = \cos(\theta_{kl}) = \frac{\vec{t}_k \cdot \vec{t}_l}{\|\vec{t}_k\| \|\vec{t}_l\|} = \frac{\sum_i t_{ki} t_{li}}{\sqrt{\sum_i (t_{ki}^2)} \sqrt{\sum_i (t_{li}^2)}}$$

Cosine similarity is one of the most commonly applied measures used in computational linguistics (see Sebastiani, 2002 for an example) both for its simple interpretation and its simple normalization which provides a natural control for document length. Note that because of the length-normalization in the formula above,

similarity between each pair of papers is bounded between zero (no textual overlap) and 1 (all terms in each document occur in the other).

Appendix F shows the distribution of cosine similarity across all pairs of paper submissions and accepted paper submissions received in 2009 at Journals 1 through 5. These similarities are calculated based on all one-word terms that occur in at least two manuscripts. As these graphs show, the average cosine similarity between two submissions to the same journal is between 4.9%-8.6% depending on the journal, with the average being slightly higher when limited only to accepted papers.

In order to accommodate the fact that a journal's niche reflects not just a singular paper but rather a corpus of somewhat loosely related past publications, I average each submission's similarity across all papers  $l$  accepted at the journal from the previous year to measure overall fit. Because pair-wise similarities are restricted between 0 and 1, this method provides a measure of relation to the niche recently covered by the journal.

$$fit_k = \left(\frac{1}{n}\right) \sum_l^n similarity_{kl}$$

where " $n$ " is the number of papers " $l$ " accepted at the journal the previous year

In addition to storing term frequency vectors as described above, I also store all occurrences of the last names of the journals' primary coeditors in both earliest and latest revisions of all manuscripts for subsequent econometric analysis of niche and bias in decisions.

## *5. Modeling Impact using Referee Language & Other Determinants*

### *5.1 The LASSO Estimator and Model of Citation Impact*

Like many facets of products and securities which we send and receive signals about and which we would like to forecast, the number of citations a paper will receive is challenging to predict empirically because the factors we hypothesize to affect impact outcomes -- things like whether a paper contains novel content, is written on a hot topic of the moment, or challenges previous seminal work -- are traditionally hard to measure explicitly.

In order to address this measurement problem, I exploit the text of referee reviews written about papers at the time of submission which comment on a paper's relevance, merits and other characteristics. Casting a broad net on language that could be meaningful, I examine one- to three-word phrases of at least four characters in the earliest available versions of referee reports and comments to editors. By restricting these phrases to those that occur in at least fifteen referee evaluations, I minimize the possibility that these phrases predict citations just by singling out individual papers. At Journal 4, this leaves 5,724 terms used by referees to describe at least fifteen papers.

While the text of these reviews provides a rich source of information on observable characteristics of papers that might otherwise be difficult to measure, they introduce a statistical challenge in that the number of possible predictors far exceeds the number of observations. In order to select the most informative predictors of citations without exceeding the allowable degrees of freedom, I employ an L1 model

selection method called Least Angle Regression (LAR) for fitting referee language and other paper characteristics to citation impact.

Like AIC and BIC methods, which are commonly used in economics and finance for lag selection in time-series models and fall under the same class of L1 models, Least Angle Regression uses shrinkage to force some coefficients towards zero, thereby punishing the model for over fitting. LAR fits coefficients  $\beta_j$  to a linear regression on  $x$  that is quite similar to ordinary least squares (OLS) except that in addition to minimizing the sum of the squares of the residuals, there is an additional constraint that the sum of the absolute values of the coefficients must be less than some shrinkage parameter,  $t$ , or alternatively a fixed fraction  $s$  of the OLS coefficients  $\beta_j^0$ :

$$(\hat{\beta}) = \operatorname{argmin} \left\{ \sum_{i=1}^N \left( y_i - \sum_j \beta_j x_{ij} \right)^2 \right\} \quad \text{subject to} \quad \sum_j |\beta_j| \leq t \equiv s \sum_j |\beta_j^0|$$

As described by Tibshirani (1996), the parameter  $s$  (or alternatively  $t$ ) controls the amount of shrinkage by constraining the number of predictors permitted in the model and the size of their coefficients. Values of  $s \in (0,1)$  will always result in some amount of shrinkage, but the appropriate level can be estimated based on cross-validation or analytical estimation of overfitting risks. Tibshirani also describes a number of consistent computational heuristics for estimating LAR models, including LASSO (for ‘least absolute shrinkage and selection operator’), which I use to estimate citation impact based on referee language. The LASSO first computes separate OLS

on each predictor, adding to the model the predictor that is most highly correlated with the residuals, subject to the shrinking constraint. Taking this first predictor as a given in the model, LASSO proceeds to recalculate the residuals with a second coefficient on each remaining predictor, again adding the predictor that is most highly correlated with the dependent variable at that step, repeating until the shrinking constraint becomes binding.

Besides addressing concerns about overidentification, additional benefits of using the LASSO are that the model provides coefficients with greater accuracy (lower variances) than OLS and which are much more easily interpretable than those proposed by many machine learning models which might perform as well. The results from the first stage of the LASSO can be used to evaluate how informative different predictors are on their own, as described in the following two subsections.

As discussed by Tibshirani, since the LASSO estimate is a non-linear and non-differentiable function of the response values for a fixed value of  $s$  or  $t$ , it is difficult to obtain an accurate estimate of its standard error. To estimate an acceptable range of values for  $s$ , I estimate the prediction error for the LASSO procedure by five-fold cross-validation as described in Efron and Tibshirani (1993), noting the value of  $\hat{s}$  that minimizes the prediction error ( $\hat{s}=.22$ , Cross-Validated PE=34). See Appendix G for a diagram. While Efron and Tibshirani recommend setting  $s = \hat{s}$ , a more conservative approach is to treat their value as an upper bound for  $s$ . Willey (2011) recommends selecting a value of  $s$  that falls somewhere below  $\hat{s}$  but above the minimal value with an MSE within a standard error of  $\hat{s}$ . For the sake of parsimony and to further alleviate any concerns that too many predictors in the model could be

singling out individual papers, I choose a conservative value of  $s = 0.088$  which lies at the lower bound of this range and which in my model, permits 20 predictors.

The coefficient path for this regression is shown in Appendix H. In general, coefficient paths for LASSO need not be smooth or monotone because the best subset of predictors of size  $n$  need not be contained in the best subset of size  $n+1$ . If the process of adding predictors to the LASSO is singling out individual papers, we would expect to see many coefficients' values and signs oscillating as predictors are added and subtracted to single out unique papers with significant numbers of citations. Instead, in the model of citation impact, all coefficient paths are continuous and show minimal oscillation (only one of the twenty coefficients ever changes direction and none change sign), once again alleviating concerns that predictors could be singling out individual papers.

The OLS Adjusted  $R^2$  can also be used to assess the goodness of the LASSO fit. Using referee language and submission date<sup>4</sup>, the LASSO model predicts 62% of variation in the number of citations received by published, accepted papers. I can conclude that via the LASSO, referee language and submission date together provide an informative, early-stage signal of citation impact that can be calculated for both published and unpublished papers and used in subsequent analysis of editorial

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<sup>4</sup> Interestingly, I find that when modeling impact, estimating a coefficient on the date on which the submission was received is more significant than the date on which the submission was accepted. This may reflect a trend in certain fields such as economics and finance, of authors broadcasting working versions of papers which can get cited, sometimes long before they get accepted at any journal. It is important to control for date in each regression, since later publications enjoy less time in which to build citations.

decisions. Although in theory, published papers may reflect a selection bias, this can be controlled for by using referee scores, which are also available. See section 6 for results and a further analysis of this approach.

### *5.2 Relationship Between Referee Score and Impact*

Since the LASSO captures information about citation impact from referee comments, it seems relevant to consider how much of this information is also captured in referee scores (i.e. referee recommendations to accept, strong reject, weak revise, resubmit etc.). Regressing referee score and submission date on citations yields an adjusted  $R^2$  of just 0.05 compared to an adjusted  $R^2$  of 0.62 from the LASSO on referee language and submission date. Put differently, this means that referee scores and submission date alone capture just 5% of the variation in citations whereas the LASSO considering text of referee comments captures 62% of this variation. This suggests that referees both have and broadcast, whether knowingly or otherwise, more information on a submission's citation impact than they incorporate into scores. This could reflect either or both a limitation in the bandwidth of scores for communicating information and/or referees who (whether strategically or through ignorance) do not consider this citation information entirely relevant to scoring recommendations.

To conduct a deeper analysis of how informativeness of a predictor of score relates to its informativeness on citations and vice versa, we can revisit the first-stage LASSO results from the previous section, combining them with additional first-stage results from a LASSO to predict referee score. As discussed above, the first step of a



LASSO is equivalent to estimating a separate OLS regression on each referee term. In order to control for the possibility that older papers have more time during which to accumulate citations as well as time trends in scoring, I also control for submission date. I conduct two regressions for each of the referee terms considered in the previous analysis, which yields estimated values of  $\alpha_j$ ,  $\beta_j$ ,  $\gamma_j$ ,  $\mu_j$ ,  $\rho_j$ , and  $\varphi_j$  for 5,724 values of  $j$ :

$$(citations_i) = \alpha_j + \beta_j (submission\ date_i) + \gamma_j (term_{ij}) + \varepsilon_{ij} \quad \text{for each term } j$$

$$(referee\ score_i) = \mu_j + \rho_j (submission\ date_i) + \varphi_j (term_{ij}) + \varepsilon_{ij} \quad \text{for each term } j$$

The significance and informativeness of each referee term in predicting citations and scores, respectively, can be interpreted based on its normalized coefficients,  $\gamma_j/\alpha_j$  and  $\varphi_j/\mu_j$ , and from the p-values of the coefficients  $\gamma_j$  and  $\varphi_j$ . The results showing the relationship between  $\gamma_j$  and  $\varphi_j$  are graphed in Appendix I. As described below, these demonstrate (1) that the informativeness of referee language about citation impact is poorly or not-at-all correlated with informativeness about referee score and (2) that referee terms contain more information about both citations and referee scores than would be expected at random.

The upper left panel of Appendix I shows a plot of the raw coefficients  $\varphi_j$  versus  $\gamma_j$ . The  $R^2$  of their relationship is 0.03, reflecting very low correlation. The right-hand panels show plots of the p-values of the same coefficients. The lower two panels show plots by rank order, which captures each term's order of importance relative to others, spreading out the data points evenly much like a log-log plot and making it easier to view very large and very small values on one plot. The low correlation ( $R^2 = 10^{-5}$ ) between raw p-values for score versus citations (upper, right-hand plot) is the

most revealing about the lack of correlation between terms' informativeness in predicting score versus citations. Despite this lack of correlation, a careful look at this plot shows a higher density of terms at very significant p-values ( $\leq 0.05$ ) on both axes, demonstrating that a larger number of terms are statistically significant predictors of either citations or scores than would be expected at random. This result can be seen even more clearly in the frequency distributions of p-values shown in Appendix J, which show that the cumulative density of p-values  $\leq 0.05$  (and particularly those below 0.025) are two to three times higher than would be expected at random. In other words there are several times as many terms that are significant predictors of score and citations than we would expect at random.

Given the breadth of p-values across both score and citation predictions, it is clear that different referee phrases carry different amounts of information about predicted citations than about predicted scores, especially considering that each term plotted was applied in at least fifteen referee evaluations. As a result, I conclude that information contained in referee language about referee scores is mostly not coincident with amount of information about citations. Accordingly, the LASSO predictor of eventual citations can be employed together with first-stage referee scores as signals on largely different facets of a submission's quality.

### *5.3 Referee Language Predictors of Impact and Referee Scores*

The intermediate LASSO results from OLS on individual terms in the previous subsection highlight some interesting referee language that are significant predictors of citations and/or referee scores. Even though the LASSO results are easier to

interpret than most machine learning models, their interpretation still has its limits. Before diving into individual terms and conclusions about the meaning and direction of their significance, some standard caveats that apply to natural language processing must be noted on interpretation of this portion of the analysis.

Many factors might affect a referee's decision to use a phrase to describe a paper. Although modeling these factors explicitly is beyond the scope of this paper, it is helpful to consider various mechanisms that could affect referee language when interpreting individual term results. Some terms could convey multiple meanings depending on their context or nearby textual qualifiers. For example "errors" could be used to refer to mistakes present in a submission or to standard errors from a regression analysis that authors perform. Likewise, the term "interesting" could reflect a completely different sentiment when qualified with a negative term as in "not very interesting." The bar for calling a paper "nice" may differ from one reviewer to the next. Referees in certain niches may also be more likely to use certain terms than others, so that the significance of a term actually reflects a paper's fit within a particular niche that is more highly cited rather than referee sentiment. Furthermore, the 5,724 referee terms evaluated will certainly not subsume every sentiment that referees may convey in their reviews. Some sentiments may require complex language that could be phrased in multiple ways and/or take more than three words to describe. Significance of sentiments conveyed through multiple phrasing variations could be diluted, for example, if each variation is applied in fewer than fifteen evaluations. Altogether, these characterize just a few of the reasons that even the most basic textual models are typically difficult to interpret.

Major advances by computational linguists during the last five years have resulted in a large quantity of new methods aimed at tackling the types of challenges described above within specific contexts; for example, search engines typically infer a user's intention from a term such as "jaguar" based on the user's geographic location and the co-occurrence of other words like "zoo" or "F-Type 2013" in the search query.

However, tuning algorithms to correct for turns of phrase is still at least as much an art of balancing countervailing signals as it is a science. These more complex algorithms typically require a great deal of tailoring to detect language constructs, synonyms and context specific to each corpus. An algorithm for detecting context in search engine queries will differ substantially from one tailored to technical patent citations, twitter feeds, financial news or referee evaluations. Not only do more advanced algorithms typically require much larger datasets for training, often under supervised learning methods where the researcher or evaluator of the model plays a hand in identifying and extracting salient features, but they can conflate artifacts from multiple subalgorithms into one metric making their results harder to interpret as well. Consequently, a simple initial textual analysis like the one presented here is usually a first step towards developing tailored metrics on textual corpora and has the benefit of more clearly (if not perfectly) interpretable results.

In order to address these limitations on interpreting individual term results, I restrict the discussion below to only those terms whose occurrence alone is a significant predictor of citations or referee score at the 10% level or better. As discussed previously, each of these appears in at least fifteen evaluations also. While all of the terms that fit this specification are statistically significant predictors –

meaning that with 90% certainty or better, their presence corresponds to a concept or sentiment that predicts scores or citations—it may be easier to identify the story and reasoning for why some terms are significant drivers of scores or citations than others. The formulation of the OLS regressions helps simplify interpretation; since only one referee term is included in each regression, it is possible to evaluate differences in context by comparing coefficients and significance across variants of phrases (eg. “interesting” and “be interesting to”). In addition, I use [square brackets] in the discussion below to highlight the phrases that most commonly precede or follow significant terms to aid the reader’s interpretation of the results where applicable. Ultimately, the contribution of this analysis is that it identifies concepts that are significant predictors of scores and citations. It is a useful tool for identifying theories for further discussion and investigation.

With these caveats in mind, the results of the submission-date-controlled first-stage LASSO from the previous section highlight some interesting themes and trends among significant referee language. See Appendix K for results from a sample of significant terms. Positive predictors of citations include terms that point to a submission’s contribution to some ongoing debate, such as “debate,” “doubt” and “argue that the” or to topics of public interest, such as “public” and “government.” Likewise, referee language that suggests a submission is written on a hot topic or at least one in which there is an existing literature tend to receive more citations (eg. “literature has,” “the existing literature,” “this literature”) but also lower referee scores (eg. “literature has,” “competing,” “related,” “related to,” and “well-known”). Language that comments on the novelty of a paper, especially in the context of an existing

literature, also predicts greater citations (eg. “extends,” “the most important [contribution],” “would be interesting,” “the contribution,” “the major [innovation],” “value of the,” and “the authors propose”). The term “from [year] to [year]” which occurs when a referee is characterizing a unique dataset used in a paper also reflects a kind of submission novelty that significantly and positively predicts citations.

Referee advice for revising a paper can sometimes indicate greater citations (eg. “the authors need,” “the current version,” “would be interesting,” and “highlight”) but also not surprisingly, lower scores indicating greater room to improve in the first round (“be helpful to” and “authors should”). Conditional on being accepted, it seems that some referee suggestions do improve the citation impact of papers as Laband theorizes or at least highlight aspects of citateability that can be improved with revision, as discussed by Ellison.

Some referee terms raise concerns and potential shortcomings in a submission. These tend to predict lower scores (eg. “problems of,” “problems with the,” “problematic,” “assumes that,” “did not,” “do not see,” “they do not,” “misleading,” “not clear,” “unclear,” “assumptions,” “the assumption that,” “assumes that,” “not seem to,” “not allow,” and “not understand the”) and almost all of these also predict lower citations. Only “unclear” is a positive, statistically significant predictor of citations, which could again reveal a productive and addressable referee comment that ultimately leads to improvements in the paper and more citations in the long run.

Language that connotes the referee’s opinion can be much trickier to interpret. Positive terms (eg. “nice paper,” “think the authors,” “important,” “sensible,” “I agree,” “in my opinion,” and “in favor of”) show up as significant positive predictors of

citations and, more rarely, significant positive predictors of referee scores (eg. “sophisticated,” “nicely,” and “minor [concern]”). Likewise, negative phrases (eg. “rejection,” “I am not,” and “I do not”) are negative indicators of score and in the case of “rejection” a negative indicator of citations also. However, it is especially important to understand context in interpreting polarizing (i.e. positive and negative) terms because these are likely to occur in the presence of qualifiers which could reverse their meanings quite easily.

Interestingly, referees’ use of the term “interesting” is predictive of lower scores on average but not a significant predictor of citations. Anecdotal discussion with several referees indicates that this may be a term used by referees who can not identify anything positive to say but feel uncomfortable using explicitly negative language. Indeed, the term “interesting” is usually followed by “but” or “however” later in the sentence. In contrast, the term “be interesting to,” which suggests a referee has identified valuable extensions to a submission, is predictive of higher citations but is not a significant predictor of referee scores.

Finally, a number of significant terms characterize the topic of a paper. Although it is difficult to discuss these here without compromising the identity of the journal, it is worthwhile to note that “[editor-in-chief’s last name] and” appears as a positive significant predictor of citation impact here and in the final LASSO model. Examination of these occurrences reveals that this language typically describe an extension or application of previous work by the editor-in-chief and coauthors. This finding suggests that (1) work in an editor’s niche at a journal receives more citations

than average and (2) provides support for the idea that coeditors are selecting for more impactful work in the editor-in-chief's area of expertise.

One way to maximize the usefulness of these results is to use them to identify data points that could be built into future online editorial (and non-editorial) information collection systems -- such as checkboxes that referees could tick to indicate unique datasets and other types of impact predictors, as well as autocomputed measures of relevance to a journal's niche -- to promote transparency in evaluating review systems while protecting the identity and privacy of stakeholders.

#### *5.4 Other Predictors of Publication Impact*

Beyond referee language, I also look at other predictors of a published submission's citation impact including paper characteristics and editor fixed effects. Appendix L shows results from an OLS of citation impact on submission characteristics of published papers. Positive coefficients on both earliest and latest version manuscript length show that longer papers at this journal go on to garner three more citations per one thousand words in earliest submitted versions of manuscripts and an additional 0.5 more citations per thousand words in the last revision of the manuscript. One interpretation of the significance of both coefficients is that editors and referees facilitate shorter lengths in final versions of less impactful papers while authors (at least those of work that is eventually published) also face compatible incentives at submission time, submitting shorter papers on average when there is less impactful content and longer papers when there is more of it.



Results of regressing citations on editor fixed effects and mentions of editor names are shown in Appendix M. Editors are numbered based on the number of submissions they have overseen, with the Editor-in-chief and Editor 1 each overseeing the most submissions and Editor 12 overseeing the fewest. Due to small sample sizes, fixed effects were excluded for Editors 10-12. Editor fixed effects vary in magnitude and significance. A few possible reasons are that some editors do a better job of selecting more impactful papers, place higher weight on impact over fit/accuracy, or they simply are assigned papers in less cited areas. Cherkashin et al (2009) hypothesize that an editor-in-chief may cherry pick better papers for his/herself or favored editors. At Journal 4, however, the coefficient on the Editor-in-chief's fixed effect variable is near the middle of the range for all editors, suggesting that s/he is not cherry picking most impactful articles for his/herself.

Mentions of the Editor-in-chief's last name and Editor 1's last name in the final versions of manuscripts are significant predictors of eventual citations. For the Editor-in-chief, the effect of being mentioned in a published submission is just over one more citation on average and highly significant at the 1% level. One interpretation is that papers closer to the Editor-in-chief's work get more visibility, perhaps because a large number of readers interested in that line of research pay attention to the journal or because the Editor-in-Chief's research is in a highly cited area. For Editor 1, the effect is negative and still significant at the 5% level suggesting that this editor's research might fall into a less cited niche. The less-than-significant fixed effects for mentions of other coeditors could be a result of the smaller sample sizes or could mean that they are less specialized or in niches with more variable levels of citations.

Interactions between coeditors and mentions of coeditor names are not significant, except in the case of the Editor-in-chief where the effect is significant and negative (though still slightly smaller in magnitude than the coefficient on mention of the Editor-in-chief's name). This tells us that on average, published papers mentioning the Editor-in-chief that were assigned to coeditors are more impactful than those assigned to the Editor-in-chief him/herself. Accordingly, we can conclude the greater citations received by papers in the Editor-in-chief's own niche are not primarily a result of his/her own greater but rather some mechanism that acts primarily through coeditors. The larger numbers of citations received by papers mentioning the Chief Editor could instead be due to the readership s/he draws or his/her ability to draw coeditors able to select for more impactful papers in this niche, via referees they select or otherwise. Alternatively, it is possible the Editor-in-chief is strategically chosen by the Journal publisher to be aligned with its current readership. In either case, these results provide evidence that the Editor-in-chief plays an important role and signal for establishing impact through the journal's readership and/or human capital.

## *6. Investigating Trends in Referee Behavior*

This section presents results on predictors of referees' decision to refer and their scoring decisions. Understanding referee behavior is a key part of understanding the editorial process in that it tells us about the signals and information captured in referee reviews as well as how these factors might figure into an editor's choice of referee.

In Appendix N, Table 1 shows the results of a binomial logit of revision round and number of previous reviews completed by the referee on referees' decision to refer. Referees are more likely to agree to review later revisions of a paper, perhaps because they are more invested in the paper by that point and because less work is required. However, referees that have completed more reviews are significantly more likely to decline additional submissions. Whatever the returns to refereeing, they seem to diminish slightly on the margin of reviewing another paper for the same journal. These results suggest editors at Journals 1 through 4 face constraints on the amount of referee capital they have and support Laband's hypothesis that editors must spend effort matching reviewers to submissions who will raise the quality of these submissions to the extent possible. In contrast, at Journal 5, the estimated coefficients on the previous referee reviews are not significant, which may reflect less exhausted or more committed referee resources.

Results from a multinomial logit on referee-assigned scores across Journals 1 through 5 are shown in Appendix M.2. Referees at Journals 1 through 3 and 5 generally assign lower scores over the course of time when controlling for number of past revisions. The exception is Journal 4 where referees grade slightly but significantly more generously with time. This effect disappears, however, when the analysis is restricted to first revisions only and controls for a reviewers' total reviews are removed (see Table O and its discussion below). The negative coefficient on total reviews everywhere except Journal 5 suggests that either referees grade more harshly later in their tenures or that referees who are selected for and agree to review more papers are more harsh.

The estimated coefficients on length are significant and negative in all journals. This could mean that referees prefer shorter papers, or it could reflect greater effort and revision rounds devoted to editing down final versions of papers that go on to be accepted. Subsequent results on editorial preference for length help to detangle these alternatives, providing support for the former explanation.

Finally, coefficients on average similarity to previous years' accepted papers vary in sign and significance across journals. One interpretation is that at some journals referees may take a greater interest in whether a submission fits the relevant niche, while at others referees may be concerned with broadening the journal's niche. These results suggest that it is important to interpret the results regarding referee preferences in a journal-specific context.

Appendix O gives a more in-depth look at first-round referee evaluations at Journal 4. As discussed in the previous section, there is a significant and negative coefficient on submission receipt date in this specification, reflecting greater selectivity by referees over time on first-round submissions.

Coefficients on editor fixed effects are all positive and significant but vary in magnitude. One explanation is that the quality of papers may vary across editors and/or their field specialties. An alternative explanation is that put forth by Laband that some editors consistently do a better job of matching referees who are able to improve the quality of marginal papers. It is also possible that referees in certain fields are generally more lenient than others.

## 7. *Results from Editorial Decision Analysis*

Results from a series of binomial logits on ultimate editorial decisions to accept or reject submissions at Journal 4 are shown in Appendix P. As discussed previously, positive scores are defined as any type of accept or revise and resubmit recommendation by a referee while any type of reject recommendation is considered negative. As the results of the first two regressions show, the LASSO-generated  $E[\text{citations}]$  is not a significant predictor of editorial decisions when considered by itself. However, the third and fourth regressions show that there is in fact a significant interaction between  $E[\text{citations}]$  and both the number of positive and negative scores received in the first round. The fourth regression shows that the number of first-round positive and negative scores received by submissions are quite significant on their own, although their interactions with  $E[\text{citations}]$  also continue to be significant in this specification. The fifth regression shows that these effects persist when controlling for  $E[\text{citations}]$ , although the positive interaction loses significance. Additional point estimate analyses of significance presented in Appendix P are consistent with these findings.

Coefficients on the cosine similarity measure of fit within a journal's niche are also significant here and in the point estimate analysis. When available, a submission's *fit* (that is, its cosine similarity to previous year's accepted papers) is a significant and positive predictor of editorial decisions in all specifications. The

variable *fit\_flag* controls for the availability of manuscripts for textual analysis<sup>5</sup>, taking on a value of one when a measure of *fit* is available and zero otherwise.

These results are quite fascinating for several reasons: First they show that both the LASSO-generated predictor of citations and cosine similarity measure of fit isolate information from textual content that plays a role in editorial decisions beyond what is captured in referee scores. Secondly, it suggests that citations play a more complicated role in editorial incentives and submission quality than the literature typically assumes. For papers with consistently positive scores, citations are a positive predictor of editorial decisions. However, for submissions with more mixed reviews, citeability is an increasingly negative predictor of acceptance<sup>6</sup>. Given that referee scores seem to serve as a signal on quality, these results characterize a risk aversion on the part of editors to publishing high impact marginal-scoring work and an affinity for publishing well-scoring high impact papers. Further investigation shows that these interactions also become more pronounced in later rounds, presumably because more information or stronger signals about the manuscript are revealed in each round.

Discussion of these results with the editorship of these journals elicited comments that validated and illuminated these findings. I was told that as publishers struggle to turn profits by bundling journal subscriptions (which are measured in pages) for sale

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<sup>5</sup> As discussed in Section 3, some manuscripts could not be converted to raw text because of the format in which they were received.

<sup>6</sup> As shown in Appendix D and discussed in Section 3, submissions that received only negative scores (i.e. all reviewers recommending some form of rejection) were never accepted.

to libraries, editors face increasing pressure to avoid “thin, anemic” issues and must therefore censor preferences on other aspects of a paper including novelty and citation impact “as long as the science is technically correct.” In other words, editors are more concerned with protecting the journals and themselves from the embarrassment of technical errors than limiting publications to just the most novel or high impact content. One editor pointed out that increasing competition from online and fee-for-publication journals which generate both revenue and significant citations as a result of being open access further complicates and exacerbates these incentives.

I also carried out a binary logit of editorial decisions with fixed effects for each coeditor. Results from this analysis are included in Appendix Q. The significant variation between fixed effects, particularly for Editors 3, 4, and 5 suggests that there are differences between editors, either in the quality of the submissions they receive or in their standards or the publication quotas they aim to meet.

Results of editor fixed effect interactions with mentions of the assigned editor’s name in the final version of the manuscript are included in Appendix R. Only the interaction for Editor 1 is significant. The results indicate that Editor 1 is more likely to accept papers with his/her name in the last version but also that those papers also go on to get cited more, though the latter effect is not highly significant. This editor may be attracting more high impact work to the journal within his/her personal niche, making the case that the choice of coeditors is also important to the extent that they attract work within their niches.

Appendix S shows additional results about editorial decisions across all five journals. As in regressions explaining referee scoring, coefficients on average

similarity to previous years' accepted papers vary in sign and significance across journals. They are positive and significant at Journals 1, 2, and 4. The results suggesting that at these journals, editors take a greater interest in whether a submission fits the relevant niche and, once again, underscore the importance of regarding findings about editorial preferences in a journal-specific context. These regressions also show that unlike referees who prefer shorter papers, editors have a positive preference for submission length in earliest versions of manuscripts, perhaps a result of the publication incentives described above.

## 8. *Summary and Conclusion*

This study makes contributions both to economic methodology, by establishing a framework in which raw textual information can be captured and employed to add power to economic models, and in extending the understanding of editorial incentives in the literature, particularly how a submission's citeability may signal a kind of risk. One important takeaway for authors submitting papers, at least at certain journals, is that if results are controversial, unique, applicable to ongoing debates or otherwise likely to yield more attention, then it may be especially critical to expend extra effort into ensuring referee-friendly, accurate results and clearly demonstrating that accuracy. Alternatively, an author submitting marginal results might be able to successfully progress through the review process by making the work less attention-grabbing in order to fill editors' need for more papers without attracting the kind of attention that editors may be risk averse to. Future work could examine whether these potentially high-impact papers (both those that actually go on to receive more



citations and those rejected ones for which referee language predicts more citations) actually receive more editorial attention as measured in review times, number of assigned referees, and number of referee rounds.

The model of citation impact developed here also sheds light on journal-specific factors that drive citations, offering some measurable answers to the long-standing question of why some papers get cited more than others. For the journal investigated in greatest detail here, it seems that research employing unique datasets or of relevance to global topics, government applications or ongoing debates yields greater citations as does producing work in the journal's niche, especially that of the editor-in-chief. There is also some evidence that this latter mechanism operates in part via editors' ability to better match submissions to referees who can suggest substantial improvements to those papers. By serving as a leader and figurehead, the Editor-in-chief plays an important role in establishing impact through the journal's readership and/or coeditor and referee capital.

Although citations do not appear to enter editors' decision to accept or reject a submission directly, there is evidence that they affect the amount of space devoted to a paper. Referees are more likely to agree to review shorter papers.

It is important to note that these findings could be quite sensitive to the journal studied. In fact, the results show that journals' editors and referees differ in the direction and significance of their preferences for a number of factors, including citation impact and textual similarity to past published articles. Furthermore, an extremely highly-ranked and broad-niche journal such as *Science* might not face the same constraints on too few high impact submissions or pressure to expand

subscriptions. On the other hand, given the high public exposure of a journal like *Science*, its editors could face even greater sensitivity to risks from publishing less accurate work, even provided an already high bar on accuracy. Future work extending the citation analysis here on a broader cross-section of journals would highlight differences between journals and confirm how broadly applicable these results are.

Altogether, these findings help to characterize the complex nature of a scholarly submission's quality, indicating that for different editors quality has something to do with a combination of fit, technical merit and potential publication risks. In doing so, the findings also provide guidance on data points that could be built into future online editorial and other review systems -- such as checkboxes referees can tick for unique datasets and other types of impact predictors, and autocomputed measures of relevance to a journal's niche -- to promote transparency in evaluating review systems while protecting the identity and privacy of stakeholders.

This study also provides an example of how decision-makers who read reviews actively disambiguate and reintegrate information available in the reviews and summary ratings according to their own unique preferences rather than simply accepting (in this case, referees') summary weighting of relevant signals. A takeaway for researchers studying review systems is not to rely solely on summary ratings that accompany reviews for a full understanding of signaling without carefully examining if there is sufficient evidence of homogeneity in the availability of information and weighting of factors among users and writers of reviews.

Perhaps most importantly, the results demonstrate that it is possible for researchers to estimate and measure meaningful ex ante signals from textual reviews

when there is some observable data available on these signals, even if it is quite limited, here for example data on actual citation impact of published papers. This is the first work to my knowledge to demonstrate the role of information measured from raw text in decision outcomes. Future work could extend these methods to understanding the role of reviews in different contexts, such as adoption of new restaurants or tastes for luxury housing features under different market conditions. Having better tools for extracting signal content in reviews also makes it possible to evaluate the sophistication, rationality and naivete of players in different contexts, for example measuring types of information ignored by decisionmakers or alternately segmenting decisionmakers by whether they consider certain types of information to make a contribution along the lines of behavioral economics even in the absence of controlled experiments. Applying these methods to other review contexts could also shed light on the factors driving virality of products, tweets, videos, and other goods beyond journal submissions.

## Chapter 2: Mortgage Markets with Lender Competition and Asymmetric Information

### *1 Background*

There is a growing body of recent literature in finance and economics covering various characteristics of the mortgage market and characterizing reasons for the market crash in 2008. Despite the slew of empirical results, as well as some theory for mortgage resale, there is limited literature characterizing the incentives that shape lender behavior at origination, particularly in a competitive framework. The focus of this paper is to provide a theoretical framework for studying lender beliefs and behavior under competition with asymmetric information and to characterize effects on borrower preferences, loan quality and resale. The model makes a number of predictions that are consistent with empirical findings from Loutskina and Strahan (2010) and Panetta (2009) outlined below and provides a basis for evaluating lending mechanisms and proposed regulation.

Loutskina and Strahan argue that geographically diversified (concentrated) mortgage lenders act as uninformed (informed) investors, with concentrated firms accepting more applications, performing better in the market for jumbo loans, retaining more mortgages and making more profit off each mortgage while diversified lenders do the opposite. The authors find evidence that concentrated lenders were much better able to time resale of mortgages prior to geographic market crashes, so that as a result, their stock prices fell

less between 2007-2008. Both across time and across geography, the share of concentrated lenders is negatively correlated with the run-up to the housing market crash. Thus, the authors argue that this lack of investment in information production by diversified lenders played a role in the market crash.

Although their work is not focused on mortgage markets, Panetta et al (2009) exploit data from borrowing by Italian firms to show that mergers between lenders improve the correspondence between borrower risk and interest rate. Furthermore, they show that the size of this improvement is broadly similar for borrowers who prior to the merger borrowed from only one of the lenders and those who borrowed from both lenders involved in a merger deal. Their results suggest that mergers improve information available to the lenders involved and that this improvement is due not to a pooling of information but rather to improved abilities to process information by lenders. For the work presented here in this paper, these results suggest it is important to consider not just difference in the amount of information lenders have access to but also their ability to process this information.

On the theoretical side, Bleck and Gao (2010) develop a framework for evaluating different information accounting practices in the loan resale market. They focus especially on mark-to-market (MTM) accounting, showing that while MTM is intended to increase information available on the market, it presents opportunities for firms to exploit this information, thereby changing the reliability of information in the market and resulting in incentives to originate poorer loans, choose inefficient exposure to risk and damage price discovery.

Rajan (1992) characterizes preference for uninformed banks due to their lower enforcement abilities by firms financing risky projects. His model describes how the incentives to exert effort by a borrower are drastically reduced when an informed lender places the threat of intervention, leading to inefficiency and borrower preference for uninformed lending. While this work characterizes borrower performance and choice between informed and uninformed lenders, the lenders in the model develop offers in isolation from each other. There is still a need for a framework for these lenders to actually form beliefs about and compete with one another.

While these results are compelling and timely, they also point to the importance of developing an appropriate theory for lender behavior. Much of the discussion of lender incentives provided in the literature assumes that lenders value borrowers in isolation with no perceived or actual interaction with other lenders despite acknowledging that borrowers do in fact select between offers from multiple lenders.

The economic foundations underpinning this financial literature go back to work on signaling and equilibria in markets with incomplete or asymmetric information. Akerlof (1970) and Spence (1973, 1974a, 1974b) with later contributions from Stiglitz (1974), Rothschild and Stiglitz (1975) and Riley (1975, 1976) show that equilibrium in markets with asymmetric information and signalling may have quite different properties from equilibrium with no information transfer or with direct, costless information transfer. Signalling equilibria may not always exist, might not be sustainable, and may be economically inefficient.

In their seminal work on information asymmetries in financial markets, Leland and Pyle (1977) consider the same general class of financing projects considered within this

paper where quality is commonly valued and highly variable; but they do so the context of entrepreneurial ventures. They find that when moral hazard prevents information-sharing across informed and uninformed lenders, indirect information can come in the form of entrepreneurs who are willing to invest in their own projects.

In the context of mortgages, lenders generally prefer to see borrowers who place larger down payments in much the same vein; however, there are many cases in which the borrower may be heavily cash-constrained and thereby limited in his ability to signal any private information he has about being a good investment. Lenders face the problem of distinguishing these borrowers from low-type borrowers. Furthermore, borrowers may not be fully informed about their future likelihood of repayment and might have even less information about the market's effects on their likely repayment than informed lenders do. When concentrated and diversified lenders compete against each other, there is indirect information-sharing involved in the competitive process which is important to take into account in modelling lender incentives.

Part of the challenge in modelling information revelation and accounting mechanisms in a lending market is that players are constantly updating information about each other from each other's actions. It is therefore important to consider how lenders derive information from their beliefs about each other and to understand which conclusions are robust to equilibria in which lenders fully exploit available information or to other factors. Do lenders make offers expecting that they are competing with one or more other lenders? Do they set offers rationally screening borrowers on added information that may come from a borrower's accepting their offers or do they give naive offers based solely

on their priors? It is important to understand the implications of each of these scenarios for lender behavior and for evaluating regulatory proposals.

As discussed, the focus of this paper is to address the role of competition and its interaction with asymmetric noisy information in a mortgage market. Here we will focus primarily on developing a theoretical framework for comparing the behavior of concentrated and diversified firms and deriving implications from it. Lenders form expectations about borrowers prior to origination that are updated at origination based on the level of competition in the market. If lenders do not behave naively, equilibrium offers take this ex post learning into account and yield results that are generally consistent with existing empirical literature: Higher-quality borrowers prefer informed lenders whereas the lowest quality borrowers prefer uninformed lenders. Informed lenders are better able to distinguish between highest quality borrowers for jumbo loans. And lastly, competition improves the amount of information in the origination market for both informed and uninformed lenders. However, I also find evidence that lenders may face incentives to deliberately make naive offers that do not take ex post learning and additional information processing into account if they expect to resell loans and are able to do so without revealing ex post information. This finding enlightens and supports those by Panetta et al, suggesting that post-merger lenders in their study should resell fewer loans post-merger.

The rest of this paper is organized as follows: First, I introduce a basic model in section 2 that features heterogeneous borrower types, asymmetric information, and competition amongst two representative lenders. In Section 3, I derive some of the equilibrium characteristics of rational lenders' beliefs and of loans made within this



framework. In Section 4, I provide a look at behavior of naive lenders when faced with competition against each other or against rational lenders of either type. The discussion in Section 5 addresses the implications of the results for mortgage markets and discusses extensions for a framework in which there are more than two lenders and where lenders can sell off or securitize loans, concluding with ideas for extensions and further research. Section 6 concludes.

## 2 *The Model*

In this model, borrowers are rational and seek loans to finance particular projects. They compare rates from concentrated and diversified lenders and choose the mortgage package with the highest net present value. For lenders facing competition, this amounts to a first-price common value simultaneous bid auction with noisy asymmetric information.

### 2.1 *Borrowers*

Each borrower  $k$  seeks financing for a project that he considers to be profitable and would like to undertake as long as he can obtain financing  $L$  with a net present value of at least  $\underline{L}$ . Without loss of generality, we assume here that  $\underline{L} = 0$  so that the borrower will accept the best financing package  $L$  that he is offered such that  $L \geq 0$ . If he accepts a financing offer, he signs a contract agreeing to make repayment subject to its terms. But after that fact, the actual repayment received by his lender will be subject to his idiosyncratic type  $\theta$ .

In other words,  $L$  captures the net present value of the cash advance and repayment expected by the lender and borrower under the loan's terms. It includes the interest rate, repayment term, and any other terms associated with the loan that affect the net present value of the net transfer from lender to borrower.

Idiosyncratic variations across buyer-projects, such as the possibility of foreclosure, market fluctuations, and refinancing/repayment that occurs earlier or later than expected are all captured by  $\theta$ . In other words, subject to the whims of nature and the market, a borrower will find it optimal repay a certain amount ex post, and  $\theta$  reflects how much that optimally chosen repayment varies from expectation. We assume that lenders' contract enforcement mechanisms such as nasty letters, reductions to the borrower's credit rating, and the possibility of foreclosure provide increasing disincentives for repayment shortfalls, so that a borrower does not find it optimal to repay substantially less than he is contractually obligated to repay, except in increasingly extreme states of nature. So, it is important to note that because repayments are optimally chosen within this framework, borrowers would never be able induce a better repayment just by posing as a lower type  $\theta$ .

There is a unit measure of borrowers on the market and nature distributes their types normally, according to:  $\theta \sim h(\theta) = N(\mu_\theta, \sigma_\theta)$  which is known by all. We will assume that the mean borrower idiosyncrasy is  $\mu_\theta = 0$  for purposes of some illustrations of the treatment of the model, although the results are generalizable to other values of  $\mu_\theta$ . A borrower's type is not observable or contractible to lenders, and indeed a borrower may not fully know his own type when signing a contract.

In the discussion here and below, we consider the market for each borrower separately, so we omit the subscript  $k$  for each borrower.

## 2.2 Lenders

The primary difference between lenders in this model is the accuracy of their ability to predict borrowers' types based on information that is available to them. Lenders come in two types: concentrated and diversified (denoted by subscripts  $c$  and  $d$  respectively), and each receives a noisy signal ( $t_i$ ) for each borrower's idiosyncratic type:

$$t_i = \theta + \varepsilon_i \quad \text{where } \varepsilon_i \sim f_i(\varepsilon_i) = N(0, \sigma_i) \quad \text{and } i = c, d$$

Because of their specialized knowledge of local markets and borrowers, concentrated lenders' signals are more informative than those of diversified lenders, which we reflect by assuming that  $\sigma_c < \sigma_d$ . We further assume that the uncertainty of the lenders' signals ( $\sigma_c$  and  $\sigma_d$ ) are known to all.

For a given borrower and associated signal  $t_i$ , lender  $i$  chooses a package of loan terms  $l_i$  to offer. Here,  $l_i$  reflects the lender's net outlay in making a loan. Since borrowers and lenders are likely to have different outside costs of capital, we represent the net present value to the borrower of  $l_i$  as  $L(l_i)$  and make the assumption that  $L(\cdot)$  is an increasing function so that for each additional dollar the lender spends on the net present cost of the loan, it can spend it in a way that increases the borrower's preference for the loan.

The lender chooses  $l_i$  in order to maximize the expectation of profits from that loan. Once realized, profits from an accepted loan offer  $l_i$  to borrower of type  $\theta$  equal the borrower's idiosyncratic repayment  $\theta$  minus the net transfer  $l_i$  to the buyer. Loan offers

that are not accepted are neither costly nor profitable to the lender to make, as reflected in the expression for profit below:

$$\pi_i = \theta - l_i \quad \text{if } i\text{'s loan is accepted by the borrower.}$$

$$0 \quad \text{if } i\text{'s loan offer is not accepted.}$$

In addition, we assume that lenders each have a very large supply of funds to invest in borrowers, such that they do not face wealth constraints. In other words, each lender could fund all borrowers if it so chose.

Besides differences in type, a second possible difference between lenders is how they process the information that is available to them. Rational lenders make offers that take into account the additional signal they receive once they find out they have made the highest offer and won the borrower's account; in this model, naive lenders, on the other hand, make offers based on their prior beliefs, ignoring this secondary information. I assume that all borrowers are rational in the main treatment of this model (here and in Section 3) then discuss behavior of and interactions between naive lenders in Section 4. Although naivete in this model is due to a lack of updating for secondary information on the borrower's type, the results extend to other motivations for overvaluing a loan as well and are discussed in Section 5.

### 2.3 *Timing*

The model plays out in three periods. At time  $s = 0$ , nature selects a type  $\theta$  for each borrower according to the known distribution  $\theta \sim h(\theta) = N(\mu_\theta, \sigma_\theta)$ . At time  $s = 1$ , one or two representative firms  $c$  and  $d$  observe their respective signals  $t_c$  and  $t_d$  and make simultaneous offers,  $l_c$  and  $l_d$ , for each borrower. At time  $s = 2$ , each borrower selects

the lender that made the highest offer  $l_i \geq 0$ . At some future date,  $s = 3$ ,  $\theta$  is revealed and profits for each lender are realized. Resale of loans, if it occurs, happens sometime in between times  $s = 2$  and  $s = 3$ .

### 3 Characterizing Lender Behavior and Equilibrium

#### 3.1 Lender Beliefs

We begin characterizing the equilibrium in this loan market by considering the beliefs that the lenders form about each borrower. Unless given below, proofs for each proposition are presented in the appendix, as noted.

**Proposition 1:** *Lender  $i$ 's expectations about each borrowers' type are an average of the mean borrower type ( $\mu_\theta$ ) and  $i$ 's private signal,  $t_i$ , weighted by the relative reliability of each of these sources of information. In other words, lender  $i$  forms expected beliefs  $b_i(t_i)$  about each borrower's type according to:*

$$b_i(t_i) \equiv E_i[\theta|t_i] = (1 - w_i) \cdot \mu_\theta + w_i \cdot t_i \quad \text{where } w_i = \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_i^2}$$

$$P_i[\theta|t_i] \equiv g_i(\theta|t_i) = N(b_i(t_i), \sigma_i^2 + \sigma_\theta^2).$$

The proof of Proposition 1 is given in the appendix.

Note that in the expression above,  $w_i$  reflects the relative reliability of the lender's signal  $t_i$  compared with the known population mean ( $\mu_\theta$ ) and distribution  $N(\mu_\theta, \sigma_\theta)$  of  $\theta$ . For  $\mu_\theta = 0$ , as the population distribution becomes relatively less dispersed ( $\sigma_\theta \ll \sigma_i$ ),  $w_i$  approaches zero, thereby diminishing the weight that  $i$  puts on his personal signal  $t_i$ , pushing  $b_i$  towards  $b_i(t_i) \approx 0$ . On the other hand, as the population distribution becomes

more dispersed, reflected in  $\sigma_\theta \ll \sigma_i$ , we observe that  $w_i$  approaches unity and the lender relies almost solely on his private signal to form his beliefs ( $b_i(t_i) \approx t_i$ ).

**Corollary 1 to Proposition 1:** *Lender c uses a higher weighting factor for its private signal than does lender d:*

$$w_c > w_d$$

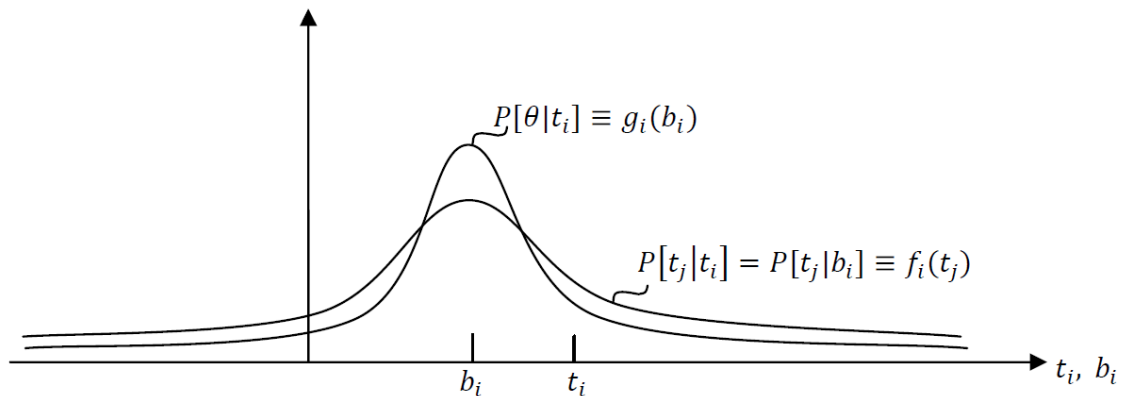
This follows directly from the expression for  $w_i$  in Proposition 1 and our assumption that  $\sigma_c < \sigma_{di}$ . This result is intuitive because lender c knows how accurate his signal is and thus relies on it more than if the signal was more noisy, as it is for lender d.

**Corollary 2 to Proposition 1:** *For the same signal, lender c's beliefs are further from the mean  $\mu_\theta$  than lender d's beliefs:*

$$|b_c(t) - \mu_\theta| > |b_d(t) - \mu_\theta|$$

This statement follows directly from C1.1 and the expression for  $b_i(t_i)$  in Proposition 1. It reflects the diversified lender's propensity to make up for his more dispersed signal by placing less weight on it.

Figure 1: Distribution of Lender Signals for  $\theta = \hat{\theta}$



**Proposition 2: Lender  $i$ 's beliefs about lender  $j$ 's signal  $t_j$  and beliefs  $b_j$**

For the same beliefs ( $b_i = b_j \equiv b$ ), lender  $i$ 's expectations and distribution about  $j$ 's signal are the same as  $j$ 's expectations and distribution about  $i$ 's signal:

$$E_i(t_j|b_i = b) = E_j(t_i|b_j = b) \quad (2.1)$$

$$f_i(t_j|b_i = b) = N(E_i[b_i|t_i], \sigma_\theta^2 + \sigma_i^2 + \sigma_j^2) \quad (2.2)$$

For the same signal ( $t_i = t_j \equiv t$ ), lender  $i$ 's expectations about  $j$ 's beliefs are the same as  $j$ 's expectations about  $i$ 's beliefs:

$$E_i(b_j|t_i = t) = E_j(b_i|t_j = t) \quad (2.3)$$

The proof of Proposition 2 is given in the appendix. We use this proposition as we think about how each lender forms expectations about outbidding the other, which play into its expected profits.

Given this information, we can go on to characterize equilibrium belief formation, updating, offers and borrower behavior.

### 3.2 Equilibrium

Each lender  $i$  chooses its optimal offer  $l_i^*$  in order to maximize its expected profits  $\pi_i$ :

$$\max_{l_i} E[\pi_i|b_i, l_i] = P[\text{win}|b_i, l_i] \cdot E[\pi_i|\text{win}, b_i, l_i]$$

**Proposition 3:** *When they face no competitors, lenders will offer  $l = l^{-1}(\underline{L})$  if they make any offer.*

In the absence of competition,  $P[\text{win}|b_i, l_i] = 1$  for  $l_i > l^{-1}(\underline{L})$  and  $E[\pi_i|\text{win}, b_i, l_i] = b_i - l_i$  so regardless of their type, lenders will always offer  $l = l^{-1}(\underline{L})$  to maximize profit as long as  $b_i > l^{-1}(\underline{L})$  and will not make an offer otherwise. The situation is much more complicated when lenders compete because lenders need to form expectations on each other's signals and beliefs to evaluate both  $P[\text{win}]$  and  $E[\pi_i]$ .

### 3.2.1 Winner's Curse and Belief Formation Under Competition

Competition introduces the potential for winner's remorse in our framework. Specifically, in a first price common value auction, there are at least two driver's of "winner's curse" that may occur, causing lenders to shade their offers compared to their expected valuations of the borrower  $b_i = E[\theta|t_i]$ . A third driver of winner's curse can occur when at least one lender behaves naively, and is discussed in Section 4. The first two reasons for shading behavior are motivated by:

1. **Updated beliefs about  $P(win|l_j)$ :** Winning means that the winning lender could have decreased its offer slightly and still won which is a strictly better outcome regardless of any other model parameters. This reasoning thus applies equally to concentrated and diversified lenders.
2. **Updated beliefs about  $\theta$ :** An outcome of win or lose contains an additional signal about the competitor's beliefs on  $\theta$  that the winning lender could have used to update its own beliefs on  $\theta$ . For any  $l < \infty$ , a win indicates that competitors' beliefs were lower than previously expected, thus resulting in a lower overall valuation of the borrower. A naive lender that does not heed this fact will find itself winning borrowers' business ( $E[\theta|win] < l$ ) that it does not want ex post to the bidding process.<sup>1</sup>

In this section we will consider the effect of both of the first and second drivers of winner's remorse in the design of rational lenders' offers and borrower preferences. In the next section, we consider the behavior of lenders who for one reason or another

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<sup>1</sup> Note that this could still be profitable if the lender is able to sell the loan based on its *ex ante* valuation.



behave naively, in other words ignoring winner's remorse of the second type described above.

The amount of information revealed during a win/lose outcome can vary for each lender involved and depends on the informativeness of the lender's prior  $g_i(\theta|t_i)$  as well as the lender's offer  $l_i$ , and the type  $(c, d)$  of lenders competing. Since a lender's prior on its competitors' signal  $f_i(t_j)$  is always more noisy than its own signal  $g_i(\theta|t_i)$ , the lender's update on that prior could still be quite noisy; even for a diversified lender competing with a concentrated one, the signal from winning over the concentrated lender could technically still be more noisy than its own signal. Propositions 4 and 5 characterize this learning which occurs during the win/lose outcome.

**Proposition 4: Information Content of Winning Offers**

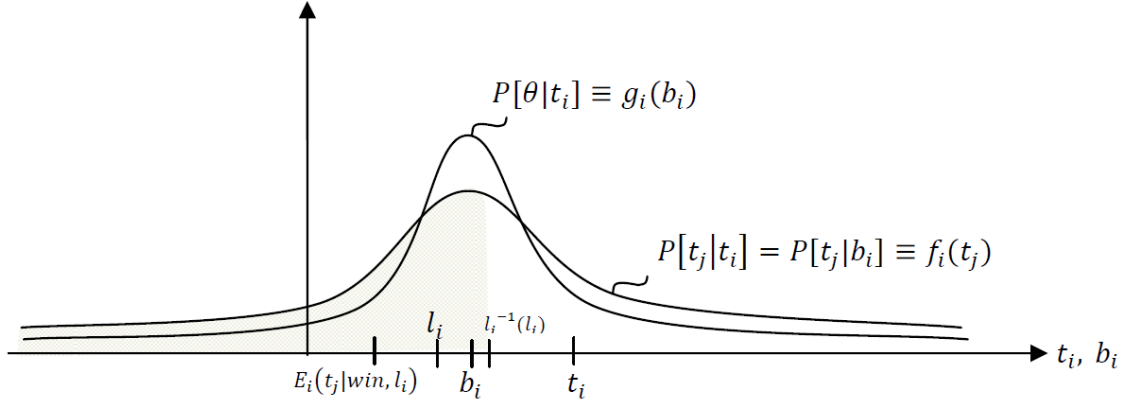
*A winning offer brings with it information about the other lender's signal  $t_j$ . (We will show later that this information content increases as  $l_i$  falls):*

$$E_i(t_j|win, l_i, t_i) < E_i(t_j|t_i)$$

This information content is illustrated in Figure 2, where  $g_i(\theta)$  reflects the lender's own belief distribution on  $\theta$  and  $f_i(t_j)$  reflects the lender's belief distribution about its competitor's signal immediately prior to the win/lose outcome being revealed.

Immediately upon winning with offer  $l_i$ , lender  $i$  learns some additional information about  $j$ 's signal. Given his win, he knows that  $t_j < l_j^{-1}(l_i)$ , which is equivalent to saying that  $t_j$  must be below whatever threshold  $\bar{t}_j = l_j^{-1}(l_i)$  would have induced  $j$  to bid  $l_i$ . In other words, winning truncates  $i$ 's prior  $f_i(t_j)$  to only the lefthand (shaded) portion of the distribution on the interval  $(-\infty, l_j^{-1}(l_i)]$  as shown in Figure 2. The newly updated  $E_i(t_j|win, l_i, t_i)$  is simply the expected value of this shaded portion, which is also shown.

Figure 2: Information Content of a Win With Offer  $l_i$



Updating  $i$ 's prior results in an updated expected value for  $i$ 's believed distribution of  $t_j$  which is lower than his prior on  $t_j$ :

$$E_i(t_j|win, l_i) = \int_{-\infty}^{l_i^{-1}(l_i)} t_j \cdot f_i(t_j|b_i) dt_j < \int_{-\infty}^{\infty} t_j \cdot f_i(t_j|b_i) dt_j = E_i(t_j|t_i)$$

As a result, of its lower expectations about its competitors' signal, the winning lender also updates its own beliefs to a lower value than previously expected:

**Proposition 5: Winning Lowers Lender Expectations of Borrower Type  $\theta$**

*A winning offer lowers lender  $i$ 's beliefs about the borrower's true type:*

$$E_i(\theta|win, l_i, t_i) < E_i(\theta|t_i)$$

Specifically, the winning lender updates its expectation of the borrower's type from  $b_i$  to a weighted average of  $b_i$  and its updated beliefs about  $j$ 's prior beliefs  $E_i(b_j|win, l_i)$ , or equivalently, to a weighted average of the signals it now has access to:  $E_i(t_j|win, l_i)$ ,  $t_i$ , and  $\mu_\theta$ . Note that the weights in the expression below are different from those given in Proposition 1.

$$\begin{aligned}
E_i(\theta|win, l_i, t_i) &= b_i w_l + E_i(b_j|win, l_i)(1 - w_l) \\
&= t_i w_{ii} + \mu_\theta w_{i\theta} + [E_i(t_j|win, l_i, t_i)] \cdot w_{ij} \\
&= t_i w_{ii} + \mu_\theta w_{i\theta} + \left[ \int_{-\infty}^{l_j^{-1}(l_i)} t_j \cdot f_i(t_j|b_i) dt_j \right] \cdot w_{ij}
\end{aligned}$$

where the weights  $w_{ix}$  represent the weight that  $i$  places on each signal  $x = \{t_i, t_j, \mu_\theta\}$  and reflect the relative reliability of each signal:

$$\begin{aligned}
w_{ii} &= \frac{\sigma_i^2 + \sigma_j^2 + 2\sigma_\theta^2}{4\sigma_i^2 + 2\sigma_j^2 + 4\sigma_\theta^2 - \tau(l_i)} & w_{ij} &= \frac{\sigma_i^2 + \sigma_\theta^2}{4\sigma_i^2 + 2\sigma_j^2 + 4\sigma_\theta^2 - \tau(l_i)} \quad \text{and} \\
w_{i\theta} &= \frac{2\sigma_i^2 + \sigma_j^2 + \sigma_\theta^2}{4\sigma_i^2 + 2\sigma_j^2 + 4\sigma_\theta^2 - \tau(l_i)}
\end{aligned}$$

Here,  $\tau(l_i)$  reflects the decrease in the variance of  $f_i(t_j)$  due to its being truncated to the interval from  $(-\infty, l_j^{-1}(l_i)]$  in the learning process that comes with winning.<sup>2</sup> Because the amount of truncation decreases as  $l_i$  increases, we can observe that  $\tau(l_i)$  falls as  $l_i$  increases, reflecting the fact that winning with a lower bid introduces more information to the lender.

Regardless of  $i$ 's and  $j$ 's type(s) and depending on  $\tau(l_i)$ , it is possible that either of  $w_{ii}$  and  $w_{ij}$  could be larger than the other. It is not possible to ascertain which will be higher because the amount of information in a winning offer varies with the offer itself. In other words, an offer that deviates further from the borrower's expected beliefs carries more information because it truncates  $i$ 's prior  $f_i(t_j|t_i)$  by a larger amount. The trade-off for this higher information that is carried by a winning lower offer is of course that lower offers carry a lower probability of winning and generating information in the first place. Also, because a lender  $i$ 's signal on  $j$ 's signal is always more noisy than its own signal (variance is  $\sigma_i^2 + \sigma_j^2 + \sigma_\theta^2$  compared to  $\sigma_i^2 + \sigma_\theta^2$ ) there is no guarantee that the signal

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<sup>2</sup> See Barr (1999) for a derivation of variances for truncated normal distributions.

from the winning outcome against a concentrated lender has greater fidelity than a diversified lender's own signal unless the diversified lender's offer is sufficiently low to generate sufficiently high  $\tau(l_i)$ .

Nonetheless, it is possible to characterize the weight that a diversified or concentrated lender puts on its updated signal from the competitor upon winning. Because  $\sigma_c < \sigma_d$ , we can see that  $w_{dj} > w_{cj}$ . In other words, the weight  $w_{ij}$  that lender  $i$  places on its competitor's signal is higher if  $i$  is a diversified lender than a concentrated lender. Furthermore,  $w_{ij}$  increases as  $\sigma_i$  increases and also as any of the variables  $\sigma_j$ ,  $\sigma_\theta$ , and  $l_i$  decrease. This result means that winning lowers a diversified lender's expectations more than it does a concentrated lender's expectations. Since optimal strategy in a first price common value auction is to place an ex ante bid that incorporates information from winning (Cox and Isaac, 1984), this yields Proposition 6.

**Proposition 6: Diversified Lenders Shade More than Concentrated Lenders**

*In any competitive environment (i.e. regardless of lender types and of  $\sigma_i, \sigma_j, \sigma_\theta$ ), a diversified lender will shade its beliefs more than a concentrated lender does to reflect greater updating through the win/lose process. For a given offer  $l$ :*

$$0 < E_c(\theta|t_c) - E_c(\theta|win, l, t_c) < E_d(\theta|t_d) - E_d(\theta|win, l, t_d)$$

*Since lenders seek to maximize profits according to the beliefs they will have if they win, (i.e. according to  $E_i(\theta|win, l, t_i)$ ), for given prior beliefs  $b$ :*

$$l_d(b) < l_c(b)$$

3.2.2 *Optimal Lender Behavior*

Note that  $i$ 's profit function if it wins takes the form:

$$\begin{aligned}
E[\pi_i | \text{win}, b_i, l_i] &= E_i(\theta | \text{win}, l_i, t_i) - l_i \\
&= t_i w_{ii} + \mu_\theta w_{i\theta} + \left[ \int_{-\infty}^{l_j^{-1}(l_i)} t_j \cdot f_i(t_j | b_i) dt_j \right] \cdot w_{ij} - l_i
\end{aligned}$$

So  $i$  selects  $l_i$  to maximize expected profit as follows:

$$\begin{aligned}
\max_{l_i} E[\pi_i | b_i, l_i] &= P[\text{win} | b_i, l_i] \cdot E[\pi_i | \text{win}, b_i, l_i] = P[b_j < l_j^{-1}(l_i)] \cdot E[\pi_i | \text{win}, b_i, l_i] \\
&= P[b_j < l_j^{-1}(l_i)] \cdot (E[\theta | \text{win}, b_i, l_i] - l_i) \\
&= P[b_j < l_j^{-1}(l_i)] \\
&\quad \cdot \left( t_i w_{ii} + \mu_\theta w_{i\theta} + \left[ \int_{-\infty}^{l_j^{-1}(l_i)} t_j \cdot f_i(t_j | b_i) dt_j \right] \cdot w_{ij} - l_i \right) \\
&= \int_{-\infty}^{l_j^{-1}(l_i)} f_i(t_j | b_i) dt_j \\
&\quad \cdot \left( t_i w_{ii} + \mu_\theta w_{i\theta} + \left[ \int_{-\infty}^{l_j^{-1}(l_i)} t_j \cdot f_i(t_j | b_i) dt_j \right] \cdot w_{ij} - l_i \right)
\end{aligned}$$

Note that for given prior beliefs  $b_i$ , a diversified lender will shade its expectation of beliefs conditional on winning more than a concentrated lender and thus will shade its optimal  $l_i^*$  more accordingly as stated in Proposition 5.

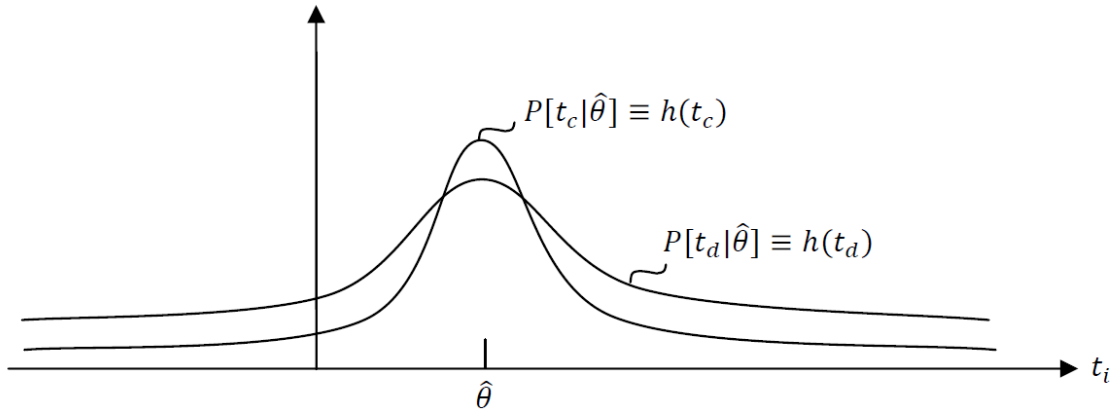
### 3.3 Aggregate Market Behavior

We now have sufficient information about equilibrium offers from lenders of both types to characterize the aggregate behavior of this system.

For the population of borrowers of a given type  $\hat{\theta}$ , we will see the following distribution of signals,  $h(t_c)$  and  $h(t_d)$ , observed by concentrated and diversified lenders, respectively. Note that for illustrative purposes, we have chosen  $\hat{\theta} > \mu_\theta$  in the diagram below. Also, note that unlike the previous figures which showed belief distributions for

single lenders at a time, these following figures show distribution of mean signals and expectations across aggregate lender populations of type c and d:

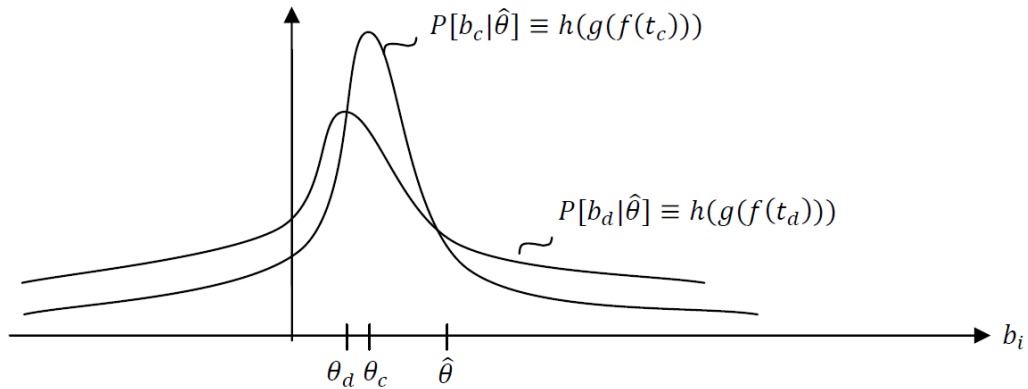
Figure 3: Distribution of Lender Signals for  $\theta = \hat{\theta}$  Over the Lender Population



Note that the peaks and means of both lenders' private signal distributions occur at  $\hat{\theta}$ .

Remembering from Proposition 1 that lender  $i$ 's beliefs reflect the weighted average of its private signal and the mean individual type (i.e.  $b_i(t_i) = (1 - w_i) \cdot \mu_\theta + w_i \cdot t_i$ ), we can graph the distribution of  $c$  and  $d$  type lenders' beliefs for a borrower of type  $\hat{\theta}$  as follows:

Figure 4: Distribution of Lender Beliefs for  $\theta = \hat{\theta} > \mu_\theta = 0$  Across Lender Population



As the diagram shows, since  $w_c < w_d$ , the peak and mean of  $h(b_d)$  are closer to  $\mu_\theta = 0$

than the peak and mean of  $h(b_c)$ , respectively. Since these belief distributions are more squished than the signal ( $t$ ) distributions, note that the magnitude of their peaks are higher, to ensure that they each integrate to unity. Note also that for illustrative purposes in the example above, we have let  $w_c = 1/2$  and  $w_d = 1/3$  so that the peak of lender  $c$ 's distribution occurs at  $\theta_c = \hat{\theta}/2$  and the peak of lender  $d$ 's belief distribution occurs at  $\theta_d = \hat{\theta}/3$ .

Figure 4 illustrates the aggregate effect of Proposition 1: On average, lenders of both types tend to undervalue borrowers with  $\hat{\theta} > \mu_\theta$  and overvalue borrowers with  $\hat{\theta} < \mu_\theta$ . Because concentrated lenders know their signals are more reliable, they do not undervalue or overvalue these borrowers as much as diversified lenders do.

For a borrower of fixed type  $\hat{\theta} > \mu_\theta$ , concentrated lenders have higher average beliefs on  $\theta$  than diversified lenders do, as stated in Corollary 2 to Proposition 1 and illustrated in Figure 4. As stated in Proposition 5, concentrated lenders also shade their beliefs less, making more competitive offers. Thus a strict majority of these borrowers will prefer and choose the offers of  $c$ -type lenders.

We will now show that for a given level  $\hat{\theta} > \mu_\theta = 0$ , we get a  $C > 1/2$  majority of borrowers with type  $\hat{\theta}$  choose lender  $c$ 's offer: Since  $w_d < w_c$  by Proposition 1 and  $E(t_d) = E(t_c)$ , we observe that  $E_d = E(b_d) < E(b_c) = E_c$ , and thus

$$C = 1 - H_{b_c}(E_d) > 1 - H_{b_c}(E_c) = 1/2$$

We have shown that a fraction  $C > 1/2$  of borrowers with  $\hat{\theta} > \mu_\theta = 0$  accept loans from concentrated lenders. Furthermore, a fraction  $N < 1 - C = 1/2$  receive no offer

$l_i < l^{-1}(\underline{L})$  and thus accept no offer. These borrowers do not undertake any project. The remaining fraction  $D < 1 - C = 1/2$  receive offers such that  $l_d > l_c$  and  $l_d > 0$ , accepting the diversified lender's offer.

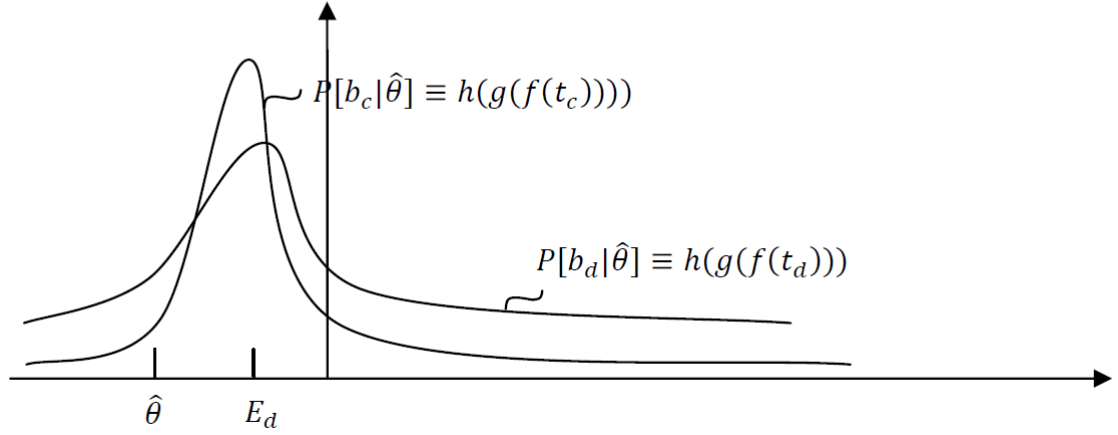
On the other hand, for  $\hat{\theta} < \mu_\theta$ , diversified lenders will overestimate borrower type more than concentrated lenders do (Figure 5). As stated in Proposition 1, this effect grows as  $\hat{\theta}$  falls farther below  $\mu_\theta$ . If there were no other distortions, then all of these borrowers would prefer offers from the diversified lender who thinks more highly of them. However, these higher beliefs from the diversified lender are partially counteracted by the greater shading of its beliefs that the diversified lender does. The amount of shading due to updated beliefs is constant across  $b$  -- it varies only with  $\sigma_i, \sigma_j$ , and  $\sigma_\theta$  whereas the overvaluation of borrowers with type  $\hat{\theta} < \mu_\theta$  increases as  $\hat{\theta}$  falls. Therefore, we have Proposition 7.

**Proposition 7: Semi-Pooling/Semi-Separating Equilibrium**

There exists  $\Theta < \mu_\theta$  such that  $\forall \theta > \Theta$ : most borrowers of type  $\theta$  who accept a loan do so from lender c and  $\forall \theta < \Theta$ : most borrowers of type  $\theta$  who accept a loan do so from lender d, resulting in a semi-pooling/semi-separating equilibrium.



Figure 5: Distribution of Lender Beliefs for  $\theta = \hat{\theta} < \mu_\theta = 0$



Note that for  $\underline{l} = 0$ , a strictly higher share of these borrowers face positive beliefs from lender  $d$  than  $c$  because  $\int_{\underline{l}}^{\infty} f(b_d) db_d > \int_{\underline{l}}^{\infty} f(b_c) db_c$ . Thus a higher share receive positive offers from lender  $d$  than  $c$ . Since for a known/given  $\hat{\theta}$ , the distributions  $b_c$  and  $b_d$  are independent of each other, a strictly higher share of borrowers with  $\hat{\theta} < \mu_\theta = 0$  accept lender  $d$ 's offer than accept lender  $c$ 's offer. To extend the result for other values of  $\underline{l}$  and  $\mu_\theta$ , when  $\hat{\theta} < \mu_\theta$  there will always exist some value of  $\theta$  above which  $h(b_d)$  first order stochastically dominates  $h(b_c)$  so that  $\int_{\underline{l}}^{\infty} h(b_d) db_d > \int_{\underline{l}}^{\infty} h(b_c) db_c$ .

Finally, since all lenders are fully rational, they effectively process and are privy to all of the information we can analyze here. For any given  $\underline{l}$ , there also exists a  $\Theta_d$  and  $\Theta_c$  below which most borrowers will not even receive an offer from the  $d$ - and  $c$ -type lenders respectively because a lender of type  $i$  will typically form beliefs about these borrowers that are below the borrowers' minimum financing amounts (i.e.  $\underline{l} > b_i$ ), as discussed above. (Note that as a consequence of Proposition 1,  $\Theta_d > \Theta_c$  for  $\underline{l} > \mu_\theta$  and  $\Theta_d < \Theta_c$  for  $\underline{l} < \mu_\theta$ .) Consequently, although less informed,  $d$ -type lenders expect to have a lower average borrower quality, their expectations are still in line with reality, and

both lenders' profits are still ex post positive in expectation. As  $\underline{L}$  increases, the value of  $\Theta_d$  may fall below  $\Theta$ . Thus, for large loan amounts -- those which carry a greater risk and which lenders will therefore only make to higher quality borrowers -- the uninformed lender may get no business.

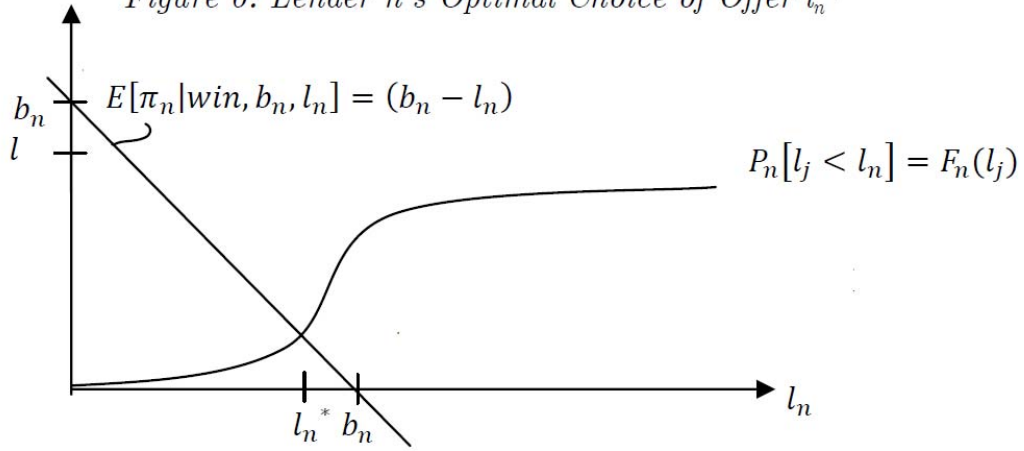
#### 4 Competition with Naive Lenders

Next, we take into account naivete, in the form of lenders who do not take into the account the information from winning when placing a bid and furthermore does not expect its competitors to take information from winning into account when bidding either. As a result, naive lenders have a much simpler objective function than rational lenders discussed in the previous section. Each naive lender  $n$  chooses its optimal offer,  $l_n^*$ , in order to maximize its expected profits:

$$\begin{aligned} \max_{l_n} E[\pi_n | b_n, l_n] &= P[\text{win} | b_n, l_n] \cdot E[\pi_n | \text{win}, b_n, l_n] = P[l_j < l_n] \cdot (b_n - l_n) \\ &= P[b_j < l_j^{-1}(l_n^*)] \cdot (b_n - l_n) \end{aligned}$$

Graphically, we can see this maximum occurs at the fixed point  $l_n^*$  such that  $P[b_j < l_j^{-1}(l_n^*)] = (b_n - l_n^*)$ :

Figure 6: Lender  $n$ 's Optimal Choice of Offer  $l_n^*$



Since the naive lenders face the same objective function and by Proposition 2 have the same beliefs about each other conditional on their own beliefs, their optimal offers as a function of their own beliefs are the same. This result is stated in Proposition 8:

Proposition 8: For the same expected beliefs ( $b_n = b_m \equiv b$ ), naive lender  $n$ 's and  $m$ 's optimal loan offers  $l_n^*$  and  $l_m^*$  will be the same regardless of their types:

$$l_n^*(b) = l_m^*(b) \equiv l^*(b)$$

Furthermore, extending what we have already observed about  $l_n^*$  to  $l^*$ , we note that:  $l^*(b)$  is an increasing function of  $b$  such that  $l^*(b) < b$ .

This optimal offer by a naive lender reflects shading of the first type but not of the second type. Accordingly, by Proposition 5, for the same signal,  $t$ , a naive lender will always shade its offer less than a rational lender of the same type. Therefore, borrowers of all types will prefer the offer they receive from a naive lender to a rational lender of the same type receiving the same signal.

When two naive lenders of opposite types compete against each other, winning contains adverse information for the  $d$ -type lender and mixed (i.e. possibly adverse or favorable) information for the  $c$ -type lender. Since  $d$ -type lenders underestimate above-

average borrowers and overestimate below-average borrowers more than  $c$ -type lenders, a win by a  $d$ -type lender contains not only information that its opponent had lower beliefs, and that it could have won with a lower offer, but also some tertiary information increasing the likelihood that the borrower was of below average type. This results in a third driver of winner's curse that applies to  $d$ -type lenders.

Meanwhile, for a  $c$ -type naive lender competing against a naive  $d$ -type lender, winning indicates that its opponent had lower beliefs about the borrower's type; surprisingly, this may not lower  $c$ 's beliefs ex post because a  $c$ -type lender expects to form higher beliefs than  $d$ -type lenders for above-average borrowers and lower beliefs for below-average borrowers. So finding out that it had the winning offer could actually increase  $c$ 's estimation of the borrower's type for certain signals, in essence serving as the opposite of a winner's curse.

Detangling the net information effect of winning against a naive lender for  $c$  depends on the exact values of  $\sigma_c$ ,  $\sigma_d$ ,  $\sigma_\theta$  and of the signal  $t_c$ . Nonetheless, for a rational observer, winning contains more adverse information for the  $d$ -type lender.

For a rational lender competing against a naive lender, there are some interesting effects to consider as well. A  $c$ -type lender competing against a naive  $d$ -type lender will shade for both types of winner's curse but will temper that shading by placing a higher probability of being in an above-average borrower regime. A  $d$ -type lender competing against a naive  $c$ -type lender will shade for both types of winner's curse and then some more by placing a higher probability of having selected a below-average borrower in the case of a win. Any rational lender competing against a naive lender of the same type will

simply shade for both types of winners curse and no more or less, because there is no tertiary information contained in a win against a naive lender of the same type.

The chart below summarizes these findings:

Table 1. Competition with Naive Lenders

Lenders Competing	Outcome
Rational c-type facing naïve d-type	<ul style="list-style-type: none"> <li>• Rational lender shades for Type I &amp; II Winner's Curse but unshade for Winner's Blessing</li> <li>• <math>\lambda</math> is higher than in fully rational case. c-type makes more offers to the highest quality borrowers while d-type makes more offers to lowest quality borrowers (if it competes), perhaps even some that result in negative expected profits.</li> <li>•</li> </ul>
Rational d-type facing naïve c-type	<ul style="list-style-type: none"> <li>• Rational lender faces type I, II, &amp; III Winner's Curse, shading more than in fully rational case.</li> <li>• <math>\lambda</math> is lower than in fully rational case. Poorest-type borrowers still prefer d-type lender if it competes. Highest-type borrowers still prefer c-type lender.</li> </ul>
Rational lender facing naïve lender of same type	<ul style="list-style-type: none"> <li>• Rational lender shades for Type I &amp; II Winner's Curse</li> <li>• No tertiary information available through borrower selection.</li> </ul>

The discussion below presents some extensions and applications of these findings.

## 5 *Discussion*

When lenders compete with asymmetric information, we find a semi-pooling/semi-separating equilibrium with a separation threshold  $\Theta$  above which most borrowers select the more informed lender and below which most borrowers select the less informed lender's offer, if it is available. The more informed lender attracts better borrowers, offering them greater credit at more favorable rates, which we can interpret as also doing better in jumbo markets. Meanwhile, less informed lenders attract a lower-payoff mass of borrowers. Because their risk correspondence is higher, the more-informed lenders will make higher profits on retained mortgages. However, rational less-informed lenders will be expected to still make weakly positive profits in equilibria.

In a competitive framework, bidding generates information and serves as a mechanism for spreading it across the market. Lenders behave differently when they know they face competition against other lenders with private signals. Rational lenders will shade their offers (i.e. underbid on their beliefs) under competition, choosing not to bid on borderline borrowers who *ex ante* seem profitable but who *ex post*, subject to information on a losing competitor's signal, will seem unprofitable. The results from this model show that there exists information on the market via competition and that rational lenders of both types benefit from it, although lenders competing against a c-type lender benefit more, screening to a greater degree through the updated signal.

Extending the results to competition amongst three or more lenders, the amount of information on the market increases with the number of competitors, screening on winning a borrower's business increases by all rational players as well, and the weight on

the updated market signal will be a weighted average of the expected accuracies (i.e.  $\sigma_i$ ) of the lenders on the market.

One puzzle that has been posed about mortgage markets is why poorer quality lenders are not crowded out of the market. If no resale market exists, market entry is restricted first and foremost by liquidity. Any lender with enough cash to lend will be able to enter until the point where there are so many lenders on the market where profits come down to zero. In practice, liquidity constraints on the mortgage market are quite significant -- see Wachter et al (2012) for a discussion on how the amount of money lent for mortgages on the market exceeds the amount of cash on the market by at least 100% as well as discussions of the separate liquidity constraints placed by federal regulations on different types of banks. As a result, we should not expect modern mortgage markets to exhibit perfect competition. Furthermore, there is evidence that borrowers approach a few lenders, not thousands, when they evaluate mortgage options. In such a market, both c-type and d-type lenders can coexist without any crowding effects, with d-type lenders simply making less profit.

If a resale market does exist, then it will provide some amount of liquidity, but in light of the model's results it may actually benefit less-informed lenders over more-informed lenders, which have relatively positive soft information the resale market could be unable to process or value. In practice, resale markets generally will not have access to all of the information lenders have access to; soft information such as a lender's type or the number of lenders it competed against for each loan may be difficult to verify in practice, particularly when loans are securitized. Assuming the resale market is not able to verify these factors, then all lenders competing in a rational framework have negative soft

information the moment they learn (or suspect) they have won. Less-informed lenders will have more negative information than informed lenders simply because they won against a more-informed competitor. Furthermore, an informed lender also has greater positive soft information knowing its own type and having greater confidence in its own signal. This makes loans originated by more-informed lenders less liquid in the resale market, because the market cannot properly value this difference in soft information. The resale process may price in a premium in anticipation of this negative soft information, but unless there is a timely reputation mechanism for separating loans by the originators' type, this "lemons premium" will only further reduce liquidity of the more-informed lenders' loans. Informed lenders will do much better to retain the loans they originate, perhaps selling some loans only if much more negative information becomes available on those borrowers down the line or if they run into cash constraints.

A resale market that evaluates net present values of loans based on a subset of information available to lenders will also facilitate strong incentives for lenders to originate loans based on that subset of information alone. As we will see, if lenders can be held accountable for negative information they have on a borrower, information may then have negative value during resale. Access to information will not improve the quality of loans on the market as lenders with more information may even wish to pose as less-informed lenders, extending offers for loans they would never plan to retain.

Naivete provides an additional explanation (beyond access to information) for why some lenders may originate poorer loan quality. Unlike less-informed rational lenders which still make positive profits in expectation, naive lenders may actually make loans



that are negative in expected profits, which was the case, it turns out, for many of the loans leading up to the 2008 mortgage crisis (see for example, Associated Press, 2012).

In this model, naivete comes from failing to fully process private ex-post information about the value of a loan that is available through the auction process. But the findings extend to most any situation in which a lender has incentives to value a loan based only on a subset of available information. Resale is a particularly relevant example of where selective naivete may actually be advantageous. A lender might not have to reveal how carefully a borrower's income level was verified or the amount of seller subsidies during resale, for example. If lenders go into the origination market with intention of possible resale, then a loan's value to the lender is actually  $\max(\theta, \text{resale value})$  rather than simply  $\theta$ . As discussed above, if a lender has positive private information about  $\theta$  that it is not required to or cannot expose during resale, it would be better off retaining the loan. On the other hand, if it has adverse information which it could withhold from the resale market, then it will be better off selling that loan. The resale process will take into account the market's expectation that lenders are more likely to sell lemons than cherries, and price in premia for resale accordingly. Not only does this further reduce liquidity for informed lenders' loans, if the terms of loans are quite long, it could also take quite a while for this information to accurately update to the market, keeping premia inefficiently low for a period of time before the market corrects.

As long as the premium for resale is not too high compared to the positive profits that come from retaining their loans, rational, more-informed lenders may have some incentive to resell some loans to get access to cash for making more loans. However, it may make sense for them to enter new markets as naive or uninformed lenders in order to

increase their liquidity, particularly if they can be held liable for negative information. Such predictions would be in line with Loutskina and Strahan's findings that concentrated lenders behave like uninformed lenders when they enter new geographical markets, making 25% fewer jumbo loans among other factors.

In practice, faked or deliberate naivete might in fact be limited to certain subsets of loans, for example those which are easily securitizable or for which government sponsored entities such as Fannie Mae and Freddie Mac provide guarantees. This would explain why lenders may behave naively with regard to certain classes of loans and not others and in particular why the borrowers with lower  $\theta$  who don't fall into government-backed categories may not receive as many offers from deliberately less-informed lenders.

To the extent that naivete rather than poorer access to information is driving lending behavior in certain segments of the market, then we would expect profits will come from resale rather than interest payments. In such a case, we might expect the velocity of loan resale as a ratio of the number of loans to be higher as poorly-incentivized naivete increases.

The findings here also suggests that the post-merger improvements due to better processing of loans identified by Panetta may actually be deliberate and signal a shift towards intentions of retaining larger numbers of self-originated loans post-merger. This is a prediction that would be valuable to check and would indicate that lenders choose to specialize in retaining or reselling loans, the latter potentially resulting in too many poor loans being made.

In fact number of legal standards facilitate and exacerbate incentives for selective naivete. As Engel and Fitzpatrick (2012) describe, in the United States, the owners of mortgages are considered “holders of due course.” They must extend “duty of care” to ensure that the mortgage is not misdocumented; however, if an originator of the loan or another lender who previously held the loan exhibited poor behavior in accounting of the mortgage, the holder of due course cannot be held legally liable. This creates incentives for overstatement of borrower collateral documented by Ben-David (2007) and Cho and Megbolugbe (1996) and for lower borrower screening by lenders characterized by Keys et al (2009 and 2010), for those loans where there is an expectation of resale, particularly if the holder of the mortgage can separate itself from the origination process, as lenders have increasingly done. A lender won’t want to know a local market is on the verge of collapse if it can still resell the loan to others who are unaware of such local circumstances.

An important distinction between uninformed and naive lending is that improved access to information via competitive bidding will not benefit to naive lenders or improve the quality or informativeness of their loans. In fact, it could have the opposite effect: increased asymmetries in information at origination yield higher expectations of ex post “learning” for rational lenders. This increases expectations of negative soft information by less-informed lenders and thus increases their expectations of resale (assuming resale markets exist), which in turn increases incentives for selective naivete at origination.

The key conclusion here is that asymmetric information can actually incentivize naivete and bad types of resale (i.e. those due to negative soft information rather than a lender’s need for liquidity).

In extensions of this work, it will be fruitful to detect short versus long term motivation of lenders by considering relative levels of informed versus less informed lenders in market, as well as the relative velocity of resale compared to the number of loans. If we define a bubble as a market in which values increase mostly because of short term expectations of others' expectations of value rather than through long term appreciation, then we would expect that leading up to a bubble, resale rather than interest rate payments would stand to make higher margins on profit. It will be helpful to know, leading up to the market crash in 2008, were uninformed lenders selling between selves, or was there some grand, particularly misincentivized aggregator, such as the government sponsored entities?

### *5.1.1 Mortgage Resale*

There are clearly some important questions to consider when evaluating the effects of mortgage resale on lender behavior: What information or accounting is used to characterize loans during resale? Are lenders' signals, beliefs, types, and/or additional information learned during the early stages following origination contractible?

Bleck and Gao evaluate the role of mark-to-market pricing compared with historical pricing, characterizing major differences between each method and situations when each outperforms the other. Developing a clearer understanding of what kinds of information are available to different lenders during resale is a major part of addressing what market structures will yield more efficient outcomes, both at resale and during origination. The findings in this study support this by showing that lender behavior, including possibly deliberate naivete, can vary significantly depending on the information available.

We have concluded that rational lenders may shade their beliefs considerably in the presence of competition, knowing that additional information about the borrower's type will be revealed through the win/lose process. However, this will not be the case if firms sell their mortgages (either directly or via securitization) through a mechanism where their lender type is hidden and the mortgage value (i.e. its future profitability) can only be ascertained based on the lender's signal  $t_i$ , which the lender may elect to share with potential buyers.

In case firms face the option to sell their mortgages via such a method where only  $t_i$  can be used to justify the sales price, it is easy to see that diversified lenders, taking this extra revealed information into account, will choose to sell all their mortgages. By doing so, they are able to obtain the full profits discussed in the model above rather than the lower profits they will know to expect if they realize that information revealed when a borrower accepts their offer indicates they are on average of lower type than previously expected and thus will bring lower expected profits.

Concentrated lenders actually may receive a higher ex ante signal upon winning a borrower's business, since especially low-type borrowers will prefer naive uninformed lenders who overvalue them more on average. So, when faced with a similar option, concentrated lenders will choose to retain all of their mortgages rather than selling, since doing so allows them to obtain additional profits from this revealed information beyond what was discussed in the model above. These are additional expected profits they are unable to prove in a sale based on their signals alone. Furthermore, concentrated lenders may even increase their offers slightly for those mortgages they anticipate retaining,

knowing that borrowers who choose them over a diversified lender are of higher type on average.

In a market focused on resale based on ex ante beliefs  $b_i$  rather than signals, naivete can actually generate more profits. If lender type is not revealed in the market, the signal can't be weighed properly to come up with the lender's own private belief,  $b_i$ , so it will be weighed based on some average lender type and distortions will occur. In such a framework, we could easily end up with incentives for diversified lenders who extract better signals from poor borrowers because that increases the number of possible loans available for resale; the fact that this borrower population is of poorer quality than the signals reveal does not matter if it is possible to resell the loans while their market value has not depreciated. This could even result in incentives for informed lenders to pose as uninformed lenders, in order to generate higher signals on lower-type lenders.

The conclusion here is that resale mechanisms that reveal information selective to different lender types can be distortionary and that a better understanding of this information is necessary to evaluate optimal resale accounting methods.

It is also important to develop a better understanding of lenders themselves, what are the different types they cluster into, what is the share of lenders of different types in the market (concentrated versus diversified, naive versus rational), and their relative correlations and signal-to-noise levels? If competitors receive a highly correlated signals then they may expect very little or no additional learning to occur through the win/lose revelation mechanism. In such a setting, even rational lenders will bid according to their ex ante beliefs and make higher offers as a result.

Of course in reality, lenders are likely to have stronger signals about some borrowers than others, so even a diversified lender may show concentrated behavior regarding a few of their loans and vice versa. In addition, concentrated lenders may be able to reveal their type to some degree, perhaps to other lenders familiar with their market, to get a higher price than just their private signal  $t_i$  would yield from a potential buyer. Thus, we might expect concentrated lenders to sell some of their loans and diversified lenders to retain some in reality.

## 5.2 *Further Study & Applications*

There are a number of areas that can be highlighted for further study based on the discussion above.

First, it is important to develop a better understanding of the level and nature of competition in existing mortgage markets. Little data seems to exist on the number of lenders and mortgage brokers that borrowers typically approach when applying for a mortgage. Barr et al (2012) summarize research on low-income communities in Detroit in which 67% of borrowers were offered loan options from only one lender by their mortgage brokers. The HMDA data discussed earlier could probably yield estimates of the number of mortgage applications borrowers submit at a time; however, if borrowers are advised, as lenders typically do, to reduce negative impacts on their credit reports by shopping for offers but finalizing only one application upon selecting a lender, then these figures could be different from the number of originators approached by a borrower.

In order to accurately model the effect of information in lending markets, it is important to understand not only how many lenders typically compete for a mortgage, but also how this number varies across geography, credit worthiness and other borrower

characteristics, since these are often tied to mortgage risk and the availability of securitization and anticipated government guarantees. Furthermore, it is important to develop a better understanding of the role mortgage brokers play in the lending process. While on one hand, mortgage brokers may improve lending competition by reducing search costs and improving access to multiple lenders, they may also have incentives to absorb any surpluses, originating loans that have higher probability of resale, leaving little incentives for lenders to continue monitoring, and facilitating naivete on the part of lenders at the time when they define “to be arranged” loan programs.

Secondly, as discussed in the previous section, it is critical to have a better understanding of resale processes and the information available to different parties when trading or guaranteeing mortgages. Incorporating not only the types of information but also the heterogeneity of mortgage buyers’ ability to process this information is absolutely key to developing realistic models of mortgage resale and origination markets and to understanding when, if ever, resale markets ultimately improve information available about loans as they were originally intended to do.

Third, the insights from the model discussed in this paper suggest that leading up to a bubble caused by naive or uninformed lending practices, the rate of resale of mortgages should increase relative to the number of loans being originated. Further empirical validation of these results could yield metrics for anticipating and preventing future bubbles and could also shed light on the role of holders of large numbers of mortgages (such as Fannie Mae and Freddie Mac) in slowing or hastening the size and speed of mortgage bubbles. Despite criticism of poor accounting of detailed loan information in the Mortgage Electronic Registration System (MERS) used by government sponsored,



MERS contains a wealth of accurate information on the holders, buyers and sellers of mortgages since 1997. This information could be used to detangle mortgage resale networks leading up to 2008, to characterize different incentives for buying and selling as well as the role of misinformation versus poor incentives that pervaded the market for different players.

Finally, the results suggest that improving availability of information on borrowers and their financing projects acts as a sort of public good. The better the accuracy and amount of information available to the whole market *ex ante*, the more accurately that lenders of all types will price mortgage offers and the lower the incentives for naivete. Policy makers may want to consider policies that would invest in public information or create incentives for lenders to share private knowledge about local employers via a common pool of information, in addition to directly increasing costs for naivete.

## *6 Conclusion*

The theoretical framework developed in this paper provides a basis for understanding lender incentives and for evaluating policy changes regarding resale and origination. The findings suggest that less-informed lenders overvalue below-average borrowers and undervalue above-average borrowers more than informed lenders do. If they are rational, less-informed lenders also take on fewer loans; these loans will be of poorer quality, and thus yield lower but still positive profits. Less-informed lenders will also go on to sell more loans due to more negative soft information while informed lenders do the opposite. These findings are consistent with empirical literature on this topic treating diversified

lenders as less-informed lenders and concentrated lenders as more-informed lenders. The model also characterizes how the presence of informed competitor lenders on the market improves the amount of information available to rational lenders, as Loutskina and Strahan speculate in their concluding remarks.

Besides providing a theoretical framework for evaluating these effects, this work shows how naivete provides an additional explanation for particularly poor lending behavior, including origination of loans with negative expected long term values to the lender. Because information asymmetry increases expectations of ex post negative soft information available for uninformed lenders in particular, it also makes resale a much more attractive option for them. Higher expectations of resale further amplify incentives for naivete on a broader range of factors beyond ex post learning, facilitating origination of low and negative expected value loans. This dynamic explains why we might expect to see increasingly poor quality loans leading up to the mortgage crisis in 2008, such as recent characterizations of blatant mortgage fraud, overstatement of assets and collateral by as much as 600% by Countrywide and other lenders by the Department of Justice.

Although the presence of informed lenders can improve the loan quality and behavior of rational uninformed lenders, it has no such effect on naive lenders. In fact, due to the winner's blessing for informed lenders and winner's curse for uninformed lenders, it can actually exacerbate the problem for uninformed, naive lenders. Accordingly, it is important not to rely on the presence or market share of informed lenders to avoid a future mortgage crisis. To the extent that naive lending is a danger, only decreases in information asymmetry -- either by removing less informed lenders from the market or

by making previously private information ex ante public to lenders -- can address poor lending behavior of naive lenders.

## Appendices

## A. Final Editorial Decisions by Journal

Panel 1. Full journal database history

Journal	1	2	3	4	5
Number of Observations	4864	4948	3597	3189	219
% summarily rejected, no reviewer input	11%	15%	21%	15%	32%
% summarily rejected, reviewer input	0%	0%	0%	5%	0%
% rejected	13%	13%	14%	61%	11%
% accepted	70%	65%	58%	15%	56%
% withdrawn by author	7%	7%	7%	4%	1%

Panel 2. Restricted history since 2006

Journal	1	2	3	4	5
Number of Observations	1377	1382	1166	1468	206
% summarily rejected, no reviewer input	28%	41%	47%	16%	34%
% summarily rejected, reviewer input	0%	0%	1%	8%	0%
% rejected	13%	11%	11%	35%	10%
% accepted	58%	47%	41%	9%	55%
% withdrawn by author	1%	1%	1%	1%	1%
Period of Observation	2006-2010	2006-2010	2006-2010	2006-2010	2006-2010

**B. Referee Review Rates and Breakdown of Referee Scores by Journal and Revision**

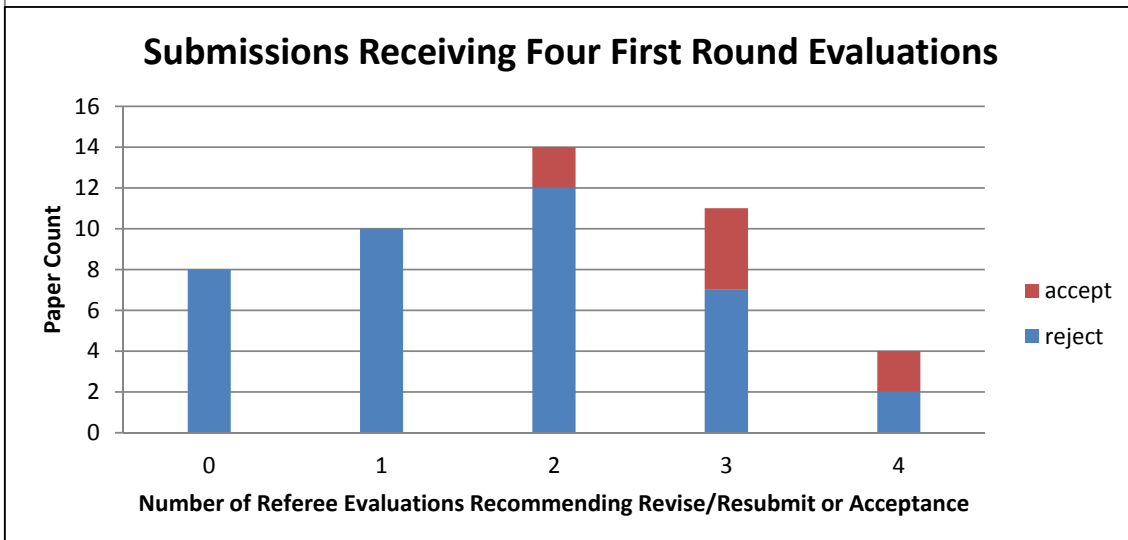
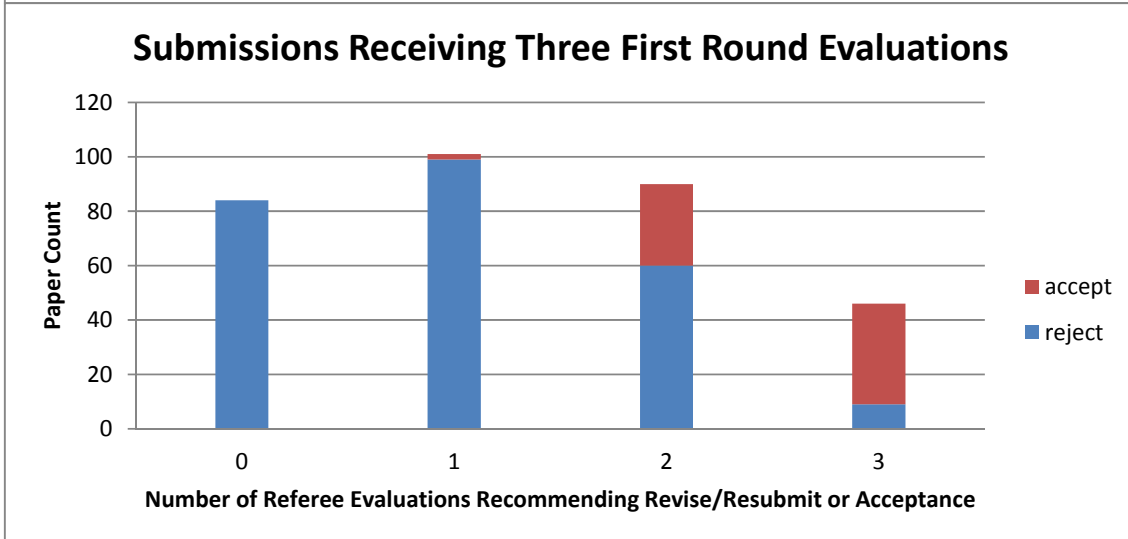
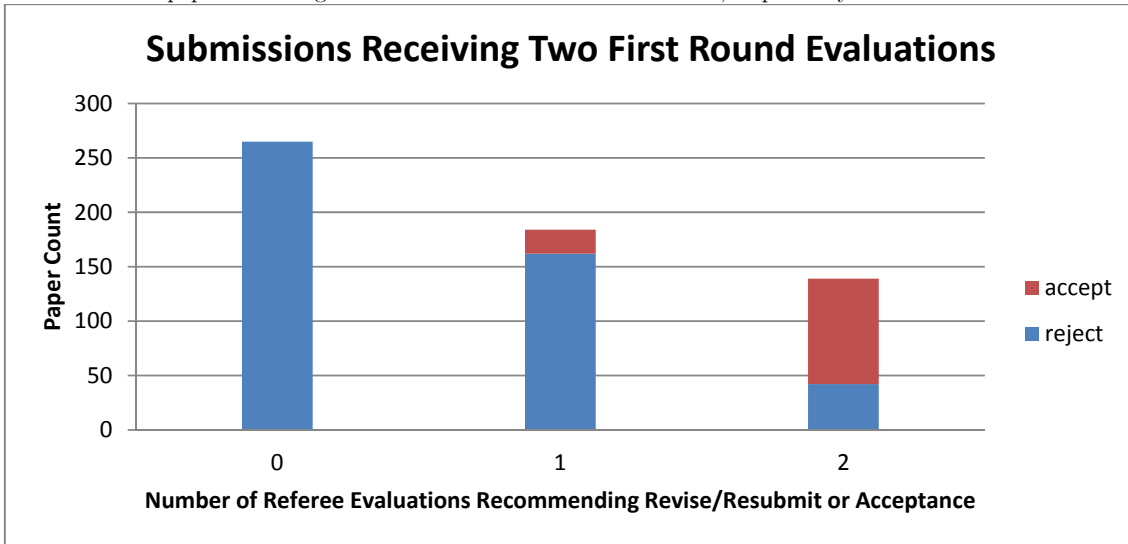
	Journal 1			Journal 2			Journal 3			Journal 4			Journal 5		
Revision	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
No. Submissions Sent for Review	1,239	60	2	1,028	49	2	754	36	1	1,533	242	65	171	6	1
As % of Incoming or Prev Round	25%	5%	3%	21%	5%	4%	21%	5%	3%	48%	16%	27%	78%	4%	17%
No. Evaluations Requested	4,295	589	132	5,497	145	4	4,818	131	2	3,590	92	1	806	20	6
% Evaluations Completed	71%	79%	80%	41%	63%	100%	40%	51%	100%	39%	59%	100%	39%	50%	17%
No. Evaluations Completed	2,256	92	4	1,921	67	2	1,405	54	1	3,040	464	106	312	10	1
No. Submissions Reviewed	1,022	59	2	843	46	2	643	33	1	1,452	231	61	147	6	1
% Definite Reject	0%	0%	0%	0%	0%	0%	0%	0%	0%	11%	2%	0%	0%	0%	0%
% Reject	14%	22%	0%	14%	21%	50%	14%	19%	100%	45%	11%	4%	14%	20%	100%
% Weak revise and resubmit	17%	10%	75%	16%	22%	50%	19%	26%	0%	15%	5%	4%	17%	20%	0%
% Revise and resubmit	24%	32%	25%	25%	31%	0%	23%	31%	0%	15%	12%	5%	21%	20%	0%
% Strong revise and resubmit	1%	0%	0%	1%	0%	0%	2%	0%	0%	8%	6%	4%	1%	0%	0%
% Accept with revisions	38%	28%	0%	39%	22%	0%	37%	20%	0%	4%	24%	20%	39%	10%	0%
% Accept	6%	9%	0%	4%	3%	0%	5%	4%	0%	2%	41%	64%	8%	30%	0%

C. Breakdown of Submissions by Number of Completed First Round Referee Evaluations and by Journal

Number of Evaluations Received	Journal 1	Journal 2	Journal 3	Journal 4	Journal 5
1	137	86	82	349	20
2	567	484	385	670	91
3	287	230	155	376	34
4	30	38	17	56	2
5	1	5	4	1	
Total Papers Receiving $\geq 1$ Completed Reviews	1,022	843	643	1,452	147

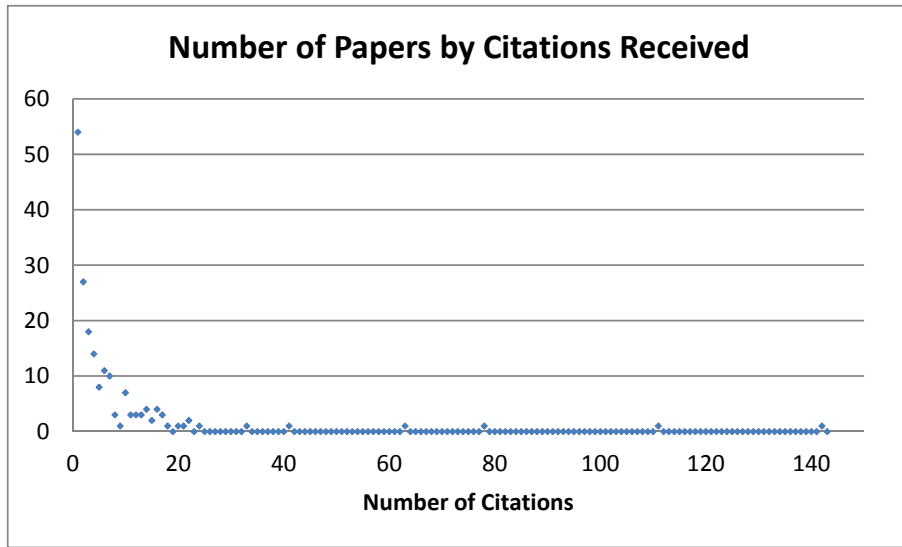
### D. Final Editorial Decisions by First Round Referee Score at Journal 4

For all papers receiving exactly two referee evaluations in the first round, the top panel shows how many received exactly zero, one and two positive referee recommendations (where positive is defined as revise/resubmit or acceptance) and how many of each of these were eventually accepted by editors (red) or rejected (blue). The lower two panels show the same distributions for papers receiving three and four total referee evaluations, respectively.

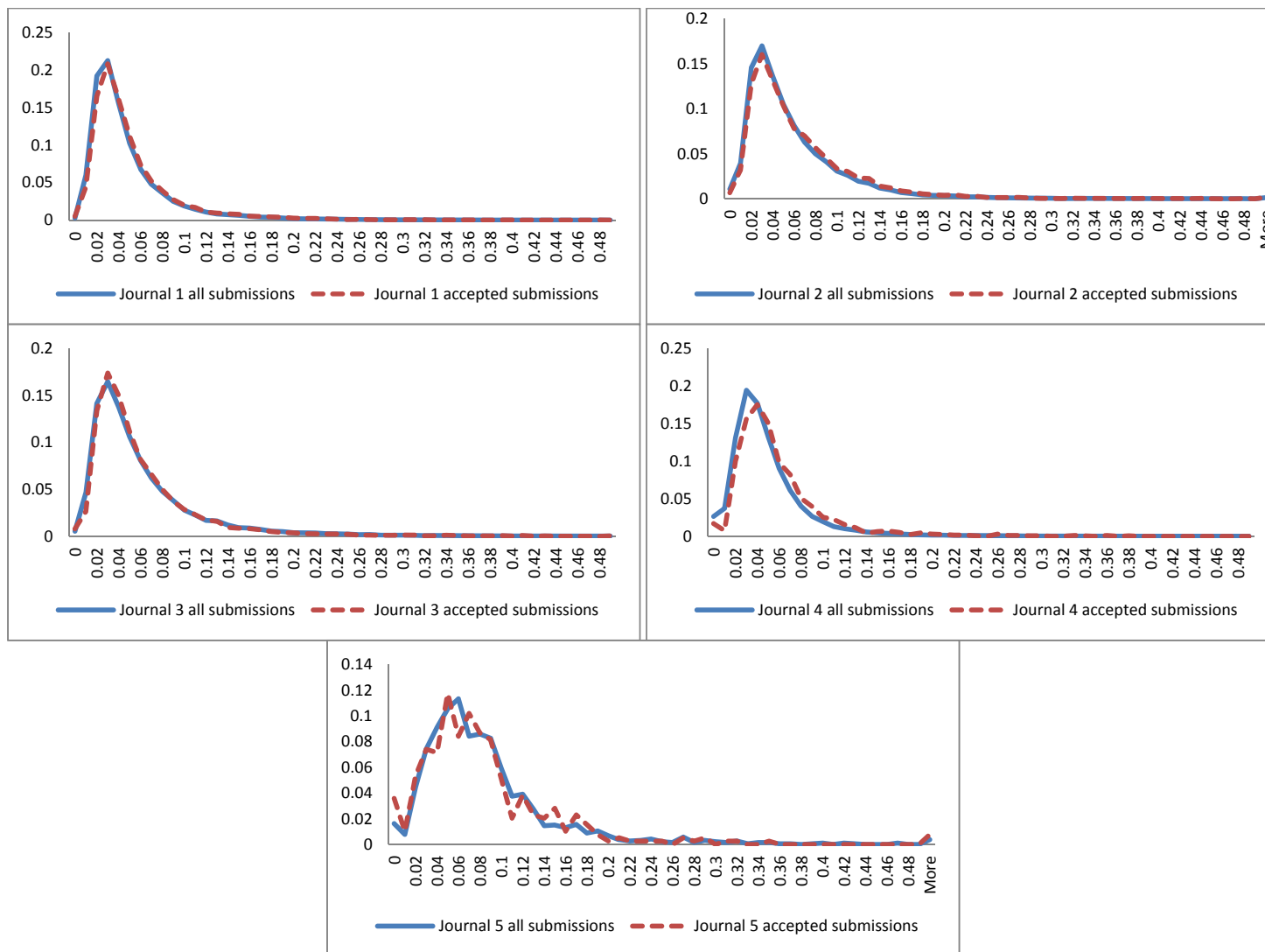




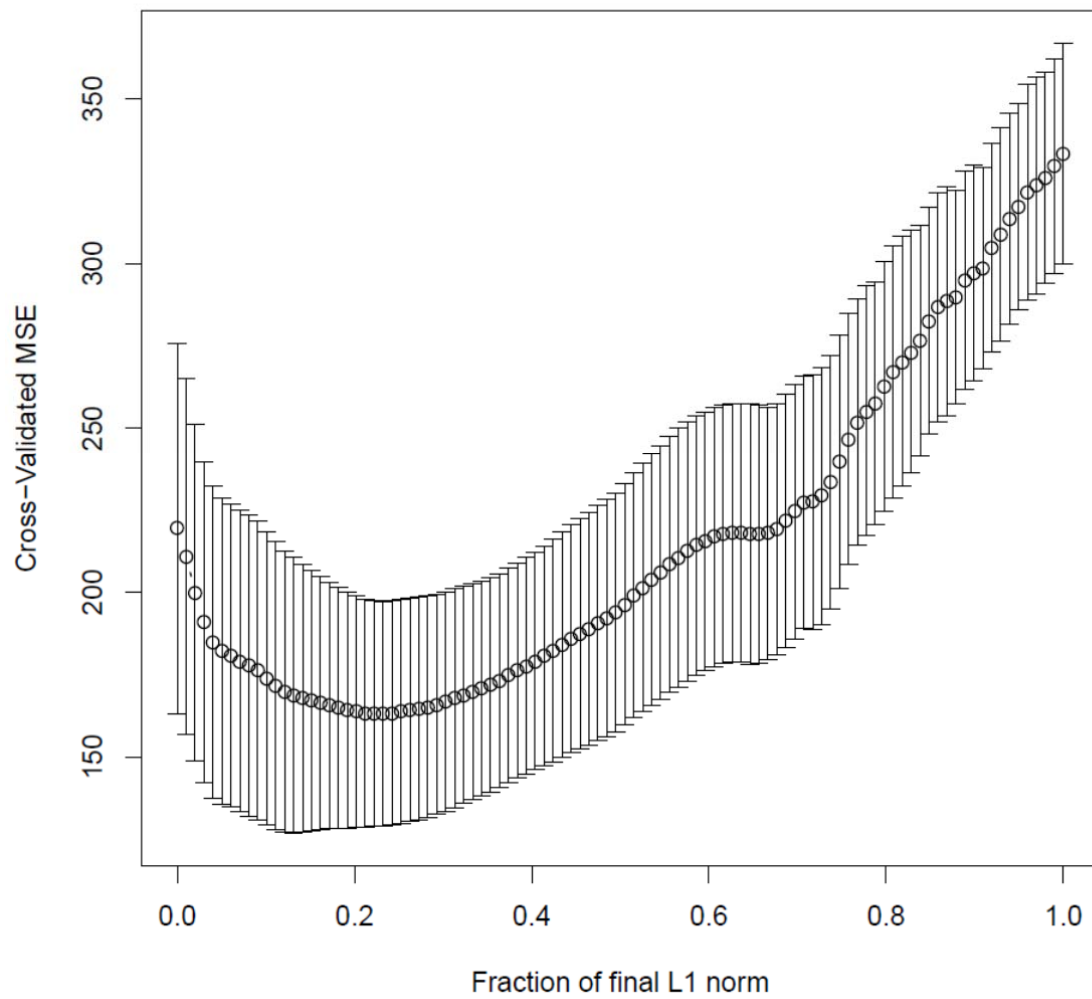
E. Distribution of Citations Received by Published Papers at Journal 4



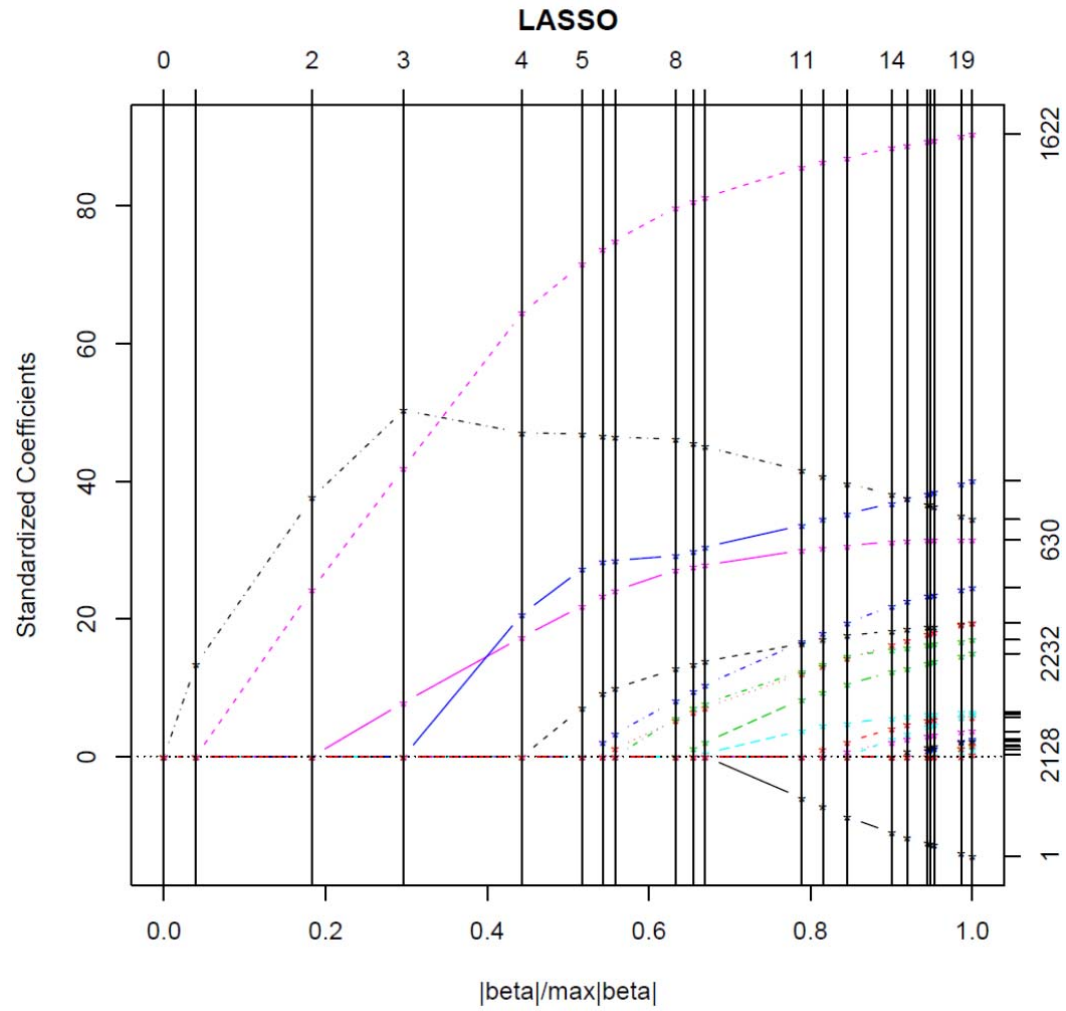
F. Distributions of pairwise relationships between submissions



## G. Cross-Validation Results

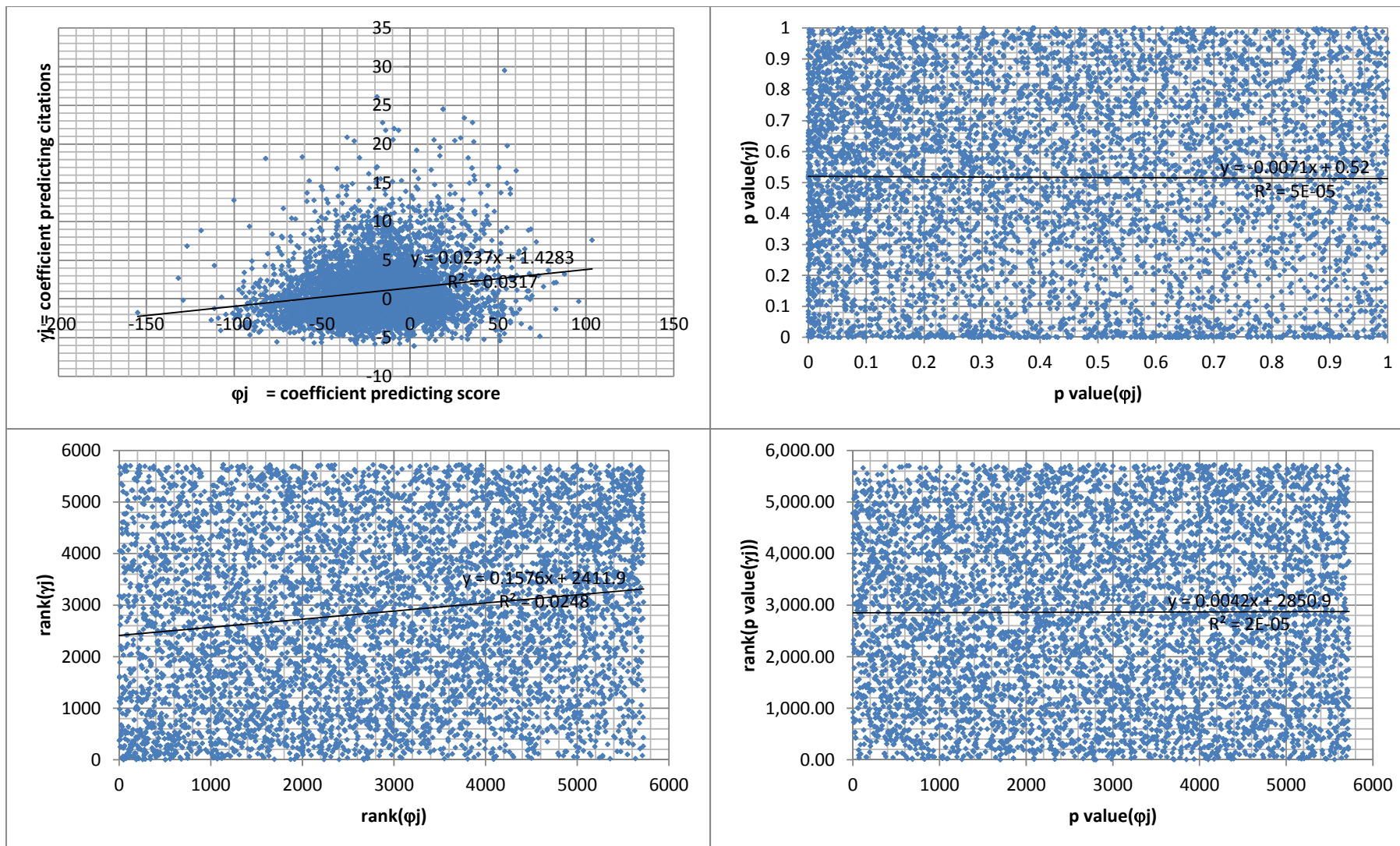


### H. Coefficient Path for LASSO Estimation



## I. Referee Language as Predictors of Score and Impact at one Journal

Plots of coefficients come from estimation of the following (n=5,724):

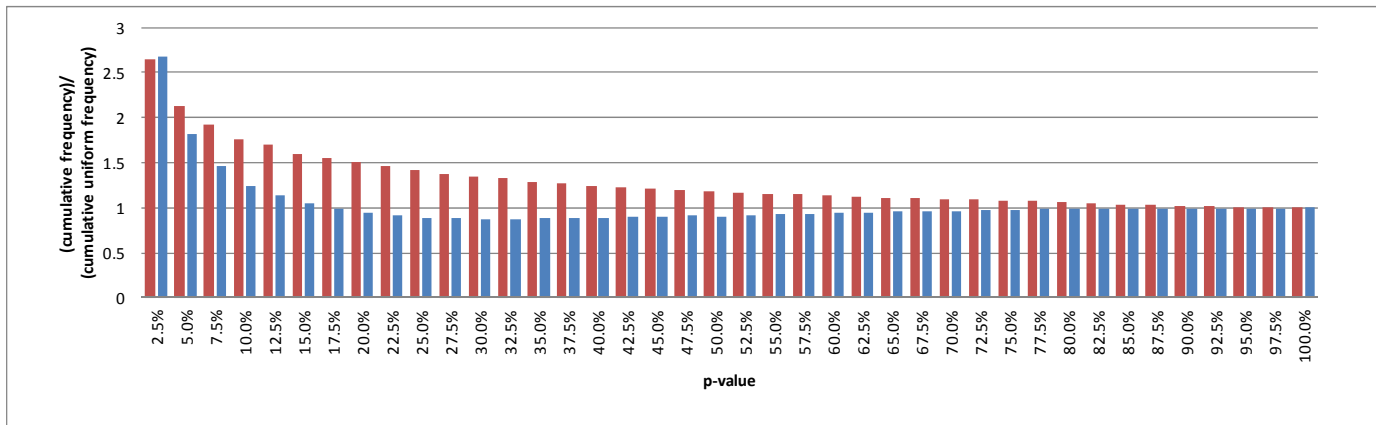
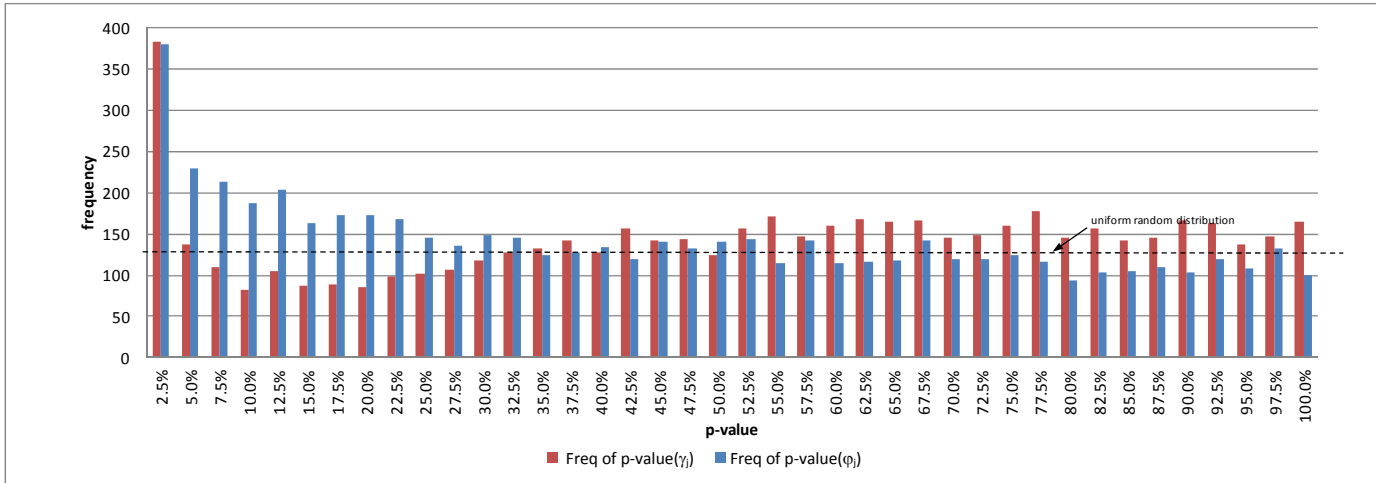
$$\begin{cases} (citations_i) = \alpha_j + \beta_j(submission\ date_i) + \gamma_j(term_{ij}) + \varepsilon_{ij} & \text{for each term } j \\ (referee\ score_i) = \mu_j + \rho_j(submission\ date_i) + \varphi_j(term_{ij}) + \varepsilon_{ij} & \text{for each term } j \end{cases}$$


## J. Histogram of p-values of referee terms in estimations of citations and referee scores

P-Values of coefficients of referee terms come from estimation of: 
$$\begin{cases} (\text{citations}_i) = \alpha_j + \beta_j(\text{submission date}_i) + \gamma_j(\text{term}_{ij}) + \varepsilon_{ij} & \text{for each term } j \\ (\text{referee score}_i) = \mu_j + \rho_j(\text{submission date}_i) + \varphi_j(\text{term}_{ij}) + \varepsilon_{ij} & \text{for each term } j \end{cases}$$
 for 5,724 values of  $j$ .

The dotted line shows the uniform distribution of  $\text{frequency} = \frac{5724 \text{ terms}}{40 \text{ bins}} = 143.1$  which would be expected if the referee term occurrence was random and contained no information.

The lower panel shows the implied cumulative frequency distribution. Both panels demonstrate that low p-values (particularly those below 2.5%) occur much more frequently than would be expected at random.



## K. Sample of Significant Referee Phrases

For each of 5,724 phrases used by referees to describe at least fifteen papers, two unique regressions were carried out to determine significance and informativeness in predicting citations and in predicting referee score. Results are shown below for a sample of 111 terms that are significant at the 10% level or better in at least one of the two regressions:

$$(citations_i) = \alpha_j + \beta_j(submission\ date_i) + \gamma_j(term_{ij}) + \varepsilon_{ij} \quad \text{for each term } j$$

$$(referee\ score_i) = \mu_j + \rho_j(submission\ date_i) + \varphi_j(term_{ij}) + \varepsilon_{ij} \quad \text{for each term } j$$

Each term's normalized coefficient for predicting citations ( $\gamma_j/\alpha_j$ ) and for predicting referee score ( $\varphi_j/\mu_j$ ) are given together with their normalized standard errors. These can be compared to the mean values in the full sample of 5,724 observations:  $\overline{\gamma_j/\alpha_j} = -0.84$  and  $\overline{\varphi_j/\mu_j} = 0.048$ . Terms are shown ranked by decreasing  $\gamma_j/\alpha_j$ . As usual, (\*\*\*) (\*\*), and (\*) indicate significance at the 1%, 5%, and 10% level or better, respectively.

Phrase	$\gamma_j/\alpha_j$	$\varphi_j/\mu_j$	Phrase	$\gamma_j/\alpha_j$	$\varphi_j/\mu_j$
the most important	2.236 (0.35)***	-0.067 (0.149)	important	0.298 (0.136)**	-0.122 (0.052)**
government	2.019 (0.365)***	-0.039 (0.165)	issues	0.268 (0.145)*	-0.128 (0.061)**
literature has	1.668 (0.385)***	-0.348 (0.17)**	minor	0.249 (0.163)	0.134 (0.072)*
debate	1.554 (0.305)***	0.26 (0.135)*	question	0.246 (0.151)	-0.119 (0.064)*
extends	1.479 (0.39)***	0.156 (0.173)	be shortened	0.241 (0.294)	-0.274 (0.129)**
[editor-in-chief] and	1.344 (0.402)***	-0.153 (0.171)	addressed	0.217 (0.204)	0.187 (0.092)**
think the authors	1.325 (0.365)***	0.019 (0.16)	not seem to	0.175 (0.274)	-0.232 (0.122)*
line with	1.205 (0.403)***	0.068 (0.18)	interesting	0.17 (0.13)	-0.102 (0.052)*
i wonder if	1.11 (0.378)***	0.07 (0.173)	journal	0.146 (0.141)	-0.134 (0.06)**
doubt	1.095 (0.294)***	0.021 (0.132)	conditions	0.145 (0.177)	-0.13 (0.078)*
reaction	1.071 (0.396)***	-0.095 (0.179)	measure	0.129 (0.168)	-0.134 (0.074)*
the current version	1.042 (0.365)***	-0.076 (0.166)	authors should	0.117 (0.171)	-0.203 (0.074)***
nice paper	1.028 (0.37)***	0.206 (0.166)	the use of	0.104 (0.155)	-0.119 (0.067)*
the authors need	1.02 (0.274)***	-0.056 (0.118)	exogenous	0.104 (0.24)	-0.227 (0.105)**
the previous literature	0.991 (0.387)**	-0.178 (0.171)	appropriately	0.102 (0.322)	0.26 (0.146)*
interesting to see	0.953 (0.341)***	0.026 (0.155)	problems	0.081 (0.146)	-0.117 (0.064)*
sensible	0.945 (0.26)***	0.048 (0.115)	problems with the	0.07 (0.381)	-0.407 (0.171)**
my knowledge	0.93 (0.381)**	-0.204 (0.171)	the assumption that	0.07 (0.259)	-0.223 (0.114)*
would be interesting	0.926 (0.257)***	-0.001 (0.115)	assumptions	0.066 (0.154)	-0.155 (0.067)**
can easily	0.921 (0.341)***	-0.206 (0.155)	related	0.04 (0.144)	-0.125 (0.063)**
the authors propose	0.92 (0.401)**	0.187 (0.18)	i do not	0.032 (0.152)	-0.224 (0.064)***
public	0.911 (0.338)***	-0.178 (0.148)	not clear	0.027 (0.164)	-0.119 (0.072)*
highlight	0.891 (0.359)**	-0.075 (0.159)	sophisticated	-0.004 (0.38)	0.293 (0.172)*
versions of	0.874 (0.395)**	-0.07 (0.181)	similar	-0.006 (0.14)	-0.118 (0.062)*
too much	0.868 (0.295)***	0.08 (0.129)	misleading	-0.033 (0.222)	-0.252 (0.098)**
contrast to	0.861 (0.323)***	0.003 (0.141)	related to	-0.035 (0.169)	-0.147 (0.076)*
the existing literature	0.85 (0.308)***	-0.01 (0.138)	structural	-0.035 (0.152)	-0.125 (0.068)*
stronger	0.845 (0.259)***	-0.156 (0.114)	unless	-0.039 (0.238)	-0.251 (0.106)**
argue that the	0.829 (0.372)**	-0.129 (0.165)	wellknown	-0.047 (0.365)	-0.388 (0.162)**
the major	0.828 (0.387)**	-0.137 (0.171)	correlated with	-0.049 (0.277)	-0.248 (0.124)**
this literature	0.828 (0.264)***	-0.103 (0.119)	one cannot	-0.051 (0.352)	-0.297 (0.157)*
the contribution	0.82 (0.258)***	-0.093 (0.117)	the specification	-0.057 (0.277)	-0.228 (0.124)*
the paper for	0.82 (0.4)**	-0.024 (0.179)	motivation for	-0.061 (0.244)	-0.253 (0.108)**
from [year] to [year]	0.82 (0.386)**	0.296 (0.173)*	errors	-0.075 (0.151)	-0.122 (0.067)*
not allow	0.815 (0.41)**	-0.496 (0.174)***	be helpful to	-0.082 (0.271)	0.212 (0.124)*
in favor of	0.801 (0.342)**	-0.093 (0.149)	this paper uses	-0.095 (0.32)	-0.239 (0.143)*
i agree	0.8 (0.355)**	0.289 (0.16)*	do not see	-0.096 (0.296)	-0.324 (0.133)**
into account the	0.799 (0.36)**	0.224 (0.161)	motivation for the	-0.101 (0.329)	-0.347 (0.147)**
be nice to	0.794 (0.383)**	-0.214 (0.171)	as it stands	-0.117 (0.321)	-0.27 (0.144)**
the value of	0.741 (0.294)**	-0.068 (0.128)	did not	-0.13 (0.213)	-0.211 (0.096)**
be interesting to	0.726 (0.238)***	-0.09 (0.104)	like to see	-0.148 (0.236)	0.198 (0.109)*
why the authors	0.722 (0.355)**	0.049 (0.16)	fine	-0.149 (0.232)	0.254 (0.108)**
heteroskedasticity	0.689 (0.386)*	0.448 (0.173)***	error	-0.15 (0.128)	-0.125 (0.058)**
this finding	0.676 (0.391)*	-0.022 (0.172)	not do	-0.166 (0.365)	-0.415 (0.163)**
a serious	0.673 (0.308)**	-0.172 (0.133)	problematic	-0.175 (0.256)	-0.207 (0.115)*
in my opinion	0.639 (0.256)**	-0.169 (0.112)	competing	-0.186 (0.295)	-0.29 (0.132)**
not understand the	0.616 (0.343)*	-0.163 (0.148)	motivate the	-0.208 (0.317)	-0.279 (0.143)*
value of the	0.608 (0.294)**	-0.128 (0.127)	i am not	-0.209 (0.153)	-0.174 (0.069)**
nicely	0.583 (0.356)	0.281 (0.16)*	specifications	-0.237 (0.207)	-0.157 (0.094)*
unclear	0.556 (0.192)***	-0.194 (0.084)**	limitation	-0.29 (0.351)	-0.268 (0.159)*
but then	0.542 (0.273)**	-0.218 (0.119)*	assumes that	-0.3 (0.288)	-0.303 (0.13)**
my opinion	0.461 (0.225)**	-0.207 (0.098)**	have done	-0.329 (0.347)	0.296 (0.161)*
finding	0.399 (0.188)**	-0.021 (0.081)	the author	-0.329 (0.134)**	-0.108 (0.065)**
they do not	0.393 (0.296)	-0.462 (0.126)***	rejection	-0.35 (0.28)	-0.255 (0.127)**
the identification	0.363 (0.299)	0.248 (0.135)*	problems of	-0.366 (0.349)	-0.268 (0.158)*

L. OLS of Citation Impact on Submission Characteristics

variable	coefficient	se	
intercept	21.870	(32.179)	
Earliest MS Available	-7.471	(9.1119)	
Earliest Version Length	0.0030	(0.0015)	*
Latest MS Available	-3.406	(3.9429)	
Latest Version Length	0.0005	(0.0001)	***
Number Revisions	-0.463	(0.4910)	
fit	37.826	(26.930)	
E(citations)	0.9515	(0.0348)	***



## M. OLS of Citation Impact on Editor Fixed Effects and Mentions

variable	coefficient	se	
Intercept	335.32	(66.455)	***
Received date	-0.008	(0.0016)	***
coeditor_chief	-6.451	(3.3847)	*
coeditor_1	5.5417	(3.0754)	*
coeditor_2	-6.463	(2.9651)	**
coeditor_3	-9.480	(4.2655)	**
coeditor_4	-3.920	(4.3875)	
coeditor_5	-3.742	(6.6674)	
coeditor_6	-5.861	(6.7446)	
coeditor_7	-5.104	(5.2049)	
coeditor_8	-4.197	(2.9883)	
coeditor_9	-10.16	(3.6600)	***
ml_coeditor_chief	1.1712	(0.2246)	***
ml_coeditor_1	-1.960	(0.7610)	**
ml_coeditor_2	-0.289	(1.1866)	
ml_coeditor_3	0.1787	(0.1579)	
ml_coeditor_4	-0.552	(1.0865)	
ml_coeditor_5	0.0517	(1.5048)	
ml_coeditor_6	-0.213	(0.2646)	
ml_coeditor_7	-1.317	(3.7155)	
ml_coeditor_8	-0.961	(0.6537)	
ml_coeditor_9	-1.322	(1.3423)	
ml_coeditor_10	0.1168	(0.3492)	
ml_coeditor_11	0.1117	(0.8174)	
coeditor_chief*ml_coeditor_chief	-0.912	(0.3038)	***
coeditor_1*ml_coeditor_1	1.2794	(0.8056)	
coeditor_2*ml_coeditor_2	0.6622	(1.4263)	
coeditor_3*ml_coeditor_3	-0.122	(0.3250)	
coeditor_4*ml_coeditor_4	1.0491	(1.6801)	
coeditor_7*ml_coeditor_7	-0.253	(11.580)	
coeditor_8*ml_coeditor_8	1.0491	(0.9077)	
coeditor_9*ml_coeditor_9	1.0846	(1.7010)	

In this table, the notation `coeditor_k` is used to denote a dummy variable indicating that coeditor `k` was assigned to the manuscript and `ml_coeditor_k` is used to denote the number of mentions of coeditor `k`'s last name in the last revision of a manuscript. The editor in chief is not assigned a number `k` but is instead called out explicitly.

N. Referee Decisions Across Journals

1. BINOMIAL LOGIT ON DECISION TO REFER

variable	1	2	3	4	5
intercept	-27.6229 ***	-27.091 ***	-15.9013 ***	15.2929 ***	6.7588
date	0.0007 ***	0.0007 ***	0.0004 ***	-0.0004 ***	-0.0002
past reviews_i	-0.0262 ***	-0.0201 ***	-0.0628 ***	0.0379 **	0.0595
past reviews^2_i	0.0001 ***	0 ***	0.0002 ***	-0.0003	0.0016
revision_p	1.1012 ***	0.2765	0.7114 ***	0.3351 ***	0.1263

2. ORDERED LOGIT ON REFEREE SCORE CONDITIONAL ON ACCEPTANCE TO REFER

variable	1	2	3	4	5
cutoff1	-11.8306	-6.6577	-23.286	-11.2867 ***	-2.8984
cutoff2	-11.2069	-6.0427	-22.6814	-7.3868 ***	-2.2737
cutoff3	12.1214 ***	16.0313 ***	1.0083	-5.0019 **	21.9296 *
cutoff4	13.1441 ***	17.0683 ***	2.1442	-4.3668 **	22.9138 *
cutoff5	14.2023 ***	18.186 ***	3.1603	-3.464 *	23.816 *
cutoff6	14.2399 ***	18.2387 ***	3.234	-2.7651	23.8677 *
cutoff7	16.8408 ***	21.108 ***	5.8947	-1.7225	26.1454 **
date (years)	-0.1326 ***	-0.1682 ***	-0.0278	0.0491 ***	-0.2203 *
past reviews_i	0.0032	0.0053 **	0.0151 ***	0.0298 ***	0.0008
revision_p	0.3002 *	0.3467 *	0.5927 **	-2.479 ***	0.1208
total reviews_i	-0.0012	-0.0026	-0.0114 **	-0.0074	0.0173
fit_p	1.1182	-5.0369 **	9.0305 ***	-8.983 ***	-4.6319
fit_avail_p	-0.5104	3.0866 **	-1.1685 ***	0.1421	0.8396
length_p (1000s)	-0.1458 ***	-0.1534 ***	-0.2013 ***	-0.1367 ***	-0.1135 **
length_avail_p	1.4889	-1.9831	1.5117 ***	0.7482 **	0.2905

O. Ordered Logit of Referee Evaluation at Journal 4

variable	Coefficient	se	
(threshold1)	-6.681	(0.4834)	***
(threshold2)	-2.6894	(0.2672)	***
(threshold3)	-0.3162	(0.2619)	
(threshold4)	0.3259	(0.262)	
(threshold5)	1.2673	(0.2632)	***
(threshold6)	2.0918	(0.2668)	***
(threshold7)	3.0553	(0.2785)	***
E(citations) (n)	0.0128	(0.0024)	***
Received Date (n)	-0.1457	(0.0258)	***
fit_flag	0.0171	(0.1592)	
fit	-3.3669	(3.5135)	
coeditor_chief	0.8986	(0.1972)	***
coeditor_1	0.8223	(0.212)	***
coeditor_2	0.9684	(0.2129)	***
coeditor_3	1.6918	(0.2079)	***
coeditor_4	1.5697	(0.2178)	***
coeditor_6	0.9857	(0.3628)	***
coeditor_7	1.3458	(0.2762)	***
coeditor_8	0.5125	(0.2116)	**
coeditor_9	0.7543	(0.2819)	***
ml_coeditor_5	1.292	(0.2092)	***

P. (1) Logit of Editorial Decisions on Fit, Scores and Expected Citation Impact at Journal 4

$x_i$	(1)		(2)		(3)		(4)		(5)		$\bar{x}_i$	$\text{var}(x_i)$
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.		
Intercept	-2.435	-0.389***	-2.06	0.5775***	-2.11	0.543***	-2.062	0.6042*	-2.177	0.7006***		
E[citations]	0.0021	0.0069	-0.015	0.057					0.0202	0.0624	6.6977	112.36
Date	0.2443	0.0511***	0.3128	0.0754***	0.3199	0.0703***	0.3575	0.0764*	0.3614	0.0774*	4.4652	2.8169
fit_flag	-0.287	0.3556	-0.814	0.4432***	-0.818	0.4428*	-0.843	0.5089*	-0.852	0.5096***	0.9411	0.0555
fit	16.889	6.1533***	17.854	7.4571**	17.971	7.4399**	17.747	8.0041**	17.945	8.0313**	0.0061	0.0001
#pos							0.8386	0.1644***	0.8784	0.206***	0.8549	0.8478
#neg							-1.672	0.2565***	-1.631	0.2853***	1.2639	0.8088
#pos*E[cit]			0.1692	0.0262***	0.1638	0.0159***	0.0303	0.0164*	0.0224	0.0295	5.7195	223.74
#neg*E[cit]			-0.364	0.0356***	-0.366	0.0342***	-0.087	0.0374**	-0.095	0.0434**	8.093	191.73

(\*\*\*) indicates significance at the 1% level or better, (\*\*) at the 5% level or better, and (\*) at the 10% level or better.

See Appendix P.2 for point estimate analysis of significance, sign, an effect size of each estimator.

**P. (2) Odds Ratios and First Difference Analysis of Logit of Editorial Decisions on Fit, Scores and Expected Citation Impact at Journal 4**

	$x_i$	coeff ( $\hat{\beta}_i$ )	s.e. ( $\hat{\sigma}_i$ )	odds ratio range <sup>♦</sup>	<sup>♦♦</sup> $\Delta P(\text{accept} \pm\sigma_{x_i})$
(1)	Intercept	-2.435	-0.389	(0.129,0.059)*	
	E[citations]	0.0021	0.0069	(0.968,1.062)	(-0.003,0.003)
	Date	0.2443	0.0511	(2.369,3.74)*	(-0.054,0.069)
	fit'flag	-0.287	0.3556	(0.546,1.067)	(0.01,-0.01)
	fit	16.889	6.1533	(1.068,1.151)*	(-0.024,0.027)
	#pos				
	#neg				
	#neg*E[cit]				
(2)	Intercept	-2.06	0.5775	(0.072,0.227)*	
	E[citations]	-0.015	0.057	(0.617,1.325)	(0.005,-0.005)
	Date	0.3128	0.0754	(2.886,5.66)*	(-0.013,0.021)
	fit'flag	-0.814	0.4432	(0.306,0.705)*	(0.007,-0.005)
	fit	17.854	7.4571	(1.065,1.167)*	(-0.005,0.006)
	#pos				
	#neg				
	#neg*E[cit]	-0.364	0.0356	(0.039,0.07)*	(0.805,-0.032)
(3)	Intercept	-2.11	0.543	(0.07,0.209)*	
	E[citations]				
	Date	0.3199	0.0703	(3.048,5.711)*	(-0.014,0.022)
	fit'flag	-0.818	0.4428	(0.305,0.703)*	(0.007,-0.006)
	fit	17.971	7.4399	(1.066,1.168)*	(-0.005,0.006)
	#pos				
	#neg				
	#neg*E[cit]	-0.366	0.0342	(0.039,0.068)*	(0.812,-0.033)
(4)	Intercept	-2.062	0.6042	(0.07,0.233)*	
	E[citations]				
	Date	0.3575	0.0764	(3.508,6.941)*	(-0.019,0.033)
	fit'flag	-0.843	0.5089	(0.28,0.73)*	(0.009,-0.008)
	fit	17.747	8.0041	(1.061,1.17)*	(-0.007,0.008)
	#pos	0.8386	0.1644	(1.78,2.357)*	(-0.023,0.047)
	#neg	-1.672	0.2565	(0.087,0.167)*	(0.128,-0.034)
	#neg*E[cit]	-0.087	0.0374	(0.365,0.669)*	(0.089,-0.03)
(5)	Intercept	-2.177	0.7006	(0.056,0.228)*	
	E[citations]	0.0202	0.0624	(0.754,1.739)	(-0.008,0.01)
	Date	0.3614	0.0774	(3.554,7.095)*	(-0.02,0.034)
	fit'flag	-0.852	0.5096	(0.278,0.725)*	(0.009,-0.008)
	fit	17.945	8.0313	(1.062,1.172)*	(-0.007,0.008)
	#pos	0.8784	0.206	(1.777,2.527)*	(-0.024,0.05)
	#neg	-1.631	0.2853	(0.089,0.183)*	(0.123,-0.034)
	#neg*E[cit]	-0.095	0.0434	(0.326,0.659)*	(0.103,-0.032)

<sup>♦</sup>Odds ratio range  $\equiv \left( e^{(\hat{\beta}_i - \hat{\sigma}_{\beta_i})\bar{x}_i}, e^{(\hat{\beta}_i + \hat{\sigma}_{\beta_i})\bar{x}_i} \right)$ . For each  $x_i$  the odds ratio is the factor by which  $x_i$  improves (or reduces) the odds of getting accepted. The range reflects a confidence interval for the odds ratio corresponding to values of  $\beta_i \in \hat{\beta}_i \pm \hat{\sigma}_{\beta_i}$  (i.e. the estimated coefficient  $\pm$  one std. error). Ratios greater than one reflect an improvement in the odds of getting accepted whereas ratios less than one reflect reduced odds of acceptance. Those  $x_i$  for which the range excludes zero can be considered significant (\*). The ratio of the high to low values in each range remains constant for all values of  $\bar{x}$ . <sup>♦♦</sup> $\Delta P \equiv \left( P(\text{accept}|\bar{x} - \sigma_{x_i}), P(\text{accept}|\bar{x} + \sigma_{x_i}) \right)$  reflects the size of  $\beta_i$ 's effect at the mean  $\bar{x}$ , i.e. increase in probability of acceptance due to a one sample standard deviation (decrease, increase) in  $x_i$  at  $\bar{x}$ .

Q. Binary Logit of Editor Decisions on Submission Characteristics

variable	coefficient	se	
(threshold)	-5.6599	0.9451	***
max_revision	2.7321	0.5289	***
Received Date (n)	0.4441	0.1245	***
pos_eval	0.9864	0.1917	***
neg_eval	-1.9567	0.2646	***
coeditor_chief	-3.8928	0.785	***
coeditor_1	-0.4415	0.6116	
coeditor_2	-0.157	0.6325	
coeditor_3	-2.1226	0.8073	***
coeditor_4	-3.7313	1.0386	***
coeditor_5	-2.9344	0.9031	***
coeditor_6	-1.7987	1.4302	
coeditor_7	-1.911	1.3671	
coeditor_8	-0.7989	0.7321	
coeditor_9	0.222	0.999	

R. Editor Decisions (Interaction with Mentions of Editor Name)

Variable	coefficient	se	
(threshold)	-6.3558	1.0763	***
max revision	3.3071	0.4134	***
Received Date (n)	0.4811	0.1361	***
pos_latest_eval	1.1511	0.2651	***
neg_latest_eval	-2.6995	0.378	***
coeditor_chief	-3.481	0.8146	***
coeditor_1	-0.6959	0.7064	
coeditor_2	-0.1908	0.7286	
coeditor_3	-2.42	0.9702	**
coeditor_4	-3.427	1.1074	***
coeditor_5	-3.5892	1.0426	***
coeditor_6	-1.4099	1.4023	
coeditor_7	-1.9232	1.6301	
coeditor_8	-1.1455	0.8122	
coeditor_9	0.5781	1.1103	
coeditor_chief*ml_coeditor_chief	0.0337	0.0723	
coeditor_1*ml_coeditor_1	0.2814	0.1343	**
coeditor_2*ml_coeditor_2	0.3699	0.434	
coeditor_3*ml_coeditor_3	0.0655	0.0817	
coeditor_4*ml_coeditor_4	-0.0256	0.5161	
coeditor_8*ml_coeditor_8	0.0719	0.1345	
coeditor_9*ml_coeditor_9	-0.1694	1.0901	

S. Editorial Decision Across Journals

**BINOMIAL LOGIT OF EDITORIAL ACCEPT/REJECT CONDITIONAL ON AVAIL. TEXT DATA**

intercept	237.3982		122.8479		372.5109		-347.054	***	-718.247	
year_p	-0.1192		-0.0629		-0.187		0.1697	***	0.3568	
fit_p	16.7509	**	16.7791	***	-6.9359		16.2972	*	-5.2142	
length_p (1000s words)	0.1952	***	0.4601	***	0.5919	***	0.1541	***	0.3023	
avg_reviewer_rating_p	0.0116	***	0.013	***	0.0163	***	0.0244	***	0.0182	***



T. *Proof of Proposition 1*

We seek an expression for  $b_i(t_i) \equiv E(\theta|t_i)$ , so we start with Lemma 1.

Lemma 1

For any normally distributed variables  $x$  and  $y$ ,  $E(y|x) = a + bx$  for constants  $a$  and  $b$  given by

$$a = \mu_y - \frac{\sigma_{xy}}{\sigma_x^2} + \mu_x$$

$$b = \frac{\sigma_{xy}}{\sigma_x^2}$$

As normal distributions,  $\theta \sim N(\mu_\theta, \sigma_\theta)$ ,  $\varepsilon_i \sim N(0, \sigma_i)$ , and  $t_i \sim N(\mu_\theta, \sigma_\theta + \sigma_i)$  have the property that conditional expectations are linear, i.e.  $E(\theta|t_i) = a + b \cdot t_i$  where:

$$a = \mu_\theta - \frac{\sigma_{\theta t_i}}{\sigma_{t_i}^2} + \mu_{t_i}$$

$$b = \frac{\sigma_{\theta t_i}}{\sigma_{t_i}^2}$$

Note that:

$$\theta = \mu_\theta + \varepsilon_\theta \quad \text{and} \quad E(\theta) \equiv \bar{\theta} = \mu_\theta$$

$$t_i = \mu_\theta + \varepsilon_\theta + \varepsilon_i \quad \text{and} \quad E(t_i) \equiv \bar{t}_i = \mu_\theta$$

Thus:

$$\frac{\sigma_{\theta t_i}}{\sigma_{t_i}^2} = \frac{E[(t_i - \bar{t}_i)(\theta - \bar{\theta})]}{E[(t_i - \bar{t}_i)^2]} = \frac{E[(\varepsilon_i + \varepsilon_\theta)(\varepsilon_\theta)]}{E[(\varepsilon_i + \varepsilon_\theta)^2]} = \frac{E[\varepsilon_i \varepsilon_\theta + \varepsilon_\theta^2]}{E[\varepsilon_i^2 + 2\varepsilon_i \varepsilon_\theta + \varepsilon_\theta^2]} = \frac{\sigma_\theta^2}{\sigma_i^2 + \sigma_\theta^2}$$

$$E[\theta|t_i] = \mu_\theta - \frac{\sigma_{\theta t_i}}{\sigma_{t_i}^2} \mu_{t_i} + \frac{\sigma_{\theta t_i}}{\sigma_{t_i}^2} t_i = \mu_\theta - \frac{\sigma_\theta^2}{\sigma_i^2 + \sigma_\theta^2} \mu_{t_i} + \frac{\sigma_\theta^2}{\sigma_i^2 + \sigma_\theta^2} t_i$$

$$= \mu_\theta - \frac{\sigma_\theta^2}{\sigma_i^2 + \sigma_\theta^2} \mu_\theta + \frac{\sigma_\theta^2}{\sigma_i^2 + \sigma_\theta^2} t_i = \mu_\theta \left[ 1 - \frac{\sigma_\theta^2}{\sigma_i^2 + \sigma_\theta^2} \right] + \frac{\sigma_\theta^2}{\sigma_i^2 + \sigma_\theta^2} t_i$$

$$= \mu_\theta [1 - w_i] + w_i t_i$$

where  $w_i \stackrel{\text{def}}{=} \frac{\sigma_\theta^2}{\sigma_i^2 + \sigma_\theta^2}$

U. *Proof of Proposition 2:*

We wish to show that for the same expected beliefs ( $b_i = b_j \equiv b$ ), lender  $i$ 's expectations about  $j$ 's beliefs are the same as  $j$ 's expectations about  $i$ 's beliefs:

$$E_i(b_j | b_i=b) = E_j(b_i | b_j=b)$$

We begin by finding an expression for  $E_i(t_j | t_i)$  using the expressions we used for  $t_i$ ,  $t_j$  and obtained for  $b_i(t_i) \equiv E(\theta|t_i)$  from the proof of Proposition 1. Thus:

$$E_i[t_j | t_i] = E[\varepsilon_j + \varepsilon_\theta | \varepsilon_i + \varepsilon_\theta] = E[\varepsilon_j | \varepsilon_i + \varepsilon_\theta] + E[\varepsilon_\theta | \varepsilon_i + \varepsilon_\theta] = E[\varepsilon_j | \varepsilon_i + \varepsilon_\theta]$$

Note that  $E[\varepsilon_j | \varepsilon_i + \varepsilon_\theta] \equiv E[\theta | t_i]$  and remember from Proposition 1 that

$$E[\theta | t_i] = \mu_\theta \left[ 1 - \frac{\sigma_\theta^2}{\sigma_i^2 + \sigma_\theta^2} \right] + \frac{\sigma_\theta^2}{\sigma_i^2 + \sigma_\theta^2} t_i$$

Thus we have:

$$E_i[t_j | t_i] = E[\varepsilon_j | \varepsilon_i + \varepsilon_\theta] = \mu_\theta \left[ 1 - \frac{\sigma_\theta^2}{\sigma_i^2 + \sigma_\theta^2} \right] + \frac{\sigma_\theta^2}{\sigma_i^2 + \sigma_\theta^2} t_i = b_i$$

Now, we can use this expression together with the known value for  $j$ 's weighting factor ( $w_j = \frac{\sigma_\theta^2}{\sigma_j^2 + \sigma_\theta^2}$ ) to obtain  $i$ 's expectation of  $j$ 's beliefs:

$$\begin{aligned} E_i[b_j | t_i] &= w_j E_i[t_j | t_i] = \frac{\sigma_\theta^2}{\sigma_j^2 + \sigma_\theta^2} \left( \mu_\theta \left[ 1 - \frac{\sigma_\theta^2}{\sigma_i^2 + \sigma_\theta^2} \right] + \frac{\sigma_\theta^2}{\sigma_i^2 + \sigma_\theta^2} t_i \right) \\ &= \frac{\sigma_\theta^2}{\sigma_j^2 + \sigma_\theta^2} \left( \frac{\sigma_i^2}{\sigma_i^2 + \sigma_\theta^2} \mu_\theta + \frac{\sigma_\theta^2}{\sigma_i^2 + \sigma_\theta^2} t_i \right) \end{aligned}$$

when  $\mu_\theta = 0$ , this expression becomes:

$$E_i[b_j | t_i] = \frac{\sigma_\theta^2}{\sigma_j^2 + \sigma_\theta^2} \left( \frac{\sigma_\theta^2}{\sigma_i^2 + \sigma_\theta^2} t_i \right) = \frac{\sigma_\theta^4}{(\sigma_i^2 + \sigma_\theta^2)(\sigma_j^2 + \sigma_\theta^2)} t_i$$

We can then see that  $E_i[b_j | t]$  and  $E_j[b_i | t]$  yield the same expression.

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