Understanding Expert Choices Using Decision Time*

David Card
UC Berkeley and NBER

Stefano DellaVigna
UC Berkeley and NBER

Chenxi Jiang
UC Berkeley

Dmitry Taubinsky
UC Berkeley and NBER

April 2024

Abstract

Laboratory experiments find a robust relationship between decision times and perceived values of alternatives. This paper investigates how these findings translate to experts' decision making and information acquisition in the field. In a stylized model of expert choice between two alternatives, we show that (i) less-commonly chosen alternatives are more likely to be chosen later than earlier; (ii) decision time is higher when the likelihood of choosing each alternative is closer to fifty percent; and (iii) the ultimate quality of the chosen alternative may increase or decrease with decision time, depending on whether earlier or later signals are more informative. We test these predictions in the editorial setting, where we observe proxies for paper quality and signals available to editors. We document that (i) the probability of a positive decision rises with decision time; (ii) average decision time is higher when our estimated probability of a positive decision is closer to fifty percent; and (iii) paper quality is positively (negatively) related to decision time for papers with Reject (R&R) decisions. Structural estimates show that the additional information acquired in editorial delays is modest, and has little impact on the quality of decisions.

*We thank Carlos Alos-Ferrer, Juan Carrillo, Ian Krajbich, Alessandro Lizzeri, Massimo Marinacci, Nick Netzer, Pietro Ortoleva, and participants in seminars at Bocconi, Cornell, Northwestern (Kellogg), NUS, Princeton, the ASSA 2024 conference, the AFE Conference, the University of Chicago, USC, and the University of Zurich for helpful comments. We are grateful to Rohan Jha and Christopher Lim for outstanding research assistance. We also thank Raj Chetty, Emmanuel Saez, and Laszlo Sandor for sharing data.

A long literature in psychology, going back at least to Dashiell (1937), provides evidence of a "chronometric effect" in decision-making: in various laboratory tasks, subjects take longer to choose between items with more similar evaluations, as they introspect to ascertain their preferences. A related literature in neuroscience models the time to a decision—often involving the decoding of complex images—using drift-diffusion models (DDMs, e.g., Ratcliff and Rouder, 1998; Milosavljevic et al., 2010; Krajbich and Rangel, 2011; Krajbich et al., 2012). In these models, faster decisions are more likely to be the ones where subjects received a strong signal favoring one of the options, and thus the speed of decision provides information on the subject preferences.

Recent studies by economists have also connected decision times to choices in lab-based settings (e.g., Krajbich et al., 2014; Chabris et al., 2008; Clithero, 2018a,b; Schotter and Trevino, 2021; Frydman and Krajbich, 2022; Reshidi et al., 2024; Alós-Ferrer and Garagnani, forthcoming). It remains an open question, however, whether decision times can contribute to a better understanding of choices in the field.[1] One potential barrier is that while psychologists typically assume that delays reflect subjects using introspection to determine their preferences for the alternatives, in field settings delays may also reflect more extensive information gathering, such as calling on additional experts or gathering external information on a case. Moreover, while the laboratory provides a measure of decision time exclusively devoted to a particular choice, delays in the field also include the time spent on alternative, intervening decisions. For example, only a fraction of the decision time of editors and referees is actively spent on evaluating a paper. Indeed, some cognitive scientists have warned explicitly about the usefulness of DDM's outside of contexts with very short decision horizons: "*The [drift-diffusion] model should be applied only to relatively fast two-choice decisions (mean RTs less than about 1000 to 1500 ms)*" (Ratcliff and McKoon, 2008).

In this paper, we investigate whether the insights from lab-based settings extend to expert decision making in the field. Guided by a stylized model of optimal information acquisition, we analyze editorial decisions at four leading economics journals. We provide both reduced-form and structural estimates of the relationship between decision time and the decisions and recommendations made by editors and referees.

The intuition of our model is simple. Consider an expert—for example, a journal editor, a patent officer, or an employer—who is tasked with making an up or down decision on a prospect such as a submitted paper, a patent filing, or a job application. The expert performs an initial evaluation (for example, reading the first referee report on the paper), and then decides whether to make the decision with only that information, or collect additional information. Collecting additional information involves costly delays, but allows a more

[1] Among the few other studies of decision time in field behaviors are the analysis of eBay bidding times in Cotet and Krajbich (2021) and of chess moves in Sunde et al. (2022). Also related is Canen and Iaryczower (2024), who study deliberation by committees.

informed decision. The value of additional information will be highest when the initial evaluation is close to the margin. Thus, an early decision implies that the initial information was strongly positive or strongly negative. In this way, decision time conveys information on the strength of the case as initially assessed by the expert.

This model makes three main predictions about the relationship between expert choices and decision time. The first is that the likelihood of choosing each alternative moves toward fifty percent as more information is acquired, and thus with decision time. Intuitively, alternatives that are ex-ante estimated to have a lower payoff will not be chosen in the absence of additional information, but their likelihood of getting chosen increases with more information. In the editorial setting, where R&R decisions are relatively uncommon, the prediction is that the likelihood of an R&R decision should increase with time.

A second prediction mirrors the "chronometric effect" that is extensively documented in laboratory studies (Clithero, 2018b). Building on Alós-Ferrer et al. (2021), who formalize this effect to concern the ex-post realized utility of each alternative, we use our model of optimal information acquisition to derive a micro-founded variation that can be implemented in field settings, where ex-posted realized utility cannot be perfectly observed. Our prediction concerns how decision times are related to the expected quality and likelihood of choosing each alternative, conditional on the information observed by the analyst. In the context of our editorial setting, our prediction is that under some regularity conditions, the closer an analyst's estimate of the paper receiving an R&R is to fifty percent, the more likely the expert is to delay to acquire additional information.

The third prediction concerns the relationship between decision time and the ultimate payoff from each alternative. We show that this depends on two competing forces. The first is a *selection effect* that arises from the tendency to make an early decision in cases with the strongest initial signals (positive or negative). The second is a *learning effect* that arises because delayed decisions are made with extra information. We show that the selection effect dominates if early signals are more informative, while the learning effect dominates if later signals are more informative. In the former case, the implication for our editorial setting is that for papers with R&R decisions, quality will decrease with decision times, while for papers with Reject decisions, quality will increase.

Guided by this stylized model, we analyze expert choices and decision times in the editorial setting, where we observe detailed information on decisions and decision times as well as a proxy for the quality of each choice. We study decision making at four high-impact economics journals: the *Quarterly Journal of the Economics*, the *Review of Economic Studies*, the *Review of Economics and Statistics*, and the *Journal of the European Economic Association.* For over 15,000 non-desk-rejected submissions, we observe the following: (i) recommendations of the referees and the editor's decision to reject the paper or invite a revision (i.e., a verdict of "revise and resubmit", R&R), (ii) the number of days from first submission to the arrival of each referee report, and to the subsequent editorial decision, and (iii) cumulative Google Scholar citations to the manuscript.[2] The simplicity of the model allows us to interpret its predictions for different types of experts (editors or referees), and various measures of decision time.

We first test that the share of positive decisions tends toward fifty percent with decision time. Across all four journals, R&R rates are far below fifty percent, but rise with decision time. The same pattern is apparent for referee recommendations: the longer the time taken by a referee, the more positive is the recommendation.

Second, we test for the chronometric effect, focusing on the decision to wait for a third referee report when two have been received. In our first set of tests, we estimate the predicted probability of R&R based on the recommendations of the first two referees, and calculate how the average propensity to wait for additional referees varies with our estimated R&R probability. We find that average decision time is increasing in the probability of an ultimate R&R for papers where we estimate the likelihood of an R&R to be below fifty percent. It is more difficult to test whether decision times fall once our estimated likelihood of an R&R exceeds fifty percent, because there are relatively few papers in that category. To obtain more variation in the predicted likelihoods of an R&R, we extend our approach by incorporating the prior publications of the first two referees to form our prediction of R&R probability, as previous work has shown that editors put more weight on the recommendations of highly-published referees (Card and DellaVigna, 2020). With this expanded set of predictors, we confirm that the likelihood of waiting for additional referees is decreasing in the extent to which our predicted R&R probability exceeds fifty percent. This confirms the second prediction of our model, and parallels findings of the "chronometric effect" in the laboratory.

Finally, we provide extensive analyses of the relationship between decision time and the quality of the available choices. This key set of results illustrates how decision time can be used to reveal additional information about the quality of alternatives, beyond what standard choice data can reveal. In our main set of results, we consider citations to be a noisy proxy for paper quality. We find that citations for rejected papers are strongly *positively* related to decision time: 100 extra days of decision time are associated with an increase of 32 points (s.e.= 3) in asinh citations. For papers that receive an R&R decision, on the other hand, we find that citations are *negatively* related to decision time: a decrease of 8 points (s.e. = 5) of asinh citations for 100 extra days of delay. Analogously, and connecting to our tests of the chronometric effect, we find that citations are strongly increasing in the number of

[2] As we discuss below, citations are imperfect and possibly biased measures of quality. Our empirical model includes controls for field and author publication record, as well as for the journal and year of submission, to address these limitations. We also consider a wide variety of alternative transformations of citations to address the skewness in the distribution of citations.

referees that the editor waits for in Reject decisions, and modestly decreasing in the number of referees the editor waits for in R&R decisions. These results hold for a rich set of controls, and are robust to variation in the controls that we use. Through the lens of our stylized model, the *selection* effect dominates the *learning* effect. This result is also consistent with the collapsing boundaries prediction derived by Fudenberg et al. (2018).

We test the robustness of these results in three ways. First, the results are consistent for different transformations of the citation variable and at different quantiles of citations, addressing concerns about any particular transformation of citations (Chen and Roth, 2023). Second, the relationship between decision time and citations, conditional on a recommendation/decisions, holds separately for both the editor and for the referees. Third, for papers with an R&R, we observe an alternative proxy for quality. Specifically, longer decision times are associated with a lower probability of ultimate publication and with longer delays until resubmission, consistent with our interpretation that these are lower quality R&Rs.

Last, we structurally estimate our model. We classify papers with above- or below-median decision time for a given journal as papers where the expert has chosen to acquire more versus less information, respectively. We consider asinh citations to be our noisy proxy for quality, allowing both idiosyncratic noise and systematic "citations bias" that comes from having a paper published in one of the four journals. Using a method of moments approach, we estimate the model to match the share of positive decisions when the expert acquires more versus less information, and the average citations for each of the four pairs of fast/slow and R&R/Reject decisions. The estimates almost perfectly match the empirical moments, and imply that above-median delays contain relatively little additional information. Indeed, there would be minimal impact on the quality of editorial decisions under a counterfactual in which none of the delays exceed the current medians. The above-median delays seem to be the consequence of low delay costs to the editors and referees—who, arguably, do not fully internalize delay-induced externalities imposed on the submitting authors.

Our paper is related to work on decision time in cognitive psychology, neuroscience and economics laboratory experiments. The stylized model that we use to organize our empirical results is complementary to continuous-time models of optimal information acquisition (e.g., Fudenberg et al., 2018; Baldassi et al., 2020; Liang et al., 2022), to optimal sequential sampling models with long horizons (e.g., Wald, 1947; Wald and Wolfowitz, 1948; Moscarini and Smith, 2001; Reshidi et al., 2024),[3] and to early drift-diffusion models from the cognitive sciences, where information acquisition strategies are assumed rather than derived as optima of some objective function (e.g., Swensson, 1972; Luce, 1986; Ratcliff and McKoon, 2008).[4] While the larger contribution of our paper is the empirical component, one advan-

[3]We note, however, that in these models quality is typically binary rather than continuous, which is another important difference from our work.

[4]The model also complements the screening framework of Lagziel and Lehrer (2019, 2022), who do not

tage of our simple model is that it allows for different signal informativeness over time, as well as variation in the costs of information acquisition—both of which may be important for understanding how decision quality varies with decision time in the field, as our structural estimates illustrate. Another advantage of our simple model is that it allows us to analyze how optimal information acquisition relates to the chronometric effects from prior work, especially in cases where the analyst only has access to noisy proxies for the utility difference between alternatives. Of course, by modeling the experts as optimizing, Bayesian decision-makers, our model does not incorporate the notion of fast heuristics that two-system models (e.g., Kahneman, 2011) stress.

Our empirical results extend the analysis of decision time to the field, building on a vast laboratory literature.[5] Our work is in the spirit of Alós-Ferrer et al. (2021) who provide an econometric framework for understanding decision time in a discrete choice setting, of Liu and Netzer (2023) who emphasize the use of decision time data to help identify preferences from survey responses, and of Cotet and Krajbich (2021) who show that decision time is correlated with the behavior of buyers and sellers on eBay. More broadly, our paper is related to work that proposes the use of "non-standard" data to understand behavior, such as survey responses, neural activity (Smith et al., 2014), or attention tracking (Wang et al., 2010; Bartoš et al., 2016). It is also related to the recent literature stressing cognitive noise in perception (e.g., Woodford, 2019; Enke and Graeber, 2023; Oprea, 2023), which may, in part, be the outcome of an internal or external information acquisition process.

The rest of the paper proceeds as follows. Section 1 introduces the model. Section 2 presents the data and summary statistics on editorial choices, which we analyze in Section 3. We present structural estimates in Section 4 and conclude in Section 5.

1 Model

1.1 Setup

Consider an expert (e.g, editor, referee, judge, doctor, manager) who must make an up-down decision, such as whether or not to invite a paper for resubmission, whether or not to convict, whether or not to recommend treatment, or whether or not to hire an employee. The expert

have a second signal, but make more general assumptions about the prior and the first signal. We also complement the two-period model in Konovalov and Krajbich (2023), where a buyer negotiating with a seller learns for free if her value for a product is above or below the price, and then can pay an additional cost c to exactly learn her value for the product.

[5]For laboratory results see, e.g.: Chabris et al. (2008); Gabaix et al. (2006); Krajbich et al. (2010); Milosavljevic et al. (2010); Caplin et al. (2011); Krajbich and Rangel (2011); Krajbich et al. (2012, 2015); Alós-Ferrer et al. (2016); Clithero (2018a); Alós-Ferrer et al. (2021); Frydman and Krajbich (2022); Reshidi et al. (2024)

begins with a prior and acquires an initial signal. After the initial signal, the expert can choose to make an up or down decision, or to acquire a second costly signal, before making the up/down decision. For concreteness, we will sometimes use language that corresponds mostly closely to the editorial setting—though our framework is of course more general.

We let q denote the quality of the paper, and q^* the "bar" for a positive decision $D = 1$ (e.g., an R&R decision), such that an expert's payoff from choosing $D = 1$ is $\kappa \cdot (q - q^*)$ (for $\kappa > 0$) and the payoff from choosing $D = 0$ is $\kappa \cdot (q^* - q)$.[6] The expert begins with a prior about q, forms a posterior after the initial signal S_1, and potentially forms an updated posterior after a potential second signal S_2. The signals S_1 and S_2 are independent conditional on q. The cost of acquiring the second signal, c_2, is observed by the expert before they decide whether or not to acquire the second signal, and may be stochastic. For example, how idiosyncratically busy an editor or referee is at a particular point influences how much time they are willing to commit to a paper. We make the technical assumption that the distribution of costs is bounded from above and below, and that c_2 is independent of q, S_1, and S_2.[7]

We make several other simplifying assumptions, for the purpose of easing exposition and connecting our model tractably to the data. We assume that q, S_1 and S_2 are all normally distributed with known variances, with $S_j \sim N\left(q, \omega_j^2\right)$ for scalars $\omega_j > 0$. Without loss of generality, we normalize the prior mean of q to be zero, and normalize $\kappa = 1$.[8]

A Simplifying Restatement Let $\mu_1 := \mathbb{E}[q|S_1]$ denote the random variable that corresponds to the expert's expectation of q after signal S_1. Let $\mu_2 := \mathbb{E}[q|S_1, S_2]$ denote the maximal-information assessment that results from acquiring both signals.[9] Our assumptions guarantee that μ_1 and μ_2 are both normally distributed, and that μ_2 is normally distributed conditional on μ_1, with $\mathbb{E}[\mu_2|\mu_1] = \mu_1$. We let σ_1^2 denote the variance of μ_1 and let σ_2^2 denote the variance of μ_2 conditional on μ_1. By the law of total variance, the *unconditional* variance of μ_2 is simply $Var(\mu_2) = \sigma_2^2 + \sigma_1^2$.

Consider now the expert's decisions: whether to decide quickly after the first signal,

[6] Plainly, the results are identical if the payoff from choosing $D = 0$ is instead $\kappa_0 \cdot (q^* - q)$ for some scalar $\kappa_0 \geq 0$. This is because all that matters is the difference in payoffs between choosing $D = 1$ and $D = 0$.

[7] Introducing an additional cost for acquiring S_1 would not add new insights: the expert would choose not to acquire S_1 for q^* sufficiently far from the prior mean, but would otherwise acquire it. The case in which q^* is sufficiently far from the prior mean is not an interesting one, as in this case all all experts behave identically and there are no comparative statics on decision time. Our set-up can be seen as making the (implicit) assumption that the cost of S_1 is sufficiently low that the expert chooses to acquire S_1 for the parameters we consider.

[8] Normalizing the prior mean of q to zero is without loss of generality because the bar q^* is left as a free parameter, and decisions depend on the difference between the prior mean and q^*. Normalizing κ to equal 1 is without loss of generality because scaling up the payoffs is equivalent to scaling up the prior standard deviation of $q - q^*$.

[9] We note that μ_2 is a well-defined object even in cases where the expert chooses not to acquire S_2—in such cases μ_2 is the posterior mean the expert would have *if* they had acquired S_2.

$\tau = 1$, or to decide more slowly after the second signal, $\tau = 2$, and whether to decide positively or negatively, $D \in \{0, 1\}$. We will refer to τ as decision time. We let $Pr(\tau, D)$ denote the ex-ante (i.e., before the realization of any signals) probability of each possible decision pair, and we let $\mathbb{E}[q|\tau, D]$ denote the average quality for each possible decision.

Lemma 1. *The ex-ante distribution of expert decisions, $Pr(\tau, D)$, as well as the resulting average quality for each decision $\mathbb{E}[q|\tau, D]$, are fully determined by the tuple $(\sigma_1^2, \sigma_2^2, q^*)$ and the distribution of c_2. The tuple (σ_1^2, σ_2^2) can be any element of $\mathbb{R}^+ \times \mathbb{R}^+$.*

Intuitively, the expert's expected payoff from choosing $D \in \{0, 1\}$ after the second signal depends only on $\mu_2 - q^*$. Consequently, the expert's decision after the first signal—up, down, or acquire S_2—depends only on $\mu_1 - q^*$ and on beliefs about μ_2. The quantity $\mu_1 - q^*$ determines the expert's payoff from making a decision after the first signal. Beliefs about μ_2, together with the cost c_2, determine the net value of acquiring more information. Moreover, by the law of iterated expectations, $\mathbb{E}[q|\tau = 1, D] = \mathbb{E}[\mu_1|\tau = 1, D]$ and $\mathbb{E}[q|\tau = 2, D] = \mathbb{E}[\mu_2|\tau = 2, D]$. Thus, once the distributions of μ_1 and μ_2 are known, additional information about the prior about q, or the precisions of the signals S_1 and S_2, is not helpful.

We make use of Lemma 1 in the analysis that follows, where we state results in terms of σ_1^2 and σ_2^2. Intuitively, σ_1^2 reveals how much information is revealed early, while σ_2^2 reveals how much additional information is revealed after additional delay.

1.2 Expert Strategies and Decisions

We begin by showing that the expert's strategy follows a symmetric threshold rule:

Lemma 2. *For each realization c_2, there exists a $\Delta(c_2) \geq 0$ such $\tau = 2$ if and only if $\mu_1 \in [q^* - \Delta(c_2), q^* + \Delta(c_2)]$, where $\Delta(c_2)$ does not depend on q^*, and is decreasing in c_2 and increasing in σ_2.*

Lemma 2 formalizes the intuition that the expert will choose to acquire more information when their initial assessment of quality is close to the bar q^*. When the expert's initial assessment is far above or below the bar, the likelihood that additional information will change the expert's decision is lower. The decision to acquire additional information depends on distance to the bar, $\mu_1 - q^*$, but not on the bar q^* itself. The expert is less likely to acquire additional information when the cost of doing so, c_2, is higher, and is more likely to acquire additional information when σ_2 is higher and thus more information is revealed by the second signal. In some of the analysis, we will use the simple characterization in Lemma 2 to discuss predictions in terms of the thresholds Δ rather than the costs c_2.

Figure 1 provides a visual illustration, for an expert who evaluates papers of quality q, choosing between R&R ($D = 1$) or Reject ($D = 0$). The figure displays the value to the agent of the R&R if deciding based only on the period-1 information, in which case the agent chooses $D = 1$ if $\mu_1 > q^*$. The higher line displays the value to the agent of acquiring additional information. The extra value of the second signal is highest when $\mu_1 = q^*$ and it declines as μ_1 moves further away from q^*. The thresholds $q^* - \Delta(c_2)$ and $q^* + \Delta(c_2)$ are where the value of additional information is c_2.

Because the expert's information changes with decision time, the likelihood of an up or down decision varies with decision time as well. Intuitively, if R&Rs are more rare than Rejects (i.e., $q^* > 0$), R&Rs are more likely when the expert has more information, all else equal. Indeed, without any information beyond the prior, the optimal decision is to always reject if $q^* > 0$. The nuance is that longer delays correspond not only to greater signal acquisition, but also to more marginal cases after the first signal. We establish below that despite this nuance, the more rare decisions (e.g., R&Rs) are more likely when more information is acquired, and also provide a simple diagnostic for establishing whether q^* is above or below 0.

Proposition 1. *The likelihood of a positive decision satisfies:*

1. $Pr(D = 1)$ *is strictly decreasing in* q^*, *with* $Pr(D = 1) = 1/2$ *when* $q^* = 0$.
2. $Pr(D = 1|\tau = 2) \geq Pr(D = 1|\tau = 1)$ *if and only if* $q^* \geq 0$, *with equality iff* $q^* = 0$.

1.3 Decision Difficulty and Decision Time

A fundamental property reported by economists and cognitive scientists working on decision time in the laboratory is that decision time increases with the utility difference between two options; see Alós-Ferrer et al. (2021) for a formal statement and review of this *chronometric* effect. One common approach is to use one set of decisions to estimate a utility difference $\tilde{v}$ between the two alternatives (e.g., using a Becker-DeGroot-Marschak, BDM, mechanism) and then show that participants take longer to decide between the alternatives when $\tilde{v}$ is closer to zero (e.g., Milosavljevic et al., 2010; Krajbich et al., 2012; Alós-Ferrer et al., 2016). Another approach is to study how participants choose in different pairs of alternatives, with each pair repeated multiple times, and to establish that participants take longest for pairs where their likelihood of choosing each alternative is closest to fifty percent, which corresponds to a $\tilde{v}$ closest to zero (e.g., Chabris et al., 2008; Milosavljevic et al., 2010; Krajbich et al., 2015; Clithero, 2018a). In this subsection, we draw connections between our model of optimal information acquisition and the chronometric effects found in laboratory experiments. We begin by considering a case where there is a proxy for the difference in the expert's expected utility between a positive versus a negative decision.

Proposition 2. *Suppose that there exists a random vector X and a real-valued function g such that $\mu_1 - q^* = g(X) + \eta$, where $\eta \perp X$, $\eta \perp c_2$, and where η is symmetrically distributed around 0 according to a single-peaked density function f_η. Then average decision time $\mathbb{E}[\tau|g(X)]$ is strictly decreasing in $|g(X)|$.*

To obtain intuition for the result, note that by Lemma 2, the likelihood of $\tau = 2$ is highest when μ_1 is most likely to be close to q^*. The variable X could be a noisy proxy for S_1, as in our empirical applications, or a noisy proxy for quality, as in the laboratory experiments with BDM elicitations.[10]

Next, we provide a result that connects $g(X)$ to observables, and motivates our tests.

Proposition 3. *Suppose that there exists a random vector X and a real-valued function g such that (i) $\mu_1 - q^* = g(X) + \eta$, with η satisfying the assumptions of Proposition 2; (ii) the distribution of $\mu_2 - q^*$ conditional on μ_1 is independent of X and η. Then $|Pr(D = 1|X) - 1/2|$ is strictly increasing in $|g(X)|$, and is 0 when $g(X) = 0$. Consequently, $\mathbb{E}[\tau|g(X)]$ is strictly decreasing in $|Pr(D = 1|X) - 1/2|$.*

Proposition 3 provides a simple approach to revealing situations in which $g(X)$ is closest to zero: these are the situations in which the likelihood of a positive decision, $Pr(D = 1|X)$, is closest to $1/2$. Consequently $|Pr(D = 1|X) - 1/2|$ is a measure of revealed decision difficulty.

Figure 2 illustrates Proposition 3 for the case in which we obtain a noisy proxy for S_1. Panel a shows how the probability of a positive decision, $Pr(D = 1)$, and the probability of acquiring a second signal, $Pr(\tau = 2)$ change with the proxy. The former is strictly increasing. The latter is an "inverse U," consistent with the threshold rule of Lemma 2. The relationship between $Pr(\tau = 2)$ and the proxy is smooth because the proxy is only an imperfect signal for μ_1. Panel b numerically illustrates the relationship between $\mathbb{E}[\tau|g(X)]$ and $Pr(D = 1|X)$.

[10] In the first example, suppose that $S_1|X \sim N(h(X), \sigma_\varepsilon^2)$ for some function h. Because $\mu_1 = \frac{Var(q)}{Var(S_1)} S_1$, $g(X) = \frac{Var(q)}{Var(S_1)} h(X) - q^*$ satisfies the assumptions of the proposition. In the case where $X = S_1 + \varepsilon_s$, where ε_s is idiosyncratic Gaussian noise, $h(X) = \frac{Var(S_1)}{Var(X)} S_1$. In the second case, consider a proxy $X = q - q^* + \varepsilon_q$, where ε_q is idiosyncratic Gaussian noise. Then

$$\begin{aligned}
\mu_1 - q^* &= \frac{Var(q)}{Var(S_1)} \mathbb{E}[S_1|q] + \frac{Var(q)}{Var(S_1)} \left(S_1 - \mathbb{E}[S_1|q]\right) - q^* \\
&= \frac{Var(q)}{Var(S_1)} \frac{Var(q)}{Var(X)} \alpha_1 X - \left(1 - \frac{Var(q)}{Var(S_1)} \frac{Var(q)}{Var(X)} \alpha_1\right) q^* + \eta
\end{aligned}$$

where $\eta = \frac{Var(q)}{Var(S_1)} \left(S_1 - \mathbb{E}[S_1|q] + \alpha_1 \left(q - \mathbb{E}[q|X]\right)\right)$. Because of the normality and independence assumptions, $\eta \perp X$.

1.4 Quality and Decision Time

Last, we turn to predictions about how $\mathbb{E}[q|D,\tau]$ varies with τ. Conditional on a decision being positive, does a longer decision time indicate that the quality of the paper is high, or that it is low? There are two opposing forces. On the one hand, longer decision time allows the expert to collect more information, which in turn allows for better screening, thus generating higher quality for positive decisions and lower quality for negative decisions. On the other hand, longer decision time means that after the first round of information gathering, the expert was sufficiently uncertain about whether the quality was above or below the bar. That is, the paper was initially assessed as fairly marginal, which pushes toward lower (higher) quality for the positive (negative) decisions.

To formalize these effects, we define the learning effect (LE) for decision D as

$$LE(D=1) := |\mathbb{E}[q|D=1,\tau=2] - \mathbb{E}[q|\mu_1 > q^*,\tau=2]|$$
$$LE(D=0) := |\mathbb{E}[q|D=0,\tau=2] - \mathbb{E}[q|\mu_1 < q^*,\tau=2]|$$

The intuition is as follows. For all papers for which the expert chooses to collect a second round of information, consider the average quality among the positive and negative decisions. A counterfactual is the average quality if the expert was forced to make an up-down decision *among that same set of papers* based on only the first signal. The learning effect is the difference in quality that results from using both signals versus just the first signal, fixing the set of "marginal" papers for which the expert chooses to collect both signals.

We define the selection effect (SE) as the expected difference in quality of "marginal" papers versus papers for which the expert makes a decision based on only the first signal:

$$SE(D=1) := |\mathbb{E}[q|D=1,\tau=1] - \mathbb{E}[q|\mu_1 > q^*,\tau=2]|$$
$$SE(D=0) := |\mathbb{E}[q|D=0,\tau=1] - \mathbb{E}[q|\mu_1 < q^*,\tau=2]|$$

We can decompose the quality change $\mathbb{E}[q|D,\tau=2] - \mathbb{E}[q|D,\tau=1]$ as

$$\mathbb{E}[q|D=1,\tau=2] - \mathbb{E}[q|D=1,\tau=1] = LE(D=1) - SE(D=1)$$
$$\mathbb{E}[q|D=0,\tau=2] - \mathbb{E}[q|D=0,\tau=1] = SE(D=0) - LE(D=0)$$

Generically, the learning effects will not equal the selection effects, and thus the quality of both positive and negative decisions should change with decision time. In a continuous time model where the signals have have time-invariant precision, Fudenberg et al. (2018) show that selection effects always dominate the learning effects, such that the expected utility difference between the two alternatives decreases with time. However, we show below that without additional assumptions about the diffusion of information, either the selection or learning effects could dominate. Intuitively, holding all else equal, learning effects dominate when more information is revealed by the second signal, so that σ_2^2 is high relative to σ_1^2, while selection effects will dominate when the converse is true. We formalize this below.

Proposition 4. *Holding q^* and the distribution of $\Delta(c_2)$ constant, for each $D \in \{0, 1\}$,*

1. $\lim_{\sigma_2 \to \infty} LE(D) = \infty$ *and* $\lim_{\sigma_2 \to 0} LE(D) = 0$
2. $\lim_{\sigma_1 \to \infty} SE(D) = \infty$ *and* $\lim_{\sigma_1 \to 0} SE(D) = \mathbb{E}[\Delta(c_2)]$
3. $\mathbb{E}[q|D, \tau = 2] - \mathbb{E}[q|D, \tau = 1]$ *is not bounded from above or below as a function of σ_1 and σ_2.*

In addition to how much information is revealed early versus late, the amount of variation in the costs of information acquisition also matters. Consider the extreme where $\Delta(c_2)$ is either extremely low or extremely high, such that whether $\tau = 1$ or $\tau = 2$ is effectively determined by $\Delta(c_2)$ rather than by μ_1. In this case, there is effectively no selection effect. Thus, all that's left is the learning effect, and the quality of positive (negative) decisions will be higher (lower) when $\tau = 2$ than when $\tau = 1$. We formalize this as follows:

Proposition 5. *Suppose that $\Delta(c_2) \in \{\Delta(c_l), \Delta(c_h)\}$. Holding constant $Pr(\Delta(c_2) = \Delta(c_l))$,*

$$\lim_{\Delta(c_h) \to 0} \lim_{\Delta(c_l) \to \infty} (\mathbb{E}[q|D = 1, \tau = 2] - \mathbb{E}[q|D = 1, \tau = 1]) = \mathbb{E}[\mu_2|\mu_2 > q^*] - \mathbb{E}[\mu_1|\mu_1 > q^*] > 0$$
$$\lim_{\Delta(c_h) \to 0} \lim_{\Delta(c_l) \to \infty} (\mathbb{E}[q|D = 0, \tau = 2] - \mathbb{E}[q|D = 0, \tau = 1]) = \mathbb{E}[\mu_2|\mu_2 < q^*] - \mathbb{E}[\mu_1|\mu_1 < q^*] < 0$$

A key implication of Proposition 5 that guides our setup of the structural model is that variation in costs may be necessary to match all of the empirical moments. While data on the joint distribution of (D, τ), together with the difference in average quality between positive and negative decisions (a total of four moments), can identify σ_1^2, σ_2^2, and q^* and a deterministic cost c_2 (a total of four parameters), matching how quality varies with τ separately for positive versus negative decisions may require variation in the costs c_2.

1.5 Discussion

We use a simple, two-period model to distill several basic insights about optimal information acquisition that can be tested and quantified in data sets such as ours. We focus on insights that we think should hold more broadly for models with more periods (or continuous time), or for models with more general assumptions about the information structure, though a complete analysis of these generalizations is beyond the scope of this paper. The prediction of Proposition 1 that more rare decisions are more likely to be taken after more information (and thus longer delays) is likely to be robust. The chronometric effect of Propositions 2 and 3, that the expert will take longer to decide in cases where the difference in expected payoffs from the two alternatives is on average small, is not only empirically robust, but also clearly follows from basic principles of optimal information acquisition. Finally, Propositions 4 and 5 present intuitive comparative statics about the role of information diffusion and cost variation that don't leverage the special assumptions of our simple setup.

Some specific predictions, such as the symmetry of the decision rule to acquire more information, are less likely to be robust. For example, if the payoff function were nonlinear, because it is more costly to accept a paper that is below the bar than it is to reject a paper that is above the bar, then the expert would be more likely to acquire additional information when the initial assessment places the paper above the bar rather than below the bar.

2 Data and Summary Statistics

Data. Our data set is based on the one collected by Card and DellaVigna (2020), with some additional processing as detailed in the Online Appendix D. The sample includes all first submissions (i.e., excluding revisions) at four leading economics journals—all using the Editorial Express (EE) manuscript system. The journals, years, and sample sizes are:

- *Quarterly Journal of Economics* (QJE), 2005-2013, $n = 10,632$
- *Review of Economic Studies* (REStud), 2005-2013, $n = 6,896$
- *Review of Economics and Statistics* (REStat), 2006-2013, $n = 5,467$
- *Journal of the European Economic Association* (JEEA), 2003-2013, $n = 4,364$.

The available information for each paper includes year of submission, number of days from initial submission until each referee report was received, number of days from submission to the first-round editor decision (rounded to the closest 10 days),[11] field (based on the first 2 characters of the JEL codes at submission), publication record of the author(s) and any assigned referee(s), summary recommendations of the referees, an (anonymized) identifier for the specific editor handling the paper (except at *REStat*), citation information from Google Scholar (GS) collected at the time of data extraction, and the editor's decisions regarding

[11] This information was not used in Card and DellaVigna (2020).

desk rejection and R&R status.[12] For confidentiality reasons, the title, the names of authors and referees, and the exact submission date were deleted in the data extraction process.

Summary Statistics. Figure 3 summarizes sample characteristics by journal. Panel a shows the fractions of papers that were desk rejected, rejected after review, or received an R&R invitation. Desk rejections were relatively common at *QJE* and *REStat* (61% and 56% of initial submissions respectively), and less common at *REStud* and *JEEA* (23% and 25%, respectively). The R&R rate ranges from 4% at *QJE* to 11% at *REStat*. Panel b shows information on the referee recommendations for papers that were sent for review. The EE system allows referees to enter one of 8 summary recommendations ranging from "Definitely Reject" to "Accept".[13] The modal recommendation is *Reject* at all four journals: between 53% (*REStat*) and 69% (*QJE*) of all recommendations are "Definitely Reject" or "Reject".

Table 1 displays the controls we use in our analysis. The JEL codes provided by the author(s) allow us to determine whether the paper belongs to one of 15 field categories listed in Table 1. To account for multiple field codes we set the indicator for a field equal to $1/J$, where J is the number of fields to which the paper is assigned. The most common fields are labor (11% of submissions), micro (11%) and macro (10%).

To measure publications of authors and referees, we constructed a database of economists who had published a paper in one of 35 high-quality journals between 1991 and 2014 (see Card and DellaVigna, 2020). We then used this database to assign to each submitted paper the number of papers published by the author in the previous 5 years (setting the number to 0 for authors with no publications in the window). For papers with multiple authors, we assigned the publication count of the most prolific coauthor. Similarly, we created a measure of the number of publications in the so-called top-5 economics journals[14] over the past 5 years by the author(s) of each submission. We used the same procedure to measure previous publications of referees at the time they were assigned to a paper.

Two key variables for analysis are citations and decision times. We recorded the number of GS citations for each paper at the time of the data extraction (in April 2015 for *QJE* and *REStat*; and in August 2015 for *REStud* and *JEEA*). We matched paper titles from the EE system to GS using the *allintitle* function, which requires *all words* in the EE title to be contained in the GS title. We then captured the top 10 entries provided by GS, and summed the citation counts for all entries for which at least one coauthor's surname matched the author list in EE. Thus we measure citations to papers regardless of publication status, and sum citations to alternative versions of a submitted paper. Papers with no GS match were

[12] The data set does not include any information on demographic characteristics of the authors or referees, such as age, year of highest degree, and does not track authors or referees across papers.

[13] We combine the categories "Conditionally Accept" and "Accept", which are rare, into the "Accept" category.

[14] The *American Economic Review* (excluding the *Papers and Proceedings*), *Econometrica*, the *Journal of Political Economy*, the *Quarterly Journal of Economics*, and the *Review of Economic Studies.*

coded as having zero citations.

Citation counts are highly skewed: about 30% of submitted papers have no citations, while some papers have hundreds of citations. In much of our analysis we use the inverse hyperbolic sine (*asinh*) of citations, and we summarize the distributions in Panel c of Figure 3. The *asinh* function closely parallels the natural logarithm function when there are 2+ citations, but is well defined at 0. We document robustness to alternative transformations in our main results.

Turning to decision times, Panel d shows the cumulative density functions (CDFs) by journal of the elapsed time from submission to the editorial decision.[15] The CDFs vary across journals, partly reflecting differences in desk rejection rates. At the *QJE*, over 50 percent of submissions were decided within 10 days, and nearly all were decided within 100 days. At the other journals the decision times are longer, with 80 percent of submissions decided within 160 days at *REStat* and *JEEA* and 180 days at *REStud*. Given these differences, we control for journal or journal×year fixed effects in our analysis.[16]

Finally, Panel e of Figure 3 reports the number of decisions for each editor in the sample. For the majority of editors we observe > 100 decisions, and in some cases over 1000, allowing us to control for editor fixed effects.

Determinants of Citations and Decision Time. Columns 2-7 of Table 1 report regressions of first-round decision time (Columns 2-4) and asinh of citations (Columns 5-7) on the variables described in the rows, as well as journal×year and editor fixed effects. We present results for all submissions (Columns 2 and 5), for submissions that were reviewed by referees and received an R&R (Columns 3 and 6), and for papers that were reviewed and rejected (Columns 4 and 7). Column 2 suggests that overall decision time (incorporating desk rejections) varies slightly by field, being lower in history and development and higher in econometrics, macroeconomics and finance. Overall decision time is similar between sole-authored papers and those with multiple authors, and is weakly positively related to author publications.

However, when separately analyzing papers receiving a Reject versus an R&R, there are larger differences across fields and across categories of authors. Among papers that receive an R&R, the difference in mean decision time between papers in development (the fastest field) and econometrics (the slowest) is about 60 days. The field differences are smaller for rejected papers (e.g., only a 13-day difference between development and econometrics). The opposite pattern emerges for differences between more- and less-published authors. Among R&Rs,

[15] In our data sharing agreements with the journals we agreed to censored decision times at 200 days. We use the censored time in all our specifications below.

[16] Appendix Figure A1 displays the distributions of two other decision time variables: the referee decision time, computed as the number of days from paper submission to the logging of a referee report on the EE system; and the editor's decision time, computed as the number of days from the last completed report to the editor's initial decision.

the differences in decision time for papers by authors with different publication records are relatively modest, whereas for rejected papers there is a clear tendency to take longer in cases where the author is more highly published.

There are also differences in citations by field, size of the co-author team, and the prior record of the authors. As shown in Column 5, papers in international economics tend to be more cited, while papers in theory garner fewer citations. Papers with larger author team or by prolific authors receive more citations. Some of these differences remain even among R&R papers.

3 Empirical Results

This section reports a series of empirical tests motivated by the theoretical results. Because the model is stylized, we can interpret it in several different says. We consider the decisions of both editors and referees in the role of "expert." We also consider several different proxies for decision time or the number of signals acquired: (i) days to decision and (ii) how many referees the editor as expert waits for.

3.1 Share of Positive Decisions Over Time

Assuming that positive decisions are relatively unlikely, Proposition 1 predicts that the probability of an R&R verdict should rise with decision time. Figure 4 shows how the prevalence of Desk Rejections, Rejections, and R&Rs varies with first-round decision time at each of the four journals in our data. Desk Rejects are the most likely outcome for decisions in the first 10-30 days, after which Rejects becomes the most common decision. Consistent with the predictions from our model, the share of R&R decisions increases monotonically, from under 5% at all four journals in the first 40 days, to about 25% at the *QJE* after 100 days, and to 20-30% for the other journals after about 150 days. Thus, the prediction is clearly supported at all four journals.

We can also test this prediction at the referee level, as we do in Appendix Figure A2. The referee recommendations become more positive over time at all journals, though the pattern is somewhat muted at REStat.

3.2 Decision Time and the Probability of an R&R Decision

Propositions 2 and 3 state that if we condition on a vector X of information on the expert's posterior after the first signal (μ_1), then the probability of delaying the decision to the second period, conditional on X, is an "inverse-U" shaped function of the conditional probability of a positive decision, symmetric around $Pr(R\&R\,|X) = 1/2$.

To test this prediction, it is important to have strong predictors of the R&R decision, so as to span a wide range for the probability of R&R. We focus on the 9,419 papers assigned to at least 3 reviewers, 2 of which have returned a report. We use the recommendations of the first two referees as the proxy X for the interim beliefs, and we measure decision time as a binary indicator of the editor's decision to wait for a third report, or as a count of the total number of days between the receipt of the second report and the editorial decision.

We group each of the first two referees' recommendation into three categories: Reject (including "Definitely Reject"), Weak R&R (including "No Recommendation") and R&R (including "Strong R&R" and "Accept"), creating 9 combinations for the 2 reports. In Panels a and b of Figure 5, we plot on the x-axis the coefficients for each of the 9 cases estimated in the linear probability model for R&R shown in Column 1 of Appendix Table A1.[17] A paper with the lowest category of recommendations (two Rejects) has only a 1.5 percent chance of an R&R, which we add to all 9 coefficients before plotting them. Using only the first two referees' (coarsened) recommendations, we obtain a range of predicted probabilities between 1.5 percent and about 65 percent.

Panel a of Figure 5 shows the relationship with the probability of waiting for the third referee, while Panel b shows the relationship with the count of days between the arrival of the second report and the editor's decision. Both figures show an increase in editorial delay as $Pr(R\&R)$ rises from the baseline level associated with two reject recommendations, reaching a maximum for papers with one Weak R&R and one R&R, which have a 45 percent chance of an R&R. In particular, the probability of waiting for the third report rises from 60 percent to 95 percent, while the number of days between the second report and the editor's decision rises from 20 to 60 days. Both increases are highly significant: as the F tests reported in the figure indicate, the average decision time for papers with a predicted R&R probability below 40 percent is significantly lower than the average decision time for papers with an R&R probability between 40 and 60 percent. Consistent with the "inverse-U" prediction of the model, both panels also show that decision time is lower for papers with an estimated R&R probability above 60 percent than for papers with an estimated R&R probability between 40 and 60 percent, though this result is only statistically significant in Panel a.

To provide a more powerful test of Propositions 2 and 3, we expand the set of X variables to use all 7 categories of each of the first two referees' recommendations. We also use information on the publication records of the first two referees, since Card and DellaVigna (2020) find that editors put more weight on recommendations from referees with more publications.

[17] This model includes fixed effects for journal×year and editor, as well as controls for the size of the author team and their prior publications.

Specifically, we estimate the following probability model:

$$R\&R_i = \alpha + \frac{1}{2}\sum_{k=1}^{2}\left[\beta_0 V_{ik} + exp\{\beta_1 V_{ik}\} \cdot R_{ik}\gamma\right] + \beta_x X_i + \varepsilon_i, \tag{1}$$

where $R\&R_i$ is an indicator that paper i received an R&R decision, V_{ik} is a vector of dummies indicating the number of publications for referee k of paper i ($k = 1, 2$), R_{ik} is a vector of dummies indicating which of the 7 possible summary recommendations referee k made for paper i (with "Definitely Reject" as the omitted category), and X_i is a set of paper-level controls from Table 1. The coefficient vector β_0 allows for the fact that papers assigned to more highly published referees may have a higher probability of R&R irrespective of the referee's recommendation (i.e., a "level effect" of the referees' publication records), while the coefficient vector β_1 allows the ratings of more published referees to have larger (or smaller) effects on the probability of an R&R verdict (i.e., a "slope effect" of the referees' publication records). We model this "slope" effect with an exponential term to ensure positive weights on the referee recommendation terms, as well as to allow an approximate percent interpretation for the impact of referee publications.

Columns 1 and 2 of Table 2 present estimates of this model, with and without the full set of controls. Focusing on the specification with controls (Column 2), the estimated γ coefficients for the categorical recommendations rise monotonically with the strength of the referees' assessments. Two recommendations of "Weak R&R", for example, raise the probability of an R&R decision by 21 percentage points ($\hat{\gamma} = 0.207$) relative to two recommendations of "Definitely Reject," while two recommendations of "Accept" (an extremely rate event) raise the probability by 57 percentage points.

The estimated β_1 coefficients show that more highly published referees are weighted more highly. For example, the recommendations of referees with 5 or more publications in the 5 years prior to the submission are given 28% more weight relative to referees with no prior publications.[18] In contrast, the estimated β_0 coefficients show little indication that the assignment of a paper to more prolific referees has any level effect on the probability of R&R.

In Panels c and d of Figure 5 we use these estimates to form 100 bins with different values for $Pr(R\&R)$. We then plot the average probability that editors wait for additional referees (Panel c) and the average elapsed time between the second referee report and the editor's decision (Panel d) against the average estimate of $Pr(R\&R)$ in each bin. We also display a fitted polynomial that is forced to be symmetric around $Pr(R\&R) = 0.5$, as well as t tests

[18]For purposes of estimating $Pr(R\&R)$ we do not need to take a position on whether the higher weighting of more prolific referees is justified by their ability to better forecast future citations. Nonetheless, we note that Card and DellaVigna (2020) find that recommendations by more- and less-published referees are equally predictive of future citations, a finding that we replicate in Table A2.

for the difference in delays between bins where the estimated probability of R&R is (i) less than 40 percent, (ii) between 40 and 60 percent and (iii) above 60 percent. In both panels, delays are significantly higher in the middle group of bins where the probability of an R&R is between 40 and 60 percent. The expanded set of predictors provides enough power to confirm that delays in the third group, where the likelihood of an R&R is above 60 percent, are significantly lower than in the middle group in both panels. Visual comparisons suggest that symmetry is approximately satisfied for both measures of delay. We conclude that the editorial data provide clear evidence of a "chronometric" pattern of delay that is in line with the model as well as with the evidence from laboratory experiments (e.g., Clithero, 2018a).

Robustness. Appendix B.3.1 presents the results by journal. While the journals differ sizably in the propensity to wait for a third referee and in the delay, the patterns are largely consistent with the chronometric effect for all journals. We also consider two different samples for the editor decision. In Appendix Figure A5a-b we include only papers assigned to exactly 3 referees, as opposed to 3+ referees in the benchmark definition. In Appendix Figure A5c-d we consider papers assigned to at least 4 reviewers, with 3 reports received. Both samples yield similar findings. Finally, we re-estimate the results using as a measure of decision time only the time taken by the editor after the arrival of the last referee report.[19] As shown in Appendix Figure A5e, the results are broadly similar to those in Figure 5d, though the fall in decision times after $Pr(R\&R)$ passes 50% is less systematic.

3.3 Quality and Decision Time

Motivated by Propositions 4 and 5, and the selection and learning effects discussed in Section 1.4, we now study how the quality of papers varies with decision time τ, separately for R&R and Reject decisions. We consider two complementary approaches to implementing a measure of decision time in the data. One approach, paralleling our analysis in Section 3.2, is to study how quality varies with the number of referees utilized by the editor. Another approach is to simply consider the total number of days in the review process. We start with the latter because it facilitates a more granular measure of τ, and thus richer analyses.

3.3.1 Empirical Specification

While we do not observe the true paper quality, we assume that citations ψ_i for paper i are related to quality q_i as follows:

[19] As our analysis of the decision about whether to wait for third referee report makes clear, the identify of the "last report" is endogenous, so there results have to be interpreted carefully.

$$\begin{aligned} asinh(\psi_i) &= \alpha_0 + \beta_0 q_i(\tau_i | X_i, RR_i = 0) + \gamma_0 X_i + \varepsilon_{0i} \text{ if } RR_i = 0 \\ &= \alpha_1 + \beta_1 q_i(\tau_i | X_i, RR_i = 1) + \gamma_1 X_i + \varepsilon_{1i} \text{ if } RR_i = 1 \end{aligned} \tag{2}$$

where $q_i(\tau_i|X_i, RR_i)$ gives the quality of a paper as a function of decision time τ_i, conditional on the covariates and the R&R decision, and where the coefficients β_0 and β_1 are both strictly positive. That is, conditional on being rejected ($RR_i = 0$) or getting a revise and resubmit ($RR_i = 1$), the inverse hyperbolic sine of citations is an increasing linear function of quality, q_i, which is itself a function of decision time τ_i. Importantly, equation (2) allows the paper characteristics X_i to shift citations up or down *controlling for quality* – i.e., to cause arbitrary biases in the mapping from quality to citations. For example, papers in theory and econometrics tend to get fewer citation than papers in, say, macroeconomics or labor economics, independent of quality. Also, network effects and other factors may cause papers by more-published authors, or by larger author teams, to receive additional citations. While we do not have perfect controls, we believe that our data set allows us to account for the main sources of bias in citations as a measure of quality. In addition, we examine coefficient movement as we add additional controls, as in Altonji et al. (2005) and Oster (2019).

We assume that

$$q_i(\tau_i|X_i, RR_i) = \begin{cases} f(\tau_i) + a_0 X_i & \text{if } RR_i = 0 \\ g(\tau_i) + a_1 X_i & \text{if } RR_i = 1. \end{cases} \tag{3}$$

That is, quality is a potentially nonlinear function of decision time that differs for R&Rs versus Rejects, and is also shifted by the covariates. If the selection effect dominates, $f(t)$ will be decreasing and $g(t)$ will be increasing; and conversely if the learning effect dominates. Combining the models for citations and quality leads to a model relating citations to decision time and the observed covariates that is fully interacted with $R\&R$ status:

$$\begin{aligned} asinh(\psi_i) &= \alpha_0 + \beta_0 f(\tau_i) + (\gamma_0 + \beta_0 a_0) X_i + \varepsilon_{0i} \text{ if } RR_i = 0 \\ &= \alpha_1 + \beta_1 g(\tau_i) + (\gamma_1 + \beta_1 a_1) X_i + \varepsilon_{1i} \text{ if } RR_i = 1 \end{aligned} \tag{4}$$

Under our assumption that $\beta_0 > 0$ and $\beta_1 > 0$, we can recover $f(\tau_i)$ and $g(\tau_i)$ up to their scaling factors, and thus draw conclusions about whether selection or learning effects dominate for R&R and Reject decisions. We can directly compare the magnitudes, and not just signs, of the relationship between decision time and quality for papers with R&R versus Reject decisions under the additional assumption that $\beta_0 = \beta_1$. This stronger assumption allows, for example, for papers with R&R decisions to get an additional additive boost in citations (reflected by $\alpha_0 \neq \alpha_1$), but otherwise requires that the relationship between citations and quality does not vary between papers with R&R versus Reject decisions.

3.3.2 Days-to-Decision Results

Table 3 presents estimated regression models that relate citations to decision time, measured by days to decision, with different coefficients for papers with R&R, Reject, and Desk-Reject decisions. As we add controls to the specification, we interact the controls with the editorial decision (R&R/Reject/Desk-Reject), consistent with equation (4), but adding a third category of Desk-Reject decisions. In Column 1 we include only journal-year fixed effects. We then add editor fixed effects (Column 2), controls for field and the number of co-authors (Column 3), controls for previous publications of the authors (Column 4), editor-year controls (Column 5) and controls for the publications of the referees (Column 6).

Across the various specifications, there is a consistent and precisely estimated positive relationship between decision time and citations for rejected papers. The estimate is 0.0040 (s.e.=0.0003) in Column 1; falls to 0.0032 (s.e.=0.0003) in Column 4, primarily due to controls for author publications; then stabilizes and ends at 0.0030 (s.e.=0.0003) in Column 6. Taking the Column 4 regression as a benchmark, for 100 days of extra decision time, citations are approximately 32 log points higher. This difference is about the same size as the gap between citations for papers submitted by authors with no previous top-5 publications versus papers from authors with one top-5 publication (see Table 1). By comparison, the relationship between citations and decision time for R&R papers is much smaller in magnitude, but is consistently negative and robust to the addition of controls. The estimate from the benchmark model in Column 4 shows that among R&R papers, 100 extra days of delay in the decision leads to a reduction in citations of about 8 log points (s.e.= 5).[20]

Figure 6 displays residualized binned scatter plots corresponding to the specification in Column 4. The data show little evidence of non-linearity in the functions $f(t_i)$ and $g(t_i)$ in equation (3). Appendix B.4.1 presents the relationship between decision time and citations for Desk-Rejects, Rejects, and R&Rs, for each of the four journals.

Heterogeneity. In Appendix Table A3 we estimate the specification in Column 4 of Table 3 separately for subsets of papers, reporting the means and standard deviations of citations and decision times in Columns 1 and 2, and the estimates of model (4) in Columns 3 and 4. Splitting by the number of prior author publications (Panel a) and by whether the paper is being handled by an editor who has herself published at least one paper in the same JEL code (which we cannot do for *REStat*) (Panel b), the estimated effects of delay on citations are similar to the effects in our baseline model. Splitting by journal, we find a consistently positive effect of decision time on citations for rejected papers, except at *REStat*.

[20]We also estimated these models excluding observations with delays of over 200 days (Figure A6). This leads to coefficients on decision time of 0.0055 (s.e.=0.0005) for rejected papers, -0.0029 (s.e.=0.0012) for R&R papers, and 0.0005 (s.e.=0.0015) for desk rejected papers. Thus the inclusion of the long-delayed papers tends to flatten the relationship between delay and citations, particularly for R&R papers.

For R&R papers there is a stronger negative relationship between decision time and citations at *QJE* and *REStud,* and a weaker relationship at *JEEA* and *REStat.*

Splitting the sample by submissions from earlier years (up to 2010) and later years (2011+) (Panel d) we obtain results very similar to the benchmark pooled model, as well as when when we consider three subgroups of fields in Panel e: (i) micro, theory and econometrics; (ii) macro and international; (iii) all remaining fields (mainly in empirical micro). Finally, when we split by editor speed (Panel f), the coefficients are larger in magnitude for the faster editors (see also Appendix Figure A9).

Transformations of citations. A concern about our baseline specification is the use of the inverse hyperbolic sine transformation for citations (Chen and Roth, 2023). Figure 7 shows that the results of Figure 6 are robust to instead using: (a) the level of citations; (b) $\ln(\psi_i + 1)$; (c) the share of papers with nonzero citations; (d) $\ln(\psi_i)$ for papers with positive citations (dropping papers with 0 citations); and (e) the percentile rank of the citations received by the paper relative to the year and journal.

Appendix Figure A10 presents residualized binned scatter plots where the outcome is the probability that a paper ends up in the top 2%, top 10%, top 50%, or top 75% of the distribution for the same submission year and journal. For rejected papers, the slope between decision time and the citation status of the paper becomes stronger as the bar is lowered: 100 extra days of decision time raises the probability of being a "superstar" paper (top 2%) by 0.3 percentage points (s.e.= 0.3), but raises the probability of being a top 10% paper by 2.2 percentage points (s.e.= 0.6) and of being a top 75% paper by 6.5 percentage points (s.e.= 0.7). For R&R papers the effects of decision time on the probability of being a top 2% or top 10% paper are insignificantly negative, while the effects on being a top 50% or top 75% paper are insignificantly positive.

Appendix Figure A11 presents the full CDFs of $asinh(\psi_i)$ for rejected (Panel a) and R&R (Panel b) papers with decisions made in the first tercile versus the 3rd tercile of decision time relative to the journal and year of submission . The shifts in citations with respect to decision time (to the right for rejected papers; to the left for R&R papers) are present at all quantiles, and are especially clear for rejected papers.

Referee versus Editor Decision Time. Our analysis thus far consider the total delay from both the editors and referees. We now consider each separately. For the referee-level analysis, we consider each referee report as an observation, and plot residualized binned scatter plots of $asinh(\psi_i)$ against the the number of days taken to complete a report, separately for each category of recommendations. Panel a of Figure 8 shows a pattern similar to the pattern in Figure 6, except that the relationship between decision time and citations is more muted for cases with positive recommendations. Overall, one would expect a more muted relationship with decision time because the referee recommendations are more granular than just an up/down decision, and thus there is less residual information that can be picked up by decision time.

Panel b consider the editor-level analysis, presenting residualized binned scatter plots analyzing editors' decision time, defined as the time from the receipt of the last report to the first-round decision. The qualitative results are again similar to Figure 6, with a positive slope between decision time and citations for Reject decisions and an essentially flat slope for R&R decisions.

Estimates with Other Quality Proxies. For papers with an R&R decision, we have two proxies for papers that are likely to be more marginal and thus lower "quality": (i) whether the paper is ultimately accepted within the time frame of the data collection[21] and (ii) the number of days between the R&R decision and the second-round re-submission (if any). A longer resubmission delay is likely related to a more difficult revision, which is plausibly more common for marginal R&Rs.

Panel a of Figure 9 displays the probability of ultimate acceptance as a function of the first-round decision time. An extra 100 days of decision time for an R&R are associated with a 4 percentage point lower probability of ultimate acceptance, relative to a baseline of about 80 percent. Panel b displays the binned scatter plot of the probability of resubmission of R&R manuscripts within a given number of days. The probability of resubmission within 90, 180, or 360 days is negatively associated with first-round decision time.

Estimates with Chetty et al. (2014) Data. We are aware of only one other data set with detailed information on editorial decisions, the Chetty et al. (2014) data set for the *Journal of Public Economics* (*JPubE*). Although this data set is nearly twenty times smaller than our main sample, the analysis in Appendix B.5 generates similar qualitative results.

3.3.3 Referee Reports Collected by Editor

Our second approach to studying the relationship between decision time and quality is to equate decision time τ with the number of referees that the editor waits for. For papers where the editor initially contacted three referees, we examine how citations vary with whether the editor waits for one, two or three referees. We conduct analogous analyses for papers where the editor initially contacted four referees. Figure 10 presents the results via binned scatter plots that residualize outcomes by the covariates in Column 4 of Table 3 for cases with three contacted referees (Panel a) and for cases with four contacted referees (Panel b). The figures show that for rejected papers, waiting for additional reports is associated with higher citations, while the opposite is generally true for R&Rs. This is consistent with our results on days-to-decision.

[21] The alternative is that the paper is rejected, not resubmitted, or still in later rounds of review by the time of data export.

3.4 Costs of Delay

How do experts react to other experts' delays, particularly when one expert must rely on data collection by another expert? In our specific context, how do editors react to longer decision time by the referees? There are two different forces. On the one hand, longer delay times by referees might signal additional information to the editors about referees' beliefs, beyond what is in the referees's summary recommendation (see, e.g., Figure 8a). On the other hand, if editors' costs of delay are nonlinear, then longer delays by say the first two referees would alter the cost of waiting for a third referee. In particular, if costs of delay are convex in total wait time, then the costs of waiting for a third report increase with the time taken for the second report to arrive.[22]

In Appendix B.6, we study how an editor's choice to wait for a third referee depends on the delays of the first and second referee. We find that the likelihood of waiting decreases substantially with the delay of the second referee, while it is not significantly impacted by the delay of the first referee. As we further elaborate in Appendix B.6, this is consistent with the cost of delay being convex in time, and with this effect being larger in magnitude than the additional information revealed by referees' delay conditional on their summary recommendations.

4 Structural Estimates

Our reduced-form results show that among rejected papers, quality is increasing in decision time, whereas among R&R papers, quality is decreasing in decision time. In the context of our model, these patterns suggest that the selection effect dominates the learning effect, and that early-arriving signals (i.e., from the first referee report(s) and the initial reading by the editor) account for much of the available information. To quantify this intuition, and obtain parameter estimates for counterfactuals, we estimate a structural model.

4.1 Setup and Approach

We combine the model in Section 1 with an appropriate adaptation of the reduced-form framework in Section 3.3. We provide an overview of our approach in this section; further details are in Appendix C.

To limit to only one type of positive and negative decision, we focus on papers that were reviewed by referees. To accommodate the binary structure of decision time τ_i, we set $\tau_i = 1$ and $\tau_i = 2$ for papers with below- and above-median decision time, respectively, conditional

[22]These comparative statics also depend on how the time taken for the second report to arrive alter the additional time that it would take for the third report to arrive. We analyze this in Appendix B.6.

on the controls. We assume that citations are related to quality according to equation (2), with the additional restriction that $\beta_0 = \beta_1$, but still allowing publication in the four journals to influence citations via $\alpha_0 \neq \alpha_1$. We assume that quality is related to τ as in equation (3).

We implement this by residualizing asinh citations and days taken to make a decision using the controls of Column 4 of Table 3, separately for R&R and Reject decisions. For citations, we then recenter the residuals of R&R and Reject papers such that (i) the mean difference in citations between R&Rs and Rejects is preserved, after adjusting for potential differences in controls (see Appendix C.2.1), and such that (ii) the overall mean of the pooled sample is zero, consistent with the normalization assumption of the model. We use $\hat{\psi}_i$ to refer to the residualized and recentered values of $asinh(\psi_i)$. For days to decision, we similarly recenter the R&R and Reject residuals such that the mean difference between R&Rs and Rejects is preserved, after adjusting for potential differences in controls. We then set $\tau_i = 1$ ($\tau_i = 2$) for cases where the residualized and recentered decision days are below (above) median. Without loss of generality, we adopt the normalization that $\beta_0 = \beta_1 = 1$, which amounts to measuring quality in "units of citations."

We parametrize the distribution of costs such that $c_2 \in \{c_l, c_h\}$ with equal likelihood, and we estimate the corresponding "thresholds" $\Delta(c_l)$ and $\Delta(c_h)$. We thus have a total of six parameters: the two possible thresholds, σ_1^2 (the variance of quality expectations after the first signal), σ_2^2 (the variance of quality expectations after the second signal, conditional on the first signal), q^* (the quality cutoff), and $\alpha_1 - \alpha_0$ (the impact of publication on citations). These six parameters are exactly identified by the following constraint and five moments: the constraint that $Pr(\tau = 1) = Pr(\tau = 2) = 1/2$, the two additional moments $Pr(D = R\&R|\tau)$ for $\tau \in \{1, 2\}$, and three moments corresponding to the mean residualized (and recentered) citations for each outcome (D, τ).[23] To implement the constraint, for each tuple $\theta = (q^*, \sigma_1^2, \sigma_2^2, \Delta(c_l), \alpha_1 - \alpha_0)$, we set $\Delta(c_h)$ to the unique value for which $Pr(\tau = 2) = 1/2$.[24]

Next, let $\hat{m}$ denote the vector of five estimated empirical moments from our sample, and let $m(\theta)$ denote the vector of predicted moments given a choice for the parameter vector $\theta = (q^*, \sigma_1^2, \sigma_2^2, \Delta(c_l), \alpha_1 - \alpha_0)$. Our parameter estimates satisfy

$$\hat{\theta} = argmin\ (\hat{m} - m(\theta))'\hat{V}^{-1}(\hat{m} - m(\theta)),$$

where $\hat{V}$ is the estimated sampling variance-covariance matrix of the vector of moments $\hat{m}$.[25]

[23] The mean residualized citations for each outcome generate only three moments because we normalize the pooled sample mean to be zero.

[24] To see that there is a unique value, note that $Pr(\tau = 2|\Delta(c_l)) \in (0, 1/2)$, and that $Pr(\tau = 2|\Delta(c_h))$ is continuous and increasing in $\Delta(c_h)$, with $\lim_{\Delta(c_h)\to\infty} Pr(\tau = 2|\Delta(c_h)) = 1/2$ and $\lim_{\Delta(c_h)\to 0} Pr(\tau = 2|\Delta(c_h)) = 0$.

[25] We construct each of the moments as an estimated coefficient from a regression model defined over the entire sample, and then use the seemingly unrelated regression framework to estimate the variance-covariance

We estimate the variance-covariance matrix of the estimated parameters by

$$Var[\hat{\theta}] = (M(\hat{\theta})'\hat{V}^{-1}M(\hat{\theta}))^{-1}$$

where $M(\theta) = [\frac{\partial m}{\partial \theta'}]$ is the Jacobian for the mapping from the parameters to the moments.[26]

4.2 Results

Table 4, Panel a, reports the parameter estimates, as well as several economically-meaningful summary statistics. The first is $\sigma_2^2/(\sigma_1^2 + \sigma_2^2)$, the share of information that is revealed late ($\tau = 2$) rather than early ($\tau = 1$). The second is $(\sigma_1^2+\sigma_2^2)/Var(\hat{\psi}_i)$, the share of the variation in citations (controlling for observable covariates) that can be explained by the information that is available during the review process.

The quality bar q^* is precisely estimated at 0.62. The estimates for Δ indicate substantial variation in the cost of acquiring additional information: $\Delta(c_h)$ is estimated at 1.19, while $\Delta(c_l)$ is estimated at 0.19. The estimated value of σ_1^2 is 0.29 while the estimated value of σ_2^2 is 0.06. Finally, we do not find evidence that papers published rather than rejected in the four journals we consider receive more citations conditional on quality. Panel b displays the goodness of fit, showing that we can match all the moments.

The estimates imply that the share of obtainable information revealed by choosing an above- versus below-median delay is 0.18. The estimates also imply that the information obtainable during the review process can explain 0.14 of the variance in citations, on top what is explained by the controls. This is approximately half of the variance explainable by observable paper and author characteristics, and journal, year, and decision fixed effects (see Table 1).

Counterfactuals. How would the likelihood of R&R and the average citations change in the counterfactual scenarios where there is no selection on the first signal, so that always one or always two signals are obtained? Panel c (see Appendix C for details) shows that the counterfactual R&R rates and citations would be similar to the empirical moments. Intuitively, the second signal carries less information, and thus whether or not it is utilized does not significantly impact the outcomes. Given the anecdotally common complaints about long decision times in Economics journals, these results suggest that earlier decisions could come at relatively little loss of information, and that the costs of information acquisition of editors and referees may not internalize the costs of delay imposed on the authors.

matrix of the five moments. $\mathbb{E}[\hat{\psi}_i|D,\tau]$ is obtained by regressing $\hat{\psi}_i$ on dummies for each outcome, and $Pr(D,\tau)$ is obtained analogously.

[26] We estimate the Jacobian numerically, by perturbing the parameters around $\hat{\theta}$. We estimate the confidence interval around $\Delta(c_h)$ numerically via bootstrap, using the variance-covariance matrix of the other five parameters.

Robustness. We estimate a few variants of the model in Appendix Table A5 to assess the robustness of the estimates and how it applies to different samples. In Column 1, we estimate the model for *QJE* papers only, given the much faster decision times at this journal. In Columns 2 and 3 we estimate the model separately for the subfields of economics in which papers are arguably more complex and thus may take longer to evaluate – micro theory and economics (Column 2) versus the other fields (Column 3). We estimate that for Micro and Econometrics the share of information revealed from additional delay is 0.41, compared to an estimate of 0.14 for the other fields, suggesting a role for paper complexity. In Column 4 we re-estimate the model using a different way to split periods, identifying $\tau = 1$ with decisions taken within the earliest 75 percent of decisions. Finally, in Columns 5 and 6 we consider separately the role of the referee and of the editor, respectively. In Column 5 we code a referee decision as positive if it is a recommendation of (weak) R&R or above and negative if it is recommendation of Reject or below. We code $\tau \in \{1, 2\}$ analogously, based on residualized days to decision of the referees. In Column 6 we set an editor's decision time $\tau \in \{1, 2\}$ based on whether the residualized number of days between the last report and the editor decision is below or above median, respectively. The estimates for both referee- and editor-level decisions are consistent with the main result that the second signal is less informative than the first one, but there are differences such as a lower q^* for the referee decision.

5 Conclusion

Building on evidence from psychology, neuroscience and economic laboratory experiments, this paper shows that decision times can play a valuable role in understanding decisions in field settings. We focus on a specific set of experts: editors and referees at scientific journals. We propose a stylized model that lays out three main predictions relating decision time to choices. We then take these predictions to a data set of over 15,000 manuscript submissions at four high-impact economic journals. We find that decision time is inverse U-shaped in the probability of a positive decision, and that citations are increasing (decreasing) in decision time for papers with Reject (R&R) decisions. Combining these findings with estimates of a structural model shows that the additional information acquired through editorial delays is modest, and thus faster editorial decisions could come at relatively little loss of information.

Altogether, our field setting illustrates how decision times can be used to better understand economic decision making outside the laboratory. Our methods may be fruitfully applied to other field settings that include information acquisition by experts, such as decisions by medical professionals, patent officers, or employers.

References

Alós-Ferrer, Carlos and Michele Garagnani, "Improving Risky-Choice Predictions Using Response Times," *Journal of Political Economy Microeconomics*, forthcoming.

_ , Ernst Fehr, and Nick Netzer, "Time Will Tell: Recovering Preferences When Choices Are Noisy," *Journal of Political Economy*, 2021, *129* (6), 1828–1877.

_ , Đura-Georg Granić, Johannes Kern, and Alexander K Wagner, "Preference Reversals: Time and Again," *Journal of Risk and Uncertainty*, 2016, *52*, 65–97.

Altonji, Joseph G, Todd E Elder, and Christopher R Taber, "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools," *Journal of Political Economy*, 2005, *113* (1), 151–184.

Baldassi, Carlo, Simone Cerreia-Vioglio, Fabio Maccheroni, Massimo Marinacci, and Marco Pirazzini, "A Behavioral Characterization of the Drift Diffusion Model and Its Multialternative Extension for Choice Under Time Pressure," *Management Science*, 2020, *66* (11), 5075–5093.

Bartoš, Vojtěch, Michal Bauer, Julie Chytilová, and Filip Matějka, "Attention Discrimination: Theory and Field Experiments with Monitoring Information Acquisition," *American Economic Review*, 2016, *106* (6), 1437–1475.

Canen, Nathan and Matias Iaryczower, "Innovation Adoption by Committee: Evaluating Decision-Making in the FDA," Technical Report, Working paper 2024.

Caplin, Andrew, Mark Dean, and Daniel Martin, "Search and Satisficing," *American Economic Review*, 2011, *101* (7), 2899–2922.

Card, David and Stefano DellaVigna, "What do Editors Maximize? Evidence from Four Economics Journals," *Review of Economics and Statistics*, 2020, *102* (1), 195–217.

_ , _ , Patricia Funk, and Nagore Iriberri, "Are Referees and Editors in Economics Gender Neutral?," *The Quarterly Journal of Economics*, 2020, *135* (1), 269–327.

Chabris, Christopher F, David Laibson, Carrie L Morris, Jonathon P Schuldt, and Dmitry Taubinsky, "Individual Laboratory-Measured Discount Rates Predict Field Behavior," *Journal of Risk and Uncertainty*, 2008, *37*, 237–269.

Chen, Jiafeng and Jonathan Roth, "Logs With Zeros? Some Problems and Solutions," *The Quarterly Journal of Economics*, 2023, p. qjad054.

Chetty, Raj, Emmanuel Saez, and László Sándor, "What Policies Increase Pro-Social Behavior? An Experiment with Referees at the Journal of Public Economics," *Journal of Economic Perspectives*, 2014, *28* (3), 169–188.

Clithero, John A, "Improving Out-of-Sample Predictions Using Response Times and a Model of the Decision Process," *Journal of Economic Behavior & Organization*, 2018, *148*, 344–375.

_ , "Response Times in Economics: Looking Through the Lens of Sequential Sampling Models," *Journal of Economic Psychology*, 2018, *69*, 61–86.

Cotet, Miruna and Ian Krajbich, "Response Times in the Wild: eBay Sellers Take Hours Longer to Reject High Offers and Accept Low Offers," Technical Report, Working paper 2021.

Dashiell, John Frederick, "Affective Value-Distances as a Determinant of Esthetic Judgment-Times," *The American Journal of Psychology*, 1937, *50* (1/4), 57–67.

Enke, Benjamin and Thomas Graeber, "Cognitive Uncertainty," *The Quarterly Journal of Economics*, 2023, *138* (4), 2021–2067.

Frydman, Cary and Ian Krajbich, "Using Response Times to Infer Others' Private Information: An Application to Information Cascades," *Management Science*, 2022, *68* (4), 2970–2986.

Fudenberg, Drew, Philipp Strack, and Tomasz Strzalecki, "Speed, Accuracy, and the Optimal Timing of Choices," *American Economic Review*, 2018, *108* (12), 3651–3684.

Gabaix, Xavier, David Laibson, Guillermo Moloche, and Stephen Weinberg, "Costly Information Acquisition: Experimental Analysis of a Boundedly Rational Model," *American Economic Review*, 2006, *96* (4), 1043–1068.

Kahneman, Daniel, *Thinking, Fast and Slow.*, Macmillan, 2011.

Konovalov, Arkady and Ian Krajbich, "Decision Times Reveal Private Information in Strategic Settings: Evidence from Bargaining Experiments," *The Economic Journal*, 2023, *133* (656), 3007–3033.

Krajbich, Ian and Antonio Rangel, "Multialternative Drift-Diffusion Model Predicts the Relationship Between Visual Fixations and Choice in Value-Based Decisions," *Proceedings of the National Academy of Sciences*, 2011, *108* (33), 13852–13857.

_ , Bastiaan Oud, and Ernst Fehr, "Benefits of Neuroeconomic Modeling: New Policy Interventions and Predictors of Preference," *American Economic Review*, 2014, *104* (5), 501–506.

_ , Carrie Armel, and Antonio Rangel, "Visual Fixations and the Computation and Comparison of Value in Simple Choice," *Nature Neuroscience*, 2010, *13* (10), 1292–1298.

_ , Dingchao Lu, Colin Camerer, and Antonio Rangel, "The Attentional Drift-Diffusion Model Extends to Simple Purchasing Decisions," *Frontiers in Psychology*, 2012, *3* (193).

_ , Todd Hare, Björn Bartling, Yosuke Morishima, and Ernst Fehr, "A Common Mechanism Underlying Food Choice and Social Decisions," *PLOS Computational Biology*, 2015, *11* (10), 1–24.

Lagziel, David and Ehud Lehrer, "A Bias of Screening," *American Economic Review: Insights*, 2019, *1* (3), 343–356.

_ and _ , "Screening Dominance: A Comparison of Noisy Signals," *American Economic Journal: Microeconomics*, 2022, *14* (4), 1–24.

Liang, Annie, Xiaosheng Mu, and Vasilis Syrgkanis, "Dynamically Aggregating Diverse Information," *Econometrica*, 2022, *90* (1), 47–80.

Liu, Shuo and Nick Netzer, "Happy Times: Measuring Happiness Using Response Times," *American Economic Review*, 2023, *113* (12), 3289–3322.

Luce, R Duncan, *Response Times: Their Role in Inferring Elementary Mental Organization*, Oxford University Press, USA, 1986.

Milosavljevic, Milica, Jonathan Malmaud, Alexander Huth, Christof Koch, and Antonio Rangel, "The Drift Diffusion Model Can Account for the Accuracy and Reaction Time of Value-Based Choices Under High and Low Time Pressure," *Judgment and Decision Making*, 2010, *5* (6), 437–449.

Moscarini, Giuseppe and Lones Smith, "The Optimal Level of Experimentation," *Econometrica, Journal of the Econometric Society*, 2001, *69* (6), 1629–1644.

Oprea, Ryan, "Simplicity Equivalents," Technical Report, Working paper 2023.

Oster, Emily, "Unobservable Selection and Coefficient Stability: Theory and Evidence," *Journal of Business & Economic Statistics*, 2019, *37* (2), 187–204.

Ratcliff, Roger and Gail McKoon, "The Diffusion Decision Model: Theory and Data for Two-Choice Decision Tasks," *Neural Computation*, 2008, *20* (4), 873–922.

_ **and Jeffrey N Rouder**, "Modeling Response Times for Two-Choice Decisions," *Psychological Science*, 1998, *9* (5), 347–356.

Reshidi, Pëllumb, Alessandro Lizzeri, Leeat Yariv, Jimmy Chan, and Wing Suen, "Sequential Sampling by Individuals and Groups: An Experimental Study," Technical Report, Working paper 2024.

Schotter, Andrew and Isabel Trevino, "Is Response Time Predictive of Choice? An Experimental Study of Threshold Strategies," *Experimental Economics*, 2021, *24*, 87–117.

Smith, Alec, B. Douglas Bernheim, Colin F. Camerer, and Antonio Rangel, "Neural Activity Reveals Preferences Without Choices," *American Economic Journal: Microeconomics*, 2014, *6* (2), 1–36.

Sunde, Uwe, Dainis Zegners, and Anthony Strittmatter, "Speed, Quality, and the Optimal Timing of Complex Decisions," *arXiv preprint arXiv:2201.10808*, 2022.

Swensson, Richard G, "The Elusive Tradeoff: Speed vs. Accuracy in Visual Discrimination Tasks," *Perception & Psychophysics*, 1972, *12* (1), 16–32.

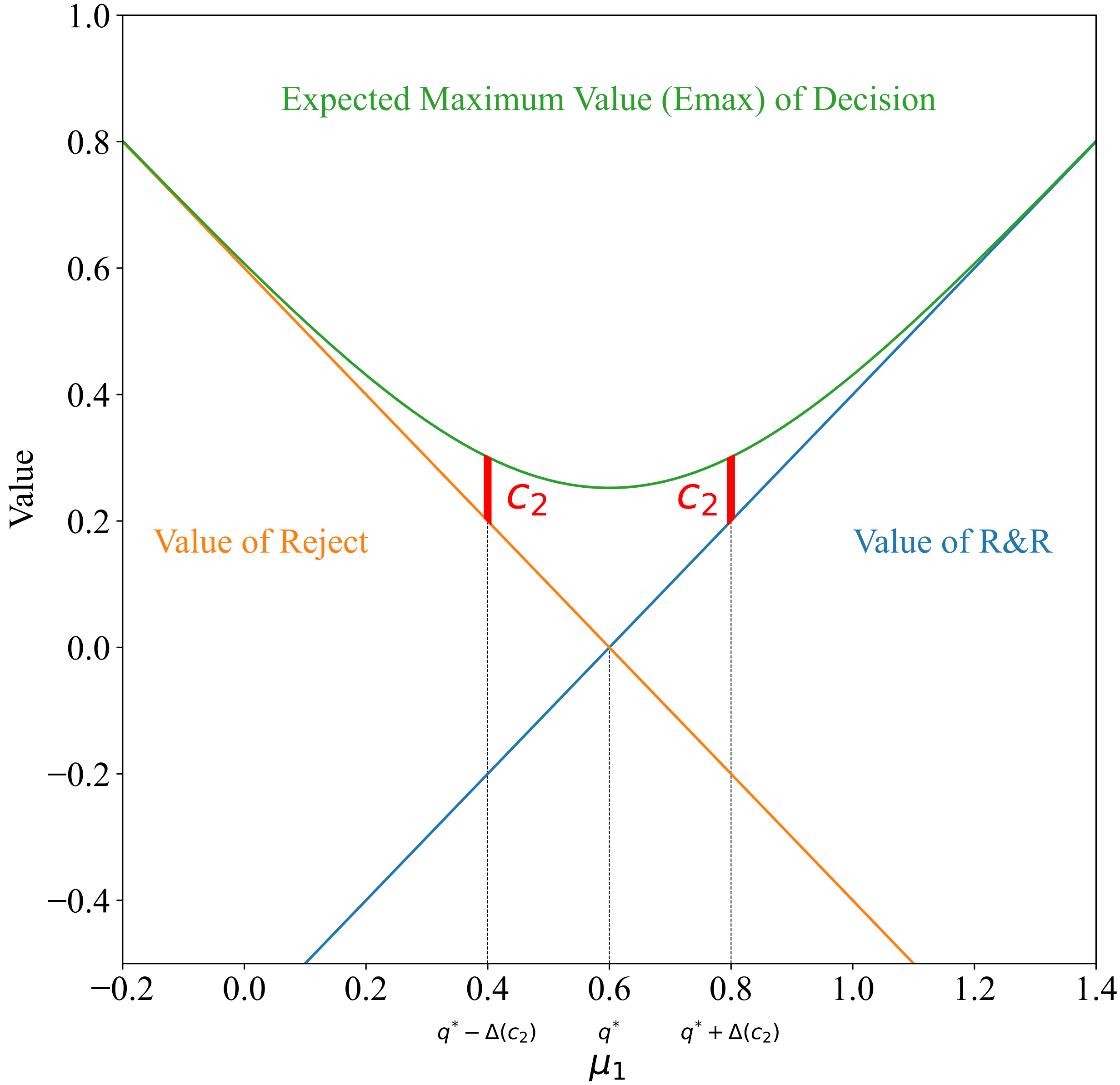
Wald, Abraham, *Sequential Analysis*, John Wiley & Sons, New York, 1947.

_ **and Jacob Wolfowitz**, "Optimum Character of the Sequential Probability Ratio Test," *The Annals of Mathematical Statistics*, 1948, pp. 326–339.

Woodford, Michael, "Modeling Imprecision in Perception, Valuation and Choice," *Annual Review of Economics*, 2019, *12*, 579–601.

yi Wang, Joseph Tao, Michael Spezio, and Colin F. Camerer, "Pinocchio's Pupil: Using Eyetracking and Pupil Dilation to Understand Truth Telling and Deception in Sender-Receiver Games," *American Economic Review*, 2010, *100* (3), 984–1007.

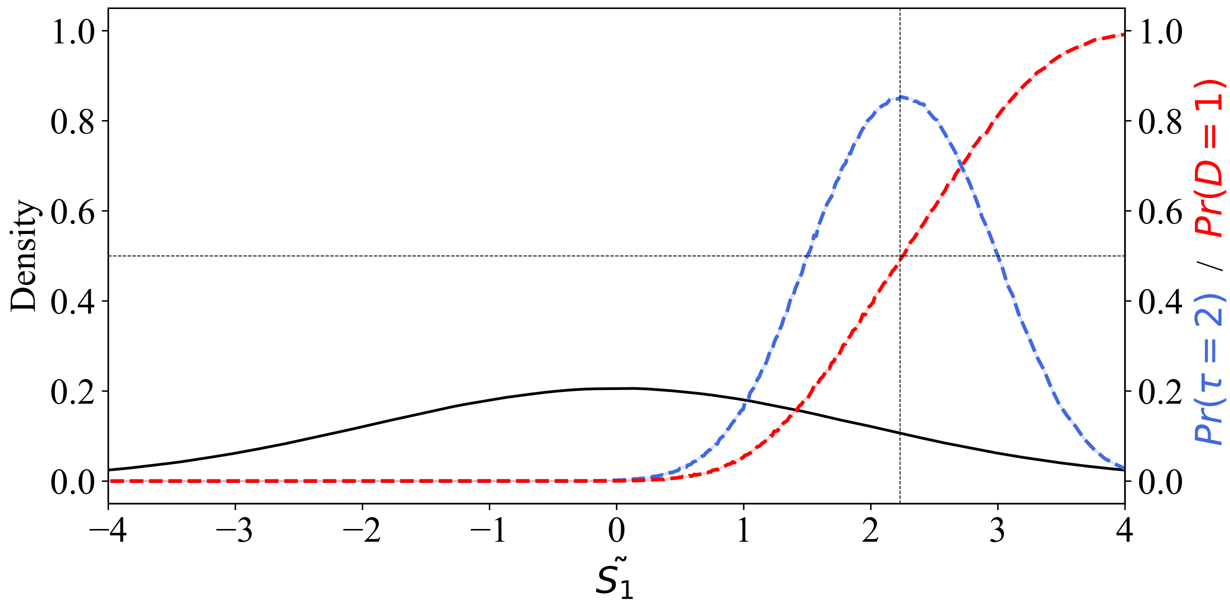
Figure 1: Value and Threshold of Acquiring S_2



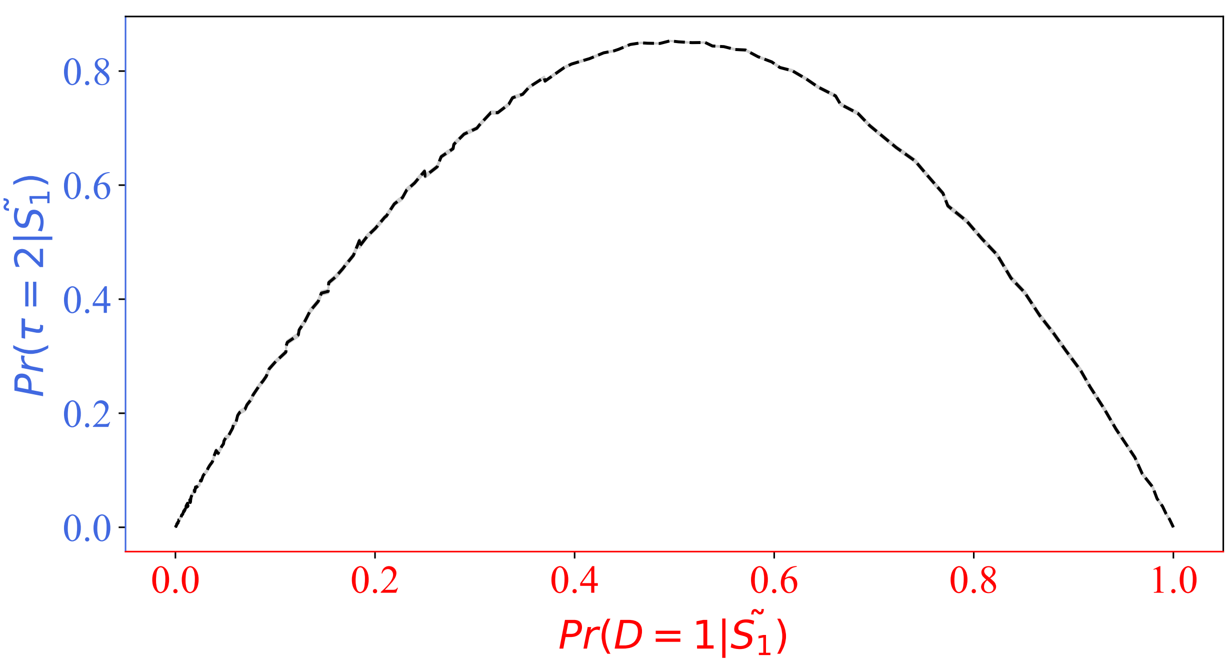
Notes: In this example, $q^* = 0.6, \sigma_1^2 = 0.3, \sigma_2^2 = 0.1, \Delta(c_2) = 0.2$.

Figure 2: $Pr(\tau = 2)$ and $Pr(D = 1)$ for a Noisy Proxy of S_1

(a) The Distribution of S_1, P(New Signal|S_1), P(R&R|S_1)



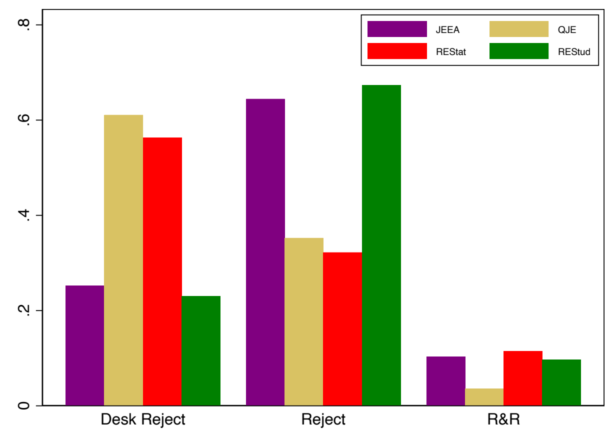
(b) P(New Signal | S_1) vs. P(R&R | S_1)



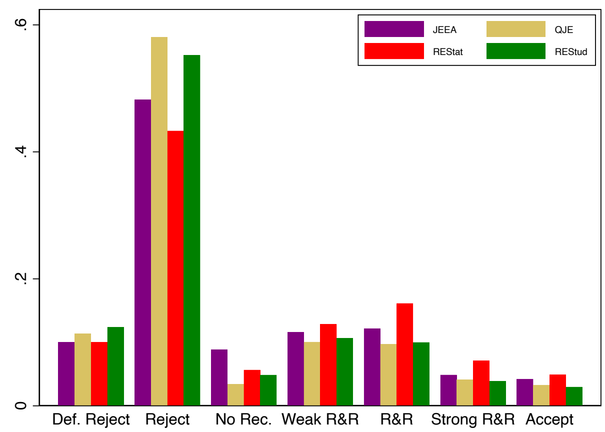
Notes: In this example, the distribution of $\tilde{S_1} = S_1 + \epsilon_s$, $\epsilon \sim N(0, \sigma_\epsilon^2)$ and the probabilities are derived from the simulation of 10 million independent draws of q, S_1, S_2 from their specified distributions. $q^* = 0.6, \mu = 0, Var(q) = 1, Var(S_1|q) = 2.5, Var(S_2|q) = 6, \Delta(c_2) = 0.2, \sigma_\epsilon^2 = 0.25$.

Figure 3: The Distributions of Key Variables

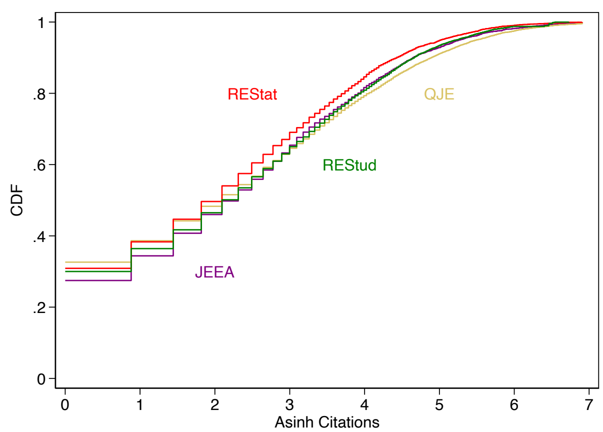
(a) The Distribution of Editor Decisions by Journal



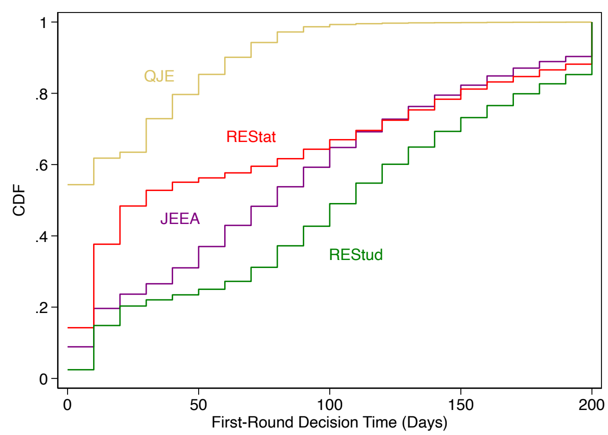
(b) The Distribution of Referee Recommendations by Journal



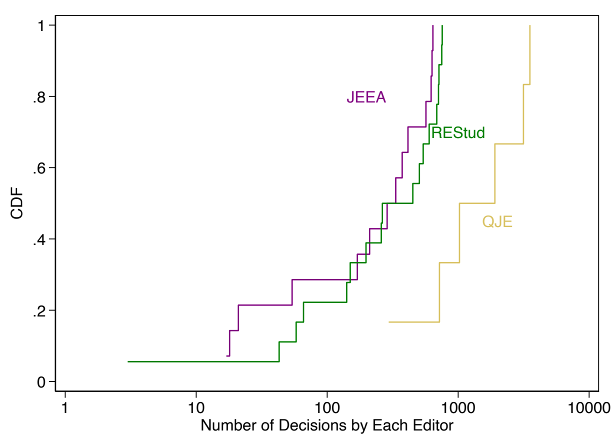
(c) The Distribution of Asinh Citations by Journal



(d) The Distribution of First-Round Decision Time by Journal

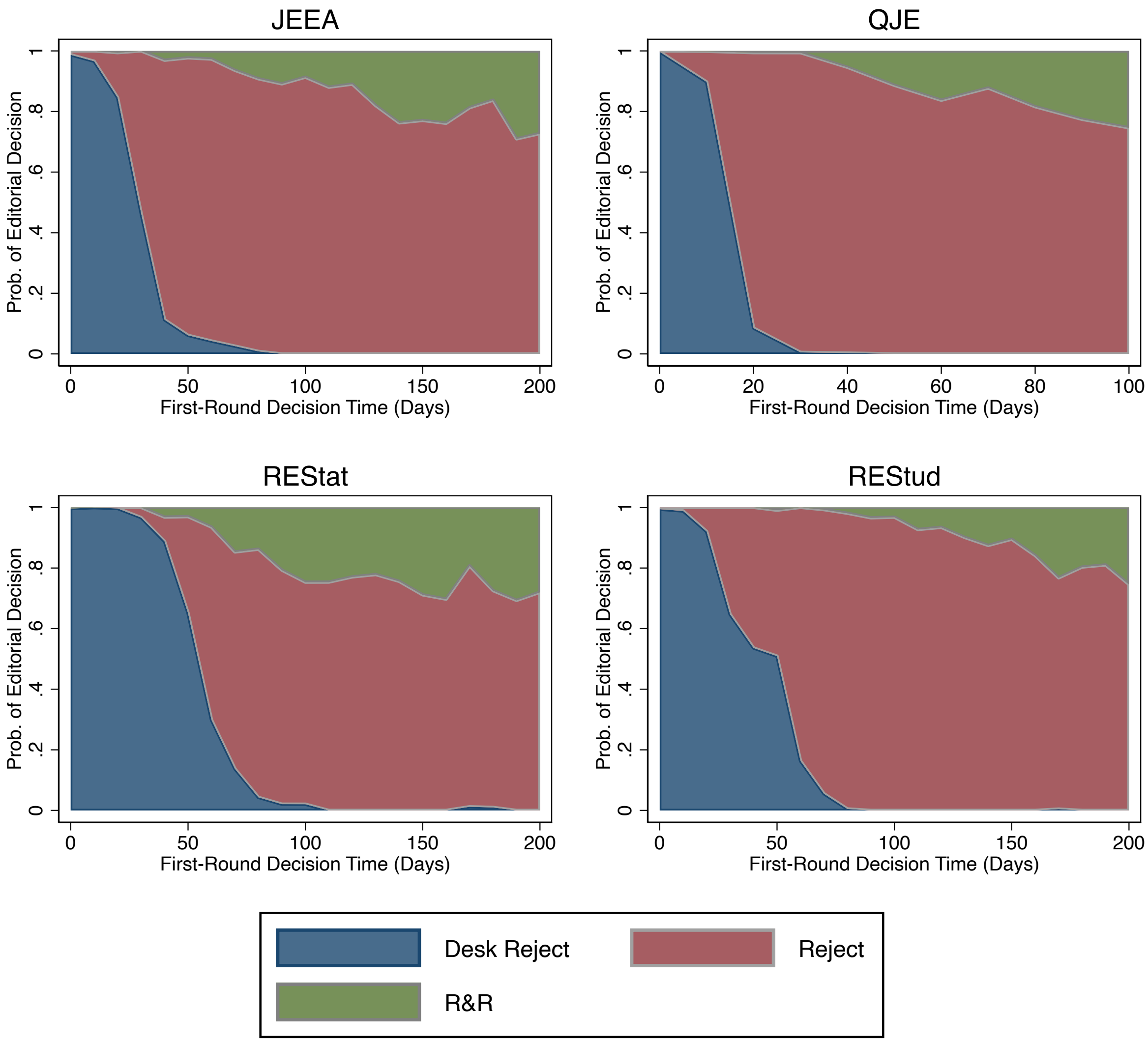


(e) The Distribution of the Number of Decisions by Journal



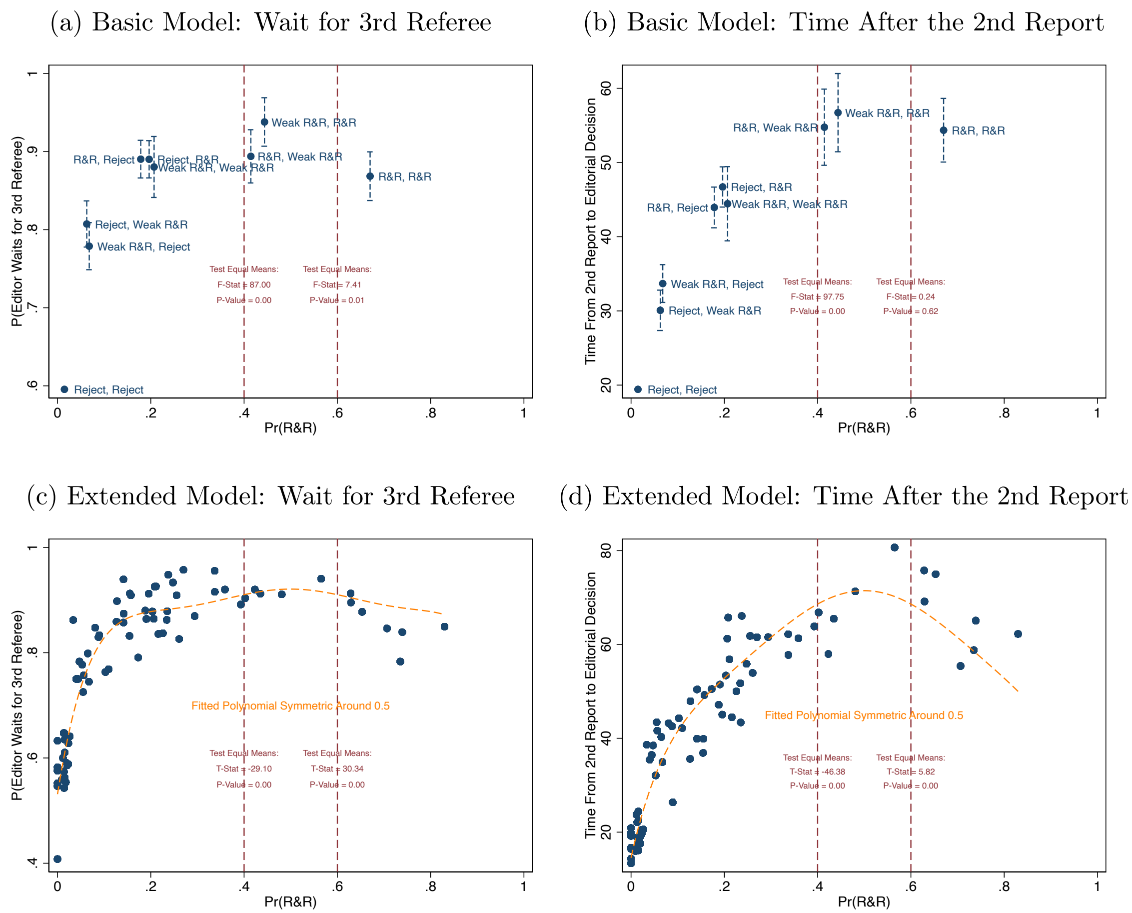
Notes: In Panel c, the number of citations is winsorized at 500 times for *JEEA*, *QJE*, and *REStat*. For *REStud*, the number of citations is winsorized at 200 times and then imputed using the average citations by year of papers cited more than 200 times in the other journals. In Panel d, the first-round decision time is winsorized at 200 days (to comply with the data confidentiality restrictions). The first-round decision time has already been rounded to the nearest 10 when the data was exported. In Panel e, the distribution for *REStat* is not displayed to comply with the data confidentiality restrictions on editor IDs.

Figure 4: Probability of Editorial Decision vs. Decision Time, by Journal



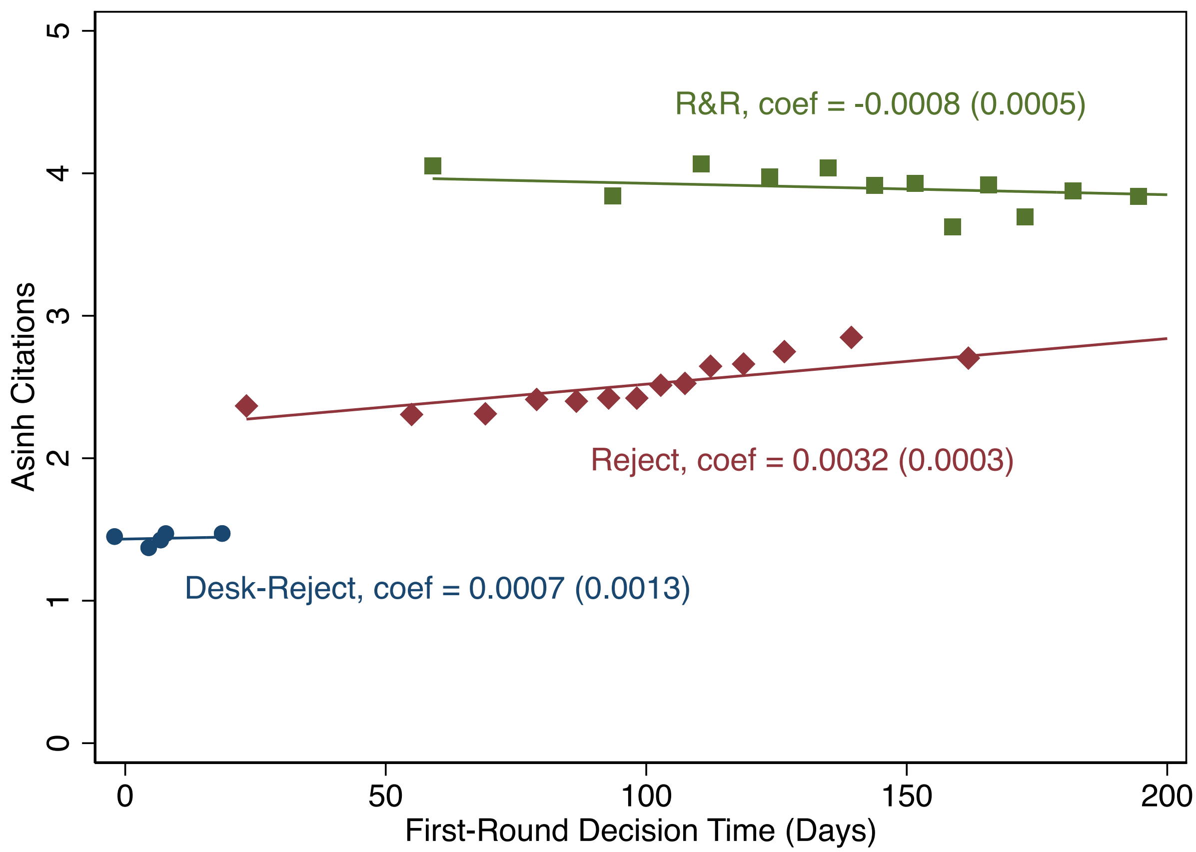
Notes: The figure above shows the proportions of editorial decisions in each discrete bin of first-round decision time (which has already been rounded to the nearest 10 when the data was exported). The first-round decision time is top-coded at the minimum of (i) the 99th percentile of the decision time in the journal and (ii) 200 days to comply with the data confidentiality restrictions.

Figure 5: Stopping Predictions



Notes: Only papers with at least three referees assigned and at least two referees responded are included in the analysis. In Panels a and b, the *Reject* category includes both "Definitely Reject" and "Reject" recommendations; the *Weak R&R* category includes "No Recommendations" and "Weak R&R"; the *R&R* category includes "R&R", "Strong R&R", and "Accept." For each combination of the categories (the order of items represents the order of recommendation arrival), we plot the average $Pr(R\&R)$ and the average value of the waiting variable controlling for journal, year, editor, and other paper characteristics (Table A1 shows the details). In Panels c and d, we estimate the model described by Equation 1 and derive the predicted $Pr(R\&R)$ based purely on referee recommendations and prominence for each paper. We then create 100 bins based on the predicted values. For the papers in each bin, we plot their empirical $Pr(R\&R)$ and empirical average value of the waiting variable. Time from the second report to the editorial decision is winsorized at 231 days (the 99th percentile). For the intervals [0, 0.4), (0.4, 0.6), (0.6, 1] on the x-axis, we test if the increasing / decreasing trend in the adjacent intervals is statistically significant and report the testing statistics in annotations. The polynomial in orange is derived by fitting the dots into the function $y = k + a(x - 0.5)^2 + b(x - 0.5)^4 + c(x - 0.5)^6$, which is flexible and always symmetric around $x = 0.5$.

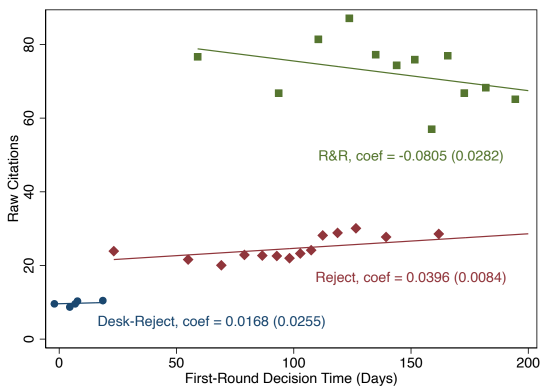
Figure 6: Citations as a Function of Decision Time



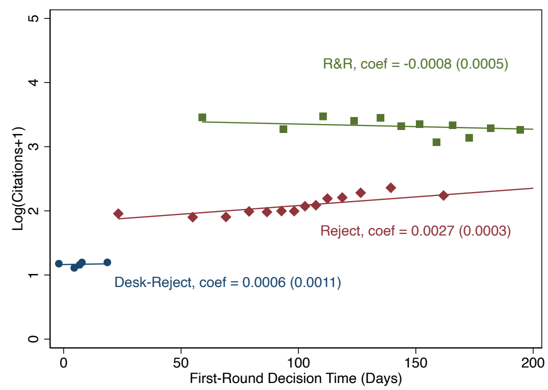
Notes: The binned scatter plot above controls for the following fixed effects: journal, year, journal×year, editor, the field(s) of the paper, the number of author(s), the highest number of publications in top-5 economic journals among all author(s), the highest number of publications in top-35 economic journals (identified in Online Appendix Table 1 of Card and DellaVigna (2020)) among all author(s). The first-round decision time is winsorized at 320 days (the 99th percentile). To comply with the data confidentiality restrictions, only bins with decision time ≤ 200 are displayed. Nevertheless, the fitted lines are created based on all observations. The bins are created separately for desk-reject, reject, and R&R papers. The coefficients of the controls are allowed to vary across the categories.

Figure 7: Robustness to Different Transformations of Citations

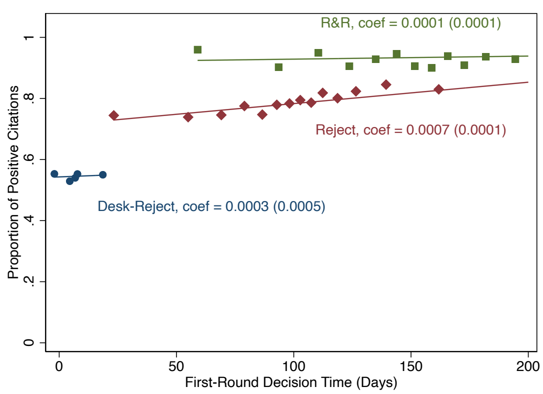
(a) Raw Citations



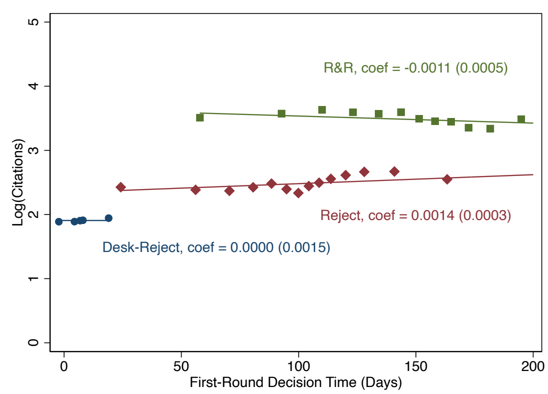
(b) Log(Citations + 1)



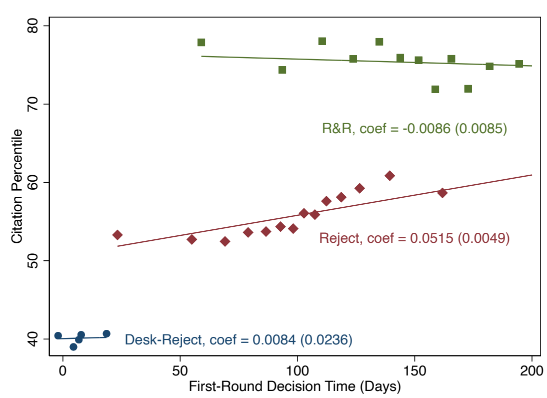
(c) Proportion of Positive Citations



(d) Log(Citations) for Positive Citations (N=18,933)



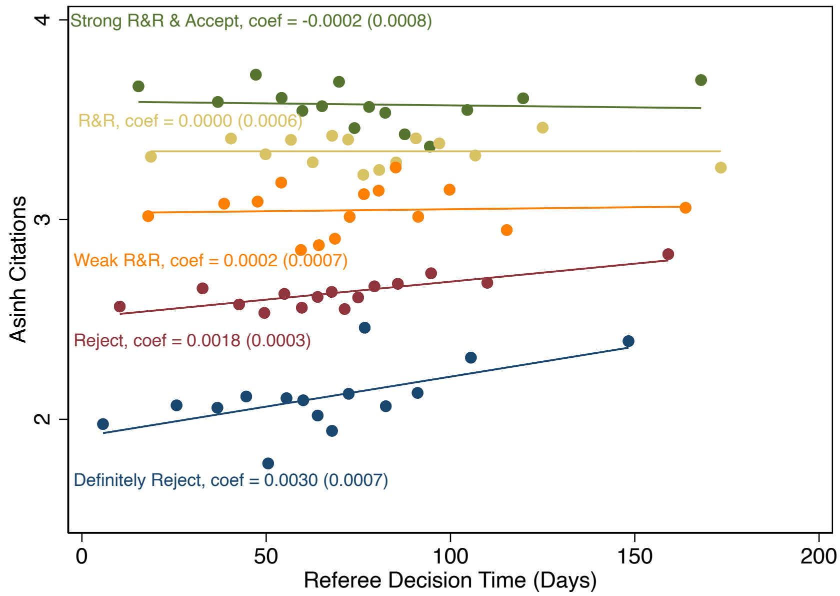
(e) Citation Percentile



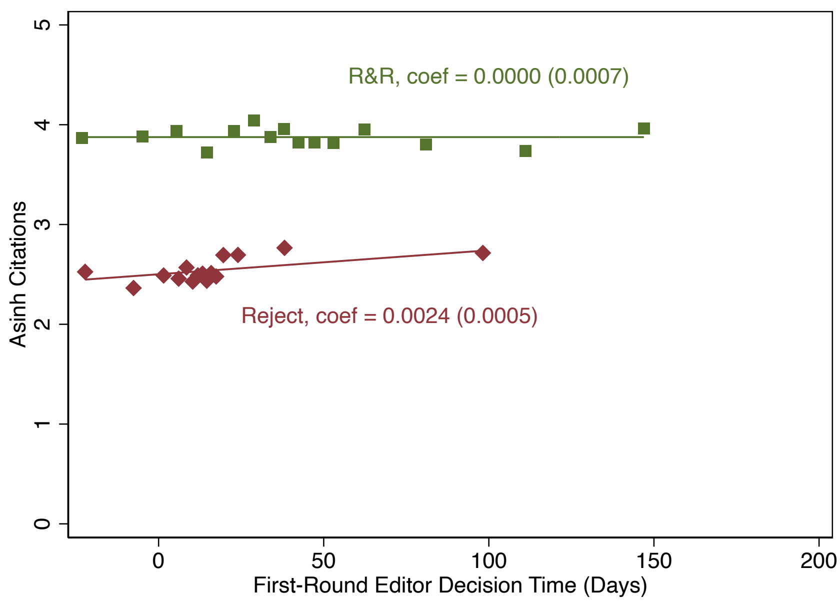
Notes: Raw citations refer to the number of Google Scholar citations without any transformations. In Panel d, only papers with positive citations are included (N=18,933). All binned scatter plots above control for the following fixed effects: journal, year, journal×year, editor, the field(s) of the paper, the number of author(s), the highest number of publications in top-5 economic journals among all author(s), the highest number of publications in top-35 economic journals among all author(s). The first-round decision time is winsorized at 320 days (the 99th percentile). To comply with the data confidentiality restrictions, only bins with decision time ≤ 200 are displayed. Nevertheless, the fitted lines are created based on all observations. The bins are created separately for desk-reject, reject, and R&R papers. The coefficients of the controls are allowed to vary across the categories.

Figure 8: Decomposing First-Round Decision Time

(a) Citations vs. Referee Decision Time



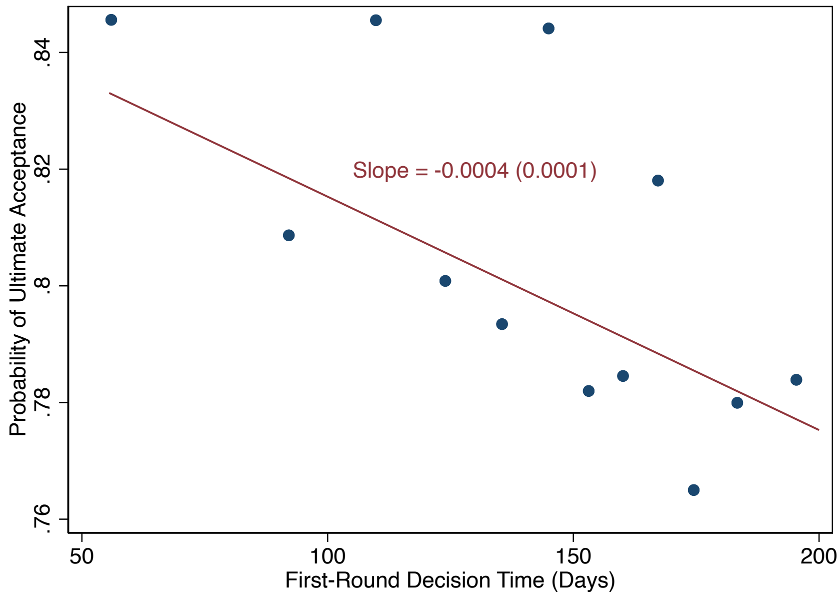
(b) Citations vs. Editor Decision Time



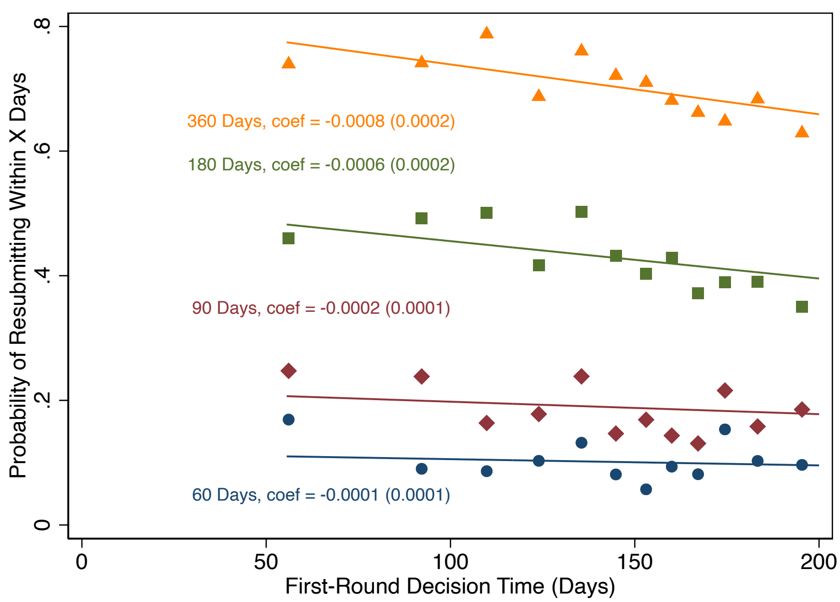
Notes: In Panel a, each observation is a referee recommendation. The referee decision time is winsorized at 244 days (the 99th percentile). In Panel b, each observation is a paper. The editor decision time is winsorized at 175 days (the 99th percentile). Both figures control for the following fixed effects: journal, year, journal×year, editor, the field(s) of the paper, the number of author(s), the highest number of publications in top-5 economic journals among all author(s), the highest number of publications in top-35 economic journals among all author(s). Panel a additionally controls for the number of referees assigned and the average number of publications of all referees assigned. The bins are created separately for different recommendations / editorial decisions. The coefficients of the controls are allowed to vary across the categories.

Figure 9: Other Outcome Variables for R&R Papers

(a) Probability of Ultimate Acceptance as a Function of Decision Time



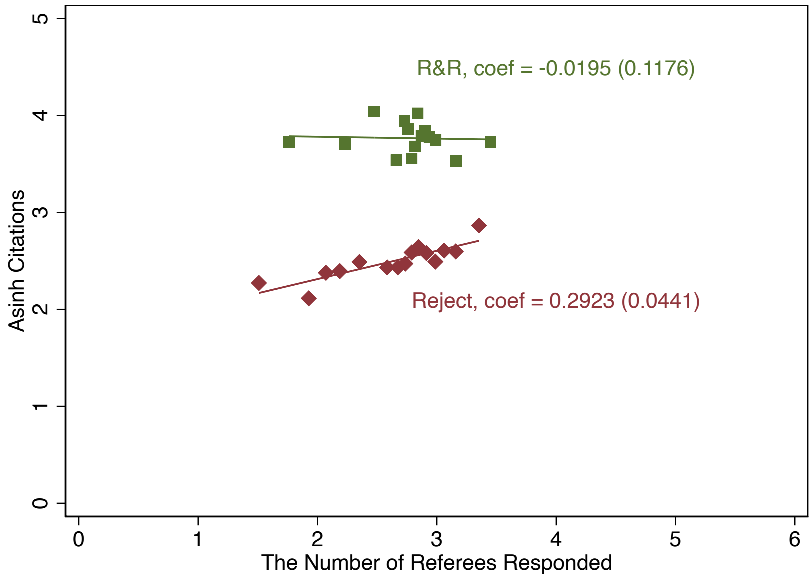
(b) Time to Resubmit as a Function of Decision Time



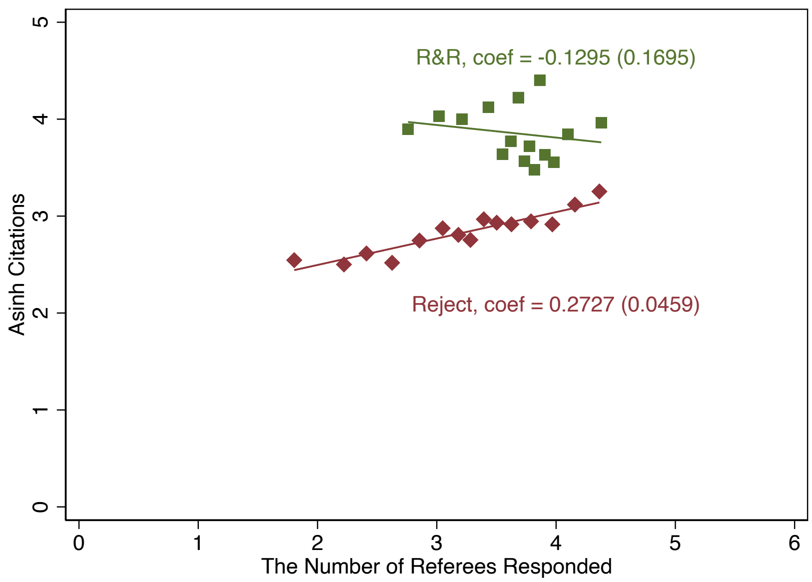
Notes: The binned scatter plots above include R&R papers only. The outcome in Panel a is the probability that a first-round R&R paper is accepted for publication at a date before the data extraction. The outcome in Panel b is the probability that a first-round R&R paper is resubmitted within X days. Both figures above control for the following fixed effects: journal, year, journal×year, editor, the field(s) of the paper, the number of author(s), the highest number of publications in top-5 economic journals among all author(s), the highest number of publications in top-35 economic journals among all author(s). The first-round decision time is winsorized at 410 days (the 99th percentile of R&R papers). To comply with the data confidentiality restrictions, only bins with decision time ≤ 200 are displayed. Nevertheless, the fitted lines are created based on all observations.

Figure 10: Citations as a Function of the Number of Referee Reports Collected

(a) Three Referees Assigned (N=6,065)



(b) Four Referees Assigned (N=2,720)



Notes: In both panels, desk-reject papers are omitted since they don't receive any referee response. In Panel a, only papers where three referees were initially contacted and didn't decline are included in the analysis. In Panel b, only papers where four referees were contacted and didn't decline are included in the analysis. Both figures control for the following fixed effects: journal, year, journal×year, editor, the field(s) of the paper, the number of author(s), the highest number of publications in top-5 economic journals among all author(s), the highest number of publications in top-35 economic journals among all author(s). The bins are created separately for reject and R&R papers. The coefficients of the controls are allowed to vary across the categories.

Table 1: Descriptive Regressions

	Summary Stats	First-Round Decision Time			Asinh Citations		
	(1) Mean	(2) All	(3) R&R	(4) Reject	(5) All	(6) R&R	(7) Reject
Field Missing	0.102						
	(0.002)						
Field Fraction: Lab/Experiments	0.023	-2.65	11.50	-11.20	0.12	0.31	-0.48
	(0.001)	(2.70)	(12.24)	(4.51)	(0.11)	(0.36)	(0.16)
Field Fraction: Labor	0.110	-0.30	6.59	-2.55	0.32	0.23	0.08
	(0.001)	(1.71)	(7.27)	(3.24)	(0.05)	(0.17)	(0.09)
Field Fraction: Health, Urban, Law	0.052	-3.16	-4.37	-7.02	0.28	-0.16	0.04
	(0.001)	(1.90)	(9.94)	(3.63)	(0.07)	(0.25)	(0.11)
Field Fraction: Development	0.049	-6.87	-22.27	-9.89	0.33	-0.04	0.16
	(0.001)	(1.99)	(8.63)	(3.75)	(0.08)	(0.23)	(0.12)
Field Fraction: History	0.011	-7.23	-5.79	-1.48	0.27	-0.18	-0.09
	(0.000)	(3.54)	(14.42)	(5.79)	(0.14)	(0.50)	(0.22)
Field Fraction: Public	0.048	-3.17	-4.03	-6.63	0.23	0.15	-0.02
	(0.001)	(2.04)	(8.65)	(3.74)	(0.07)	(0.21)	(0.12)
Field Fraction: Industrial Organization	0.051	1.97	-7.17	-2.57	0.25	-0.09	0.07
	(0.001)	(2.03)	(8.88)	(3.84)	(0.07)	(0.23)	(0.11)
Field Fraction: Finance	0.068	4.42	11.95	0.97	0.17	-0.38	0.05
	(0.001)	(1.84)	(8.99)	(3.77)	(0.06)	(0.23)	(0.11)
Field Fraction: Macro	0.103	5.01	18.47	6.37	0.10	-0.04	0.05
	(0.001)	(1.79)	(7.57)	(3.55)	(0.06)	(0.19)	(0.10)
Field Fraction: Micro	0.108	1.38	-4.09	-1.19	-0.11	-0.23	-0.31
	(0.001)	(1.75)	(7.14)	(3.43)	(0.06)	(0.20)	(0.10)
Field Fraction: Unclassified	0.061	-1.08	-2.49	-7.18	-0.03	-0.02	-0.07
	(0.001)	(1.89)	(10.11)	(3.92)	(0.07)	(0.26)	(0.12)
Field Fraction: Theory	0.088	2.78	0.57	-3.65	-0.20	-0.41	-0.41
	(0.001)	(1.89)	(7.46)	(3.53)	(0.06)	(0.20)	(0.10)
Field Fraction: Econometrics	0.066	7.29	36.60	3.46	-0.07	-0.42	-0.17
	(0.001)	(1.99)	(9.57)	(3.96)	(0.06)	(0.20)	(0.11)
Field Fraction: International	0.061	-2.35	4.24	-5.56	0.57	0.66	0.50
	(0.001)	(1.80)	(7.88)	(3.56)	(0.06)	(0.20)	(0.11)
1 Author	0.362						
	(0.003)						
2 Authors	0.394	1.09	7.71	0.97	0.29	-0.08	0.24
	(0.003)	(0.61)	(3.47)	(1.05)	(0.02)	(0.09)	(0.04)
3 Authors	0.196	-0.43	0.18	0.00	0.33	-0.03	0.30
	(0.002)	(0.79)	(4.09)	(1.30)	(0.03)	(0.11)	(0.04)
4+ Authors	0.048	-2.42	4.18	-1.93	0.41	0.03	0.44
	(0.001)	(1.24)	(5.85)	(1.88)	(0.05)	(0.15)	(0.07)
Top 35 Publications: 0	0.449						
	(0.003)						
Top 35 Publications: 1	0.168	1.10	-0.68	4.71	0.42	0.28	0.30
	(0.002)	(0.73)	(4.79)	(1.26)	(0.03)	(0.12)	(0.04)
Top 35 Publications: 2	0.109	2.50	0.83	6.18	0.61	0.24	0.50
	(0.002)	(0.93)	(5.29)	(1.48)	(0.03)	(0.14)	(0.05)
Top 35 Publications: 3	0.085	3.02	2.38	5.60	0.69	0.53	0.57
	(0.002)	(1.13)	(5.33)	(1.64)	(0.04)	(0.13)	(0.05)
Top 35 Publications: 4-5	0.098	1.31	0.21	5.31	0.80	0.63	0.67
	(0.002)	(1.12)	(5.18)	(1.58)	(0.04)	(0.13)	(0.06)
Top 35 Publications: 6+	0.090	4.78	0.44	10.19	0.85	0.52	0.75
	(0.002)	(1.38)	(5.52)	(1.88)	(0.05)	(0.16)	(0.07)
Top 5 Publications: 0	0.778						
	(0.003)						
Top 5 Publications: 1	0.127	3.05	0.46	7.81	0.34	0.21	0.36
	(0.002)	(0.97)	(3.76)	(1.24)	(0.03)	(0.10)	(0.04)
Top 5 Publications: 2	0.047	4.16	2.34	11.85	0.48	0.17	0.54
	(0.001)	(1.55)	(4.64)	(1.80)	(0.05)	(0.13)	(0.06)
Top 5 Publications: 3+	0.049	2.00	5.28	12.51	0.64	0.38	0.68
	(0.001)	(1.74)	(4.91)	(1.93)	(0.06)	(0.14)	(0.07)
Group Median		40.00	150.00	90.00	2.09	4.09	2.64
Journal × Year FE		✓	✓	✓	✓	✓	✓
Editor FE		✓	✓	✓	✓	✓	✓
Decision FE		✓			✓		
Observations	27359	27359	2132	12967	27359	2132	12967
R-Squared		0.70	0.52	0.52	0.31	0.28	0.21

Notes: Field fractions are indicators of JEL codes at paper submission. If N codes are listed, the indicator of each field equals 1/N. For example, if a paper lists JEL codes that match macro and international, both the macro indicator and the international indicator are set to 0.5. The top-35 journals are the ones identified in Online Appendix Table 1 of Card and DellaVigna (2020). The top-5 journals are the *American Economic Review* (excluding the *Papers and Proceedings*), *Econometrica*, the *Journal of Political Economy*, the *Quarterly Journal of Economics*, and the *Review of Economic Studies*. First-round decision time is winsorized at 320 days (the 99th percentile).

Table 2: Predicted P(R&R) Based on a Nonlinear Least Squares Model

	Pr(R&R)	
	(1)	(2)
Recommendations		
Definitely Reject (omitted)		
Reject	0.024	0.013
	(0.008)	(0.007)
No Recommendation	0.193	0.143
	(0.023)	(0.023)
Weak R&R	0.235	0.207
	(0.019)	(0.018)
R&R	0.486	0.443
	(0.028)	(0.027)
StrongRR	0.619	0.573
	(0.038)	(0.037)
Accept	0.623	0.567
	(0.040)	(0.039)
Referee Publication Level Effect		
1-2 Publications	0.003	-0.005
	(0.012)	(0.012)
3-4 Publications	-0.016	-0.020
	(0.013)	(0.013)
5+ Publications	0.003	-0.001
	(0.013)	(0.013)
Referee Publication Slope Effect		
1-2 Publications	0.078	0.093
	(0.069)	(0.072)
3-4 Publications	0.263	0.277
	(0.069)	(0.072)
5+ Publications	0.263	0.284
	(0.067)	(0.071)
FE: Journal × Year		✓
FE: Editor		✓
FE: Paper Characteristics		✓
FE: Author Prominence		✓
Observations	9419	9419
R-Squared	0.27	0.30

Notes: The table above shows the estimates of the model described by Equation 1 with and without controls. Only papers with at least three referees assigned and at least two referees responded are included in the analysis. Paper characteristics include field fractions and the number of author(s). Field fractions are indicators of JEL codes at paper submission. If N codes are listed, the indicator of each field equals 1/N. For example, if a paper lists JEL codes that match macro and international, both the macro indicator and the international indicator are set to 0.5. Author prominence is defined as the highest number of publications in the top-35 journals (identified in Online Appendix Table 1 of Card and DellaVigna (2020)) among all author(s) and the highest number of publications in the top-5 journals among all author(s).

Table 3: Predicting Citations With Decision Time

	Asinh Citations					
	(1)	(2)	(3)	(4)	(5)	(6)
Desk Reject × First-Round Decision Time	0.0037	0.0014	0.0011	0.0007	0.0004	
	(0.0014)	(0.0015)	(0.0014)	(0.0013)	(0.0014)	
Reject × First-Round Decision Time	0.0040	0.0047	0.0043	0.0032	0.0032	0.0030
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
R&R × First-Round Decision Time	-0.0008	-0.0007	-0.0007	-0.0008	-0.0009	-0.0008
	(0.0005)	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0005)
FE: Journal × Year × Decision	✓	✓	✓	✓	✓	✓
FE: Editor × Decision		✓	✓	✓	✓	✓
FE: Paper Characteristics × Decision			✓	✓	✓	✓
FE: Author Prominence × Decision				✓	✓	✓
FE: Editor × Year × Decision					✓	✓
FE: Referee Statistics × Decision						✓
Observations	27359	27359	27359	27359	27359	15099
R-Squared	0.24	0.26	0.29	0.33	0.34	0.27

Notes: Paper characteristics include field fractions and the number of author(s). Field fractions are indicators of JEL codes at paper submission. If N codes are listed, the indicator of each field equals 1/N. For example, if a paper lists JEL codes that match macro and international, both the macro indicator and the international indicator are set to 0.5. Author prominence is defined as the highest number of publications in the top-35 journals (identified in Online Appendix Table 1 of Card and DellaVigna (2020)) among all author(s) and the highest number of publications in the top-5 journals among all author(s). Referee statistics is defined as the number of referees assigned to the paper and the average number of publications by the referees assigned.

Table 4: Structural Estimates

Panel (a). Estimates

Parameter in Model	Interpretation	Estimate	95% CI (Lower)	95% CI (Upper)
q^*	R&R quality cutoff	0.619	0.512	0.726
$\Delta(c_l)$	Low-cost info threshold	1.190	0.982	1.442
$\Delta(c_h)$	High-cost info threshold	0.188	0.158	0.209
σ_1^2	Variance of assessments after initial info	0.289	0.214	0.391
σ_2^2	Conditional variance of assessments after additional info	0.064	0.027	0.150
$\alpha_1 - \alpha_0$	R&R citation bias	-0.002	-0.182	0.179

Additional Statistics	Interpretation	Estimate	95% CI (Lower)	95% CI (Upper)
$\frac{\sigma_2^2}{\sigma_1^2+\sigma_2^2}$	Share of information revealed after additional delay	0.181	0.102	0.304
$\frac{\sigma_1^2+\sigma_2^2}{Var(\hat{\psi}_i)}$	Share of citation variation explained by available info	0.135	0.093	0.205

Panel (b). Goodness of Fit

	Pr(R&R, $\tau=1$)	Pr(R&R, $\tau=2$)	Pr(Reject, $\tau=1$)	Pr(Reject, $\tau=2$)
Empirical	0.034	0.108	0.466	0.392
	(0.001)	(0.003)	(0.004)	(0.004)
Estimated	0.034	0.108	0.466	0.392

	$\mathbb{E}[\hat{\psi}_i$ |R&R, $\tau=1]$	$\mathbb{E}[\hat{\psi}_i$ |R&R, $\tau=2]$	$\mathbb{E}[\hat{\psi}_i$ |Reject, $\tau=1]$	$\mathbb{E}[\hat{\psi}_i$ |Reject, $\tau=2]$
Empirical	1.037	0.896	-0.298	0.020
	(0.071)	(0.039)	(0.019)	(0.021)
Estimated	1.046	0.893	-0.297	0.019

Panel (c). Counterfactuals

Condition	Pr(R&R)	$\mathbb{E}[\hat{\psi}_i$ |R&R]-$\mathbb{E}[\hat{\psi}_i$ |Reject]	Expected Value
Baseline	0.143	1.087	0.709
	(0.003)	(0.038)	(0.052)
Only Get 1 Signal	0.126	1.011	0.686
	(0.005)	(0.038)	(0.048)
Always Get 2 Signals	0.151	1.093	0.713
	(0.005)	(0.040)	(0.053)

Notes: Details of the structural estimation can be found in the Appendix C.

Online Appendix

Table of Contents

A Proofs of Propositions

We let F_1 and $F_2(\cdot|\mu_1)$ denote the cumulative density functions (CDFs) of μ_1 and of μ_2 conditional on μ_1, respectively, an we let f_1 and f_2 denote the corresponding density functions.

A.1 Lemma 1

Proof. To simplify the algebra, here we make the normalization assumption that the payoff from choosing $D = 0$ is 0 (see footnote 6). The expected payoff from a positive decision when $\tau = 2$ is simply $\mu_2 - q^*$, and the likelihood of a positive decision given μ_1 is

$$Pr(D = 1|\tau = 2, \mu_1) = 1 - F_2(q^*|\mu_1)$$

The expected payoff from deciding when $\tau = 1$ is $\mu_1 - q^*$ if $D = 1$ and 0 otherwise. The expected payoff from acquiring a second signal is

$$\begin{aligned}\pi_2(\mu_1) &= \int_{q^*}^{\infty} \int_q \mathbb{E}[q - q^*|\mu_2] dF_2(\mu_2|\mu_1) d\mu_2 \\ &= \int_{q^*}^{\infty} (\mu_2 - q^*) dF_2(\mu_2|\mu_1) d\mu_2\end{aligned}$$

The agent thus chooses $\tau = 2$ if $\pi_2(\mu_1) - c_2 \geq \pi_1(\mu_1) := \max(\mu_1 - q^*, 0)$, and the likelihood of this for each draw of c_2 is

$$Pr(\tau = 2|c_2) = \int_{\pi_2(\mu_1) \geq \pi_1(\mu_1) + c_2} dF_1(\mu_1) d\mu_1$$

Thus,

$$\begin{aligned}Pr(D = 1, \tau = 2|c_2) &= \int_{\pi_2(\mu_1) \geq \pi_1(\mu_1) + c_2} \left[1 - F_2(q^*|\mu_1)\right] dF_1(\mu_1) d\mu_1 \\ Pr(D = 0, \tau = 2|c_2) &= \int_{\pi_2(\mu_1) \geq \pi_1(\mu_1) + c_2} F_2(q^*|\mu_1) dF_1(\mu_1) d\mu_1\end{aligned}$$

Similarly,

$$\begin{aligned}Pr(D = 1, \tau = 1|c_2) &= \int_{\mu_1 - q^* \in (0, \pi_2(\mu_1) - c_2)} dF_1(\mu_1) d\mu_1 \\ Pr(D = 1, \tau = 1|c_2) &= \int_{\mu_1 - q^* < \min(0, \pi_2(\mu_1) - c_2)} dF_1(\mu_1) d\mu_1\end{aligned}$$

Thus, the likelihood of each type of decision depends only on F_1 and $F_2(\cdot|\mu_1)$. Moreover, by the law of iterated expectations, the expected value of q for each type of decision will also depend only on the realized values of μ_1 and μ_2.

Finally, to see that (σ_1^2, σ_2^2) can take on any value in the positive real plane, the law of total variance implies that

$$\begin{aligned}\sigma_1^2 &= Var\left(\mathbb{E}[q|S_1]\right)\\ &= Var(q) - \mathbb{E}Var(q|S_1)\\ &= Var(q) - \frac{1}{1/Var(q) + 1/Var(S_1|q)}\end{aligned} \tag{5}$$

Building on this,

$$\begin{aligned}\sigma_2^2 &= \mathbb{E}Var\left(\mathbb{E}[q|S_1,S_2]|S_1\right)\\ &= Var\left(\mathbb{E}[q|S_1,S_2]\right) - Var\left(\mathbb{E}\left[\mathbb{E}[q|S_1,S_2]|S_1\right]\right)\\ &= \left(Var(q) - \frac{1}{1/Var(q) + 1/Var(S_1|q) + 1/Var(S_2|q)}\right) - Var\left(\mathbb{E}[q|S_1]\right)\\ &= \left(Var(q) - \frac{1}{1/Var(q) + 1/Var(S_1|q) + 1/Var(S_2|q)}\right) - \sigma_1^2\\ &= \left(\sigma_1^2 + \frac{1}{1/Var(q) + 1/Var(S_1|q)} - \frac{1}{1/Var(q) + 1/Var(S_1|q) + 1/Var(S_2|q)}\right) - \sigma_1^2\\ &= \frac{1}{1/Var(q) + 1/Var(S_1|q)} - \frac{1}{1/Var(q) + 1/Var(S_1|q) + 1/Var(S_2|q)}\end{aligned} \tag{6}$$

Equation (5) shows that σ_1^2 is strictly increasing in $Var(q)$, with $\lim_{Var(q)\to\infty}\sigma_1^2 = \infty$ and $\lim_{Var(q)\to 0}\sigma_1^2 = 0$; and strictly decreasing in $Var(S_1|q)$, with $\lim_{Var(S_1|q)\to\infty}\sigma_1^2 = 0$ and $\lim_{Var(S_1|q)\to 0}\sigma_1^2 = Var(q)$. Equation (6) shows that σ_2^2 is strictly increasing in $Var(q)$, with $\lim_{Var(q)\to\infty}\sigma_2^2 = \frac{1}{1/Var(S_1|q)} - \frac{1}{1/Var(S_1|q)+1/Var(S_2|q)}$ and $\lim_{Var(q)\to 0}\sigma_2^2 = 0$; strictly increasing in $Var(S_1|q)$, with $\lim_{Var(S_1|q)\to\infty}\sigma_2^2 = \frac{1}{1/Var(q)} - \frac{1}{1/Var(q)+1/Var(S_2|q)}$ and $\lim_{Var(S_1|q)\to 0}\sigma_2^2 = 0$; and strictly decreasing in $Var(S_2|q)$, with $\lim_{Var(S_2|q)\to\infty}\sigma_2^2 = 0$ and $\lim_{Var(S_2|q)\to 0}\sigma_2^2 = \frac{1}{1/Var(q)+1/Var(S_1|q)}$. To make σ_2^2 arbitrarily large while holding σ_1^2 constant, let $Var(q)$ grow without bound while increasing $Var(S_1|q)$ to keep σ_1^2 constant; then σ_2^2 can be made arbitrarily large by choosing $Var(S_2|q)$ sufficiently small because $\lim_{Var(S_2|q)\to 0}\sigma_2^2 = \frac{1}{1/Var(q)+1/Var(S_1|q)}$. To make σ_2^2 arbitrarily small while holding σ_1^2 constant, simply choose $Var(S_2|q)$ sufficiently large. To make σ_1^2 arbitrarily large while holding σ_2^2 constant, choose $Var(q)$ sufficiently large to attain the desired value of σ_1^2, and then choose $Var(S_2|q)$ sufficiently large so as to keep σ_1^2 fixed at some desired value. To make σ_1^2 arbitrarily small while holding σ_2^2 constant, choose $Var(S_1|q)$ sufficiently large. Then, because $\lim_{Var(S_1|q)\to\infty}\sigma_1^2 = 0$, while σ_2^2 is increasing in $Var(S_1|q)$ with $\lim_{Var(S_1|q)\to\infty}\sigma_2^2 = \frac{1}{1/Var(q)} - \frac{1}{1/Var(q)+1/Var(S_2|q)}$,the value of σ_2 can be held constant as $Var(S_1|q)$ increases by simply choosing an appropriately large value of $Var(S_2|q)$. $\square$

A.2 Lemma 2

Proof. Consider first the case where $\mu_1 > q^*$. The expected payoff of deciding positively when $\tau = 1$ is $\pi_1(\mu_1) = \mu_1 - q^*$. The expected payoff if acquiring a second signal is

$$\begin{aligned}\pi_2(\mu_1) &= \int_{q^*}^{\infty} (\mu_2 - q^*)\phi\left(\frac{\mu_2 - \mu_1}{\sigma_2}\right) d\mu_2 \\ &= \int_{q^*-\mu_1}^{\infty} (x + \mu_1 - q^*)\phi\left(\frac{x}{\sigma_2}\right) dx \end{aligned} \tag{7}$$

where the second line follows by a change of variable. Thus

$$\pi_2'(\mu_1) = 1 - \Phi\left(\frac{q^* - \mu_1}{\sigma_2}\right) < 1 \tag{8}$$

Now it is optimal to acquire a second signal if $\pi_1(\mu_1) \leq \pi_2(\mu_1) - c_2$. Observe that $\pi_1(q^*) = 0$ while $\pi_2(q^*) > 0$, so $\pi_2(q^*) - \pi_1(q^*) > 0$. On the other hand, $\pi_2'(\mu_1) - \pi_1'(\mu_1) < 0$, and thus there exists a unique value, call it $\Delta(c_2)$, for which $\pi_2(u_1) - c_2 > \pi_1(\mu_1)$ if and only if $\mu_1 > q^* + \Delta$. Note that $\Delta(c_2) = 0$ if $\pi_2(q^*) - c_2 > \pi_1(q^*)$. Moreover, by line (7), $\pi_2(q^*) - \pi_1(q^*)$ is not a function of q^*, and by line (8), $\pi_2'(\mu_1)$ is not a function of q^*. Thus, $\Delta(c_2)$ is not a function of q^*. Finally, note that

$$\frac{\partial}{\partial \sigma_2}\pi_2 = \int_{q^*-\mu_1}^{\infty} (x + \mu_1 - q^*)\left(\frac{x^2}{\sigma_2^3}\right)\phi\left(\frac{x}{\sigma_2}\right) dx > 0$$

meaning that the benefit of acquiring additional information is increasing in σ_2.

By symmetry, if $\mu_1 < q^*$, then the agent acquires a second signal if and only if $\mu_1 < q^* - \Delta(c_2)$. This completes the proof. □

A.3 Proposition 1

Proof. We first prove this for a degenerate distribution of c_2 where there is just a single value of the threshold rule $\Delta(c_2)$. The result generalizes immediately to any distribution of c_2 (and thus $\Delta(c_2)$) with bounded support: integrating over the different values of c_2 does not alter any of the relationships, since each one holds point-wise for each c_2.

We proceed in three steps. First, we show that $Pr(D = 1|\tau = 2)$ is increasing in σ_2, and thus attains its infimum when $\sigma_2 \to 0$. Because $Pr(D = 1|\tau = 1)$ does not depend on σ_2, it is thus sufficient to establish that $Pr(D = 1|\tau = 2) \geq Pr(D = 1|\tau = 1)$ in the limit of $\sigma_2 \to 0$, which we do in step 2. In step 3 we prove the second part of the proposition.

Step 1. Consider $\int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)}(1-F_2(q^*|\mu_1))f_1(\mu_1)d\mu_1$ as a function of σ_2. The derivative with respect to σ_2 is

$$\int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)}\left(\frac{q^*-\mu_1}{\sigma_2^2}\right)\phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)f_1(\mu_1)d\mu_1$$

where ϕ is the standard normal PDF. Now notice that $h(\mu_1) := \left(\frac{q^*-\mu_1}{\sigma_2^2}\right)\phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)$ satisfies $h(q^*+x) = -h(q^*-x) < 0$ for any $x > 0$. However, $f_1(q^*+x) < f_1(q^*-x)$ for $q^* > 0$. Thus,

$$\begin{aligned}\int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)}h(\mu_1)f_1(\mu_1)d\mu_1 &= \int_{q^*}^{q^*+\Delta(c_2)}h(\mu_1)f_1(\mu_1)d\mu_1 + \int_{q^*-\Delta(c_2)}^{q^*}h(\mu_1)f_1(\mu_1)d\mu_1 \\ &= \int_0^{\Delta(c_2)}h(q^*+x)f_1(q^*+x)dx + \int_{-\Delta(c_2)}^0 h(q^*+x)f_1(q^*+x)dx \\ &= \int_0^{\Delta(c_2)}h(q^*+x)f_1(q^*+x)dx - \int_{-\Delta(c_2)}^0 h(q^*-x)f_1(q^*+x)dx \\ &> \int_0^{\Delta(c_2)}h(q^*+x)f_1(q^*+x)dx - \int_{-\Delta(c_2)}^0 h(q^*-x)f_1(q^*-x)dx \\ &= \int_0^{\Delta(c_2)}h(q^*+x)f_1(q^*+x)dx - \int_0^{\Delta(c_2)}h(q^*+x)f_1(q^*+x)dx \\ &= 0\end{aligned}$$

In the limit of $\sigma_2 \to 0$, $\int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)}(1-F_2(q^*|\mu_1))$ approaches a step function that is 0 for $\mu_1 < q^*$ and 1 for $\mu_1 > q^*$. Thus, the infimum of $\int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)}(1-F_2(q^*|\mu_1))f_1(\mu_1)d\mu_1$ is simply $F_1(q^*+\Delta(c_2)) - F_1(q^*)$.

Step 2. We thus need to show that

$$\begin{aligned}\frac{1-F_1(q^*+\Delta(c_2))}{1-F_1(q^*+\Delta(c_2))+F_1(q^*-\Delta(c_2))} &\leq \frac{F_1(q^*+\Delta(c_2))-F_1(q^*)}{F_1(q^*+\Delta(c_2))-F_1(q^*-\Delta(c_2))} \\ &= \frac{F_1(q^*+\Delta(c_2))-F_1(q^*)}{(F_1(q^*+\Delta(c_2))-F_1(q^*))+(F_1(q^*)-F_1(q^*-\Delta(c_2)))}\end{aligned}$$

Equivalently, this reduces to

$$\frac{1-F_1(q^*+\Delta(c_2))}{F_1(q^*-\Delta(c_2))} \leq \frac{F_1(q^*+\Delta(c_2))-F_1(q^*)}{F_1(q^*)-F_1(q^*-\Delta(c_2))}$$

As

$$\frac{1-F_1(q^*+\Delta(c_2))}{F_1(q^*-\Delta(c_2))} \leq \frac{1-F_1(q^*)}{F_1(q^*)},$$

it is sufficient to show that

$$\frac{1-F_1(q^*)}{F_1(q^*)} \leq \frac{F_1(q^*+\Delta(c_2))-F_1(q^*)}{F_1(q^*)-F_1(q^*-\Delta(c_2))}$$

or, equivalently, that

$$\frac{1-F_1(q^*)}{F_1(q^*)}\left(F_1(q^*)-F_1(q^*-\Delta(c_2))\right)-\left(F_1(q^*+\Delta(c_2))-F_1(q^*)\right) \leq 0$$

To that end, consider the function

$$\lambda(\Delta(c_2)) := \frac{1-F_1(q^*)}{F_1(q^*)}\left(F_1(q^*)-F_1(q^*-\Delta(c_2))\right)-\left(F_1(q^*+\Delta(c_2))-F_1(q^*)\right)$$

We shall argue, by contradiction, that $\lambda(\Delta(c_2)) > 0$ is not possible. To begin, note that $\lambda(0) = 0$ and

$$\lambda'(\Delta(c_2)) = \frac{1-F_1(q^*)}{F_1(q^*)} f_1(q^*-\Delta(c_2)) - f_1(q^*+\Delta(c_2))$$

Thus, $\lambda'(0) < 0$. However, $\frac{f_1(q^*-\Delta(c_2))}{f_1(q^*+\Delta(c_2))}$ is strictly increasing in $\Delta(c_2)$ and grows without bound, and thus there is a unique $\Delta(c_2)^*$ such that $\lambda'(\Delta(c_2)) < 0$ for $\Delta(c_2) < \Delta(c_2)^*$ and $\lambda'(\Delta(c_2)) > 0$ for $\Delta(c_2) > \Delta(c_2)^*$. Plainly, $\lambda(\Delta(c_2)) < 0$ for $\Delta(c_2) < \Delta(c_2)^*$. Thus, if there exists a value of $\Delta(c_2)$ for which $\lambda(\Delta(c_2)) > 0$, then it must be that $\Delta(c_2) > \Delta(c_2)^*$ and thus

$$\lim_{\Delta(c_2)\to\infty} \lambda(\Delta(c_2)) > 0.$$

This is a contradiction because

$$\begin{aligned}\lim_{\Delta(c_2)\to\infty} \lambda(\Delta(c_2)) &= \frac{1-F_1(q^*)}{F_1(q^*)}\left(F_1(q^*)\right)-\left(1-F_1(q^*)\right)\\ &= 0\end{aligned}$$

Step 3.

$$\begin{aligned}Pr(D=1) &= 1-F_1(q^*+\Delta(c_2)) + \int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)} (1-F_2(q^*|\mu_1))f_1(\mu_1)d\mu_1\\ &= 1-F_1(q^*+v) + \int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)} \left(1-\Phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)\right) f_1(\mu_1)d\mu_1\end{aligned}$$

Now

$$\frac{\partial}{\partial q^*}\left[1-F_1(q^*+\Delta(c_2))\right] = -f_1(q^*+\Delta(c_2))$$

and

$$\begin{aligned}\frac{\partial}{\partial q^*}\int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)}\left(1-\Phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)\right)f_1(\mu_1)d\mu_1 &= \left[1-\Phi\left(\frac{-\Delta(c_2)}{\sigma_2}\right)\right]f_1\left(q^*+\Delta(c_2)\right)\\ &-\left[1-\Phi\left(\frac{\Delta(c_2)}{\sigma_2}\right)\right]f_1\left(q^*-\Delta(c_2)\right)\\ &+\int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)}\left(-\frac{1}{\sigma_2}\phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)\right)f_1(\mu_1)d\mu_1\end{aligned}$$

Thus,

$$\begin{aligned}\frac{\partial}{\partial q^*}Pr(D=1) &= \left[-\Phi\left(\frac{-\Delta(c_2)}{\sigma_2}\right)\right]f_1\left(q^*+\Delta(c_2)\right)\\ &-\left[1-\Phi\left(\frac{\Delta(c_2)}{\sigma_2}\right)\right]f_1\left(q^*-\Delta(c_2)\right)\\ &-\int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)}\frac{1}{\sigma_2}\phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)f_1(\mu_1)d\mu_1\\ &<0\end{aligned}$$

□

A.4 Proposition 2

Proof. We first prove this for a degenerate distribution of c_2 where there is just a single value of the threshold rule $\Delta(c_2)$. The result generalizes immediately to any distribution of c_2 (and thus $\Delta(c_2)$) with bounded support: integrating over the different values of c_2 does not alter any of the relationships, since each one holds point-wise for each c_2.

Let F_η denote the CDF of η. By Lemma 2, decision time is strictly increasing in the probability that $\mu_1 - q^* \in [-\Delta(c_2), \Delta(c_2)]$. This probability is given by

$$Pr(g(X)) := F_\eta(-g(X)+\Delta(c_2)) - F_\eta(-g(X)-\Delta(c_2)).$$

Taking the derivative with respect to $g(X)$ gives

$$\begin{aligned}Pr'(g(X)) &= -f_\eta(-g(X)+\Delta(c_2)) + f_\eta(-g(X)-\Delta(c_2))\\ &= -f_\eta(g(X)-\Delta(c_2)) + f_\eta(g(X)+\Delta(c_2))\end{aligned}$$

where the second line follows by symmetry of the density function. Also by symmetry of f_η, $Pr' > 0$ if and only if $|g(X)+\Delta(c_2)| < |g(X)-\Delta(c_2)|$, which holds if and only if $g(X) > 0$. Consequently, $Pr(g(X))$ is decreasing in $g(X)$ when $g(X) > 0$, and is increasing in $g(X)$

when $g(X) < 0$. Last, note that

$$\begin{aligned} Pr'(-g(X)) &= -f_\eta(g(X) + \Delta(c_2)) + f_\eta(g(X) - \Delta(c_2)) \\ &= -Pr'(g(X)) \end{aligned}$$

meaning that $|Pr'(g(X)|$ depends on $|g(X)|$ only. Putting this together implies that $|Pr(g(X))|$ is strictly decreasing in $|g(x)|$. □

A.5 Proposition 3

Proof. We first prove this for a degenerate distribution of c_2 where there is just a single value of the threshold rule $\Delta(c_2)$. The result generalizes immediately to any distribution of c_2 (and thus $\Delta(c_2)$) with bounded support: integrating over the different values of c_2 does not alter any of the relationships, since each one holds point-wise for each c_2.

Begin by decomposing $Pr(D = 1)$ into the period 1 and period 2 components.

$$\begin{aligned} Pr(D = 1) &= Pr(D = 1|\tau = 1)\,(1 - Pr(g(X))) + Pr(D = 1|\tau = 2)Pr(g(X)) \\ &= (1 - F_\eta(-g(X) + \Delta(c_2))) + Pr(\mu_2 - q^* > 0|\ |\mu_1 - q^*| < \Delta(c_2), g(X))Pr(g(X)) \\ &= (1 - F_\eta(-g(X) + \Delta(c_2))) + \mathbb{E}\left[Pr(\mu_2 - q^* > 0|\mu_1)|\ g(X), |\mu_1 - q^*| < \Delta(c_2)\right] Pr(g(X)) \end{aligned}$$

where $Pr(g(X))$ is defined as in the proof of Proposition 2.

Taking the derivative with respect to $g(X)$,

$$\begin{aligned} \frac{d}{dg(X)} Pr(D = 1) &= f_\eta\left(-g(X) + \Delta(c_2)\right) \\ &\quad + \mathbb{E}\left[Pr(\mu_2 - q^* > 0|\mu_1)|\ g(X), |\mu_1 - q^*| < \Delta(c_2)\right]\left(-f_\eta(g(X) - \Delta(c_2)) + f_\eta(g(X) + \Delta(c_2))\right) \\ &\quad + \left(\frac{d}{dg(X)}\mathbb{E}\left[Pr(\mu_2 - q^* > 0|\mu_1)|\ g(X), |\mu_1 - q^*| < \Delta(c_2)\right]\right) Pr(g(X)) \\ &= \left(1 - \mathbb{E}\left[Pr(\mu_2 - q^* > 0|\mu_1)|\ g(X), |\mu_1 - q^*| < \Delta(c_2)\right]\right) f_\eta\left(-g(X) + \Delta(c_2)\right) \quad (9) \\ &\quad + \mathbb{E}\left[Pr(\mu_2 - q^* > 0|\mu_1)|\ g(X), |\mu_1 - q^*| < \Delta(c_2)\right] f_\eta(g(X) + \Delta(c_2)) \quad (10) \\ &\quad + \left(\frac{d}{dg(X)}\mathbb{E}\left[Pr(\mu_2 - q^* > 0|\mu_1)|\ g(X), |\mu_1 - q^*| < \Delta(c_2)\right]\right) Pr(g(X)) \quad (11) \end{aligned}$$

The term in (9) is positive because $Pr(\mu_2 - q^* > 0|\mu_1) < 1$. The term in (10) is positive because it is the product of two positive numbers. The term in (11) is non-negative because $Pr(\mu_2 - q^* > 0|\mu_1)$ is increasing in μ_1, and assumptions (i) and (ii) imply that the distribution of μ_1 conditional on $g(X), |\mu_1 - q^*| < \Delta(c_2)$ is increasing in $g(X)$ in the first-order stochastic dominance order.

Next, observe that when $g(X) = 0$,

$$Pr(D = 1) = (1 - F_\eta(\Delta(c_2))) + \mathbb{E}\left[Pr(\mu_2 - q^* > 0|\mu_1)|\; g(X), |\mu_1 - q^*| < \Delta(c_2)\right] P(0)$$

Now by symmetry, $P(0) = F_\eta(\Delta(c_2)) - F_\eta(-\Delta(c_2)) = 2F_\eta(\Delta(c_2))$. Next, note that the distribution of μ_1 is centered around q^* when $g(X) = 0$, and thus by symmetry

$$\mathbb{E}\left[Pr(\mu_2 - q^* > 0|\mu_1)|\; g(X), |\mu_1 - q^*| < \Delta(c_2)\right] = 1/2$$

. Thus, $Pr(D = 1) = 1/2$ when $g(X) = 0$. A similar symmetry argument shows that $\frac{d}{dg(X)} Pr(D = 1)$ depends only on $|g(X)|$. □

A.6 Proposition 4

Proof. We first prove this for a degenerate distribution of c_2 where there is just a single value of the threshold rule $\Delta(c_2)$. The result generalizes immediately to any distribution of c_2 (and thus $\Delta(c_2)$) with bounded support: integrating over the different values of c_2 does not alter any of the relationships, since each one holds point-wise for each c_2.

$$\begin{aligned}
\mathbb{E}[q|D = 1, \tau = 2] &= \frac{\int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)} \left(\int_{q^*}^{\infty} \mu_2 f_2(\mu_2|\mu_1) d\mu_2\right) f_1(\mu_1) d\mu_1}{\int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)} \left(\int_{q^*}^{\infty} f_2(\mu_2|\mu_1) d\mu_2\right) f_1(\mu_1) d\mu_1} \\
&= \frac{\int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)} \left(\int_{q^*}^{\infty} \mu_2 \phi\left(\frac{\mu_2-\mu_1}{\sigma_2}\right) d\mu_2\right) f_1(\mu_1) d\mu_1}{\int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)} \left(\int_{q^*}^{\infty} \phi\left(\frac{\mu_2-\mu_1}{\sigma_2}\right) d\mu_2\right) f_1(\mu_1) d\mu_1} \\
&= \frac{\int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)} \left[\left(\mu_1 + \sigma \frac{\phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)}{1-\Phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)}\right)\left(1 - \Phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)\right)\right] f_1(\mu_1) d\mu_1}{\int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)} \left(1 - \Phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)\right) f_1(\mu_1) d\mu_1} \\
&= \frac{\int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)} \left[\mu_1\left(1 - \Phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)\right) + \sigma_2 \phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)\right] f_1(\mu_1) d\mu_1}{\int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)} \left(1 - \Phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)\right) f_1(\mu_1) d\mu_1} \\
&= \frac{\int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)} \left[\mu_1 \Phi\left(\frac{\mu_1-q^*}{\sigma_2}\right) + \sigma_2 \phi\left(\frac{\mu_1-q^*}{\sigma_2}\right)\right] f_1(\mu_1) d\mu_1}{\int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)} \Phi\left(\frac{\mu_1-q^*}{\sigma_2}\right) f_1(\mu_1) d\mu_1}
\end{aligned}$$

Now

$$\lim_{\sigma_2\to\infty}\mathbb{E}[q|D=1,\tau=2]=\lim_{\sigma_2\to\infty}\frac{\int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)}\left(\frac{\mu_1}{2}+\sigma_2\right)f_1(\mu_1)d\mu_1}{\int_{q^*-\Delta(c_2)}^{q^*+\Delta(c_2)}\left(\frac{1}{2}\right)f_1(\mu_1)d\mu_1}$$
$$=\infty \tag{12}$$

and

$$\lim_{\sigma_2\to 0}\mathbb{E}[q|D=1,\tau=2]=\frac{\int_{q^*-\Delta(c_2)}^{q^*}(0)\,f_1(\mu_1)d\mu_1+\int_{q^*}^{q^*+\Delta(c_2)}\mu_1 f_1(\mu_1)d\mu_1}{\int_{q^*-\Delta(c_2)}^{q^*}(0)\,f_1(\mu_1)d\mu_1+\int_{q^*}^{q^*+\Delta(c_2)}f_1(\mu_1)d\mu_1}$$
$$=\mathbb{E}[\mu_1|q^*\le\mu_1\le q^*+\Delta(c_2)] \tag{13}$$

Symmetrically,

$$\lim_{\sigma_2\to\infty}\mathbb{E}[q|D=0,\tau=2]=-\infty$$
$$\lim_{\sigma_2\to 0}\mathbb{E}[q|D=0,\tau=2]=\mathbb{E}[\mu_1|q^*-\Delta(c_2)\le\mu_1\le q^*]$$

Putting this together, the implications for the learning effect are that

$$\lim_{\sigma_2\to\infty}\mathbb{E}[q|D=1,\tau=2]-\mathbb{E}[q|\mu_1>q^*,\tau=2]=\infty$$
$$\lim_{\sigma_2\to 0}\mathbb{E}[q|D=1,\tau=2]-\mathbb{E}[q|\mu_1>q^*,\tau=2]=0$$
$$\lim_{\sigma_2\to\infty}\mathbb{E}[q|D=0,\tau=2]-\mathbb{E}[q|\mu_1<q^*,\tau=2]=-\infty$$
$$\lim_{\sigma_2\to 0}\mathbb{E}[q|D=0,\tau=2]-\mathbb{E}[q|\mu_1<q^*,\tau=2]=0$$

Next, consider

$$\mathbb{E}[q|\mu_1>q^*,\tau=2]=\mathbb{E}[\mu_1|q^*\le\mu_1\le q^*+\Delta(c_2)]$$
$$=\sigma_1\frac{\phi\left(\frac{q^*}{\sigma_1}\right)-\phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right)}{\Phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right)-\Phi\left(\frac{q^*}{\sigma_1}\right)}$$

When σ_1 is large, first-order Taylor expansions applied to the numerator and denominator of the below give

$$\frac{\phi\left(\frac{q^*}{\sigma_1}\right)-\phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right)}{\Phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right)-\Phi\left(\frac{q^*}{\sigma_1}\right)}=\frac{1}{2}\frac{\frac{(q^*+\Delta(c_2))^2}{\sigma_1^2}\phi(0)-\frac{(q^*)^2}{\sigma_1^2}\phi(0)+O\left(1/\sigma_1^2\right)}{\frac{(q^*+\Delta(c_2))}{\sigma_1}\phi(0)-\frac{q^*}{\sigma_1}\phi(0)+O\left(1/\sigma_1^2\right)}$$
$$=\frac{1}{\sigma_1}\frac{(q^*+\Delta(c_2))^2-(q^*)^2}{2\Delta(c_2)}+O\left(1/\sigma_1^2\right)$$
$$=\frac{1}{\sigma_1}\left(q^*+\frac{\Delta(c_2)}{2}\right)+O\left(1/\sigma_1^2\right)$$

Thus,

$$\lim_{\sigma_1\to\infty}\mathbb{E}[q|\mu_1>q^*,\tau=2]=q^*+\frac{\Delta(c_2)}{2} \tag{14}$$

On the other hand, because

$$\lim_{\sigma_1\to 0}\frac{\phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right)}{\phi\left(\frac{q^*}{\sigma_1}\right)}=0,$$

an application of L'hopital's rule gives

$$\lim_{\sigma_1\to 0}\sigma_1\frac{\phi\left(\frac{q^*}{\sigma_1}\right)-\phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right)}{\Phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right)-\Phi\left(\frac{q^*}{\sigma_1}\right)}=\lim_{\sigma_1\to 0}\sigma_1\frac{\phi\left(\frac{q^*}{\sigma_1}\right)\left(1-\phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right)/\phi\left(\frac{q^*}{\sigma_1}\right)\right)}{\Phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right)-\Phi\left(\frac{q^*}{\sigma_1}\right)}$$
$$=\lim_{\sigma_1\to 0}\frac{\sigma_1\phi\left(\frac{q^*}{\sigma_1}\right)}{\Phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right)-\Phi\left(\frac{q^*}{\sigma_1}\right)}$$
$$=\lim_{\sigma_1\to 0}\frac{\phi\left(\frac{q^*}{\sigma_1}\right)-\frac{(q^*)^2}{\sigma_1^2}\phi\left(\frac{q^*}{\sigma_1}\right)}{\frac{(q^*+\Delta(c_2))}{\sigma_1^2}\phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right)-\frac{q^*}{\sigma_1^2}\phi\left(\frac{q^*}{\sigma_1}\right)}$$
$$=q^* \tag{15}$$

Next, consider

$$\mathbb{E}[q|D=1,\tau=1]=\mathbb{E}[\mu_1|q^*+\Delta(c_2)\leq\mu_1]$$
$$=\sigma_1\frac{\phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right)}{1-\Phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right)}$$

Note that

$$\lim_{\sigma_1\to\infty} \frac{\phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right)}{1-\Phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right)} = \frac{1}{1/2}$$

and thus

$$\lim_{\sigma_1\to\infty} \sigma_1 \frac{\phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right)}{1-\Phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right)} = \infty. \tag{16}$$

Further, by L'hopital's rule,

$$\begin{aligned}\lim_{\sigma_1\to 0} \sigma_1 \frac{\phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right)}{1-\Phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right)} &= \lim_{\sigma_1\to 0} \frac{\phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right) - \frac{(q^*+\Delta(c_2))^2}{\sigma_1^2}\phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right)}{\frac{(q^*+\Delta(c_2))}{\sigma_1^2}\phi\left(\frac{q^*+\Delta(c_2)}{\sigma_1}\right)} \\ &= q^* + \Delta(c_2) \end{aligned} \tag{17}$$

Putting this together, the implications for the selection effect are that

$$\begin{aligned}
&\lim_{\sigma_1\to\infty} \mathbb{E}[q|D=1,\tau=1] - \mathbb{E}[q|\mu_1 > q^*, \tau=2] = \infty \\
&\lim_{\sigma_1\to 0} \mathbb{E}[q|D=1,\tau=1] - \mathbb{E}[q|\mu_1 > q^*, \tau=2] = (q^*+\Delta(c_2)) - q^* = \Delta(c_2) \\
&\lim_{\sigma_2\to\infty} \mathbb{E}[q|D=0,\tau=1] - \mathbb{E}[q|\mu_1 < q^*, \tau=2] = -\infty \\
&\lim_{\sigma_2\to 0} \mathbb{E}[q|D=0,\tau=1] - \mathbb{E}[q|\mu_1 < q^*, \tau=2] = -\Delta(c_2)
\end{aligned}$$

Last, note that because $SE(D=1)$ is not a function of σ_2, $LE(D=1)-SE(D=1)$ can be made arbitrarily large by holding σ_1 constant and choosing σ_2 to be sufficiently large. To show that $LE(D=1)-SE(D=1)$ can be made arbitrarily small, first note that by part 2, for any $\bar{s}>0$ there exists a σ_1 such that $SE(D=1)>\bar{s}$. Then, holding this σ_1 constant, part 1 implies that for any $\underline{l}>0$, there exists a σ_2 such that $LE(D=1)<\underline{l}$. Thus, for any $\bar{s}>0$ and $\underline{l}>0$, there exist σ_1 and σ_2 such that $LE(D=1)-SE(D=1)<\underline{l}-\bar{s}$. □

A.7 Proposition 5

Proof. First, note that

$$\lim_{\Delta(c_l)\to\infty} Pr(\tau = 2|\Delta(c_2) = \Delta(c_l)) = 1$$
$$\lim_{\Delta(c_h)\to 0} Pr(\tau = 2|\Delta(c_2) = \Delta(c_h)) = 0$$

Thus,

$$\lim_{\Delta(c_h)\to 0} \lim_{\Delta(c_l)\to\infty} Pr(\Delta(c_2) = \Delta(c_l)|\tau = 2)$$
$$= \lim_{\Delta(c_h)\to 0} \lim_{\Delta(c_l)\to\infty} \frac{Pr(\tau = 2|\Delta(c_2) = \Delta(c_l))Pr\left(\Delta(c_2) = \Delta(c_l)\right)}{Pr(\tau = 2|\Delta(c_2) = \Delta(c_l))Pr\left(\Delta(c_2) = \Delta(c_l)\right) + Pr(\tau = 2|\Delta(c_2) = \Delta(c_h))Pr\left(\Delta(c_2) = \Delta(c_h)\right)}$$
$$=1$$

and similarly

$$\lim_{\Delta(c_h)\to 0} \lim_{\Delta(c_l)\to\infty} Pr(\Delta(c_2) = \Delta(c_h)|\tau = 1) = 1.$$

Additionally,

$$\lim_{\Delta(c_l)\to\infty} \mathbb{E}[q|D = 1, \tau = 2, \Delta(c_2) = \Delta(c_l)] = \mathbb{E}[\mu_2|\mu_2 > q^*]$$
$$\lim_{\Delta(c_l)\to\infty} \mathbb{E}[q|D = 0, \tau = 2, \Delta(c_2) = \Delta(c_l)] = \mathbb{E}[\mu_2|\mu_2 < q^*]$$
$$\lim_{\Delta(c_h)\to 0} \mathbb{E}[q|D = 1, \tau = 1, \Delta(c_2) = \Delta(c_h)] = \mathbb{E}[\mu_1|\mu_1 > q^*]$$
$$\lim_{\Delta(c_h)\to 0} \mathbb{E}[q|D = 0, \tau = 1, \Delta(c_2) = \Delta(c_h)] = \mathbb{E}[\mu_1|\mu_1 < q^*]$$

The result then follows from the expansion

$$\mathbb{E}[q|D,\tau] = Pr\left(\Delta(c_2) = \Delta(c_l)|\tau\right)\mathbb{E}[q|D,\tau,\Delta(c_2) = \Delta(c_l)] + Pr\left(\Delta(c_2) = \Delta(c_h)|\tau\right)\mathbb{E}[q|D,\tau,\Delta(c_2) = \Delta(c_h)]$$

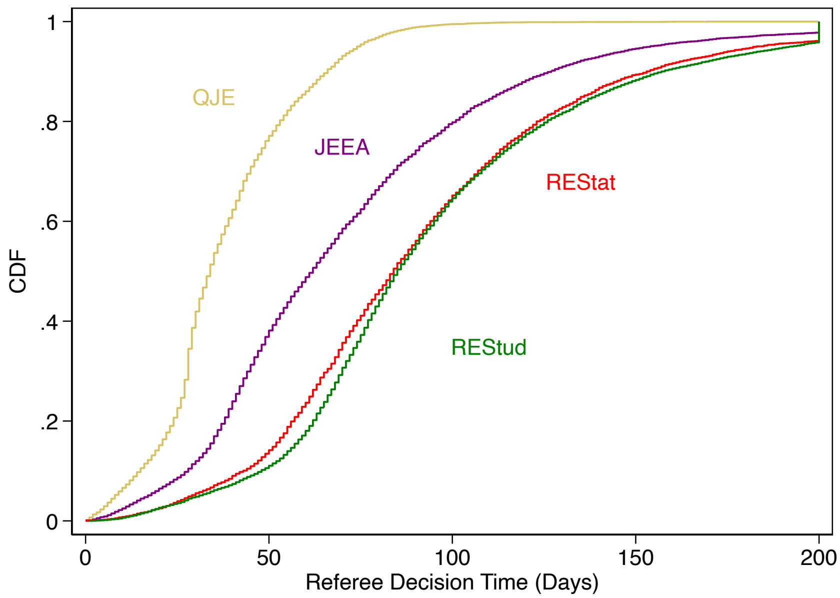
□

B Supplementary Empirical Results

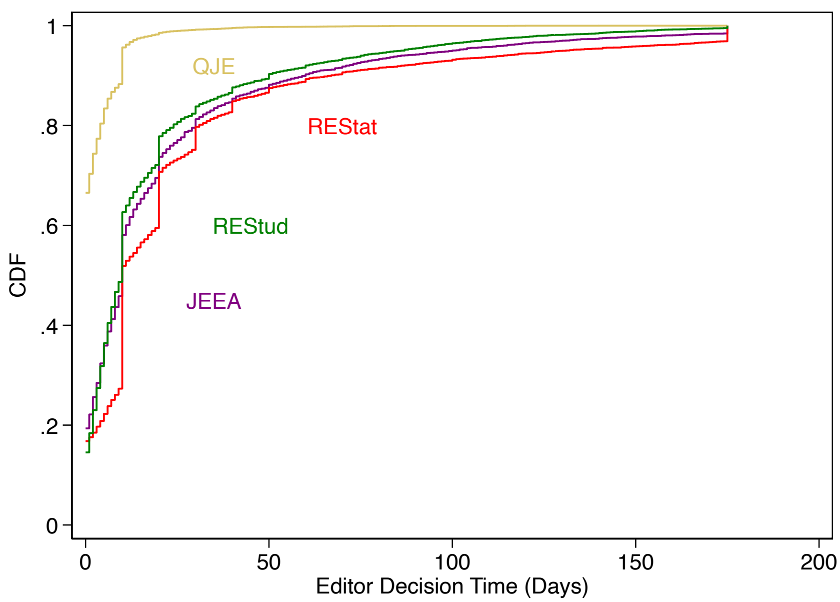
B.1 Additional Descriptive Statistics

Figure A1: The Distributions of Referee & Editor Decision Time, by Journal

(a) Referee Decision Time



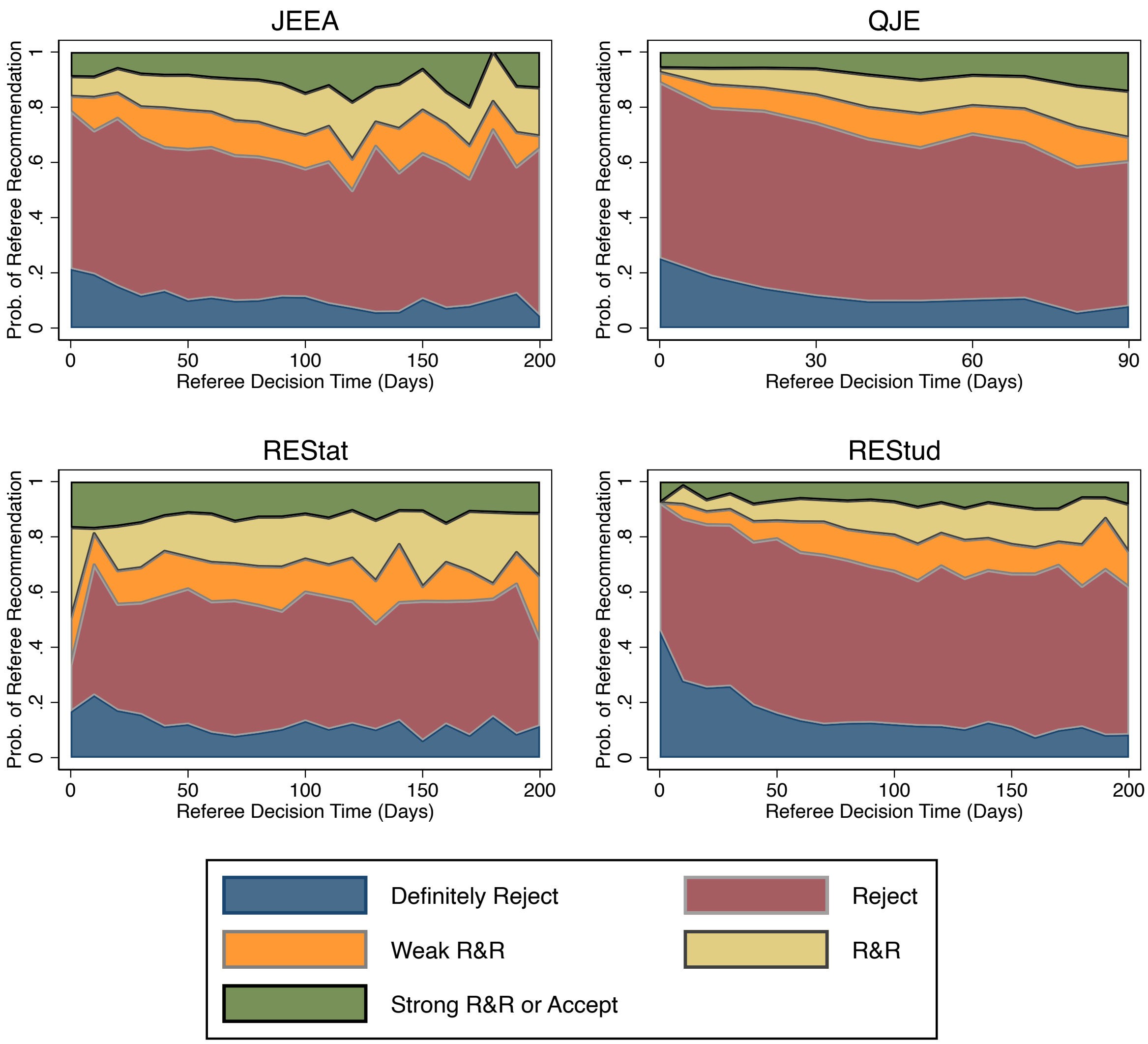
(b) Editor Decision Time



Notes: Referee decision time and editor decision time are winsorized at 200 days. Editor decision time is defined as the first-round decision time for desk-rejects or the days between the arrival of the last report and the editorial decision. Given that the first-round decision time is rounded to the nearest 10, the observations with editor decision time = 0 should be interpreted as the editor making a decision within 5 days.

B.2 Additional Results for the Share of Positive Decisions Over Time

Figure A2: Probability of Each Referee Recommendation vs. Decision Time, by Journal



Notes: The referee decision time is top-coded at the minimum of (i) the 99th percentile of the decision time in the journal and (ii) 200 days to comply with the data confidentiality restrictions. Referee reports with “No Recommendation” is omitted in the analysis.

B.3 Additional Results for Testing the Inverse U Shape

Column 1, 3, 5 of Table A1 show the regressions run to obtain the estimates in Figure 5: (i) the probability of receiving an R&R decision, (ii) the probability of waiting for a third referee, and (iii) the average time from receiving the second report to the editorial decision for each recommendation combination. To show that the inverse-U shape is robust to different types of models, we also use the probit model instead of the linear probability model in Column 2 and 4 of Table A1.

Table A1: Time and Decision Given Recommendations of the First Two Referees

	Pr(R&R)		Pr(Wait for 3rd Report)		Time After 2nd Report
	(1)	(2)	(3)	(4)	(5)
Decision 1 = Reject × Decision 2 = Reject (omitted)					
Decision 1 = Reject × Decision 2 = Weak R&R	0.048	0.705	0.212	0.714	10.650
	(0.009)	(0.085)	(0.015)	(0.062)	(1.388)
Decision 1 = Weak R&R × Decision 2 = Reject	0.053	0.754	0.183	0.615	14.259
	(0.010)	(0.083)	(0.015)	(0.057)	(1.300)
Decision 1 = R&R × Decision 2 = Reject	0.164	1.302	0.295	1.159	24.516
	(0.013)	(0.071)	(0.012)	(0.064)	(1.400)
Decision 1 = Reject × Decision 2 = R&R	0.182	1.362	0.295	1.122	27.279
	(0.012)	(0.069)	(0.012)	(0.061)	(1.383)
Decision 1 = Weak R&R × Decision 2 = Weak R&R	0.192	1.391	0.285	1.085	25.018
	(0.024)	(0.100)	(0.020)	(0.117)	(2.551)
Decision 1 = R&R × Decision 2 = Weak R&R	0.400	1.990	0.298	1.197	35.330
	(0.026)	(0.089)	(0.017)	(0.097)	(2.619)
Decision 1 = Weak R&R × Decision 2 = R&R	0.429	2.070	0.342	1.484	37.294
	(0.026)	(0.087)	(0.016)	(0.115)	(2.690)
Decision 1 = R&R × Decision 2 = R&R	0.655	2.695	0.273	1.001	34.922
	(0.019)	(0.079)	(0.016)	(0.076)	(2.189)
Baseline: Average of D1 = Reject × D2 = Reject	0.015	0.015	0.596	0.596	19.427
FE: Year × Journal	✓	✓	✓	✓	✓
FE: Editor	✓	✓	✓	✓	✓
FE: Author Statistics	✓	✓	✓	✓	✓
FE: Author Prominence	✓	✓	✓	✓	✓
Model	Linear Prob.	Probit	Linear Prob.	Probit	OLS
Observations	9419	9396	9232	9218	9419

Notes: Only papers with at least three referees assigned and at least two referees responded are included in the analysis. Decision 1 is the recommendation by the first referee; Decision 2 is by the second referee. The *Reject* category includes both "Definitely Reject" and "Reject" recommendations; the *Weak R&R* category includes "No Recommendations" and "Weak R&R"; the *R&R* category includes "R&R", "Strong R&R", and "Accept." Columns 1-2 show the probability of getting a R&R editorial decision conditional on the first two recommendations, using both the linear probability model and the probit model. Columns 3-4 show the probability of waiting for a third referee conditional on the first two recommendations, using both the linear probability model and the probit model. Column 5 shows the time between the second report arrival and the editorial decision conditional on the first two recommendations. The set of controls is the same as Column 4 of Table 3. Appendix D.2 explains the fewer observations in Column 3 than in Column 1.

Table A2 presents the estimates of using the model described by Equation 1 to predict citations. From Table 2 and A2, while the recommendations from referees with more publications are highly predictive of an R&R decision, they are less predictive of future citations.

Table A2: Predicted Citations Based on a Nonlinear Least Squares Model

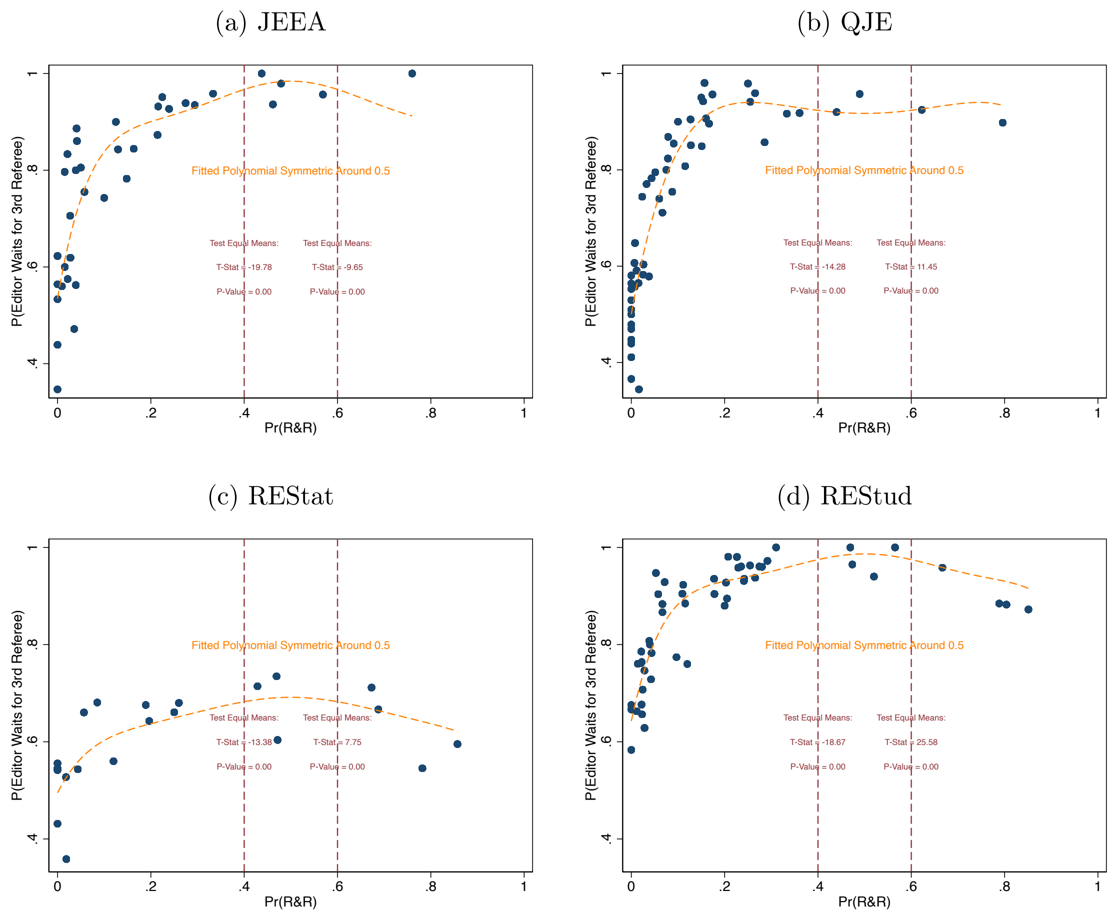
	Asinh(Citations)
	(1)
Recommendations	
Definitely Reject (omitted)	
Reject	0.613
	(0.090)
No Recommendation	1.097
	(0.160)
Weak R&R	1.209
	(0.135)
R&R	1.546
	(0.154)
Strong R&R	1.866
	(0.192)
Accept	1.767
	(0.188)
Referee Publication Level Effect	
1-2 Publications	0.175
	(0.122)
3-4 Publications	0.387
	(0.129)
5+ Publications	0.445
	(0.130)
Referee Publication Slope Effect	
1-2 Publications	-0.013
	(0.120)
3-4 Publications	-0.146
	(0.140)
5+ Publications	-0.042
	(0.131)
FE: Journal × Year	✓
FE: Editor	✓
FE: Paper Characteristics	✓
FE: Author Prominence	✓
Observations	9419
R-Squared	0.28

Notes: The table above shows the estimates of using the model described by Equation 1 to predict asinh citations. Only papers with at least three referees assigned and at least two referees responded are included in the analysis. Paper characteristics include field fractions and the number of author(s). Field fractions are indicators of JEL codes at paper submission. If N codes are listed, the indicator of each field equals 1/N. For example, if a paper lists JEL codes that match macro and international, both the macro indicator and the international indicator are set to 0.5. Author prominence is defined as the highest number of publications in the top-35 journals (identified in Online Appendix Table 1 of Card and DellaVigna (2020)) among all author(s) and the highest number of publications in the top-5 journals among all author(s).

B.3.1 Testing the "Inverse-U" Results by Journal

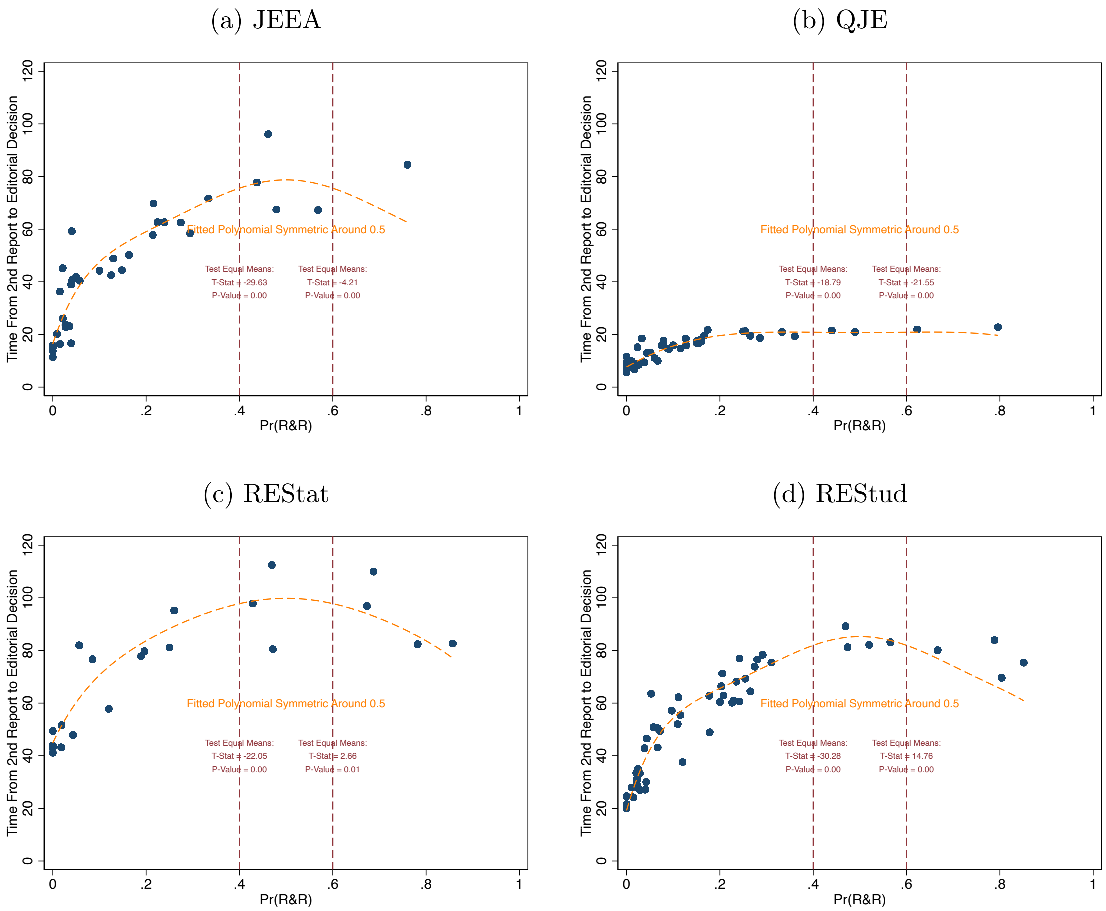
Appendix Figures A3 and A4 show results by journal using the approach underlying Panels c and d of Figure 5, respectively. The patterns are similar across journals, though the probability of waiting for a third referee peaks at a substantially lower level (around 50%) at *REStat* than at the other three journals (around 90%), while the mean number of days from the second report to the editor's decision peaks at a much lower level at *QJE* (around 20 days) than at the other journals (around 80 days). In addition, while *REStud, REStat,* and *JEEA* all show inverse U-shaped patterns with peak delays for papers with $P(R\&R)$ between 40% and 60%, delays at the *QJE* are relatively flat for $P(R\&R) > 20\%$. On balance, we conclude that the results are fairly similar across journals, and broadly consistent with the patterns in the pooled sample.

Figure A3: Stopping Predictions: P(Editor Waits for 3rd Referee), by Journal



Notes: Only papers with at least three referees assigned and at least two referees responded in each journal are included in the analysis. We run the same analysis as Panel c of Figure 5. Specifically, we estimate the model described by Equation 1 and derive the predicted $Pr(R\&R)$ based purely on referee recommendations and prominence for each paper. We then create bins based on the predicted values such that each bin represents about 50 observations. For the papers in each bin, we plot their empirical $Pr(R\&R)$ and empirical average probability of waiting for a third referee. For the intervals [0, 0.4), (0.4, 0.6), (0.6, 1] on the x-axis, we test if the increasing / decreasing trend in the adjacent intervals is statistically significant and report the testing statistics in annotations. The polynomial in orange is derived by fitting the dots into the function $y = k + a(x-0.5)^2 + b(x-0.5)^4 + c(x-0.5)^6$, which is flexible and always symmetric around $x = 0.5$.

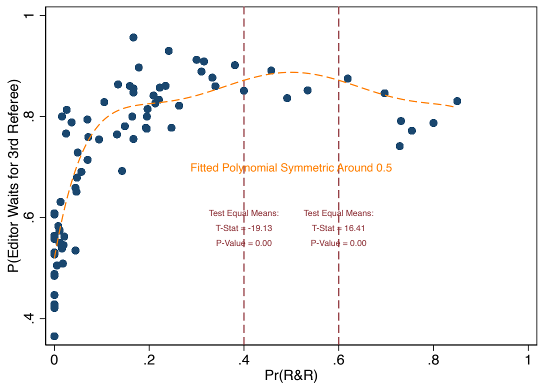
Figure A4: Stopping Predictions: Time From 2nd Report to Editorial Decision, by Journal



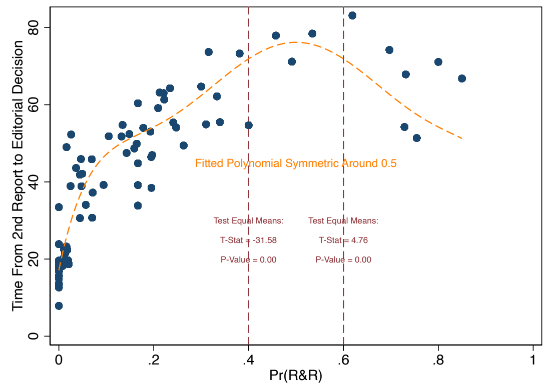
Notes: Only papers with at least three referees assigned and at least two referees responded in each journal are included in the analysis. We run the same analysis as Panel d of Figure 5. Specifically, we estimate the model described by Equation 1 and derive the predicted $Pr(R\&R)$ based purely on referee recommendations and prominence for each paper. We then create bins based on the predicted values such that each bin represents about 50 observations. For the papers in each bin, we plot their empirical $Pr(R\&R)$ and empirical average time from the second report to the editorial decision. Time from the second report to the editorial decision is winsorized at 231 days (the 99th percentile). By splitting the x-axis into 3 intervals: [0, 0.4), (0.4, 0.6), (0.6, 1], we test if the increasing / decreasing trend in the adjacent intervals is statistically significant and report the testing statistics through annotations. The polynomial in orange is derived by fitting the dots shown in the figure into the function $y = k + a(x - 0.5)^2 + b(x - 0.5)^4 + c(x - 0.5)^6$, which is always symmetric around $x = 0.5$.

Figure A5: Additional Results on Stopping Predictions

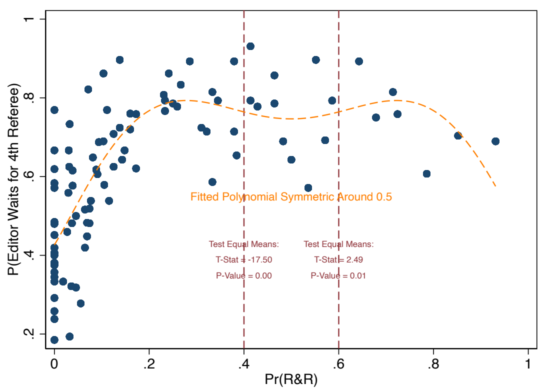
(a) Pr(3rd Referee) vs. P(R&R), Exactly 3 Referees Assigned



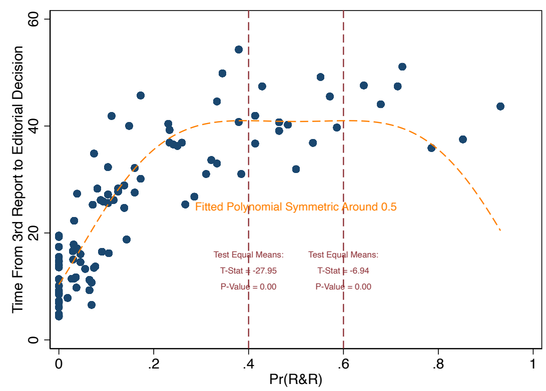
(b) Time After 2nd Report vs. P(R&R), Exactly 3 Assigned



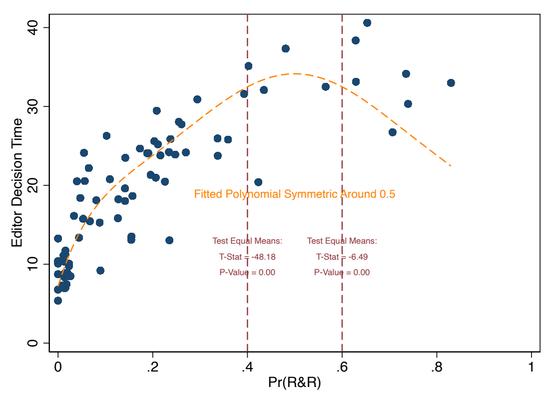
(c) Pr(Waits for 4th Referee) vs. P(R&R)



(d) Time After 3rd Report vs. P(R&R)



(e) Editor Decision Time vs. P(R&R)

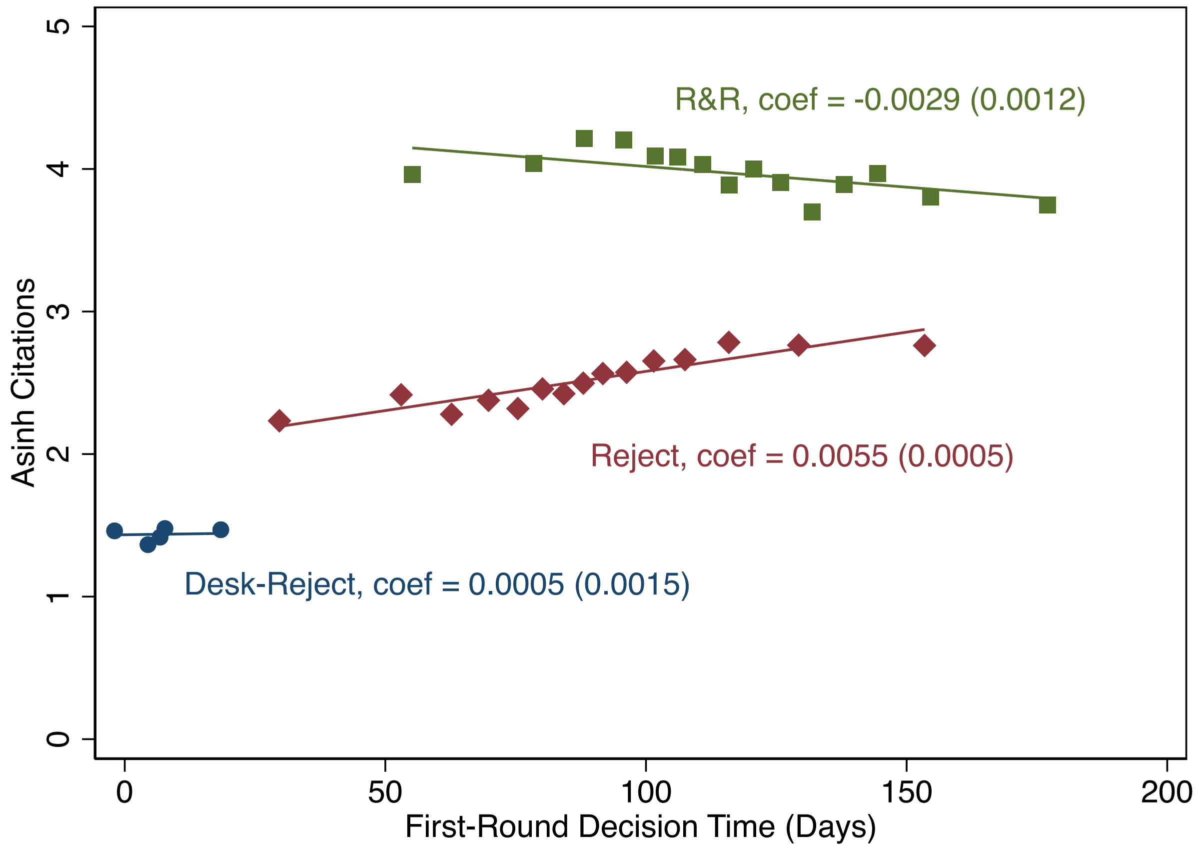


Notes: In Panels a and b, only papers assigned to exactly three referees assigned and at least two referees responded are included in the analysis. In Panels c and d, only papers assigned to at least four referees assigned and at least three referees responded are included in the analysis. In Panel e, we use editor decision time as the waiting variable. In all panels, we estimate the model described by Equation 1 and derive the predicted $Pr(R\&R)$ based purely on referee recommendations and prominence for each paper. We then create 100 bins based on the predicted values. For the papers in each bin, we plot their empirical $Pr(R\&R)$ and empirical average value of the waiting variable. Time from the second report to the editorial decision is winsorized at 231 days (the 99th percentile). Time from the third report to the editorial decision is winsorized at 193 days (the 99th percentile). For the intervals [0, 0.4), (0.4, 0.6), (0.6, 1] on the x-axis, we test if the increasing / decreasing trend in the adjacent intervals is statistically significant and report the testing statistics in annotations. The polynomial in orange is derived by fitting the dots into the function $y = k + a(x - 0.5)^2 + b(x - 0.5)^4 + c(x - 0.5)^6$, which is flexible and always symmetric around $x = 0.5$.

B.4 Additional Results for Quality and Decision Time

This section presents additional results on the relationship between citations and first-round decision time. The increase of citations for rejected paper and the decrease of citations for R&R papers in decision time are observed in different subsamples (Figure A6, Figure A7, Table A3, Figure A9) and for other transformations of citations (Figure A10, Figure A11).

Figure A6: Citations vs. First-Round Decision Time, Papers with Decision Time ≤ 200 Only



Notes: This figure is supplementary to Figure 6 by showing the fitted lines using only papers with first-round decision time < 200. It controls for the following fixed effects: journal, year, journal×year, editor, the field(s) of the paper, the number of author(s), the highest number of publications in top-5 economic journals among all author(s), the highest number of publications in top-35 economic journals (identified in Online Appendix Table 1 of Card and DellaVigna (2020)) among all author(s). The bins are created separately for desk-reject, reject, and R&R papers. The coefficients of the controls are allowed to vary across the categories.

B.4.1 Relationship Between Decision Time and Citations, by Journal

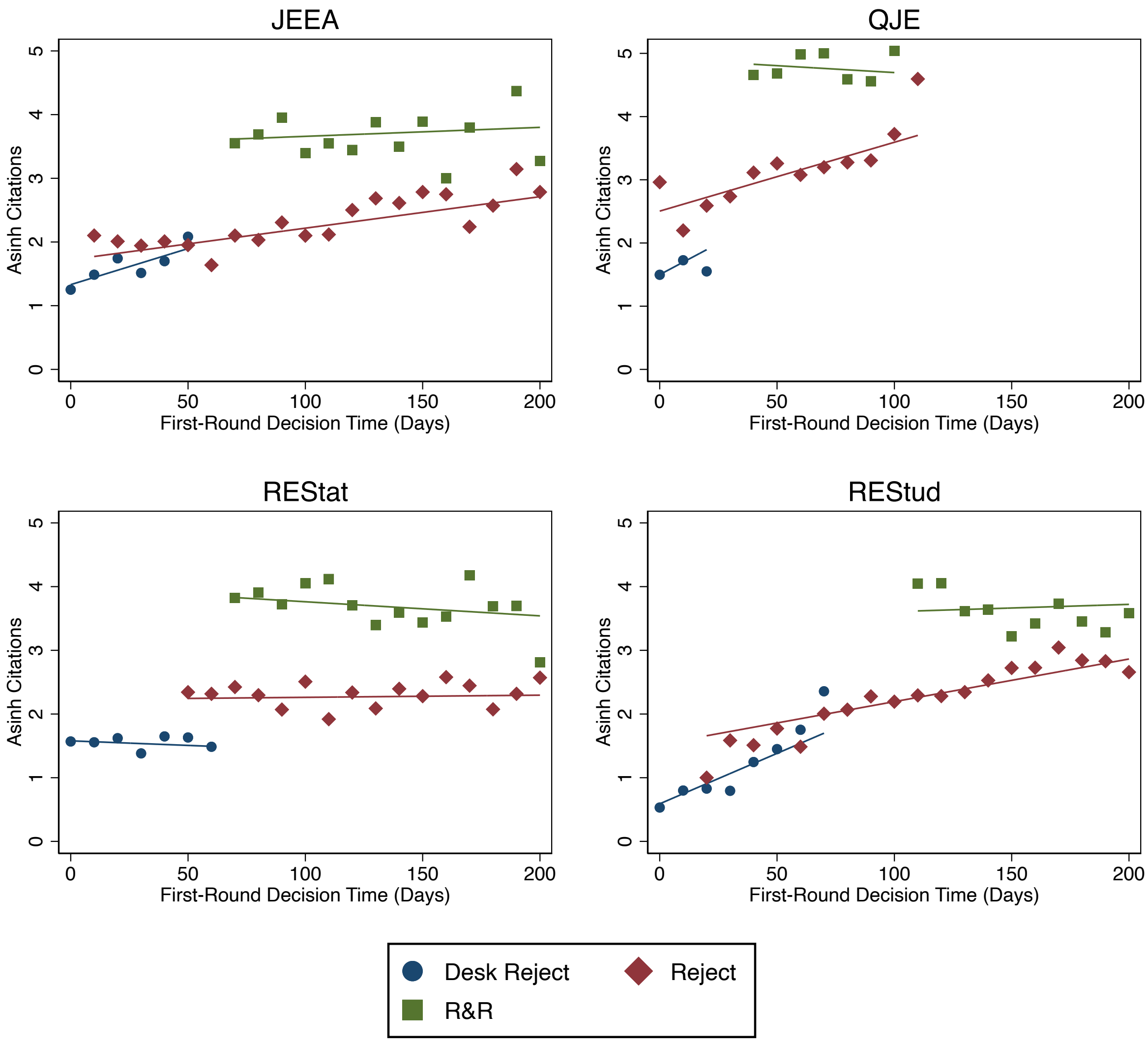
The binned scatter plots in Figure A7 summarize the raw relationship between citations and decision times for desk-rejects, rejects, and R&R's at each of the four journals in our sample.[27] As we have noted already, the four journals have different average decision times,

[27] Since our decision time variable is rounded to 10 day increments we use 10-day bins in the figure. The original data agreement negotiated by Card and DellaVigna (2020) specified that we not disclose decision

with the *QJE* standing out for its relatively quick decisions. At all four journals, desk rejects are decided relatively early, while rejects after review take longer and R&R's take the longest time. Among desk-rejected papers and those rejected after review, citations are positively correlated with decision times at three journals, and rather flat at *REStat.* The pattern for R&R's is a little more variable, with a slight negative slope at *QJE* and *REStat* and a slight positive slope at *JEEA* and *REStud.* Interestingly, for each of the three decision categories and each of the four journals the relationship between citations and decision time is approximately linear. Figure A8 shows the relationship between citations and decision times controlling for the set of fixed effects listed in Column 4 of Table 3, and similar patterns are preserved.

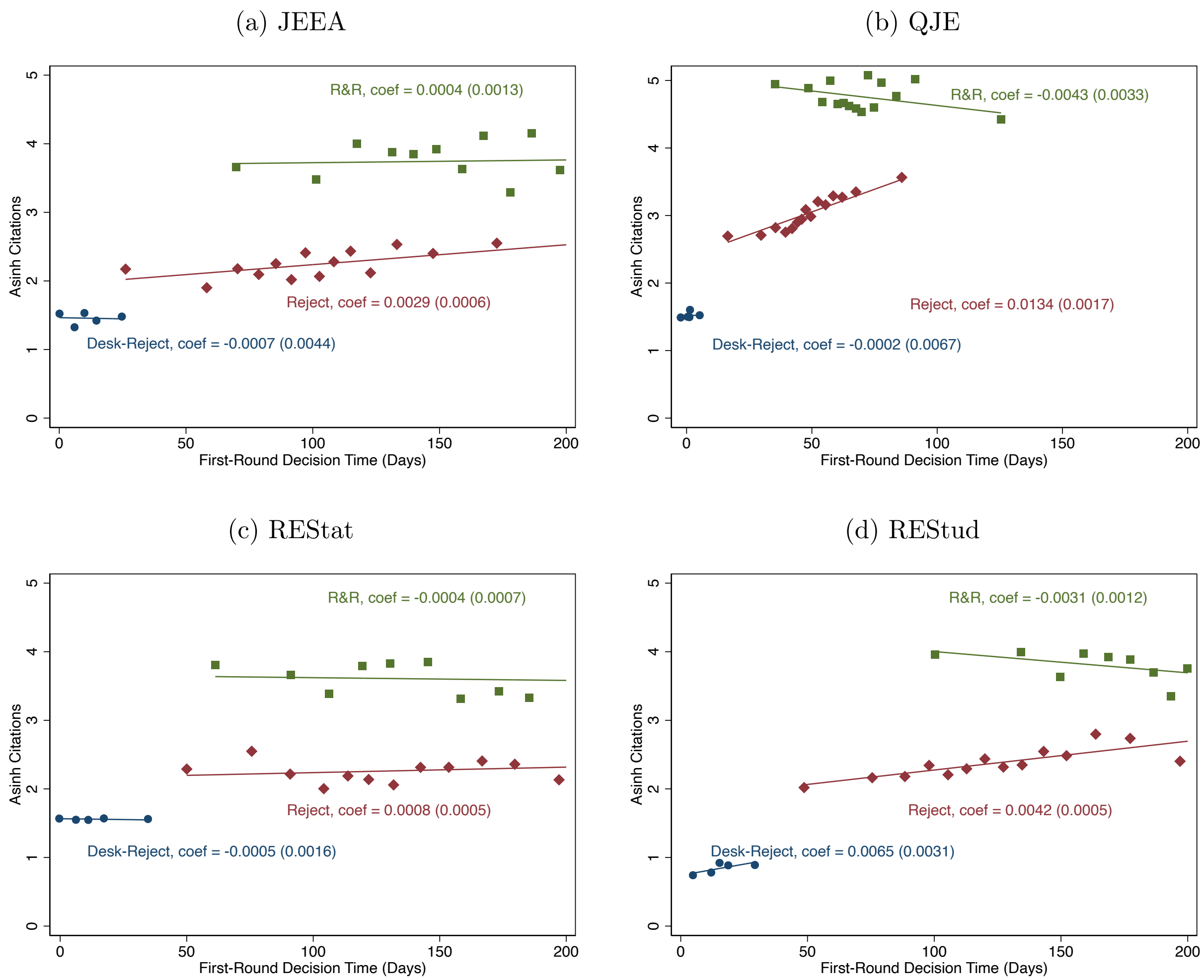
times above 200 days. We therefore exclude these bins in Figure A7, though the data are used in estimating the fitted lines (and all models in this paper).

Figure A7: Citations as a Function of Decision Time: No Controls, by Journal



Notes: The first-round decision time is winsorized at 320 days (the 99th percentile). To comply with the data confidentiality restrictions, only bins with decision time $\leq$ 200 are displayed in the figure above. Nevertheless, the fitted lines are created based on all observations. The bins are created separately for desk-reject, reject, and R&R papers. Given that the first-round decision time is rounded to the nearest 10, each bin corresponds to a 10-day increment (a bin is not displayed if it represents fewer than 15 observations).

Figure A8: Citations as a Function of Decision Time: With Controls, by Journal



Notes: The figure above controls for the following fixed effects: journal, year, journal×year, editor, the field(s) of the paper, the number of author(s), the highest number of publications in top-5 economic journals among all author(s), the highest number of publications in top-35 economic journal among all author(s). The first-round decision time is winsorized at 320 days (the 99th percentile). To comply with the data confidentiality restrictions, only bins with decision time ≤ 200 are displayed. Nevertheless, the fitted lines are created based on all observations. The bins are created separately for desk-reject, reject, and R&R papers. The coefficients of the controls are allowed to vary across the categories.

Table A3: Heterogeneity of Citations vs. Decision Time Analysis

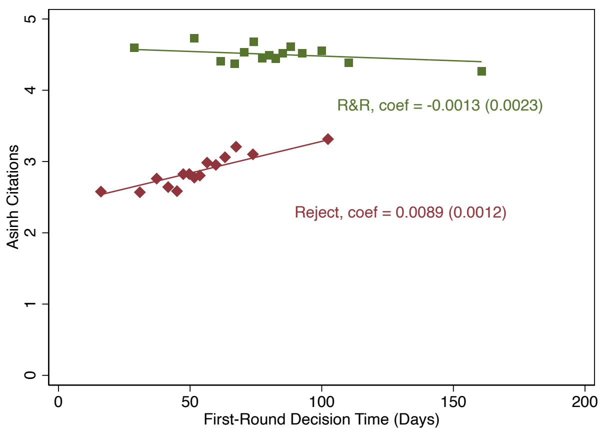
Dependent Variable: Asinh Citations

	Asinh Citations Mean/SD	Decision Time Mean/SD	Reject × First-Round Decision Time	R&R × First-Round Decision Time
Panel A. By Author Prominence				
Less Published (N: 9230)				
	2.3540	112.4366	0.0033	-0.0014
	(1.7824)	(69.7597)	(0.0003)	(0.0007)
More Published (N: 5869)				
	3.3220	116.2685	0.0030	-0.0003
	(1.7645)	(72.6618)	(0.0004)	(0.0007)
Panel B. By Editor Expertise				
No Editor Expertise (N: 4105)				
	2.7070	116.6017	0.0037	0.0009
	(1.8196)	(69.3233)	(0.0005)	(0.0009)
Editor Expertise (N: 9426)				
	2.7213	106.5892	0.0039	-0.0016
	(1.8346)	(68.9183)	(0.0004)	(0.0007)
Panel C. By Journal				
JEEA (N: 3264)				
	2.4706	117.7819	0.0027	0.0002
	(1.8260)	(69.1637)	(0.0006)	(0.0013)
QJE (N: 4136)				
	3.1979	50.7689	0.0134	-0.0045
	(1.8760)	(23.8392)	(0.0017)	(0.0033)
REStat (N: 2390)				
	2.6243	160.5439	0.0007	-0.0001
	(1.7606)	(73.3698)	(0.0005)	(0.0007)
REStud (N: 5309)				
	2.5734	139.7721	0.0045	-0.0030
	(1.7808)	(61.1375)	(0.0005)	(0.0012)
Panel D. By Year Block				
2003-2010 (N: 9105)				
	3.0599	121.0379	0.0034	-0.0011
	(1.9048)	(74.2426)	(0.0004)	(0.0006)
2011-2013 (N: 5994)				
	2.2296	103.1231	0.0029	-0.0001
	(1.6046)	(64.0756)	(0.0005)	(0.0010)
Panel E. By Field				
Micro & Theory & Metrics (N: 2557)				
	2.3976	125.7685	0.0027	0.0019
	(1.6889)	(67.0010)	(0.0006)	(0.0011)
Macro & International Trade (N: 1127)				
	3.0004	123.6469	0.0039	-0.0009
	(1.8948)	(69.9956)	(0.0009)	(0.0015)
Other (N: 5546)				
	2.8452	95.1659	0.0041	-0.0004
	(1.8530)	(67.2289)	(0.0005)	(0.0009)
Panel F. By Editor Speed				
Fastest 1/3 (N: 5081)				
	3.0222	55.8551	0.0089	-0.0018
	(1.8767)	(31.0540)	(0.0011)	(0.0021)
Middle 1/3 (N: 5192)				
	2.4233	121.0189	0.0046	-0.0012
	(1.7736)	(53.6668)	(0.0005)	(0.0011)
Slowest 1/3 (N: 4826)				
	2.7532	167.4347	0.0016	-0.0006
	(1.8100)	(71.8136)	(0.0004)	(0.0006)

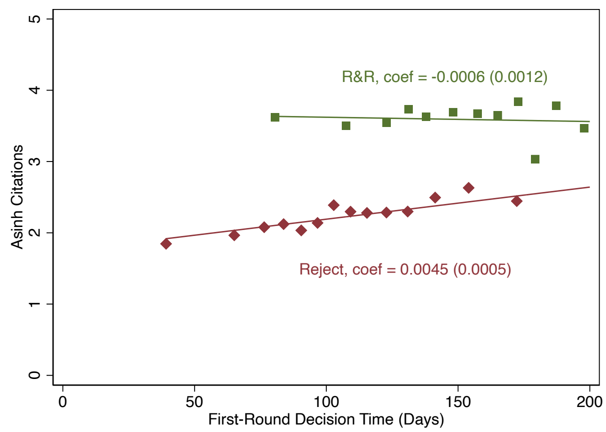
Notes: We drop desk-rejects and use the same specification as Column 4 of Table 3 in all panels above. In Panel A, we split the full sample into the "more published" group (the highest number of publications in top-35 economic journals among all author(s) is at least 3) and the "less published" group (the highest number of publications is at most 2). In Panel B, we split the sample based on whether the JEL code(s) of the paper matches the JEL codes of previous publications by the editor (papers with missing field or from *REStat* lack this information and are therefore omitted). In Panels C and D, we run the analysis for specific journals and year blocks. In Panel E, we sum up the field fractions and run the analysis separately for papers mainly in the fields of micro, economics theory, and econometrics (the sum of these field fractions exceeds 0.5), papers mainly in the fields of macro and international trade (the sum of these field fractions exceeds 0.5), and papers mainly in other fields (the sum of other field fractions exceeds 0.5). In Panel F, we group the papers based on the average speed of their editors. Average editor speed is defined as the average first-round decision time of all non-desk rejected papers reviewed by the editor. *REStat* papers are grouped together since we lack the information on individual editors.

Figure A9: Citations as a Function of Decision Time: Split by Editor Speed

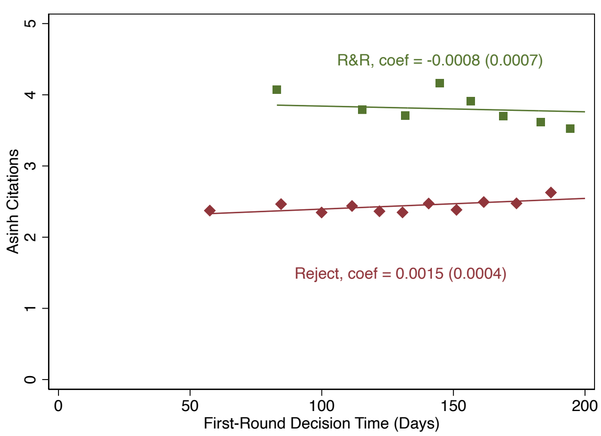
(a) Fastest 1/3 (Average Speed≤90 Days, N=5,081)



(b) Middle 1/3 (Average Speed∈(90, 145.5) Days, N=5,192)

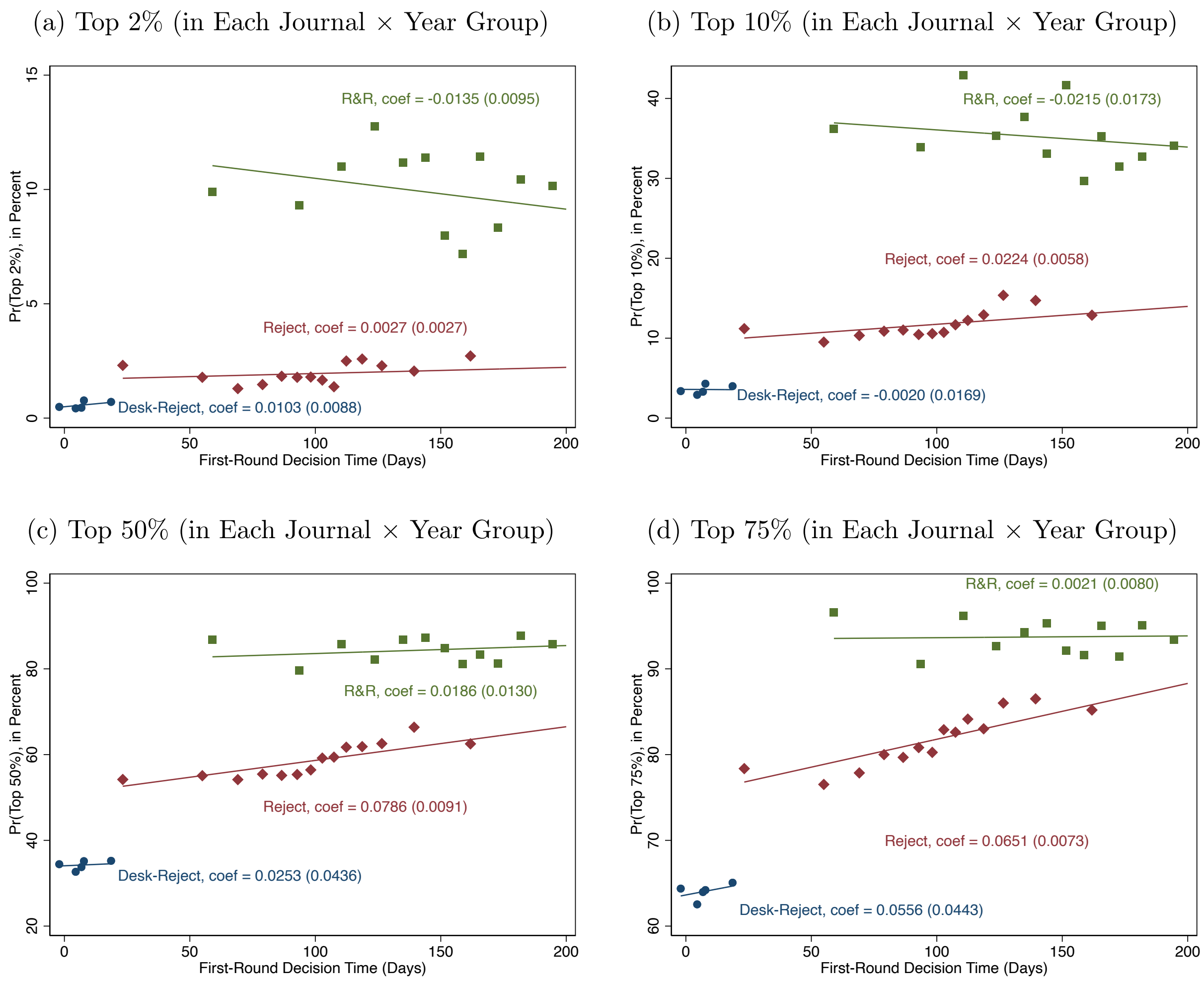


(c) Slowest 1/3 (Average Speed≥145.5 Days, N=4,826)



Notes: Average editor speed is defined as the average first-round decision time of all non-desk rejected papers reviewed by the editor. *REStat* papers are grouped together since we lack the information on individual editors. We split the papers into thirds based on the average speed of their editors. All panels control for the following fixed effects: journal, year, journal×year, editor, the field(s) of the paper, the number of author(s), the highest number of publications in top-5 economic journals among all author(s), the highest number of publications in top-35 economic journals among all author(s). The first-round decision time is winsorized at 320 days (the 99th percentile). To comply with the data confidentiality restrictions, only bins with decision time ≤ 200 are displayed. Nevertheless, the fitted lines are created based on all observations. The bins are created separately for desk-reject, reject, and R&R papers. The coefficients of the controls are allowed to vary across the categories. The coefficients are slightly different from Table A3 because the control variables are estimated separately for the three editor-speed samples.

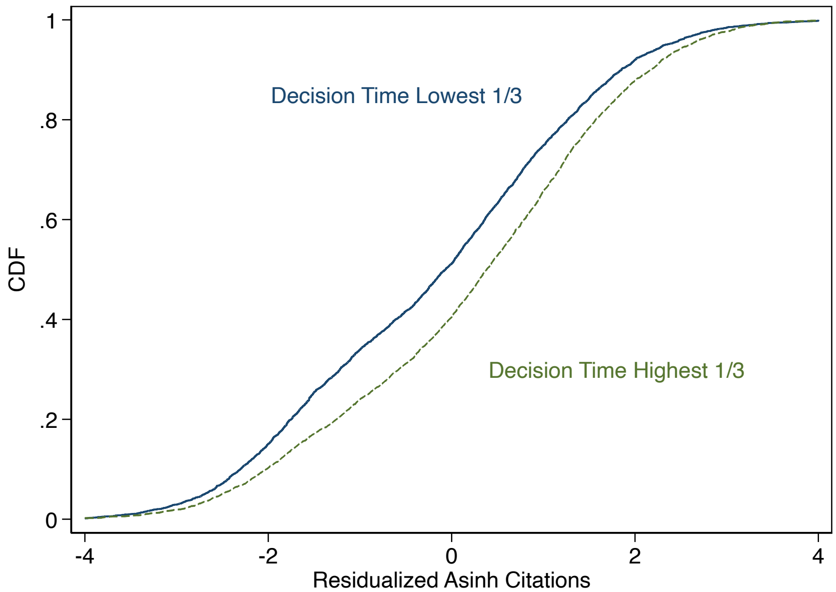
Figure A10: Quantiles of Citations as a Function of Decision Time



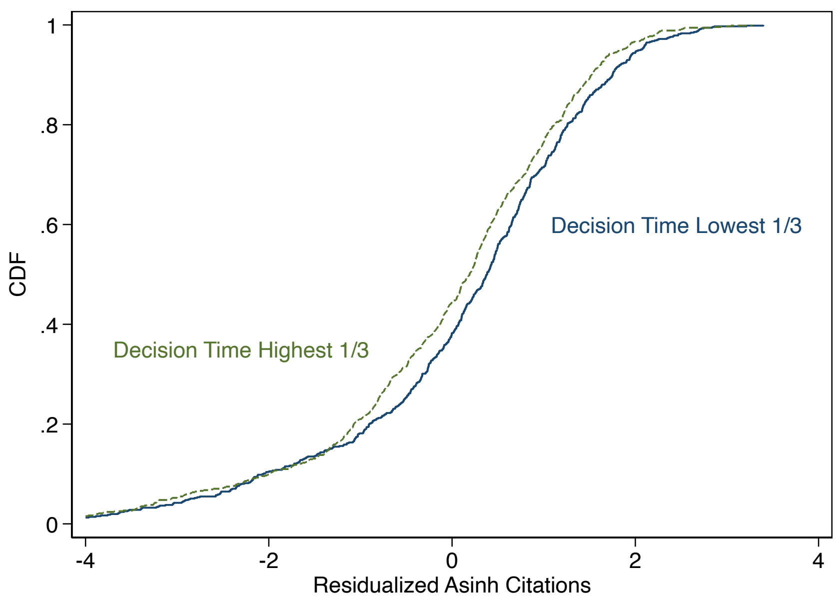
Notes: All panels control for the following fixed effects: journal, year, journal×year, editor, the field(s) of the paper, the number of author(s), the highest number of publications in top-5 economic journals among all author(s), the highest number of publications in top-35 economic journals among all author(s). The first-round decision time is winsorized at 320 days (the 99th percentile). To comply with the data confidentiality restrictions, only bins with decision time ≤ 200 are displayed. Nevertheless, the fitted lines are created based on all observations. The bins are created separately for desk-reject, reject, and R&R papers. The coefficients of the controls are allowed to vary across the categories.

Figure A11: The Distribution of Asinh Citations by Decision Type and Time

(a) Reject (N = 12,967)



(b) R&R (N = 2,132)



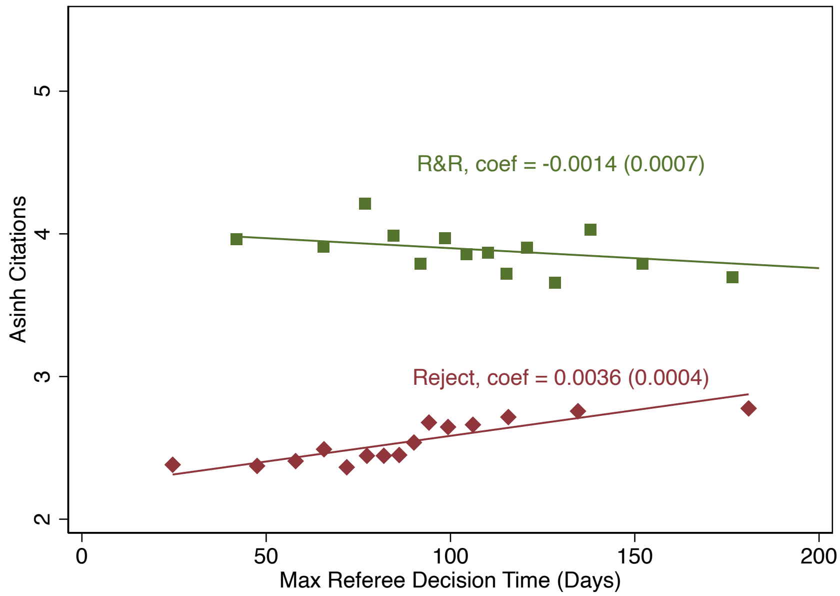
Notes: Asinh citations and first-round decision time are residualized with respect to the following set of controls: journal, year, journal×year, editor, the field(s) of the paper, the number of author(s), the highest number of publications in top-5 economic journals among all author(s), the highest number of publications in top-35 economic journal among all author(s). The tertiles of decision time are created separately for the R&R and reject samples.

B.5 Replication with Chetty et al. (2014) *JPubE* Data

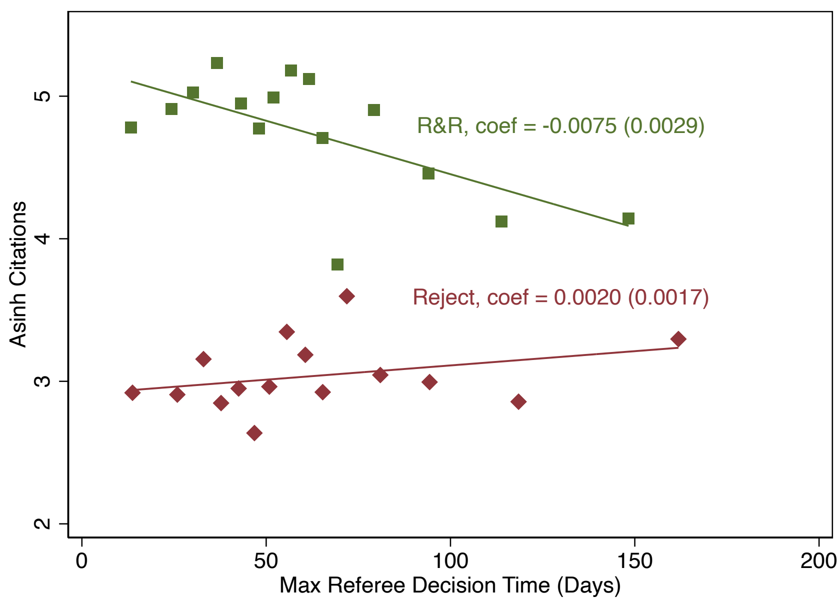
Using the data made available by the authors, we use the paper title to obtain Google Scholar citations (as of 2023). Since the data set does not have the decision time for the editor but only the decision time for the referees, we replicate the main analysis using the longest decision time across referees. Appendix Figure A12a-b displays the relationship between this decision time measure and asinh citations in our main sample (Figure A12a) and in the *JPubE* sample (Figure A12b). The patterns are largely similar, with the familiar fanning-in pattern between rejected papers and R&Rs, but the pattern is much noisier in the JPubE sample, which is nearly 20 times smaller than our main sample.

Figure A12: Main Data Set vs. JPubE Data Set

(a) Max Referee Decision Time, Main Dataset (N = 15,099)



(b) Max Referee Decision Time, *JPubE* Data Set (N = 811)



Notes: Both figures use the maximum referee decision time to approximate the first-round decision time since the *JPubE* data set doesn't contain this information. Desk-reject papers are dropped from Panel a since the *JPubE* data set doesn't contain desk-reject papers. Panel a controls for the following fixed effects: journal, year, journal×year, editor, the field(s) of the paper, the number of author(s), the highest number of publications in top-5 economic journals among all author(s), and the highest number of publications in top-35 economic journals among all author(s). Since all papers in the *JPubE* belong to the same journal and field, Panel b controls for the fixed effects of year, editor, the number of author(s), the highest number of publications in top-5 economic journals among all author(s), and the highest number of publications in top-35 economic journals among all author(s). Since the *JPubE* data set displays only one author for each paper, we record the number of authors based on the information on Google Scholar. Papers with no match in Google Scholar are coded as having one author and zero citations, and we count the number of publications by the only author listed in the data set. The bins are created separately for reject and R&R papers. The coefficients of the controls are allowed to vary across the categories.

Table A4: Descriptive Regressions (*JPubE* Data Set)

	Summary Stats	Max Referee Decision Time			Asinh Citations		
	(1) Mean	(2) All	(3) R&R	(4) Reject	(5) All	(6) R&R	(7) Reject
1 Author	0.349						
	(0.017)						
2 Authors	0.401	2.40	-7.45	3.79	1.14	0.48	1.22
	(0.017)	(3.40)	(9.03)	(3.80)	(0.14)	(0.28)	(0.16)
3 Authors	0.207	-2.63	-12.16	-0.26	1.42	0.65	1.54
	(0.014)	(3.97)	(10.77)	(4.28)	(0.17)	(0.33)	(0.19)
4+ Authors	0.043	3.51	10.94	4.28	1.17	0.57	1.21
	(0.007)	(7.87)	(24.67)	(8.18)	(0.33)	(0.53)	(0.39)
Publications: 0	0.461						
	(0.018)						
Publications: 1	0.187	3.94	-3.49	4.72	0.43	-0.50	0.60
	(0.014)	(4.01)	(10.97)	(4.54)	(0.16)	(0.35)	(0.18)
Publications: 2	0.112	3.76	9.04	0.68	0.46	-0.27	0.59
	(0.011)	(4.78)	(11.93)	(5.43)	(0.19)	(0.34)	(0.23)
Publications: 3	0.094	5.52	6.53	5.13	0.25	-0.18	0.22
	(0.010)	(5.12)	(12.07)	(5.74)	(0.21)	(0.35)	(0.27)
Publications: 4-5	0.084	0.42	-1.91	0.07	0.66	0.29	0.77
	(0.010)	(5.10)	(11.50)	(6.13)	(0.19)	(0.47)	(0.22)
Publications: 6+	0.062	-5.41	-16.93	-5.41	0.40	0.74	0.30
	(0.008)	(6.62)	(14.07)	(7.90)	(0.26)	(0.51)	(0.30)
Top 5 Publications: 0	0.861						
	(0.012)						
Top 5 Publications: 1	0.089	-1.69	-1.07	-0.88	0.15	-0.07	0.26
	(0.010)	(4.59)	(9.78)	(5.34)	(0.20)	(0.28)	(0.28)
Top 5 Publications: 2	0.031	17.63	2.07	26.36	0.06	0.00	0.09
	(0.006)	(8.98)	(11.05)	(11.75)	(0.26)	(0.59)	(0.33)
Top 5 Publications: 3+	0.020	13.18	11.96	18.04	0.68	-0.07	0.96
	(0.005)	(12.85)	(17.80)	(19.55)	(0.35)	(0.57)	(0.36)
Group Median		53.01	52.07	53.31	3.69	5.04	3.40
Year FE		✓	✓	✓	✓	✓	✓
Decision FE		✓			✓		
Observations	811	811	157	654	811	157	654
R-Squared		0.03	0.13	0.05	0.34	0.31	0.26

Notes: Since the *JPubE* data set displays only one author for each paper, we record the number of authors based on the information on Google Scholar. Papers with no match in Google Scholar are coded as having one author and zero citations, and we count the number of publications by the only author listed in the data set. The top 35 journals are the ones identified in Online Appendix Table 1 of Card and DellaVigna (2020). The top 5 journals are the *American Economic Review* (excluding the *Papers and Proceedings*), *Econometrica*, the *Journal of Political Economy*, the *Quarterly Journal of Economics*, and the *Review of Economic Studies*. The max referee decision time is winsorized at 187 days.

B.6 The Cost of Delay

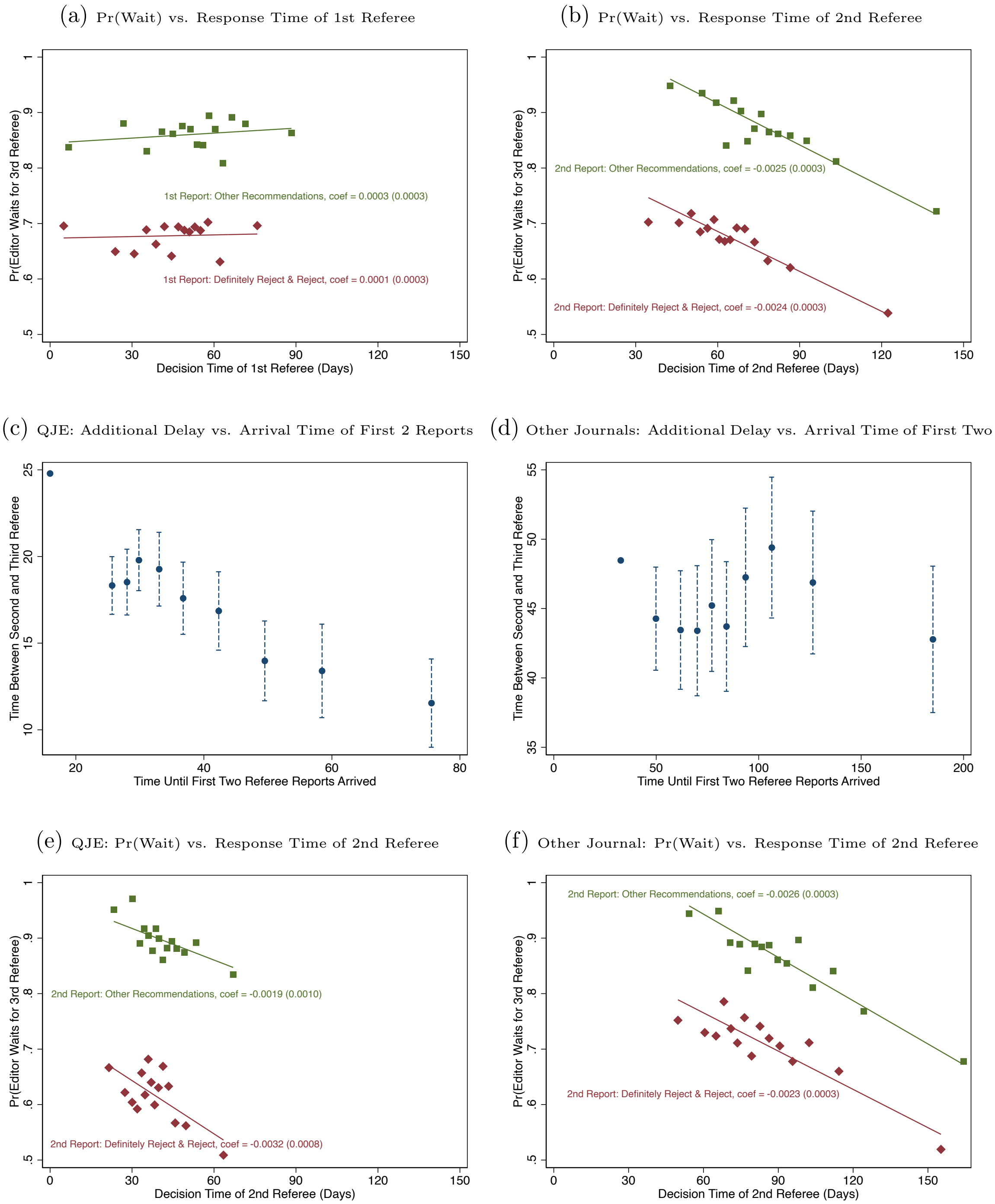
We study how an editor's choice to wait for a third referee depends on the delays of the first and second referee. We first consider how the editorial decision to delay depends on the time taken by the first referee, holding constant the time taken, and the recommendation, of the second referee. To the extent that the editor is aware of the information embedded in the response time of reviewers, we would expect the editor to interpret more positively a negative report that comes in with a longer delay compared to a similarly negative report that comes in sooner, given that the longer decision time likely signals that the referee is more likely to be on the fence. For more positive reports the relationship is likely to be, if anything, in the other direction. This interpretation is consistent with the results in Figure 8a. Figure A13a shows that the probability of delay appears to be largely orthogonal to the decision time of the first referee, both for the case of negative referee recommendations, as well as for the case of more positive recommendations. While this specification does not allow us to test the null hypothesis of how *much* editors should respond to the referee decision time if they were to optimally extract that signal, it does indicate that this force does not appear to be of large magnitude.

In comparison, in Figure A13b we estimate a similar specification, but focusing on the impact on editorial delay of the decision time of the second referee, controlling for the decision time of the first referee and the recommendation of the first referee. The decision time of the second referee, in addition to potentially carrying signal information, can also directly affect the decision to wait for a third referee by affecting the cost of waiting c_2.

Two plausible models for such cost of waiting have different predictions for the probability of waiting. A first model, which we will call "linear," is that the editor's cost of waiting for a third referee is linear in the expected additional number of days to wait; that is, the expected incremental cost of waiting for the third referee is $\rho \cdot \mathbb{E}[t_3 - t_2]$ for some scalar ρ, where t_3 and t_2 are, respectively, the delays in days by the third and second referee. In our sample, the expected additional delay, $\mathbb{E}[t_3 - t_2]$, is decreasing in the number of days taken by the second referee (at the *QJE*) and is about independent of t_2 (at the other journals), as Figure A13c-d show. Thus, under this model, provided $\zeta > 0$, we would expect that a longer delay by the second referee is associated with a constant, or higher, probability of waiting, as the expected cost of waiting should be similar or lower. A second model, which we will call "convex," is that the editor's total cost of delay is a convex function of total weight time t_3:$\varsigma(t_3)$ for a convex function ς. This could be because, for example, authors are more likely to complain as total decision time passes a certain threshold. Under this second model, the editorial decision to wait should be negatively related to the delay by the second referee, as a longer delay by the second referee results, in expectation, in a higher expected incremental cost of waiting for the third referee, $\mathbb{E}[\varsigma(t_3) - \varsigma(t_2)]$. Thus the two models make opposite predictions.

As Figure A13b shows, there is a strong *negative* relationship between the decision time of the second referee and the probability that the editor waits for the third referee, whether the second referee recommendation is positive or negative. This relationship is consistent with the "convex" model for the cost of delay. Figures A13e-f show that this pattern is clear both at the *QJE* and at the other journals. We interpret these findings as suggestive of the fact that editors' cost of delay reflects the fact that they care about the total number of delays of delay, as opposed to just the expected extra days of delay.

Figure A13: Stopping Predictions and the Delay of Reports



(a) Pr(Wait) vs. Response Time of 1st Referee
(b) Pr(Wait) vs. Response Time of 2nd Referee
(c) QJE: Additional Delay vs. Arrival Time of First 2 Reports
(d) Other Journals: Additional Delay vs. Arrival Time of First Two
(e) QJE: Pr(Wait) vs. Response Time of 2nd Referee
(f) Other Journal: Pr(Wait) vs. Response Time of 2nd Referee

Notes: In Panel a, we plot the probability of waiting for a third report and the decision time of the first referee, controlling for the recommendation and decision time of the second referee as well as the set of controls in Column 4 of Table 3. We estimate separately for papers with a negative recommendation by the first referee ("Reject" or "Definitely Reject") and for papers with a more positive recommendation (any other category). Conversely, in Panel b, we plot the probability of waiting for a third report and the decision time of the second referee, controlling for the recommendation and decision time of the first referee as well as the set of controls in Column 4 of Table 3. Again, we estimate separately for papers with a negative recommendation by the second referee and papers with a more positive recommendation. For Panel c and d, we create bins based on the deciles of the time until the first two reports arrive. On the x-axis, we show the average time until the first two reports arrive in each bin. Since the time between the second and third report is potentially right-censored by the editorial decision, we run a tobit regression of the time between the second and third report on the dummies of the bins and the control variables (the fixed effects for recommendation combinations and the set of controls in Column 4 of Table 3). The coefficient estimates of the dummies are shown on the y-axis. In Panels f and g, we run the same analysis as Panel d but on two separate subsamples: papers from *QJE* and papers from other journals.

B.7 Robustness of Structural Estimation

Table A5: Robustness of Structural Estimation

	(1) QJE	(2) Micro & Metrics & Theory	(3) Other Fields	(4) 75-25 Split	(5) Referee Time	(6) Editor Time
Panel A. Estimates						
q^*	0.886	0.541	0.636	0.547	0.171	0.608
	(0.537, 1.236)	(0.322, 0.760)	(0.516, 0.757)	(0.450, 0.644)	(0.144, 0.197)	(0.498, 0.719)
$\Delta(c_l)$	1.514	0.940	1.236	0.532	0.770	1.310
	(0.970, 2.365)	(0.599, 1.473)	(1.001, 1.525)	(0.431, 0.656)	(0.650, 0.912)	(1.081, 1.587)
$\Delta(c_h)$	0.322	0.206	0.189	0.028	0.029	0.107
	(0.178, 0.375)	(0.109, 0.261)	(0.156, 0.213)	(0.000, 0.051)	(0.021, 0.037)	(0.082, 0.127)
σ_1^2	0.384	0.185	0.312	0.219	0.134	0.254
	(0.197, 0.750)	(0.090, 0.380)	(0.225, 0.433)	(0.160, 0.299)	(0.101, 0.178)	(0.181, 0.357)
σ_2^2	0.086	0.129	0.052	0.104	0.002	0.134
	(0.014, 0.525)	(0.038, 0.437)	(0.017, 0.156)	(0.050, 0.218)	(0.000, 0.972)	(0.081, 0.224)
$\alpha_1 - \alpha_0$	-0.004	-0.001	0.002	0.097	-0.011	-0.005
	(-0.531, 0.523)	(-0.384, 0.383)	(-0.200, 0.203)	(-0.067, 0.261)	(-0.094, 0.073)	(-0.187, 0.176)
$\frac{\sigma_2^2}{\sigma_1^2+\sigma_2^2}$	0.183	0.412	0.143	0.322	0.018	0.346
	(0.057, 0.449)	(0.249, 0.597)	(0.063, 0.295)	(0.218, 0.453)	(0.000, 0.907)	(0.276, 0.429)
$\frac{\sigma_1^2+\sigma_2^2}{Var(\hat{\psi}_i)}$	0.174	0.150	0.135	0.123	0.053	0.148
	(0.079, 0.496)	(0.064, 0.397)	(0.091, 0.219)	(0.082, 0.198)	(0.040, 0.515)	(0.101, 0.220)
Panel B. Goodness of Fit - Empirical; Estimated						
Pr(R&R, $\tau = 1$)	0.013; 0.013	0.021; 0.021	0.035; 0.035	0.060; 0.060	0.149; 0.149	0.039; 0.039
	(0.002); (-)	(0.003); (-)	(0.002); (-)	(0.002); (-)	(0.002); (-)	(0.002); (-)
Pr(R&R, $\tau = 2$)	0.081; 0.081	0.124; 0.124	0.105; 0.105	0.081; 0.082	0.172; 0.172	0.102; 0.102
	(0.004); (-)	(0.007); (-)	(0.003); (-)	(0.002); (-)	(0.002); (-)	(0.002); (-)
$\mathbb{E}[\hat{\psi}_i$ |R&R, $\tau = 1]$	1.390; 1.441	0.914; 0.925	1.089; 1.079	1.018; 0.936	0.400; 0.430	0.904; 0.938
	(0.225); (-)	(0.198); (-)	(0.078); (-)	(0.049); (-)	(0.021); (-)	(0.063); (-)
$\mathbb{E}[\hat{\psi}_i$ |R&R, $\tau = 2]$	1.185; 1.177	0.836; 0.834	0.907; 0.910	0.864; 0.924	0.409; 0.375	0.939; 0.926
	(0.088); (-)	(0.080); (-)	(0.044); (-)	(0.042); (-)	(0.020); (-)	(0.037); (-)
$\mathbb{E}[\hat{\psi}_i$ |Reject, $\tau = 1]$	-0.320; -0.319	-0.249; -0.249	-0.308; -0.309	-0.216; -0.208	-0.260; -0.248	-0.217; -0.216
	(0.036); (-)	(0.041); (-)	(0.021); (-)	(0.016); (-)	(0.014); (-)	(0.019); (-)
$\mathbb{E}[\hat{\psi}_i$ |Reject, $\tau = 2]$	0.101; 0.099	-0.009; -0.009	0.024; 0.025	0.106; 0.151	-0.119; -0.138	-0.078; -0.082
	(0.039); (-)	(0.047); (-)	(0.023); (-)	(0.031); (-)	(0.014); (-)	(0.020); (-)
Minimized Objective Function Value	0.065	0.005	0.025	6.755	5.969	0.417

Notes: All estimation above follows the same procedures as the structural estimation of the main sample and uses the same set of controls: journal, year, journal×year, editor, the field(s) of the paper, the number of author(s), the highest number of publications in top-5 economic journals among all author(s), the highest number of publications in top-35 economic journal among all author(s). In Column 1-3, we show the estimation for different subsamples. In Column 4, we split decision time into two discrete time periods not by the median but by the 75th percentile. In Column 5-6, we use the decisions and decision times of referees and editors to set up the estimation. An R&R decision in the referee case is defined as a recommendation that is accept, strong R&R, R&R, or weak R&R. A reject decision in the referee case is defined as a recommendation that is reject or definitely reject.

C Structural Estimation Details

C.1 Analytic Solutions of Moments

As before, let f_1 and f_2 denote the PDFs of μ_1, and of μ_2 conditional on μ_1 , respectively. Let F_1 and F_2 denote the respective CDFs. Then

$$\begin{aligned} Pr(D=1,\tau=1) =& Pr(D=1,\tau=1|\Delta(c_2)=\Delta(c_l))\cdot Pr(\Delta(c_2)=\Delta(c_l)) \\ &+ Pr(D=1,\tau=1|\Delta(c_2)=\Delta(c_h))\cdot Pr(\Delta(c_2)=\Delta(c_h)) \\ =& 0.5\left[1-F_1(q^*+\Delta(c_l))\right]+0.5\left[1-F_1(q^*+\Delta(c_h))\right] \end{aligned}$$

Similarly:

- $Pr(D=0,\tau=1)=0.5F_1(q^*-\Delta(c_l))+0.5F_1(q^*-\Delta(c_h))$
- $Pr(D=1,\tau=2)=0.5\int_{q^*-\Delta(c_l)}^{q^*+\Delta(c_l)} f_1(\mu_1)\cdot(1-F_2(q^*))\,d\mu_1+0.5\int_{q^*-\Delta(c_h)}^{q^*+\Delta(c_h)} f_1(\mu_1)\cdot(1-F_2(q^*))\,d\mu_1$
- $Pr(D=0,\tau=1)=0.5\int_{q^*-\Delta(c_l)}^{q^*+\Delta(c_l)} f_1(\mu_1)\cdot F_2(q^*)d\mu_1+0.5\int_{q^*-\Delta(c_h)}^{q^*+\Delta(c_h)} f_1(\mu_1)\cdot F_2(q^*)d\mu_1$

For the moments related to expected quality,

$$\begin{aligned} \mathbb{E}[\hat{\psi}_i|D=1,\tau=1] =& \mathbb{E}\left[\mathbb{E}[\mu_2+\alpha_1-\alpha_0|D=1,\tau=1,\Delta(c_2)]\,|D=1,\tau=1\right] \\ =& \mathbb{E}\left[\mathbb{E}[\mu_1+\alpha_1-\alpha_0|\mu_1>q^*+\Delta(c_2)]\,|\Delta(c_2),D=1,\tau=1\right] \\ =& \frac{1-F_1(q^*+\Delta(c_l))}{1-F_1(q^*+\Delta(c_l))+1-F_1(q^*+\Delta(c_h))}\cdot\left[\mu+\sigma_1\cdot\frac{\phi\left(\frac{q^*+\Delta(c_l)-\mu}{\sigma_1}\right)}{1-\Phi\left(\frac{q^*+\Delta(c_l)-\mu}{\sigma_1}\right)}\right] \\ &+ \frac{1-F_1(q^*+\Delta(c_h))}{1-F_1(q^*+\Delta(c_l))+1-F_1(q^*+\Delta(c_h))}\cdot\left[\mu+\sigma_1\cdot\frac{\phi\left(\frac{q^*+\Delta(c_h)-\mu}{\sigma_1}\right)}{1-\Phi\left(\frac{q^*+\Delta(c_h)-\mu}{\sigma_1}\right)}\right]+\alpha_1-\alpha_0 \end{aligned}$$

Similarly,

$$\begin{aligned} \mathbb{E}[\hat{\psi}_i|D=0,\tau=1] =& \mathbb{E}\left[\mathbb{E}[\mu_1|\mu_1<q^*-\Delta(c_2)]\,|\Delta(c_2),D=0,\tau=1\right] \\ =& \frac{F_1(q^*-\Delta(c_l))}{F_1(q^*-\Delta(c_l))+F_1(q^*-\Delta(c_h))}\cdot\left[\mu-\sigma_1\cdot\frac{\phi\left(\frac{q^*-\Delta(c_l)-\mu}{\sigma_1}\right)}{\Phi\left(\frac{q^*-\Delta(c_l)-\mu}{\sigma_1}\right)}\right] \\ &+ \frac{F_1(q^*-\Delta(c_h))}{F_1(q^*-\Delta(c_l))+F_1(q^*-\Delta(c_h))}\cdot\left[\mu-\sigma_1\cdot\frac{\phi\left(\frac{q^*-\Delta(c_h)-\mu}{\sigma_1}\right)}{\Phi\left(\frac{q^*-\Delta(c_h)-\mu}{\sigma_1}\right)}\right] \end{aligned}$$

$$\begin{aligned}
\mathbb{E}[\hat{\psi}_i|D=1,\tau=2] =& \mathbb{E}\left[\mathbb{E}[\mu_2+\alpha_1-\alpha_0|\mu_2>q^*, q^*-\Delta(c_2)<\mu_1<q^*+\Delta(c_2)]\,|\Delta(c_2), D=1,\tau=2\right] \\
=& \frac{1}{2\cdot Pr(D=1,\tau=2)}\cdot\left(\int_{q^*-\Delta(c_l)}^{q^*+\Delta(c_l)} f_1(\mu_1)\cdot(1-F_2(q^*))\left[\mu_1+\sigma_2\cdot\frac{\phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)}{1-\Phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)}\right]d\mu_1\right) \\
+& \frac{1}{2\cdot Pr(D=1,\tau=2)}\cdot\left(\int_{q^*-\Delta(c_h)}^{q^*+\Delta(c_h)} f_1(\mu_1)\cdot(1-F_2(q^*))\left[\mu_1+\sigma_2\cdot\frac{\phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)}{1-\Phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)}\right]d\mu_1\right) \\
+& \alpha_1-\alpha_0
\end{aligned}$$

$$\begin{aligned}
\mathbb{E}[\hat{\psi}_i|D=0,\tau=2] =& \mathbb{E}\left[\mathbb{E}[\mu_2|\mu_2<q^*, q^*-\Delta(c_2)<\mu_1<q^*+\Delta(c_2)]\,|\Delta(c_2), D=0,\tau=2\right] \\
=& \frac{1}{2\cdot Pr(D=0,\tau=2)}\cdot\left(\int_{q^*-\Delta(c_l)}^{q^*+\Delta(c_l)} f_1(\mu_1)\cdot F_2(q^*)\left[\mu_1-\sigma_2\cdot\frac{\phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)}{\Phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)}\right]d\mu_1\right) \\
+& \frac{1}{2\cdot Pr(D=0,\tau=2)}\cdot\left(\int_{q^*-\Delta(c_l)}^{q^*+\Delta(c_h)} f_1(\mu_1)\cdot F_2(q^*)\left[\mu_1-\sigma_2\cdot\frac{\phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)}{\Phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)}\right]d\mu_1\right)
\end{aligned}$$

C.2 Details on Estimation Procedure

C.2.1 Recentering R&R and Reject Citations

Let X_i denote the vector of controls from Column 4 of Table 3. We first fit $asinh(\psi_i) = \alpha_0 X_i + u_i$ for the Reject decisions ($D = 0$). We set the difference in means for R&R versus reject paper residuals to be $\mathbb{E}[asinh(\psi_i)-\hat{\alpha}_0 X_i|RR_i = 1]-\mathbb{E}[asinh(\psi_i)-\hat{\alpha}_0 X_i|RR_i = 0]$. This differs from simply using the uncontrolled difference if $\mathbb{E}[\hat{\gamma}_0 X_i|RR_i = 0] \neq \mathbb{E}[\hat{\gamma}_0 X_i|RR_i = 1]$. In practice, the controlled and uncontrolled difference are very similar.

C.2.2 Satisfying the Constraint

Our constraint is that $Pr(\tau = 2) = 0.5$, where

$$\begin{aligned}
Pr(\tau=2) =& Pr(\tau=2|\Delta(c_2)=\Delta(c_l))\cdot Pr(\Delta(c_2)=\Delta(c_l)) \\
+& Pr(\tau=2|\Delta(c_2)=\Delta(c_h))\cdot Pr(\Delta(c_2)=\Delta(c_h)) \\
=& 0.5\left[F_1(q^*+\Delta(c_l))-F_1(q^*-\Delta(c_l))\right]+0.5\left[F_1(q^*+\Delta(c_h))-F_1(q^*-\Delta(c_h))\right]
\end{aligned}$$

Therefore, for any θ, there exists a unique $\Delta(c_h)$ that satisfies this restriction, as explained in footnote 24. When we run the optimization algorithm to find the best estimate of θ, every evaluation starts with some initial value θ_0 and we use the MATLAB optimizer *fmincon* to solve for the value of $\Delta_0(c_h)$ satisfying the constraint by solving $\Delta_0(c_h) = argmin_\Delta \left(Pr(\tau = 2|\theta_0, \Delta(c_h) = \Delta) - 0.5\right)^2$. We then plug θ_0 and $\Delta_0(c_h)$ into the analytic solutions of moments to get $m(\theta_0)$ in the objective function.

C.2.3 Optimization Algorithm

We estimate the model in MATLAB and use the MATLAB optimizer *fmincon* to find $\hat{\theta} = argmin\, (\hat{m} - m(\theta))'\hat{V}^{-1}(\hat{m} - m(\theta))$. We set the following optimization options:

- Maximum function evaluations: 3000
- Maximum iterations: 3000
- Function tolerance: 10^{-8}
- X tolerance: 10^{-8}
- Algorithm: sqp
- Large scale: off

In the first round, we draw 1000 initial values for each parameter from a uniform distribution with upper and lower bounds that are wide but reasonable in the editorial setting (e.g. q^* between 0 and 1). Let θ_1^* denote the best parameter estimate that minimizes the objective function in the first round. In the second round, we draw 500 initial values from a tighter support $[0.8\theta_1^*, 1.2\theta_1^*]$ and record the the best parameter estimate θ_2^*. In the last round, we draw 100 initial values from $[0.95\theta_2^*, 1.05\theta_2^*]$ and the optimal solution that minimizes the objective function is reported in Table 4.

C.2.4 Standard Errors of $\hat{\theta}$

With optimal weights $\hat{V}^{-1}$, the variance-covariance matrix of $\hat{\theta}$ is $(M(\hat{\theta})'\hat{V}^{-1}M(\hat{\theta}))^{-1}$, where $M(\hat{\theta}) = \nabla_{\hat{\theta}} m(\hat{\theta})$. $M(\hat{\theta})$ is estimated using the *Jacobianest* function in MATLAB Central File Exchange, which slightly moves the parameters near the optimal solution for numerical estimation.

C.2.5 Point Estimate and Confidence Interval of $\Delta(c_h)$

After estimating the optimal solution $\hat{\theta}$, we can derive $\hat{\Delta}(c_h) = argmin_{\Delta}\left(Pr(\tau = 2|\hat{\theta}, \Delta(c_h) = \Delta) - 0.5\right)^2$. The confidence interval of $\hat{\Delta}(c_h)$ is constructed by bootstrapping. Specifically, we draw 1000 sets of parameters $\hat{\theta}_1, \hat{\theta}_2, ..., \hat{\theta}_{1000}$ from the multivariate distribution of $\hat{\theta}$ and compute their corresponding $\hat{\Delta}_1(c_h), \hat{\Delta}_2(c_h), ..., \hat{\Delta}_{1000}(c_h)$ for the 95% confidence interval. The same procedure is used to yield the confidence intervals of summary statistics.

C.3 Counterfactuals

By constructing the counterfactual that the decision makers never or always obtain the second signal, we effectively show what proportion of people changed their decision from R&R to reject or reject to R&R from the second signal. The main strategy is to derive the analytic solutions for the counterfactuals and bootstrap based on the structural parameters we estimated. We consider two counterfactuals: (A) all decisions are based purely on the first signal, and (B) all decisions are based on two signals.

- For counterfactual A, the decision rule is: $D = 1$ if $\mu_1 < q^*$, $D = 0$ otherwise. This is the *only get 1 signal* condition of Table 4 Panel c.

- For counterfactual B, the decision rule is: $D = 1$ if $\mu_2 < q^*$, $D = 0$ otherwise. This is the *always get 2 signals* condition of Table 4 Panel c.

For counterfactual A, the moments are:

- $Pr(D = 1) = 1 - F_1(q^*)$
- $Pr(D = 0) = F_1(q^*)$
- $\mathbb{E}[\hat{\psi}_i|D = 1] = \mu + \sigma_1 \cdot \frac{\phi\left(\frac{q^*-\mu}{\sigma_1}\right)}{1-\Phi\left(\frac{q^*-\mu}{\sigma_1}\right)} + \alpha_1 - \alpha_0$
- $\mathbb{E}[\hat{\psi}_i|D = 0] = \mu - \sigma_1 \cdot \frac{\phi\left(\frac{q^*-\mu}{\sigma_1}\right)}{\Phi\left(\frac{q^*-\mu}{\sigma_1}\right)}$

For counterfactual B, the moments are:

- $Pr(D = 1) = \int_{-\infty}^{\infty} f_1(\mu_1) \cdot (1 - F_2(q^*))\, d\mu_1$
- $Pr(D = 0) = \int_{-\infty}^{\infty} f_1(\mu_1) \cdot F_2(q^*) d\mu_1$
- $\mathbb{E}[\hat{\psi}_i|D = 1] = \int_{-\infty}^{\infty} f_1(\mu_1) \cdot (1 - F_2(q^*)) \left[\mu_1 + \sigma_2 \cdot \frac{\phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)}{1-\Phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)}\right] d\mu_1 + \alpha_1 - \alpha_0$

- $\mathbb{E}[\hat{\psi}_i|D=0] = \int_{-\infty}^{\infty} f_1(\mu_1)\cdot F_2(q^*)\left[\mu_1 - \sigma_2 \cdot \frac{\phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)}{\Phi\left(\frac{q^*-\mu_1}{\sigma_2}\right)}\right] d\mu_1$

Given the optimal solution $\hat{\theta}$ estimated from the structural model, we randomly draw 1,000 values of $(q^*, \sigma_1^2, \sigma_2^2, \alpha_1 - \alpha_0)$ from their multivariate distribution. We then compute the moment values based on randomly drawn parameter values and report the average and standard deviation in Table 4 Panel c.

D Data Details

D.1 Data Extraction

Our database builds on the data set used in Card and DellaVigna (2020), which was constructed from the records in the Editorial Express (EE) system of the *Journal of the European Economic Association*, the *Quarterly Journal of Economics*, the *Review of Economic Studies*, and the *Review of Economics and Statistics*. For each submission, the CDV data set contains information on (i) the decisions it received in the editorial process, such as the recommendations by each referee and the first-round editor decision; (ii) the decision time in the editorial process, such as the days to receive a referee report and the days until the first-round editor decision; (iii) proxies of paper quality, such as Google Scholar citations; and (iv) paper characteristics, such as the fields of the paper and the number of publications in top journals by the authors. Based on the data agreement with the journals, decision time variables in the CDV data set are winsorized at 200 days and the editor information of the *Review of Economics and Statistics* is not disclosed.

Card et al. (2020) re-downloaded data from the the Editorial Express (EE) system with new variables such as the days to resubmit after receiving the first-round decision and the final-round editor decision. In addition, the unwinsorized decision time became accessible. To make use of the valuable information from the download, we matched this new data set back to the CDV data set, which enables us to use the final-round variables and the unwinsorized decision time in our analysis. Since the data set does not include paper identifiers for anonymity reasons, we used a fuzzy match algorithm based on all the identifying variables stored in the CDV data set.

To comply with the previous data agreement, all figures in this paper do not show observations beyond 200 days (for example, the binned scatter plots do not display dots with first-round decision time > 200). Meanwhile, the unwinsorized decision time is used in constructing the first-round editor decision time, the time between the second referee report and the editorial decision, and the time between the third referee report and the editoral decision.

D.2 Data Cleaning

In assembling the data set for analysis, we undertook the steps below of data cleaning.

1. We changed the referee report status to missing if the referee decision time is negative (11 cases) or if the referee decision time is greater than the first-round decision time (220 cases).

2. For the 7 cases in which the editor decision is not desk reject but has no referee report after completing the first step above, we dropped these observations from our analysis.

3. For the 79 cases in which the first-round decision time is greater than 180 days and the time to resubmit is recorded as 0 days, we dropped these observations from our analysis. These relatively rare cases are most likely to be reject-and-resubmit decisions in which the editor recodes the submission as R&R once the revision to the initially rejected paper is resubmitted.

4. For the 2,427 cases in which only one referee is assigned, following Card and DellaVigna (2020) we dropped these observations from our analysis since the assignment is open to different interpretations.

5. If the number of referees assigned and the number of referees responded are exactly equal for more than 95% of the non-desk rejected papers reviewed by an editor, we would like to account for the possibility that some referees were manually removed from the record. To minimize the influence on relevant results:

   (a) For Figure 5a and 5c, Figure A3, Figure A5a, Figure A13a-b and A13e-f, Table A1, after selecting the sample with at least three referees assigned and at least two referees responded, we marked the indicator for whether the editor waits for the third referee (the variable on the y-axis) as missing for 187 papers with an editor satisfying the above condition; for Figure A5c, after selecting the sample with at least four referees assigned and at least three referees responded, we marked the indicator for whether the editor waits for the third referee as missing for 10 papers with an editor satisfying the condition.

   (b) For Figure 10a, after selecting the sample where three referees were initially contacted and didn't decline, we dropped 177 papers with an editor satisfying the above condition; for Figure 10b, after selecting the sample where four referees were intially contacted and didn't decline, we dropped 10 papers with an editor satisfying the condition.