The Organization of Persuasion: Wald Deconstructed*

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Abstract

An agent sequentially collects information at a cost to influence a decision maker's choice between rejection and approval. We model this situation through an organizational deconstruction of Wald's classic model of sequential information acquisition. The payoff and control rights of the Wald statistician are split between the agent and the decision maker. The decision maker prefers approval in the good state and rejection in the bad state and thus benefits from information diffusion. The agent controls the information and pays for it, but benefits from approval regardless of the state and thus has no direct value for information. The agent's desire to persuade the decision maker induces an indirect demand for information. We characterize the outcome achieved by different organizational structures from a positive and normative perspective, depending on the commitment power of the agent and the decision marker. We also examine situations where the agent can misrepresent information at a cost and we show that it is socially optimal to tolerate a positive amount of misrepresentation.

Keywords: Research, organization, approval, regulation.

JEL Classification: D83 (Search; Learning; Information and Knowledge; Communication; Belief), M38 (Government Policy and Regulation).

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1 Introduction

This paper analyzes the ability of a biased agent to persuade a decision maker through costly information diffusion. For example, to persuade a doctor (decision maker) to prescribe a drug, a pharmaceutical company (agent) can perform costly clinical trials that document the drug's effectiveness and safety. Similarly, consider a company's industrial division (agent) that does research with the aim of persuading the sales division (decision maker) to commercialize a new product. In these situations, the decision maker values information about the desirability of adoption, but does not control—and does not pay for—information. The agent produces information for the sole purpose of persuading the decision maker, without directly caring about the value of information generated for the decision maker. How does the amount of information acquired and the resulting payoffs depend on the commitment ability of agent and decision maker? How should a social planner (such as a benevolent regulator or the company headquarters) who cares about the total payoff of agent and decision maker allocate power between these two parties?

We address these questions building on Abraham Wald's (1948) model of sequential information acquisition. In Wald's model a single statistician plays the role of a social planner who (i) controls both the acquisition of information and the adoption decision, (ii) pays the agent's cost of information, and (iii) obtains a decision payoff equal to the sum of the payoffs of the agent and the decision maker. Information collection is realistically modelled as a stochastic process whose drift depends on the state, in other words the result of a sequence of infinitesimal experiments. The classic solution of Wald's sequential information acquisition problem is characterized by the following s, S policy: for intermediate beliefs the statistician optimally conducts research until one of two standards is reached, and then either immediately approves when the belief becomes sufficiently optimistic and hits the adoption standard S or immediately rejects as soon as the belief becomes sufficiently pessimistic and hits the withdrawal standard s.

We contribute a strategic deconstruction of Wald's classic model. As in Wald, a choice needs to be made between rejection and approval, but now research and approval decisions are controlled by different players. The agent gets a fixed positive benefit from approval, irrespective of the state. The decision maker, instead, obtains a positive benefit if the state is good, but a negative benefit if the state is bad. Rejection yields a zero payoff to both the agent and the decision marker, who both discount future payoffs at the same rate. In each instant the agent can conduct additional research at a cost to obtain additional information about the state. The analysis proceeds by comparing different institutions governing the persuasion process that vary in the way decision rights are allocated.

Consider first a scenario with agent commitment, whereby the agent can make a single take it or leave it approval request to the decision maker (and commits to stop research more in case of rejection). Practically, in the drug adoption application, this was the case before the introduction of pharmaceutical regulation when doctors were powerless relatively to the pharmaceutical companies. Equivalently, in this scenario the decision maker cannot mandate research by the agent. In this case, as soon as the belief moves above the belief such that the decision maker is indifferent between rejection and approval (myopic cutoff), the agent submits and the decision maker approves. If the belief is below but not too pessimistic, the agent searches, trading off the expected cost of research against the benefit from a potential approval decision if the myopic cutoff is reached. These considerations determine the approval and rejection standards under agent commitment.

Note that the agent has no interest in information per se, since his payoff from approval does not depend on the underlying state. Nevertheless, the agent sometimes conducts research in the hope of convincing the decision maker to approve. This corresponds to results in the recent literature on persuasion à la Kamenica and Gentzkow (2011), KG. However, compared to KG, the agent here is restricted to choose a signal generated by a Brownian diffusion. A striking finding is that this restriction is inessential. Indeed, the value function of the agent in this model with sequential research in the limit when the cost of research goes to zero and there is no discounting converges to the value realized using the optimal signal identified by KG. Thus, KG does not really require commitment to the information structure. Also, this Wald framework allows the introduction of costly information acquisition into a persuasion model, a realistic feature for clinical trials and other applications

Within our framework, we can consider a number of organizational structures for persuasion corresponding to different extensive form games. Consider a decision maker who has the power to mandate further research if the current level is deemed insufficient, and is thus more powerful than in the agent commitment case. Allowing for such increased power leads to what we call the Nash equilibrium which can be found at the intersection of the agent's lower best response (optimal choice by the agent of the rejection standard for a given approval standard) and the decision maker's upper best response. In this outcome, both the approval standard and the rejection standard are higher than under agent commitment case. The decision maker values the information and does not pay its direct cost but only bears the cost due to the delay in obtaining the approval payoff. This leads the decision maker to always set a standard higher than the myopic cutoff. In turn, the withdrawal standard controlled by the agent increases since the adoption standard is harder to reach.

The decision maker has an interest in initially committing even further, for instance to commit to an approval policy of the type approve if and only if the evidence is above a particular standard. This Stackelberg outcome amounts to choosing the preferred point on the agent's lower best response curve. Depending on the value of the belief at the time of commitment, different types of commitments are optimal. When the initial belief is low, no standard above the myopic cutoff can encourage research by the agent, the outcome is thus no research and rejection. When the initial belief is high, the optimal commitment is immediate approval.

For intermediate beliefs, the decision maker chooses an interior commitment leading to some research by the agent. Several properties stand out. First, the decision maker commits to a standard below the Nash standard. The decision maker free rides on the cost and thus wants more research to be performed than the agent—thus the decision maker optimally commits to a lower standard in order to encourage research. Second, the commitment is increasing in the current belief. Indeed, the higher the initial belief, the lower the chances the rejection standard will be reached and thus the lower the value of commitment. Overall there are more starting beliefs for which some research is conducted under decision maker commitment than under the Nash solution.

Next, turn to a comparison of the level of social welfare under these three natural institutions. Take the perspective of the social planner having as objective the sum of the agent and the decision maker's welfare. This essentially amounts to reconstructing a Wald statistician. Two conclusions stand out from the welfare analysis:

1. The decision maker commitment institution always welfare dominates Nash: the decision maker is clearly better off as he chooses the optimal commitment. The agent turns out also to be better off since the decision maker chooses a lower commitment, meaning less research is needed to convince him.

2. The resulting choice between agent and decision maker commitment just depends on the value the agent attaches to approval and the cost of research. If the agent attaches a low value or if costs are high, agent commitment will dominate while decision maker commitment will dominate in the other cases.

The paper also discusses how the framework can be applied to the history of pharmaceutical regulation, starting from the setup in 1906 of the first regulatory board within the American Medical Association, and then with the establishment of—and the allocation of increased powers to—the Food and Drug Administration. We also consider the possibility for the agent to lie at a cost where the penalty depends on the size of the lie. We show that the social planner, if she wants to limit research at the lower end, can be better off with an intermediate penalty where some lying occurs in equilibrium. Indeed, this intermediate penalty decreases the incentives for research.

2 Model

A choice needs to be made between two alternatives, approval A or rejection R. The respective benefits depend on the state of the world ω that can be either good G or bad B.

The game involves two players: a decision maker d (she) and an agent a (he). The decision maker gets a positive benefit from approval $v_d^G > 0$ when the state is good and $v_d^B < 0$ when the state is bad. The agent gets the same benefit $v_a > 0$ from approval regardless of the state. We assume that the payoff from rejection is zero for all players, regardless of the state.

The players share a common prior about the state $q_0 = Pr\,(\omega = G)$. We denote $\hat{q}_d$ the belief such that the decision maker is indifferent between the two alternatives A and R:

$$\hat{q}_d \; v_d^G \; + \; (1 - \hat{q}_d) \; v_d^B = 0$$

Given the restrictions we imposed on the payoffs, if the decision maker is forced to make a decision at belief q, he chooses A if and only if $q > \hat{q}_d$. We call $\hat{q}_d$ the myopic cutoff of the decision maker; the same construct can be defined for the agent.

The agent can conduct research whose results are publicly disseminated. The arrival of new information is modeled as a Wiener process $d\Sigma$, whose drift is determined by the state. Specifically, the process has positive drift μ and variance ρ^2 if the state is G or drift $-\mu$ and variance ρ^2 if the state is B. Accumulating information over a period of time dt costs cdt. Finally, both players discount future payoffs at the same rate r.

The agent pays the cost of research while the decision maker does not take it into account. In sections 4 we introduce a social planner, denoted w, whose payoff is the sum of the agent and the decision maker's payoff. The social planner thus takes into account the cost of research.

3 Wald Deconstructed

3.1 Wald Baseline

Wald (1948) studied the problem of single statistician controlling both the accumulation of information and the final decision making, and furthermore paying the full cost of research. In our setting, this would correspond to a single player who pays the cost of research, makes both research and approval decisions and obtains a positive benefit from approval if the state is good and negative if the state is bad. The solution Wald obtained involved two standards s_{Wald} (the rejection standard) and S_{Wald} (the approval standard), such that:

- if $q \leq s_{Wald}$ the Wald statistician stops researching and rejects;
- if $s_{Wald} < q < S_{Wald}$ she conducts research;
- if $q \geq S_{Wald}$ she stops researching and approves.

In the rest of the text, we dub this outcome the *Wald cutoff path*. Our model is in essence a deconstruction of Wald where the research and approval decisions are split between players and the cost is born by one of the two parties. Our focus is on how different institutions governing the interaction between the agent and the decision maker affects information collection and the quality of final decisions.

3.2 Best Responses

We start by characterizing the best responses of the research problem. Specifically, for a given value of the lower standard s (resp. upper standard S) we characterize the optimal choice of the upper standard $S = BR(s)$ (resp. lower standard $s = br(S)$).

This best response analysis allows for a better understanding of our problem and will serve as a building block for the next sections. It is initially natural to examine the properties of $br_a(S)$ and $BR_d(s)$, i.e., the choice by the agent of the lower standard as a best response to a given S and the choice by the decision maker of the upper standard as a best response to a given s, since the agent in most situations will control research and the decision maker controls approval.

Proposition 1 *The lower best response of the agent $br_a(S)$ and the upper best response of the decision maker $BR_d(s)$ are independent of the current belief q. Furthermore $br_a(S)$ is increasing in S and $BR_d(s)$ is decreasing in s for $s < \hat{q}_d$*

It is essential to understand the tradeoff underlying these best responses. The agent performs research not to obtain information, since he obtains the same payoff regardless of the state, but as a mean to persuade the decision maker. Thus if an upper standard S is fixed, and the current belief q is smaller than this standard, the agent will tradeoff the expected cost of research to reach S against the expected gain which is the discounted value of v_a,

$$\underbrace{\beta_1(s,S)\ v_a}_{\text{expected gain from reaching } S} = \underbrace{\beta_2(s,S)\ c/r}_{\text{financial cost of research}} \tag{1}$$

with $\beta_1(s,S) > 0$ and $\beta_2(s,S) > 0$.

This tradeoff underlies the results presented in Proposition 1. The agent, when he chooses the lower standard, only evaluates the expected cost he will incur to reach the upper standard as well as the expected time it will take him to reach it. Naturally, $br_a(S)$ is thus increasing in S.

For the decision maker, the problem is different for two reasons. First, she does not bear the cost of research. Second, she cares about the information revealed in the research process. Note that even though research has no financial cost for her, there is still a cost if a good decision is delayed. Thus, for a given lower threshold s, the decision maker optimally chooses S so as to tradeoff the value of information and the cost of delaying a good decision. The first order condition characterizing the best response reflects this tradeoff

$$\underbrace{-\beta_3(s,S)\ v_d^B}_{\text{benefit of information}} = \underbrace{\beta_4(s,S)\ V_A(S)}_{\text{cost / benefit of delaying decision}}, \tag{2}$$

where $\beta_3(s,S) > 0$ and $\beta_4(s,S)$ and

$$V_A(S) = S\ v_d^G\ +\ (1-S)\ v_d^B$$

is the expected benefit of approval at belief $q = S$, which is positive for $q > \hat{q}_d$. When s is larger, the agent searches less and the decision maker therefore sees less benefit from information and chooses a lower S to avoid delaying the benefits $V_A(S)$. This explains why $BR_d(s)$ is decreasing in s. Of course if $s \geq \hat{q}_d$, then there is no value to information and the decision maker immediately approves.

In what follows, we use the properties of these best responses to study different institutions governing the interaction between the agent and the decision maker.

3.3 Agent Commitment

We first consider a benchmark model where the agent performs the research and can make one take it or leave it demand for approval to the decision maker who has to choose once and for all between rejection and approval. This can be seen as either a situation where the agent commits not to research further in case of rejection or alternatively a situation where the decision maker has no power to mandate further research. This assumption of agent commitment is explicitly made in the persuasion literature where the agent commits to a choice of signalling technology which will be used only once.

Specifically, we study the stationary Markov Perfect equilibrium of the following dynamic game, that we call agent commitment game. In every instant t, the state variable is represented by the belief q_t, and the decision maker and the agent move sequentially according to the following rules:

1. The agent chooses between $\mathcal{I}_a$ (information acquisition), $\mathcal{A}_a$ (application for approval), or $\mathcal{R}_a$ (rejection);
2. If the agent chooses $\mathcal{A}_a$, then the principal chooses between $\mathcal{A}_d$ (approval), or R_d (rejection)

The outcome of the game is I (information acquisition) if $(\mathcal{I}_a)$, A (approval) if $(\mathcal{A}_a, \mathcal{A}_d)$ and R (rejection) if either $(\mathcal{R}_a)$ or $(\mathcal{A}_a, \mathcal{R}_d)$.

The agent uses research to persuade the decision maker, but has no interest per say in the information revealed. He will stop and ask for approval as soon as there is sufficient evidence to convince the decision maker, in other words as soon as the belief reaches the decision maker's myopic cutoff $\hat{q}_d$. Since it is a take it or leave it offer, the decision maker approves for any $q_t \geq \hat{q}_d$. As a result, the agent chooses the lower standard s as a best response to $\hat{q}_d$. These results are summarized in the following proposition:

Proposition 2 *The unique SPE outcome of the agent commitment game is a* Wald-cutoff path with standards (s^{C_a}, S^{C_a}) *such that* $S^{C_a} = \hat{q}_d$ *and* $s^{C_a} = br_a(\hat{q}_d)$.

The fact that the agent searches for information even though he obtains the same payoff regardless of the state echoes the literature on persuasion, and in particular KG. However, compared to KG, we restrict our agent to choose a signal in a particular class of signals: the agent is restricted to Brownian diffusion. We show here that this restriction is inessential.

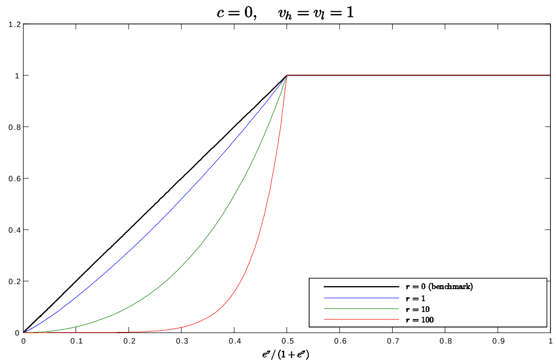

Figure 1: Agent's Value Function for Fixed $S = 1/2$.

When we compare the value function of the agent in our model, for a given choice of S by the decision maker, at the limit when $r = 0$ and c converges to zero to the value realized using the optimal signal identified by KG, we find that the two values are identical. This can be seen in Figure 1, echoing KG's Figure 2.

Proposition 3 *In the case $r = 0$, the value of the agent at the prior belief q_0 converges to the value of an optimal signal in KG when the cost of research c converges to zero.*

KG identify two key properties of the optimal signal. First, when the decision maker takes the agent's least preferred decision, she is certain of the state. Second, when the decision maker takes the agent's preferred action, the decision maker is exactly indifferent between approval and rejection. Both these properties are satisfied by our signalling technology at the limit when c goes to zero. First, when c converges to zero, $s = br_a(\hat{q}_d)$ converges to 0, in other words, when the agent stops research and induces rejection, his belief that the state is low converges to 1. Second, the agent immediately stops searching when the belief reaches the decision maker's myopic cutoff, in other words as soon as the decision maker becomes indifferent between approval and rejection.

The key advantage of our Wald approach is the ability to analyze the research decision in different extensive form games corresponding to different institutions observed in practice.

3.4 No Commitment

We now consider situations where the decision maker has more power, in particular the power to mandate further research if she finds the evidence insufficient.[1] We thus consider a slight

[1] Alternatively the agent might be unable to commit not to search further in case of rejection.

modification of the agent commitment game described above where, in a period t, if the agent chooses to apply for approval ($\mathcal{A}_a$), the decision maker, on top of the choices $\mathcal{A}_d$ (approval), or R_d (rejection), can also choose further information acquisition $\mathcal{I}_d$ by essentially mandating further research whose cost is paid by the agent.

We show in the appendix that the unique stationary Markov Perfect Equilibrium outcome of this game is a Wald-cutoff path that we denote (s^N, S^N), solves $s_N = br_a(S_N)$ and $S_N = br_d(s_N)$, i.e., is the intersection of the agent's lower best response and the decision maker's upper best response. In other words it is the same outcome as that of a simultaneous game where the agent chooses the lower standard and the decision maker the upper standard.

Proposition 4 *The unique MPE outcome of the no-commitment game is a Wald-cutoff path with standards* (s^N, S^N) *such that* $s^N = br_a(S^N)$ *and* $S^N = br_d(s^N)$. *Compared to the agent commitment solution, more information is obtained at the top* $S^N > S^{C_a}$ *and less at the bottom* $s^N > s^{C_a}$.

In the no-commitment game, the decision maker chooses the upper standard S as the best response to s. In equilibrium, this upper standard will be chosen strictly greater than S^{C_a} which is the myopic cutoff. Indeed, the decision maker values information and does not pay the cost of research. The only cost she incurs is in delaying an approval decision of positive expected value. At the myopic cutoff, there is thus no cost since the expected value of approval is zero. We will thus have more information collected at the top in no-commitment: $S^N > S^{C_a}$. We call this the *decision maker information bias effect*. From the perspective of the agent, there is a *loss of control effect*: the agent no longer controls the upper standard, it is set inefficiently high from his point of view, and this reduces the value of research at the bottom, thus we have $s^N > s^{C_a}$ (as we saw in Proposition 1, the agent's lower best response is increasing in S).

3.5 Decision Maker Commitment

Overall the decision maker is weakly better off in the no-commitment outcome than in the agent commitment case (and strictly better for a prior in (s^{C_a}, S^N)). However, she can do even better by initially committing to a certain approval rule. Specifically, we study in this section the case where the decision maker has the ability to commit, at the start of the game, to an approval standard that depends only on the current state of knowledge (and not on the path or time taken to get there), i.e., a rule of the following cutoff form: approve if and only if $q \geq S^{C_d}$.

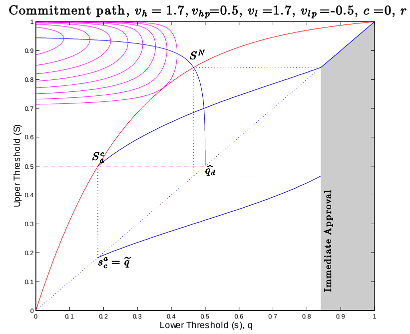

Figure 2: The Commitment Path.

This institution, that we call the decision maker commitment game, amounts for the decision maker to choosing her preferred point on the agent's lower best response. We now characterize the path of the commitment solution; see Figure 2. A key property is that dynamic consistency no longer applies: the optimal choice of commitment by the decision maker depends on the initial belief at commitment date q_0 as described in the following result.

Proposition 5 *In the decision maker commitment game, if $q_0 \in (s^{C_a}, S^N)$, the decision maker chooses an* ***interior commitment*** *$S^{C_d}(q_0)$ increasing in q_0 and such that $S^{C_d}(q_0) \leq S^N$. Furthermore, if $q_0 < s^{C_a}$, no research is performed regardless of the choice of the decision maker and if $q_0 > S^N$, the decision maker chooses to immediately approve.*

The decision maker will always commit to an approval standard above her myopic cutoff. When the initial belief is below s^{C_a}, any such commitment will push the agent to do no research since, even in the best case scenario from the agent's point of view where the standard would be set exactly at the myopic cutoff, the expected cost of research would dominate the expected gain (by definition of s^{C_a}). In this region, commitment by the decision maker has no value. At the other extreme, when the prior belief is above S^N, it is optimal for the decision maker to choose immediate approval which induces the agent to do no research.

However, when the initial belief takes intermediate values, $q_0 \in (s^{C_a}, S^N)$, it becomes optimal for the decision maker to commit to an upper standard in order to provide the agent incentives to do research. She will in fact choose an interior commitment below the Nash equilibrium level, to create this encouragement effect. We can view this as resulting from the tradeoff between the following effects:

- *A second-order negative direct effect:* holding fixed the agent's strategy s, decreasing the upper standard means an insufficient amount of research is performed at the upper end. This loss is clearly second order by the envelope theorem because we start from the decision maker's optimal choice of S holding fixed the agent's choice of s.

- *A first-order positive strategic effect:* The agent's strategic response of the decrease in the commitment S is to increase research at the lower end. Given that the agent's initial choice of s was higher than what the decision maker would have liked, this is a positive first order effect for the decision maker that dominates the second order negative effect.

As the prior belief becomes more favorable, the second effect, which can be seen as an encouragement effect, becomes less relevant since it becomes very likely that the approval standard will be quickly reached. This explains why the interior commitment is increasing in q_0. The possibility to commit makes the decision maker weakly better off and in fact strictly better off whenever $q \in (s^{C_a}, S^N)$ where she chooses the interior commitment.

Proposition 6 *In the decision maker commitment game more research is conducted in equilibrium than in the no-commitment game:* $(s^N, S^N) \subset (s^{C_a}, S^N)$*.*

Proposition 6 suggests that, in the equilibrium outcome of the decision maker commitment game, the encouragement effect means that there are more starting beliefs q_0 for which some research is conducted.

4 Wald Reconstructed: Comparing Institutions

We now turn to the design of persuasion. We attempt to answer the following questions. What institutions will maximize social welfare? In particular should commitment be given to the agent, to the decision maker or is the laissez faire regulation embodied in the no-commitment case the best institution?

To address these questions, we first need to determine the welfare criterion. We will consider a social planner w that maximizes the sum of the decision maker's and the agent's welfare. This social planner is the reconstruction of the Wald statistician with payoff $v_w^G = v_a + v_d^G$ in the good state and $v_w^B = v_a + v_d^B$ in the bad state and who bears the full cost of research. In this setting, we obtain the following results:

Proposition 7 *When the social planner chooses between the different institutions:*

- *Giving commitment power to either the agent or the social planner is always preferred to the no-commitment institution.*

- *There exists a $\tilde{v}_a$ such that the social planner chooses agent commitment if and only if $v_a \geq \tilde{v}_a$, where $\tilde{v}_a \leq -v_d^B$ is a decreasing function of c.*

- *There exists $\bar{c}$ such that if $c \geq \bar{c}$ the agent commitment institution is the preferred institution.*

The first result of Proposition 7 follows from the fact that the no-commitment outcome is always welfare dominated by the decision maker commitment outcome. It is clear that the decision maker prefers the situation where she can commit since it allows her to pick her preferred point on the agent's lower best response curve. More surprising is that the agent also prefers the decision maker commitment case to no commitment. Indeed, it leads the decision maker to choose a lower approval standard, which means that a lower cost of research will need to be incurred to hopefully obtain approval. Overall this implies that the social planner will always prefer either agent or decision maker commitment.

The choice between the two types of commitments then depends on the payoffs of the agent and the decision maker and on the cost of research, as described in the other results of Proposition7. When the payoff of the agent is sufficiently high, the social planner will naturally prefer the agent commitment solution. This is in particular the case when v_a is above $-v_d^B$ which implies that the social planner would get a positive payoff from approval even in the bad state. If that is the case, the social planner naturally prefers the agent commitment institution that minimizes research. We also establish that a higher cost of research will increase the number of instances under which agent commitment is preferred.

We now compare the research decision the social planner would implement if deciding alone, that we denote (s_w^*, S_w^*) , to the research decisions made in the different institutions. The first thing to note is that the the myopic cutoff of the social planner is below that of the decision maker: from a welfare point of view, the decision maker is too conservative in her approval preferences since she does not consider the positive externality of approving on the agent's payoff.

When deciding on the lower benchmark of search, both the agent and the decision maker take into account the cost of research and equalize the expected cost to the expected benefits upon approval, as characterized by equation (2). If the upper standard S is set at the myopic cutoff of the decision maker ($S = \hat{q}_d$), then the best response of the agent and of the social planner are confounded since the decision maker gets a zero payoff upon approval. If $S < \hat{q}_d$, the decision maker gets a negative expected payoff upon approval. The social planner takes into account this negative externality and prefers less research than the agent (lower best response of the social planner is to the right of that of the agent). When $S \geq \hat{q}_d$, the externality is on the contrary positive and the social planner wants to do more research than the agent. Since both under agent-commitment and decision-maker-commitment, the decision maker has veto power over the approval decision, she never approves for a belief below her myopic cutoff ($S^{C_d} > S^{C_a} > \hat{q}_d$) and we are thus in equilibrium, the social planner would always want do less research at the lower end than the agent does, as expressed in the the results of Proposition 8.

Proposition 8 *The social planner would optimally do more research at the lower end than what is done in agent-commitment or decision maker commitment institutions* $s_w^* < s^{C_a} < s^{C_d}$.

5 Literature

The original problem of sequential research, examining the tradeoff between the cost of an extra signal and the benefit of a more informed decision, was introduced by Wald (1945, 1947) and Wald and Wolfowitz (1948).[2] The ensuing applied probability literature of this non-strategic problem has a large impact on the actual design of clinical trials. Closely building on Wald's decision-theoretic foundational framework, we focus on the strategic issues that arise when the decisions to collect information and to make the final decision are made by two different players.

Our paper thus relates to the literature on strategic experimentation (see Bolton and Harris 1999) and especially to Strulovici (2010), who highlights how the loss of control of decision making (determined through voting in his model) reduces the incentives to acquire information and thus induces a status quo bias; see also Fernandez and Rodrik (1991). Our model is closest to Gul and Pesendorfer (2012), Lizzeri and Yariv (2011), and Chan and Suen (2012) who consider strategic settings in which public information arrives over time to voters. In Gul and Pesendorfer's (2012) model information is provided by the party that leads, whereas in Lizzeri and Yariv (2011) and Chan and Suen (2012) voters decide collectively themselves when to stop acquiring public information and reach a decision. In their setting information is revealed publicly to all voters, while we focus on the sequential interaction between an agent who collects private information

[2] Moscarini and Smith (2001) recently advanced this literature on non-strategic sequential analysis by analyzing a continuous-time model in which the decision maker can the vary number of experiments in each period. Our formulation is also in continuous time, but we focus on the simpler case with one experiment per period.

and then reports (or possibly misreports) it to a principal who makes the approval decision. We also analyze the commitment solution in which the principal moves first by setting the approval standard, and then extend the model to analyze approval in multiple stages.

For our baseline analysis we constrain reporting of the belief (corresponding to the final results) to be truthful at the moment of application, for example because misrepresentation is infinitely costly as in the disclosure models of Grossman (1981) and Milgrom (1981). We also consider the possibility of costly misreporting. While Kartik, Ottaviani and Squintani (2007) and Kartik (2009) characterize the amount of equilibrium costly lying in static models of strategic communication, in our dynamic model we show that ex post lying costs reduce the ex ante incentives for information collection. See also Shavell (1994), Henry (2009), and Dahma, Gonzalez, and Porteiro (2009) for strategic analysis of partial disclosure of research results. In Henry (2009), pharmaceutical firms are worse off when their research efforts are not observed by the regulator as they are forced to do additional tests to convince him they are not hiding any evidence. Our setup is different in the sense that information is not verifiable: in fact the possibility of hiding information here reduces research because of the cost of lying. This turns out to be beneficial for the regulator who wants to limit research at the lower end.

Finally, we do not allow our principal to use monetary transfers, in line with the literature on mechanism design without transferable utility; see Holmstrom (1977) and Alonso and Matouschek (2008), Armstrong and Vickers (2010), and Taylor and Yildirim (2011). This approach delivers a number of important insights on the functioning of approval processes that we observe in a number of practical settings where, by and large, transfers are actually not used. A complementary literature analyzes the problem of optimal incentive provision for innovation, search, and experimentation where transfers are allowed; recent papers in this area are Manso (2011), Lewis and Ottaviani (2008), Lewis (2012), Gerardi and Maestri (2012), Horner and Samuelson (2012), and Halac, Kartik, and Liu (2012).

6 Conclusion

In this paper, we have studied a deconstruction of Wald's classic problem, by considering environments where the decision rights are split between an agent in control of the rejection decision and a decision maker in control of approval. To present sharp results and to focus specifically on persuasion, we have kept throughout the assumption that the approval payoff of the agent is independent of the state.

In a companion paper, Henry and Ottaviani (2015), we analyze in detail the application to drug approval by allowing the agent's payoff is state dependent. For instance, if a drug turns out to unsafe, the pharma company suffers losses in terms of profits and reputation. In addition some liability could imposed on the pharma company, depending on the policy regime.

In fact, the evolution of the legislation on drug approval fits closely with the different institutions we considered. The first regulatory step was to implement the agent commitment institution: the 1938 Food, Drug and Cosmetic Act required that research results be submitted to obtain approval for the drugs, although the FDA had little power to mandate further research if the initial evidence was unsatisfactory. The 1962 Drug Amendments gave more power to the regulator to mandate research. As explained by Junod (2008), "FDA was given the authority to set standards for every stage of drug testing from laboratory to clinic". In essence, in 1962, the first step was to move the institution from agent commitment to Nash. More recently, the law, by allowing the FDA to intervene at each stage, created the conditions for individualized commitment. In its guidelines for meetings, the FDA specifies clearly that meeting can occur before the beginning of each phase. One of the stated goals is to define jointly the design of the future trials and the endpoints.[3] The institution thus moved closer to decision maker commitment.

Regulation of drug approval has now moved to a new phase, focusing on two main issues. First, and most importantly, regulation has started tackling the issue of withholding of negative results by firms. Second, there is renewed discussion on post-approval regulation which is currently close to non-existent. Henry and Ottaviani (2015) analyze the properties of these new regulatory efforts. Consider for instance post approval regulation. Post approval, there is a risk of catastrophic consequences if the state is bad. The decision maker can continue to monitor and pick a withdrawal standard. In fact, committing ex ante to a certain monitoring effort post approval can be a way to influence the research decision by the agent.

[3] For instance at the end of Phase 2, the goal is to plan "phase 3 trials identifying major trial features such as trial population, critical exclusions, trial design (e.g., randomization, blinding, choice of control group, with explanation of the basis for any noninferiority margin if a noninferiority trial is used), choice of dose, primary and secondary trial endpoints"

7 Appendix

Preliminaries and notation

To facilitate the derivation and exposition of the results, we use the following log-likelihood parametrization of beliefs

$$\sigma = \log \frac{q}{1-q},$$

where

$$q = \Pr(\omega = G)$$

We denoted the lower and upper standards of search in the regular space of beliefs (s, S). We will use in the log-likelihood space the notation (s, S) where:

$$\begin{aligned} \mathsf{S} &= \ln \frac{S}{1-S} \\ \mathsf{s} &= \ln \frac{s}{1-s} \end{aligned}$$

Finally we denote $\hat{\sigma}_d = ln\frac{\hat{q}_d}{1-\hat{q}_d}$ the "myopic cutoff" in the log likelihood space. **For the rest of the appendix, we derive the results in the log-likelihood space unless specified otherwise**.

Updating of beliefs

Suppose research is undertaken until time t. The realization at time t of the stochastic process will be informative about the state and will be used to update beliefs. The accumulated information at date t is given by ν_t. The log-likelihood ratio of observing $\nu_t = \gamma$ in the two states is given by

$$\log \frac{h\left(\frac{\gamma-\mu}{\rho}\right)}{h\left(\frac{\gamma+\mu}{\rho}\right)} = \frac{2\mu\gamma}{\rho^2},$$

where h is the density of a standard normal distribution. According to Bayes' rule, the log posterior probability ratio is equal to the sum of the log prior probability ratio and the log-likelihood ratio. Thus, the posterior belief at time t is given by

$$\sigma_t = \sigma_0 + \Sigma_t^{'}$$

where $d\Sigma'$ is a Wiener process with drift $2\mu^2/\rho^2$ if the state is G and $-2\mu^2/\rho^2$ if the state is B and instantaneous variance $4\mu^2/\rho^2$.

Expected utility in the search region

If the upper and lower standards (s, S) are given, for $\sigma \in (\mathsf{s}, \mathsf{S})$ we have that the utility of player i (with cost of research c_i and benefits v_i^G and v_i^B from approval) follows:

$$u_i(\sigma) = e^{-rdt} E[u_i(\sigma + d\Sigma')] - c_i dt.$$

Following Stokey (2009, Chapter 5), starting in the intermediate region, we let T be the first time the belief hits either s or S. The direct monetary cost of searching is given by $\int_0^T c_i e^{-rt} dt = \frac{c_i}{r} - \frac{c_i}{r} e^{-rT}$. Once we define, as in Stokey (2009)

$$\begin{aligned} \Psi(\sigma, \omega) &= E[e^{-rT} | \sigma(T) = \mathsf{S}, \omega] \ Pr[\sigma(T) = \mathsf{S} | \omega] \\ \psi(\sigma, \omega) &= E[e^{-rT} | \sigma(T) = \mathsf{s}, \omega] \ Pr[\sigma(T) = \mathsf{s} | \omega], \end{aligned}$$

the utility for $\sigma \in (\mathsf{s}, \mathsf{S})$ is given by

$$\begin{aligned} u_i(\sigma) &= -\frac{c_i}{r} + Pr[\omega = G] \left(v_i^G + \frac{c_i}{r} \right) \Psi(\sigma, G) \\ &+ Pr[\omega = B] \left(v_i^B + \frac{c_i}{r} \right) \Psi(\sigma, B) \\ &+ Pr[\omega = G] \left(\frac{c_i}{r} \right) \psi(\sigma, G) \\ &+ Pr[\omega = B] \left(\frac{c_i}{r} \right) \psi(\sigma, B). \end{aligned}$$

The first line corresponds to the case where the state is good and the upper benchmark S is reached first. The second line is the case where the state is bad but the upper benchmark is reached first, and so on.

Stokey (2009) derives that:

$$\begin{aligned} \Psi(\sigma, G) &= \frac{e^{-R_1(\sigma - \mathsf{s})} - e^{-R_2(\sigma - \mathsf{s})}}{e^{-R_1(\mathsf{S} - \mathsf{s})} - e^{-R_2(\mathsf{S} - \mathsf{s})}} \\ \Psi(\sigma, B) &= \frac{e^{R_2(\sigma - \mathsf{s})} - e^{R_1(\sigma - \mathsf{s})}}{e^{R_2(\mathsf{S} - \mathsf{s})} - e^{R_1(\mathsf{S} - \mathsf{s})}} \\ \psi(\sigma, B) &= \frac{e^{-R_1(\mathsf{S} - \sigma)} - e^{-R_2(\mathsf{S} - \sigma)}}{e^{-R_1(\mathsf{S} - \mathsf{s})} - e^{-R_2(\mathsf{S} - \mathsf{s})}} \\ \psi(\sigma, G) &= \frac{e^{R_2(\mathsf{S} - \sigma)} - e^{R_1(\mathsf{S} - \sigma)}}{e^{R_2(\mathsf{S} - \mathsf{s})} - e^{R_1(\mathsf{S} - \mathsf{s})}} \end{aligned}$$

with $R_1 = \frac{1}{2}\left(1 - \sqrt{1 + \frac{4r}{\mu'}}\right)$ and $R_2 = \frac{1}{2}\left(1 + \sqrt{1 + \frac{4r}{\mu'}}\right)$, so that $R_1 + R_2 = 1$.

We derive properties of the conditional probabilities Ψ and ψ in the lemma below and use these properties in results that follow.

Lemma 1 *Consider the conditional probabilities Ψ and ψ. The following hold:*

1. $\Psi(\sigma, B) = e^{\sigma - \mathsf{S}}\Psi(\sigma, G)$
2. $\psi(\sigma, B) = e^{\sigma - \mathsf{s}}\psi(\sigma, G)$,
3. $\frac{\partial\Psi(\sigma,G)}{\partial \mathsf{s}} = a \cdot \psi(\sigma, G) < 0$
4. $\frac{\partial\psi(\sigma,G)}{\partial \mathsf{s}} = b \cdot \psi(\sigma, G) > 0$
5. $\frac{\partial\Psi(\sigma,G)}{\partial \mathsf{S}} = f \cdot \Psi(\sigma, G) < 0$
6. $\frac{\partial\psi(\sigma,G)}{\partial \mathsf{S}} = g \cdot \Psi(\sigma, G) > 0$

where:

$$\begin{aligned}
a &= \frac{R_1 - R_2}{e^{-R_1(\mathsf{S}-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})}} < 0 \\
b &= \frac{R_2 e^{R_2(\mathsf{S}-\mathsf{s})} - R_1 e^{R_1(\mathsf{S}-\mathsf{s})}}{e^{R_2(\mathsf{S}-\mathsf{s})} - e^{R_1(\mathsf{S}-\mathsf{s})}} > 0 \\
f &= \frac{R_1 e^{-R_1(\mathsf{S}-\mathsf{s})} - R_2 e^{-R_2(\mathsf{S}-\mathsf{s})}}{e^{-R_1(\mathsf{S}-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})}} < 0 \\
g &= \frac{R_2 - R_1}{e^{R_2(\mathsf{S}-\mathsf{s})} - e^{R_1(\mathsf{S}-\mathsf{s})}} > 0
\end{aligned}$$

Proof Lemma 1

1. We have:

$$\begin{aligned}
\Psi(\sigma, B) &= \frac{e^{R_2(\sigma-\mathsf{s})} - e^{R_1(\sigma-\mathsf{s})}}{e^{R_2(\mathsf{S}-\mathsf{s})} - e^{R_1(\mathsf{S}-\mathsf{s})}} \\
&= \frac{1}{e^{(\mathsf{S}-\mathsf{s})}} \frac{e^{R_2(\sigma-\mathsf{s})} - e^{R_1(\sigma-\mathsf{s})}}{e^{(R_2-1)(\mathsf{S}-\mathsf{s})} - e^{(R_1-1)(\mathsf{S}-\mathsf{s})}} \\
&= e^{-(S-s)} \frac{e^{R_2(\sigma-\mathsf{s})} - e^{R_1(\sigma-\mathsf{s})}}{e^{-R_1(\mathsf{S}-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})}} \\
&= e^{\sigma-S} \frac{e^{-R_1(\sigma-\mathsf{s})} - e^{-R_2(\sigma-\mathsf{s})}}{e^{-R_1(\mathsf{S}-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})}} \\
&= e^{\sigma-S}\Psi(\sigma, G)
\end{aligned}$$

2. We can express:

$$\begin{aligned}
\psi(\sigma, B) =& \frac{e^{-(1-R_2)(\mathsf{S}-\sigma)} - e^{-(1-R_1)(\mathsf{S}-\sigma)}}{e^{-(1-R_2)(\mathsf{S}-\mathsf{s})} - e^{-(1-R_1)(\mathsf{S}-\mathsf{s})}} \\
=& \frac{e^{-\mathsf{S}+\sigma+R_2(\mathsf{S}-\sigma)} - e^{-\mathsf{S}+\sigma+R_1(\mathsf{S}-\sigma)}}{e^{-\mathsf{S}+\mathsf{s}+R_2(\mathsf{S}-\mathsf{s})} - e^{-\mathsf{S}+\mathsf{s}+R_1(\mathsf{S}-\mathsf{s})}} \\
=& \frac{e^{\sigma-\mathsf{S}}}{e^{\mathsf{S}-\mathsf{s}}} \frac{e^{R_2(\mathsf{S}-\sigma)} - e^{R_1(\mathsf{S}-\sigma)}}{e^{R_2(\mathsf{S}-\mathsf{s})} - e^{R_1(\mathsf{S}-\mathsf{s})}} \\
=& e^{\sigma-\mathsf{s}}\psi(\sigma, G).
\end{aligned}$$

3. Taking derivatives and rearranging terms, we obtain:

$$
\begin{aligned}
\frac{\partial \Psi(\sigma, G)}{\partial \mathsf{s}} =&(R_1 - R_2)\frac{\left[e^{-R_1(\mathsf{S}-\mathsf{s})-R_2(\sigma-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})-R_1(\sigma-\mathsf{s})}\right]}{\left[e^{-R_1(\mathsf{S}-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})}\right]^2}\\
=&(R_1 - R_2)e^{\mathsf{s}-\sigma}\frac{\left[e^{-R_1(\mathsf{S}-\sigma)} - e^{-R_2(\mathsf{S}-\sigma)}\right]}{\left[e^{-R_1(\mathsf{S}-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})}\right]^2}\\
=&(R_1 - R_2)e^{\mathsf{s}-\sigma}\frac{\psi(\sigma, B)}{\left[e^{-R_1(\mathsf{S}-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})}\right]}\\
=&(R_1 - R_2)e^{\mathsf{s}-\sigma+\sigma-\mathsf{s}}\frac{\psi(\sigma, G)}{\left[e^{-R_1(\mathsf{S}-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})}\right]}\\
=&(R_1 - R_2)\frac{\psi(\sigma, G)}{\left[e^{-R_1(\mathsf{S}-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})}\right]}\\
=&a \cdot \psi(\sigma, G),
\end{aligned}
$$

where $a < 0$ since $\left(e^{-R_1(\mathsf{S}-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})}\right) > 0$ and $(R_1 - R_2) < 0$ and a is independent of σ.

4. Similarly,

$$
\begin{aligned}
\frac{\partial \psi(\sigma, G)}{\partial \mathsf{s}} =& -\frac{\left(-R_2 e^{R_2(\mathsf{S}-\mathsf{s})} + R_1 e^{R_1(\mathsf{S}-\mathsf{s})}\right)\left(e^{R_2(\mathsf{S}-\sigma)} - e^{R_1(\mathsf{S}-\sigma)}\right)}{\left[e^{R_2(\mathsf{S}-\mathsf{s})} - e^{R_1(\mathsf{S}-\mathsf{s})}\right]^2}\\
=&\frac{\left(R_2 e^{R_2(\mathsf{S}-\mathsf{s})} - R_1 e^{R_1(\mathsf{S}-\mathsf{s})}\right)}{e^{R_2(\mathsf{S}-\mathsf{s})} - e^{R_1(\mathsf{S}-\mathsf{s})}}\psi(\sigma, G)\\
=&b \cdot \psi(\sigma, G).
\end{aligned}
$$

where $b > 0$ since both $\left(e^{R_2(\mathsf{S}-\mathsf{s})} - e^{R_1(\mathsf{S}-\mathsf{s})}\right) > 0$ and $\left(R_2 e^{R_2(\mathsf{S}-\mathsf{s})} - R_1 e^{R_1(\mathsf{S}-\mathsf{s})}\right) > 0$ and b is independent of σ

5. We also have

$$
\begin{aligned}
\frac{\partial \Psi(\sigma, G)}{\partial S} &= \frac{\partial}{\partial S}\left(\frac{e^{-R_1(\sigma-\mathsf{s})} - e^{-R_2(\sigma-\mathsf{s})}}{e^{-R_1(\mathsf{S}-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})}}\right)\\
&= -\frac{\left(e^{-R_1(\sigma-\mathsf{s})} - e^{-R_2(\sigma-\mathsf{s})}\right)\left(-R_1 e^{-R_1(\mathsf{S}-\mathsf{s})} + R_2 e^{-R_2(\mathsf{S}-\mathsf{s})}\right)}{\left(e^{-R_1(\mathsf{S}-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})}\right)^2}\\
&= \frac{\left(R_1 e^{-R_1(\mathsf{S}-\mathsf{s})} - R_2 e^{-R_2(\mathsf{S}-\mathsf{s})}\right)}{\left(e^{-R_1(\mathsf{S}-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})}\right)}\Psi(\sigma, G)\\
&= f \cdot \Psi(\sigma, G)
\end{aligned}
$$

$f < 0$ since $\left(e^{-R_1(\mathsf{S}-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})}\right) > 0$ and $\left(R_1 e^{-R_1(\mathsf{S}-\mathsf{s})} - R_2 e^{-R_2(\mathsf{S}-\mathsf{s})}\right) = -\left(R_2 e^{R_2(\mathsf{S}-\mathsf{s})} - R_1 e^{R_1(\mathsf{S}-\mathsf{s})}\right) < 0$ and f is independent of σ

6. Similarly

$$\begin{aligned}
\frac{\partial \psi(\sigma,G)}{\partial \mathsf{S}} &= \frac{\partial}{\partial S}\left(\frac{e^{R_2(\mathsf{S}-\sigma)}-e^{R_1(\mathsf{S}-\sigma)}}{e^{R_2(\mathsf{S}-\mathsf{s})}-e^{R_1(\mathsf{S}-\mathsf{s})}}\right)\\
&= (R_2-R_1)\,\frac{e^{R_1(\mathsf{S}-\sigma)+R_2(\mathsf{S}-\mathsf{s})}-e^{R_2(\mathsf{S}-\sigma)+R_1(\mathsf{S}-\mathsf{s})}}{\left(e^{R_2(\mathsf{S}-\mathsf{s})}-e^{R_1(\mathsf{S}-\mathsf{s})}\right)^2}\\
&= (R_2-R_1)\,e^{(\mathsf{S}-\sigma)}\frac{e^{R_2(\sigma-\mathsf{s})}-e^{R_1(\sigma-\mathsf{s})}}{\left(e^{R_2(\mathsf{S}-\mathsf{s})}-e^{R_1(\mathsf{S}-\mathsf{s})}\right)^2}\\
&= (R_2-R_1)\,e^{(\mathsf{S}-\sigma)}\frac{\Psi(\sigma,B)}{e^{R_2(\mathsf{S}-\mathsf{s})}-e^{R_1(\mathsf{S}-\mathsf{s})}}\\
&= (R_2-R_1)\,e^{(\mathsf{S}-\sigma+\sigma-\mathsf{S})}\frac{\Psi(\sigma,G)}{e^{R_2(\mathsf{S}-\mathsf{s})}-e^{R_1(\mathsf{S}-\mathsf{s})}}\\
&= (R_2-R_1)\,\frac{\Psi(\sigma,G)}{e^{R_2(\mathsf{S}-\mathsf{s})}-e^{R_1(\mathsf{S}-\mathsf{s})}}\\
&= g\cdot\Psi(\sigma,G)>0.
\end{aligned}$$

where $g>0$ since both $(R_2-R_1)=-(R_1-R_2)>0$ and $\left(e^{R_2(\mathsf{S}-\mathsf{s})}-e^{R_1(\mathsf{S}-\mathsf{s})}\right)>0$ and g does not depend on σ.

Proof Proposition 1

In this proof we derive the most general expressions for lower and upper best responses. We characterize them for a player i who gets a payoff v_i^G in the good state and v_i^B in the bad state and pays a cost of research c_i per unit of time.

The result of Proposition 1 is a special case where:

- For the lower best response, i is the agent, $v_i^G=v_i^B=v_a$ and $c_i=c$
- For the upper best response, i is the decision maker, $v_i^G=v_d^G$, $v_i^B=v_d^B$ and $c_i=0$

We first examine the best response of player i to an lower standard s, denoted, $BR_i(\mathsf{s})$. Using the formula for $u_i(\sigma)$ given in the preliminaries, we have:

$$\begin{aligned}
u_i(\sigma) &= -\frac{c_i}{r}+\frac{e^\sigma}{1+e^\sigma}\left(v_i^G+\frac{c_i}{r}\right)\Psi(\sigma,G)\\
&+ \frac{1}{1+e^\sigma}\left(v_i^B+\frac{c_i}{r}\right)\Psi(\sigma,B)\\
&+ \frac{e^\sigma}{1+e^\sigma}\left(\frac{c_i}{r}\right)\psi(\sigma,G)\\
&+ \frac{1}{1+e^\sigma}\left(\frac{c_i}{r}\right)\psi(\sigma,B).
\end{aligned}$$

Using lemma 1 results 1 and 2, we can rewrite the expression above as:

$$\begin{aligned} u_i(\sigma) &= -\frac{c_i}{r} + \frac{e^\sigma}{1+e^\sigma}\Psi(\sigma,G)\left[v_i^G + e^{-\mathsf{S}}v_i^B + \left(1+e^{-\mathsf{S}}\right)\frac{c_i}{r}\right] \\ &+ \frac{e^\sigma}{1+e^\sigma}\psi(\sigma,G)\left[(1+e^{-\mathsf{s}})\frac{c_i}{r}\right] \end{aligned}$$

Taking derivatives we have:

$$\begin{aligned} \frac{\partial u(\sigma)}{\partial \mathsf{S}} &= \frac{e^\sigma}{1+e^\sigma}\left[\frac{\partial \Psi(\sigma,G)}{\partial \mathsf{S}}\left[v_i^G + e^{-\mathsf{S}}v_i^B + \left(1+e^{-\mathsf{S}}\right)\frac{c_i}{r}\right] - \Psi(\sigma,G)e^{-\mathsf{S}}\left(v_i^B + \frac{c_i}{r}\right)\right] \\ &+ \frac{e^\sigma}{1+e^\sigma}\frac{\partial \psi(\sigma,G)}{\partial \mathsf{S}}\left[(1+e^{-\mathsf{s}})\frac{c_i}{r}\right] \end{aligned}$$

Using the results 5 and 6 of lemma 1, we have:

$$\frac{\partial u(\sigma)}{\partial \mathsf{S}} = \frac{e^\sigma}{1+e^\sigma}\Psi(\sigma,G)\left[f.\left[v_i^G + e^{-\mathsf{S}}v_i^B + \left(1+e^{-\mathsf{S}}\right)\frac{c_i}{r}\right] - e^{-\mathsf{S}}\left(v_i^B + \frac{c_i}{r}\right) + g.\left[(1+e^{-\mathsf{s}})\frac{c_i}{r}\right]\right]$$

This establishes that $BR_d(\mathsf{s})$ is independent of σ, which implies in the regular space that $BR_d(s)$ is independent of q_0. In the particular setting of Proposition 1, the upper best reply can be simplified to

$$f.\left[v_d^G + e^{-S}v_d^B\right] - e^{-\mathsf{S}}v_d^B = 0.$$

We now examine the second order conditions (in the setting of proposition 1)

$$\frac{\partial^2 u(\sigma)}{\partial \mathsf{S}^2} = \frac{e^\sigma}{1+e^\sigma}\left(\frac{\partial \Psi(\sigma,G)}{\partial \mathsf{S}}\left[f.\left[v_i^G + e^{-\mathsf{S}}v_i^B\right] - e^{-\mathsf{S}}v_i^B\right] + \Psi(\sigma,G)\frac{\partial f}{\partial \mathsf{S}}\left[v_i^G + e^{-\mathsf{S}}v_i^B\right] + \Psi(\sigma,G)e^{-\mathsf{S}}v_i^B(1-f)\right)$$

For a value of S that satisfies the first order condition we have:

$$f.\left[v_i^G + e^{-\mathsf{S}}v_i^B\right] - e^{-\mathsf{S}}v_i^B = 0 \Leftrightarrow \left[v_i^G + e^{-\mathsf{S}}v_i^B\right] = \frac{e^{-\mathsf{S}}v_i^B}{f}$$

So that the second order condition can be rewritten:

$$\frac{\partial^2 u(\sigma)}{\partial \mathsf{S}^2} = \frac{e^\sigma}{1+e^\sigma}\Psi(\sigma,G)e^{-\mathsf{S}}v_i^B\left(\frac{\partial f}{\partial \mathsf{S}}\frac{1}{f} + (1-f)\right)$$

We can show that:

$$\frac{\partial f}{\partial \mathsf{S}} = \frac{(R_2-R_1)^2 e^{-(\mathsf{S}-\mathsf{s})}}{\left(e^{-R_1(\mathsf{S}-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})}\right)^2} > 0$$

We also have

$$-f(1-f) = \frac{\left(R_2^2+R_1^2\right)e^{-(\mathsf{S}-\mathsf{s})} - R_1R_2\left(e^{-2R_1(\mathsf{S}-\mathsf{s})} + e^{-2R_2(\mathsf{S}-\mathsf{s})}\right)}{\left(e^{-R_1(\mathsf{S}-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})}\right)^2} > 0$$

Since $e^{-(1-x)(\mathsf{S}-\mathsf{s})} + e^{-(1+x)(\mathsf{S}-\mathsf{s})}$ is increasing in x, and given the expressions for R_1 and R_2, we have:

$$e^{-2R_1(\mathsf{S}-\mathsf{s})} + e^{-2R_2(\mathsf{S}-\mathsf{s})} > 2e^{-(\mathsf{S}-\mathsf{s})}$$

So that

$$\frac{\partial f}{\partial \mathsf{S}} < -f(1-f)$$

And thus the second order condition is satisfied

$$\frac{\partial^2 u(\sigma)}{\partial \mathsf{S}^2} < 0$$

Note that the first order condition can be further rewritten as condition (2) in the main text (defined in the regular space):

$$-\beta_3(s,S)\ v_d^B = \beta_4(s,S)\ V_A(S)$$

where

$$\begin{aligned}\beta_3(s,S) &= (1-S)\\ \beta_4(s,S) &= -f(s,S) > 0\end{aligned}$$

Finally we can show that $BR_d(\mathsf{s})$ is decreasing in s for $\mathsf{s} < \hat{\sigma}_d$. According to the implicit function theorem

$$\frac{\partial BR(s)}{\partial \mathsf{s}} = -\frac{\frac{\partial^2 u(\sigma)}{\partial \mathsf{S}\partial \mathsf{s}}}{\frac{\partial^2 u(\sigma)}{\partial \mathsf{S}^2}}$$

We have:

$$\frac{\partial^2 u(\sigma)}{\partial \mathsf{S}^2} < 0$$

and

$$\frac{\partial^2 u(\sigma)}{\partial \mathsf{S}\partial \mathsf{s}} = -\frac{\partial f}{\partial \mathsf{s}}\left[v_i^G + e^{-\mathsf{S}} v_i^B\right] < 0$$

So overall we have that the upper best response is decreasing in s.

We now turn to the lower best response of player i to an upper standard S, denoted, $br_i(\mathsf{S})$. Using the expression above:

$$\begin{aligned}u_i(\sigma) &= -\frac{c_i}{r} + \frac{e^{\sigma}}{1+e^{\sigma}}\Psi(\sigma,G)\left[v_i^G + e^{-\mathsf{S}}v_i^B + \left(1+e^{-\mathsf{S}}\right)\frac{c_i}{r}\right]\\ &\quad + \frac{e^{\sigma}}{1+e^{\sigma}}\psi(\sigma,G)\left[(1+e^{-\mathsf{s}})\frac{c_i}{r}\right]\end{aligned}$$

Taking derivatives we have:

$$\begin{aligned}\frac{\partial u_i(\sigma)}{\partial \mathsf{s}} &= \frac{e^{\sigma}}{1+e^{\sigma}}\frac{\partial \Psi(\sigma,G)}{\partial \mathsf{s}}\left[v_i^G + e^{-\mathsf{S}}v_i^B + \left(1+e^{-\mathsf{S}}\right)\frac{c_i}{r}\right]\\ &\quad + \frac{e^{\sigma}}{1+e^{\sigma}}\left[\frac{\partial \psi(\sigma,G)}{\partial \mathsf{s}}(1+e^{-\mathsf{s}})\frac{c_i}{r} - \psi(\sigma,G)e^{-\mathsf{s}}\frac{c_i}{r}\right]\end{aligned}$$

Using the results 3 and 4 of lemma 1, we have:

$$\frac{\partial u_i(\sigma)}{\partial \mathsf{s}} = \frac{e^{\sigma}}{1+e^{\sigma}}\psi(\sigma,G)\left[a.\left[v_i^G + e^{-\mathsf{S}}v_i^B + \left(1+e^{-\mathsf{S}}\right)\frac{c_i}{r}\right] + \frac{c_i}{r}\left(b.(1+e^{-\mathsf{s}}) - e^{-\mathsf{s}}\right)\right]$$

So that the first order condition is characterized by

$$a.\left[v_i^G + e^{-\mathsf{S}}v_i^B + \left(1+e^{-\mathsf{S}}\right)\frac{c_i}{r}\right] + \frac{c_i}{r}\left(b(1+e^{-\mathsf{s}}) - e^{-\mathsf{s}}\right) = 0 \qquad (3)$$

This establishes the first part of Proposition 1: $br_a(\mathsf{S})$ is independent of σ and thus $br_a(S)$ (in the regular space) is independent of q_0.

We now examine the second order condition. Taking derivatives, we have:

$$\begin{aligned}\frac{\partial^2 u_i(\sigma)}{\partial \mathsf{s}^2} &= \frac{e^{\sigma}}{1+e^{\sigma}}\frac{\partial\psi(\sigma,G)}{\partial \mathsf{s}}\left[a.\left[v_i^G + e^{-\mathsf{S}}v_i^B + \left(1+e^{-\mathsf{S}}\right)\frac{c_i}{r}\right] + \frac{c_i}{r}\left(b.(1+e^{-\mathsf{s}}) - e^{-\mathsf{s}}\right)\right] \\ &\quad +\psi(\sigma,G)\frac{\partial a}{\partial \mathsf{s}}\left[v_i^G + e^{-\mathsf{S}}v_i^B + \left(1+e^{-\mathsf{S}}\right)\frac{c_i}{r}\right] + \psi(\sigma,G)\frac{c_i}{r}\frac{\partial b}{\partial \mathsf{s}}(1+e^{-s}) + \psi(\sigma,G)\frac{c_i}{r}(-b+1)e^{-s}\end{aligned}$$

For values of s that satisfy the first order condition, we have:

$$\begin{aligned}a.\left[v_i^G + e^{-\mathsf{S}}v_i^B + \left(1+e^{-\mathsf{S}}\right)\frac{c_i}{r}\right] + \frac{c_i}{r}\left(b(1+e^{-\mathsf{s}}) - e^{-\mathsf{s}}\right) &= 0 \\ \Leftrightarrow \quad \left[v_i^G + e^{-\mathsf{S}}v_i^B + \left(1+e^{-\mathsf{S}}\right)\frac{c_i}{r}\right] &= -\frac{1}{a}\frac{c_i}{r}\left(b(1+e^{-\mathsf{s}}) - \right.\end{aligned}$$

We can thus rewrite the second order condition as:

$$\frac{\partial^2 u_i(\sigma)}{\partial \mathsf{s}^2} = -\psi(\sigma,G)\frac{\partial a}{\partial \mathsf{s}}\frac{1}{a}\frac{c_i}{r}\left(b(1+e^{-\mathsf{s}}) - e^{-\mathsf{s}}\right) + \psi(\sigma,G)\frac{c_i}{r}\frac{\partial b}{\partial \mathsf{s}}(1+e^{-\mathsf{s}}) + \psi(\sigma,G)\frac{c_i}{r}(-b+1)e^{-\mathsf{s}}$$

We can show that

$$\frac{\partial a}{\partial \mathsf{s}} = (R_1 - R_2)\frac{R_2 e^{-R_2(\mathsf{S}-\mathsf{s})} - R_1 e^{-R_1(\mathsf{S}-\mathsf{s})}}{\left(e^{-R_1(\mathsf{S}-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})}\right)^2} < 0$$

So that

$$\begin{aligned}-\frac{\partial a}{\partial \mathsf{s}}\frac{1}{a} &= \frac{R_2 e^{-R_2(\mathsf{S}-\mathsf{s})} - R_1 e^{-R_1(\mathsf{S}-\mathsf{s})}}{e^{-R_1(\mathsf{S}-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})}} \\ &= 1 - b < 0\end{aligned}$$

So the second order condition can be rewritten as:

$$\frac{\partial^2 u_i(\sigma)}{\partial \mathsf{s}^2} = \psi(\sigma,G)(1+e^{-\mathsf{s}})\frac{c_i}{r}\left(b(1-b) + \frac{\partial b}{\partial \mathsf{s}}\right)$$

We have:

$$\frac{\partial b}{\partial \mathsf{s}} = \frac{(R_1 - R_2)^2}{\left(e^{-R_1(\mathsf{S}-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})}\right)^2} > 0$$

and

$$b(b-1) = \frac{\left(R_2 e^{-R_2(\mathsf{S}-\mathsf{s})} - R_1 e^{-R_1(\mathsf{S}-\mathsf{s})}\right)\left(R_2 e^{-R_1(\mathsf{S}-\mathsf{s})} - R_1 e^{-R_2(\mathsf{S}-\mathsf{s})}\right)}{\left(e^{-R_1(\mathsf{S}-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})}\right)^2}$$

As above we can show that:

$$b(1-b) + \frac{\partial b}{\partial \mathsf{s}} < 0$$

So that overall:

$$\frac{\partial^2 u_i(\sigma)}{\partial \mathsf{s}^2} < 0$$

We now examine the comparative statics using the implicit function theorem

$$\frac{\partial br(S)}{\partial \mathsf{S}} = -\frac{\frac{\partial^2 u(\sigma)}{\partial \mathsf{s} \partial \mathsf{s}}}{\frac{\partial^2 u(\sigma)}{\partial \mathsf{S}^2}}$$

We have:

$$\frac{\partial^2 u(\sigma)}{\partial \mathsf{S}^2} < 0$$

and we can show

$$\frac{\partial^2 u(\sigma)}{\partial \mathsf{s} \partial \mathsf{S}} > 0$$

So overall we establish that $br_a(S)$ is increasing in S.

In the particular setting of Proposition 1, the first-order condition can be simplified to:

$$a.\left(1+e^{-\mathsf{S}}\right)\left(v_a + \frac{c}{r}\right) + \frac{c}{r}\left(b(1+e^{-\mathsf{s}}) - e^{-\mathsf{s}}\right) = 0$$

and this expression can be restated as condition (1) in the main text, defined in the regular space:

$$\beta_1(s,S)\ v_a = \beta_2(s,S)\ c/r$$

where

$$\begin{aligned} \beta_1(s,S) &= -a(s,S).\left(1+\frac{1-S}{S}\right) > 0 \\ \beta_2(s,S) &= b(s,S).(1+\frac{1-s}{s}) - \frac{1-s}{s} + a(s,S).\left(1+\frac{1-S}{S}\right) > 0 \end{aligned}$$

Proposition 2

In any period t where the belief is q_t, if the agent chooses $\mathcal{A}_a$ (apply for approval), by construction the game ends after the decision maker's choice. The best response is then for the decision maker to choose approval $\mathcal{A}_d$ if and only if $q_t \geq \hat{q}_d$ (by definition of $\hat{q}_d$). Thus, if $q_t \geq \hat{q}_d$, the unique strategy part of a SPE is for the agent to choose $\mathcal{A}_a$.

For $q_t < \hat{q}_d$, we have the property that, if in equilibrium the agent chooses $\mathcal{I}_a$, then for all periods t' where $\hat{q}_d > q_{t'} > q_t$, the agent must also choose $\mathcal{I}_a$. Suppose that were not the case, and there exists a belief $\tilde{q}$, with $\hat{q}_d > \tilde{q} > q_t$, such that the agent does not choose $\mathcal{I}_a$ at $\tilde{q}$. The outcome at $\tilde{q}$ is then rejection: either the agent chooses $\mathcal{R}_a$ or he chooses $\mathcal{A}_a$ which will be followed by $\mathcal{R}_d$ since $\hat{q}_d > \tilde{q}$. We thus reach a contradiction since the agent would then want to deviate at belief q_t since choosing $\mathcal{I}_a$ just means incurring a cost without a chance of obtaining approval.

Thus all SPE are characterized by an interval $(\underline{q}, \hat{q}_d)$ where the agent chooses $\mathcal{I}_a$. Suppose $\underline{q} \neq br_a(\hat{q}_d)$, then, by definition of br_a, the agent has a profitable deviation: for instance if $\underline{q} > br_a(\hat{q}_d)$, at belief $q_t = \underline{q}$, deviating to $\mathcal{I}_a$ is optimal. Thus, in all MPE, for $q_t \in (br_a(\hat{q}_d), \hat{q}_d)$, the agent chooses $\mathcal{I}_a$.

Finally if $q_t < br_a(\hat{q}_d)$, the agent is indifferent between $\mathcal{R}_a$ and $\mathcal{A}_a$ which will be followed by $\mathcal{R}_d$. Both strategies lead to rejection. We thus conclude that the unique equilibrium outcome is the one described in Proposition 2.

Proposition 3

We first examine the utility of the agent at the limit when c and r converge to 0.

According to the proof of Proposition 2, for all values of c and r, the agent chooses $S = \hat{\sigma}_d$ and $s = br_a(\hat{\sigma}_d)$. Furthermore using the characterization of the lower best response of the agent (equation 3), we see that as c converges to 0, s converges to $-\infty$ (i.e., when there is no cost of research, the agent never abandons). We can now examine the limit of the agent's utility.

We have that $u_a(\sigma)$ converges to

$$\frac{e^\sigma}{1+e^\sigma}\Psi(\sigma, G)\left[v_a(1+e^{-\mathsf{S}})\right]$$

Furthermore we have:

$$\Psi(\sigma, G) \quad = \quad \frac{e^{-R_1(\sigma-\mathsf{s})} - e^{-R_2(\sigma-\mathsf{s})}}{e^{-R_1(\mathsf{S}-\mathsf{s})} - e^{-R_2(\mathsf{S}-\mathsf{s})}}$$

with $R_1 = \frac{1}{2}\left(1 - \sqrt{1+\frac{4r}{\mu'}}\right)$ and $R_2 = \frac{1}{2}\left(1 + \sqrt{1+\frac{4r}{\mu'}}\right)$. So, for $r = 0$ and c converging to 0, we have $R_1 = 0$ and $R_2 = 1$ and $\Psi(\sigma, G)$ converges to 1.

Overall we find that the limit of $u_a(\sigma)$ is

$$\frac{e^{\sigma}}{1+e^{\sigma}}\left[v_a(1+e^{-\mathsf{S}})\right] = \frac{e^{\sigma}}{1+e^{\sigma}}\frac{1+e^{\mathsf{S}}}{e^{\mathsf{S}}}v_a$$

which in the regular space means that

$$u_a(q_0) \longrightarrow \frac{q_0}{\hat{q}_d}v_a$$

The utility is a linear function of the starting belief and is equal to $V(\mu_0)$ derived in Kamenica and Gentzkow (2011) p2597-2598.

Proposition 4

We first show that for all MPE equilibria of the no-commitment game, the outcome is characterized by a Wald-cutoff strategy with standards $s^N = br_a(S^N)$ and $S^N = br_d(s^N)$.

Step 1: In any equilibrium, the decision maker chooses $\mathcal{R}_d$ over $\mathcal{A}_d$ if and only if $q_t < \hat{q}_d$

Step 2: There cannot be disjoint intervals of beliefs such that the equilibrium outcome is research. Furthermore $\hat{q}_d$ must belong to any interval of beliefs such that the equilibrium outcome is research.

Consider such an interval $(\underline{q}, \overline{q})$. If $\underline{q} > \hat{q}_d$, then it means that at belief $q_t = \underline{q}$ the outcome is approval: by definition of the interval, the players do not choose strategy $(\mathcal{I}_a)$ or $(\mathcal{I}_d)$ and according to step 1, if the agent chooses $\mathcal{A}_a$, the decision maker will choose $\mathcal{A}_d$. Similarly, at belief $q_t = \overline{q}$, the outcome is $\mathcal{A}$. As a consequence, for any period t with belief $q_t \in (\underline{q}, \overline{q})$, if the agent chooses $\mathcal{A}_a$, the decision maker will choose $\mathcal{A}_d$: $\mathcal{R}_d$ is not a best response by step 1 and $\mathcal{I}_d$ also gives a lower payoff since it just delays obtaining the approval payoff. In turn the agent will necessarily choose $\mathcal{A}_a$. We conclude that such an interval $(\underline{q}, \overline{q})$ cannot exist. Similarly, if $\overline{q} < \hat{q}_d$, we reach the same conclusion. So we must have that $\hat{q}_d$ must belong to any interval of beliefs such that the equilibrium outcome is research. This directly implies that there cannot be two disjoint such intervals.

Step 3: all MPE equilibrium the outcome is characterized by a Wald-cutoff strategy with standards $s^N = br_a(S^N)$ and $S^N = br_d(s^N)$

Step 2 establishes that in all MPE equilibrium the outcome is characterized by a Wald-cutoff strategy and that $\hat{q}_d$ must belong to the research interval. For any belief $q_t < \hat{q}_d$ in the interval of beliefs such that the outcome is research, if the agent chooses $\mathcal{A}_a$, the decision maker chooses $\mathcal{I}_d$ (because research is the equilibrium outcome). Thus the agent gets the same payoff form $\mathcal{A}_a$ and $\mathcal{I}_a$. Therefore, $\underline{q}$ must be a belief such that the agent is indifferent between all three choices and in particular between $\mathcal{I}_a$ and $\mathcal{R}_a$. By definition of br_a it implies that $\underline{q} = br_a(\overline{q})$. If $q_t > \hat{q}_d$, when the agent chooses $\mathcal{A}_a$, the principal chooses between $\mathcal{A}_d$ and $\mathcal{I}_d$. By the same logic, by definition of BR_d, it has to be the case that $\overline{q} = BR_d(\underline{q})$

We have established that the outcome of the no-commitment game is at the intersection of $br_a(S)$ and $BR_d(s)$. We showed in proposition 1 that $br_a(S)$ is increasing in S and $BR_d(s)$ is decreasing in s for $s < \hat{q}_d$ and follows the diagonal for $s > \hat{q}_d$. Given that $br_a(S) < S$ for all $S < 1$, $br_a(S)$ is always above the diagonal and thus $BR_d(s)$ can only cross once: if the Nash equilibrium exists, it is unique. To see that it exists, we have $br_a(0) = 0$ and $BR_d(0) > 0$ while $BR_d(\hat{q}_d) = \hat{q}_d$ and $br_a(\hat{q}_d) < \hat{q}_d$. Thus the two curves necessarily cross once and for a value $S > \hat{q}_d$, so that $S^N > \hat{q}_d$. Finally, since br_a is increasing in S this also implies that $s^N = br_a(S^N) > br_a(\hat{q}_d) = s^{C_a}$

Proposition 5

We first study what happens for extreme beliefs. For all q_0, the decision maker's commitment is necessarily above the myopic cutoff $S^{C_d}(q_0) > \hat{q}_d$ since the decision maker would never approve at a belief below her myopic cutoff. So we have that, for all q_0, since br_a is increasing in S, $br_a(S^{C_d}(q_0)) > br_a(\hat{q}_d) = br_a(s^{C_a})$. By definition of br_a this implies that the agent does not do research for $q_0 < s^{C_a}$.

For $\hat{q}_d > q_0 > s^{C_a}$, the agent will conduct research if $S^{C_d}(q_0) < br_a^{-1}(q_0)$, where br_a^{-1} is well defined since the lower best response of the agent is strictly increasing. Given that the decision maker does not pay the cost of research, for $q_0 < \hat{q}_d$ any commitment leading to some research will be preferable to a no research outcome. Thus, the outcome will be an interior commitment. We now characterize the properties of the interior commitment.

We first show that $S^{C_d}(q_0) \leq S_N$. We have

$$\frac{du_d}{dS}\left(br_a(S), S\right) \;=\; \frac{\partial u_d}{\partial s}\left(br_a(S), S\right)\,\frac{dbr_a(S)}{dS} \;+\; \frac{\partial u_d}{\partial S}\left(br_a(S), S\right)$$

We have by construction of S^N that

$$\frac{\partial u_d}{\partial S}\left(br_a(S^N), S^N\right) = \frac{\partial u_d}{\partial S}\left(s^N, S^N\right) = 0 \qquad (4)$$

Since br_a is strictly increasing in S,

$$\frac{dbr_a(S)}{dS} > 0$$

Finally, using the expression for the lower best reply in the proof of Proposition 1 for the decision maker (who does not pay for research so that $c_d = 0$), we have:

$$\frac{\partial u_d}{\partial \mathsf{s}} = \frac{e^{\sigma}}{1+e^{\sigma}}\psi(\sigma, G)a. \left[v_d^G + e^{-\mathsf{S}} v_d^B\right]$$

For $S > \hat{q}_d$, we will have, since $a < 0$, that the utility of the decision maker is always decreasing in s since she does not pay for the research.

$$\frac{\partial u_d}{\partial \mathsf{s}} \leq 0$$

overall we have

$$\frac{du_d}{dS}\left(br_a(S_N), S_N\right) \quad \leq 0$$

This establishes the result that $S^{C_d}(q_0) \leq S_N$.

We now show that the commitment is increasing in q_0. Since according to Proposition 1, br_a is independent of σ, we have

$$\frac{d^2 u_d}{dSd\sigma}\left(br_a(S), S\right) \quad = \quad \frac{\partial^2 u_d}{\partial s \partial \sigma}\left(br_a(S), S\right) \ \frac{dbr_a(S)}{dS} \quad + \quad \frac{\partial^2 u_d}{\partial S \partial \sigma}\left(br_a(S), S\right)$$

We have

$$\frac{\partial u_d(\sigma)}{\partial \mathsf{s}} \quad = \quad \frac{e^{\sigma}}{1+e^{\sigma}}\psi(\sigma, G)a. \left[v_d^G + e^{-\mathsf{S}} v_d^B\right]$$

So that

$$\frac{\partial^2 u_d}{\partial \mathsf{s} \partial \sigma} = \frac{\partial\left(\frac{e^{\sigma}}{1+e^{\sigma}}\psi(\sigma, G)\right)}{\partial \sigma} a. \left[v_d^G + e^{-\mathsf{S}} v_d^B\right]$$

We have

$$\frac{\partial\left(\frac{e^{\sigma}}{1+e^{\sigma}}\psi(\sigma, G)\right)}{\partial \sigma} = \frac{e^{\sigma}\psi(\sigma, G) + (1+e^{\sigma})e^{\sigma}\psi_{\sigma}(\sigma, H)}{(1+e^{\sigma})^2}$$

where

$$\psi_{\sigma}(\sigma, G) = \frac{-R_2 e^{R_2(S-\sigma)} + R_1 e^{R_1(S-\sigma)}}{e^{R_2(S-s)} - e^{R_1(S-s)}} < 0.$$

We have:

$$-\psi_{\sigma}(\sigma, G) = \frac{R_2 e^{R_2(S-\sigma)} - R_1 e^{R_1(S-\sigma)}}{e^{R_2(S-s)} - e^{R_1(S-s)}} > \frac{e^{R_2(S-\sigma)} - e^{R_1(S-\sigma)}}{e^{R_2(S-s)} - e^{R_1(S-s)}} = \psi(\sigma, G).$$

So that

$$\frac{\partial\left(\frac{e^{\sigma}}{1+e^{\sigma}}\psi(\sigma, G)\right)}{\partial \sigma} = \frac{e^{\sigma}\psi(\sigma, G) + (1+e^{\sigma})e^{\sigma}\psi_{\sigma}(\sigma, H)}{(1+e^{\sigma})^2} < 0$$

Overall

$$\frac{\partial^2 u_d}{\partial \mathsf{s} \partial \sigma} > 0$$

Similarly we have

$$\frac{\partial^2 u_d}{\partial \mathsf{S} \partial \sigma} > 0$$

Overall we find

$$\frac{d^2 u_d}{dS d\sigma} \left(br_a(S), S \right) \quad > 0$$

Thus as σ increases, u_d reaches a maximum for higher values of σ, so that we obtain the result that $S^{C_d}(\sigma)$ is increasing in σ.

Finally we show that at $\sigma = S_N$, the optimal commitment is $S^{C_d}(\sigma) = S_N$.

We have already shown in equation (4) that $\frac{\partial u_d}{\partial S} \left(br_a(S^N), S^N \right) = 0$. Using the equation for $\sigma = S_N$, since $\psi(S_N, G) = 0$

$$\frac{\partial u_d}{\partial \mathsf{s}} = 0$$

So overall

$$\frac{du_d}{dS} \left(br_a(S_N), S_N, \sigma = S_N \right) \quad = 0$$

Proposition 6

The result was derived in the proof of Proposition 5

Proposition 7

The welfare of the social planner is an average of the agent and the decision maker's utilities. The decision maker unambiguously prefers the decision maker commitment outcome to the no-commitment outcome. The agent also prefers the decision maker commitment outcome. Indeed, for all σ, $S^{C_d}(\sigma) \leq S^N$, so that the agent needs do less research to obtain approval. Furthermore, whenever the agent does research under no-commitment, he also does under decision maker commitment: for $\sigma \leq S^N$, $\sigma \leq S^{C_d}(\sigma) \leq S^N$. Therefore this establishes the first result: the social planner strictly prefers the decision maker commitment to no commitment.

We now compare the decision maker commitment institution to the agent commitment.

The utility of the social planner is given by:

$$\begin{aligned}
u_w(\mathsf{s},\mathsf{S},\sigma) &= 0 \text{ if } \sigma < \mathsf{s} \\
u_w(\mathsf{s},\mathsf{S},\sigma) &= -\frac{c}{r} + \frac{e^{\sigma}}{1+e^{\sigma}}\Psi(\sigma,G)\left[\frac{1}{2}(v_i^G+v_a) + e^{-\mathsf{S}}\frac{1}{2}(v_i^B+v_a) + \left(1+e^{-\mathsf{S}}\right)\frac{c}{r}\right] \\
&\quad + \frac{e^{\sigma}}{1+e^{\sigma}}\psi(\sigma,G)\left[(1+e^{-\mathsf{s}})\frac{c}{r}\right] \text{ if } \mathsf{s} \le \sigma \le \mathsf{S} \\
u_w(\mathsf{s},\mathsf{S},\sigma) &= \frac{1}{2}\frac{(v_i^B+v_a) + e^{\sigma}(v_i^G+v_a}{1+e^{\sigma}} \text{ if } \sigma < \mathsf{S}
\end{aligned}$$

We know that if $\sigma < s^{C_a}$, both institutions lead to the same outcome which is rejection and the social planner gets a payoff for 0 in both cases.

If $s^{C_a} < \sigma < S^{C_a}$, research is done for both institutions

If $S^{C_a} < \sigma < s^N$ under agent commitment there is immediate approval while decision maker commitment leads to research

If $\sigma > s^N$ both institutions lead to immediate approval and give the same payoff to the decision maker.

We define $D(\sigma)$ as the difference in utilities the social planner obtains from decision maker commitment versus agent commitment.

$$D(\sigma) = u_w(\mathsf{s}^{C_d},\mathsf{S}^{C_d},\sigma) - u_w(\mathsf{s}^{C_a},\mathsf{S}^{C_a},\sigma)$$

We first examine how D varies with v_a when $s^{C_a} < \sigma < S^{C_a}$, i.e., when research is done for both institutions

$$\frac{\partial D(\sigma)}{\partial v_a} = \frac{e^{\sigma}}{1+e^{\sigma}}\frac{1}{2}\left[\Psi(\mathsf{s}^{C_d},\mathsf{S}^{C_d},\sigma,G)(1+e^{-\mathsf{S}^{C_d}}) - \Psi(\mathsf{s}^{C_a},\mathsf{S}^{C_a},\sigma,G)(1+e^{-\mathsf{S}^{C_a}})\right]$$

We have that $(1+e^{-\mathsf{S}})$ is decreasing in S and so is $\Psi(\sigma,G)$ according to lemma 1, result 5. Therefore, since $\mathsf{S}^{C_a} < \mathsf{S}^{C_d}$, $D(\sigma)$ is decreasing in v_a when $s^{C_a} < \sigma < s^{C_d}$.

When $S^{C_a} < \sigma < s^N$ (i.e., research is done only under decision maker commitment), we have:

$$\frac{\partial D(\sigma)}{\partial v_a} = \frac{e^{\sigma}}{1+e^{\sigma}}\left[\Psi(\mathsf{s}^{C_d},\mathsf{S}^{C_d},\sigma,G)(1+e^{-\mathsf{S}^{C_d}})\right] - 1 < 0$$

So overall we see that for all values of σ, D is weakly decreasing in v_a and strictly decreasing for some values. This establishes the second result that states there exists a value $\widetilde{v}_a$ such that if $v_a \le \widetilde{v}_a$, agent commitment is the preferred institution.

We now establish properties of $\widetilde{v}_a$. We of course have that if $v_a > -v_d^B$, then the social planner gets a positive payoff in both states and thus prefers agent commitment which is the institution that minimizes research to obtain approval. So we have: $\widetilde{v}_a \ge -v_d^B$.

We now examine how D varies with c when $s^{C_a} < \sigma < s^{C_d}$, i.e., when research is done for both institutions

$$\frac{\partial D(\sigma)}{\partial c} = \frac{e^{\sigma}}{1+e^{\sigma}}\left[U(\mathsf{s}^{C_d}, \mathsf{S}^{C_d}, \sigma) - U(\mathsf{s}^{C_a}, \mathsf{S}^{C_a}, \sigma)\right]$$

where

$$U(\mathsf{s}, \mathsf{S}, \sigma) = \Big(\Psi(\mathsf{s}, \mathsf{S}, \sigma, G)(1+e^{-\mathsf{S}}) + \psi(\mathsf{s}, \mathsf{S}, \sigma, G)(1+e^{-\mathsf{s}})\Big)$$

We now show that $U(br_a(\mathsf{S}), \mathsf{S}, \sigma)$ is decreasing in S for

$$\begin{aligned}\frac{\partial U}{\partial \mathsf{S}} &= \frac{\partial br_a(\mathsf{S})}{\partial \mathsf{S}}\left[\frac{\partial \Psi}{\partial \mathsf{s}}(1+e^{-\mathsf{S}}) + \frac{\partial \psi}{\partial \mathsf{s}}(1+e^{-\mathsf{s}}) - \psi e^{-\mathsf{s}}\right] \; + \; \left[\frac{\partial \Psi}{\partial \mathsf{S}}(1+e^{-\mathsf{S}}) - \Psi e^{-\mathsf{S}} + \frac{\partial \psi}{\partial \mathsf{S}}(1+e^{-\mathsf{s}})\right] \\ &= \frac{\partial br_a(\mathsf{S})}{\partial \mathsf{S}}\psi\left[a(1+e^{-\mathsf{S}}) + b(1+e^{-\mathsf{s}}) - e^{-\mathsf{s}}\right] \; + \; \Psi\left[f(1+e^{-\mathsf{S}}) + g(1+e^{-\mathsf{s}}) - e^{-\mathsf{S}}\right]\end{aligned}$$

For $s = br_a(S)$, the first order condition corresponding to the agent's problem implies that $\left[a(1+e^{-\mathsf{S}}) + b(1+e^{-\mathsf{s}}) - e^{-\mathsf{s}}\right] < 0$. We now examine the second term:

We have

$$\begin{aligned}& f(1+e^{-\mathsf{S}}) + g(1+e^{-\mathsf{s}}) - e^{-\mathsf{S}} \\ =\; & \tfrac{1}{e^{R_2(\mathsf{S}-\mathsf{s})} - e^{R_1(\mathsf{S}-\mathsf{s})}}\left[(-R_2 e^{R_2(\mathsf{S}-\mathsf{s})} + R_1 e^{R_1(\mathsf{S}-\mathsf{s})})e^{-\mathsf{S}} + (R_1 e^{R_2(\mathsf{S}-\mathsf{s})} - R_2 e^{R_1(\mathsf{S}-\mathsf{s})}) + (R_2 - R_1)(1+e^{-\mathsf{s}})\right]\end{aligned}$$

We can show that this term is increasing in s for $\mathsf{s} < \mathsf{S}$ and for $s = S$ is negative. Thus overall we find that:

$$\frac{\partial U}{\partial \mathsf{S}} < 0$$

Therefore this implies that D is decreasing in c and that $\widetilde{v}_a$ is thus decreasing in c.

We now establish the last result. As c converges to $+\infty$, $br_a(S)$ converges to S. Given that the myopic cutoff of the decision maker is strictly above that of the social planner, we will have that there exists $\overline{c}$ such that $\widehat{q}_w = br_a(\widehat{q}_d)$. For all $c > \overline{c}$, we will have $\widehat{q}_w < br_a(\widehat{q}_d)$, which implies that research will always be of no use for the social planner. Thus the social planner strictly prefers the agent commitment institution that minimizes research.

In the proof of Proposition 4, we used the fact that for the special case where the agent gets a constant value from approval regardless of the state and where the decision maker does not care about the cost, $br_a(S)$ was strictly increasing in S and $RB_d(s)$ decreasing in s. With the more general preferences and replacing the decision maker by the social planner, this is no longer the case. We therefore prove the result in a number of steps:

Step 1: $br_i(S)$ reaches its minimum at S_i^* and $BR_i(s)$ reaches its maximum at s_i^*.

According to the smooth pasting condition, given that rejection always yields a zero value, we have:

$$\frac{\partial u_i}{\partial s}(s^*, S^*) = 0.$$

Taking derivatives with respect to S, taking into account that $s = br(S)$ yields

$$\frac{\partial^2 u_i}{\partial s \partial S}(s^*, S^*) + br_1(S^*)\frac{\partial^2 u_i}{\partial s^2}(s^*, S^*) = 0.$$

Furthermore, given that $\frac{\partial u_i}{\partial s}(S^*) = 0$, we have

$$br_1(S^*) = 0.$$

The best response function $br(S)$ reaches a minimum for $S = S^*$.

Similarly

$$\frac{\partial u_i}{\partial S}(s^*, S^*) = \frac{\partial(\frac{e^S}{1+e^S}v_i^G + \frac{1}{1+e^S}v_i^B)}{\partial S}.$$

Taking derivatives with respect to s yields

$$BR_1(s^*, S^*)\left[\frac{\partial^2 u_i}{\partial S^2}(S^*) - \frac{\partial^2(\frac{e^S}{1+e^S}v_i^G + \frac{1}{1+e^S}v_i^B)}{\partial S^2}\right] = 0$$

The best response function $BR(s)$ reaches a maximum for $s = s^*$.

Step 2: $\forall S$, $br_a(S) \leq br_s(S)$ and, $\forall s$ $BR_s(s) \geq BR_a(s)$

The only difference between the agent a and the social planner s is the value in the bad state: $v_a^B > v_s^B$. We therefore need to show that $br_i(S)$ and $BR_i(s)$ are decreasing in v_a^i. TBA

Step 3: If br_a and BR_p cross it is for values such that $BR_p(s)$ is increasing in s and $br_a(S)$ is decreasing in S.

We showed in step 2 that $br_a(S) \leq br_p(S)$ and $BR_p(s) \geq BR_a(s)$. According to step 1, BR_p crosses br_p at (s_p^*, S_p^*) where BR_s is maximum. Given that $br_a(S) \leq br_s(S)$, and that br_a is single peaked, it has to be the case that br_a and BR_s cross for values such that $BR_s(s)$ is increasing in s. The same logic applies to show that $br_a(S)$ is increasing in S when br_a and BR_p cross.

Step 3: $\frac{\partial BR(s)}{\partial s} < 1$.

We derived in the proof of Proposition 1, that $BR(s)$ is defined by

$$-e^f e^s \left(\left(v_H + \frac{c}{r} \right) + e^{-S} \left(v_L + \frac{c}{r} \right) \right) + \frac{c}{r} (1 + e^s) - e^{f'} \left(v_L + \frac{c}{r} \right) = 0.$$

defining $y = S - s$, and taking derivatives of the implicit equation above, we have

$$\begin{aligned} & -\frac{\partial f}{\partial y} \left(\frac{\partial S}{\partial s} - 1 \right) e^f e^s \left(\left(v_H + \frac{c}{r} \right) + e^{-S} \left(v_L + \frac{c}{r} \right) \right) - e^f e^s \left(\left(v_H + \frac{c}{r} \right) + e^{-S} \left(v_L + \frac{c}{r} \right) \right) \\ & + \frac{\partial S}{\partial s} e^f e^s e^{-S} \left(v_L + \frac{c}{r} \right) + \frac{c}{r} e^s - \frac{\partial f'}{\partial y} e^{f'} \left(\frac{\partial S}{\partial s} - 1 \right) \left(v_L + \frac{c}{r} \right) \\ = \; & 0. \end{aligned}$$

This can be rewritten as

$$\begin{aligned} & \left(\frac{\partial S}{\partial s} - 1 \right) \left[-\frac{\partial f}{\partial y} e^f e^s \left(\left(v_H + \frac{c}{r} \right) + e^{-S} \left(v_L + \frac{c}{r} \right) \right) + e^f e^s e^{-S} \left(v_L + \frac{c}{r} \right) - \frac{\partial f'}{\partial y} e^{f'} \left(v_L + \frac{c}{r} \right) \right] \\ = \; & e^f e^s \left(v_H + \frac{c}{r} \right) - \frac{c}{r} e^s. \end{aligned}$$

Furthermore we have

$$e^f e^s e^{-S} = \frac{\partial f'}{\partial y} e^{f'}.$$

So that

$$\left(\frac{\partial S}{\partial s} - 1 \right) \left[-\frac{\partial f}{\partial y} e^f e^s \left(\left(v_H + \frac{c}{r} \right) + e^{-S} \left(v_L + \frac{c}{r} \right) \right) \right] = e^f e^s \left(v_H + \frac{c}{r} \right) - \frac{c}{r} e^s.$$

Given that $e^f > 1$ the right hand side is positive. Furthermore, we have that along $BR(s)$ that $v_H + \frac{c}{r} + e^{-S} \left(v_L + \frac{c}{r} \right) > 0$. Therefore, since we established that $\frac{\partial f}{\partial y} > 0$, we conclude that $\frac{\partial S}{\partial s} < 1$.

Step 4: $\frac{\partial br^{-1}(s)}{\partial s} > 1$ for values such that $br(S)$ is decreasing in S.

$br(S)$ is defined by the following implicit function

$$\left(\left(v_H + \frac{c}{r} \right) + e^{-S} \left(v_L + \frac{c}{r} \right) \right) - e^g \frac{c}{r} \left(1 + e^{-s} \right) + e^{-S} e^{g'} \frac{c}{r} = 0.$$

We have shown that for $s > s^*$, $br(S)$ is an increasing function. On this interval, $br^{-1}(s)$ is a well defined function. Taking derivatives of the implicit equation above, we have

$$-\frac{\partial S}{\partial s} e^{-S} \left(v_L + \frac{c}{r} \right) - \frac{\partial g}{\partial y} \left(\frac{\partial S}{\partial s} - 1 \right) e^g \frac{c}{r} \left(1 + e^{-s} \right) + e^g \frac{c}{r} e^{-s} - \frac{\partial S}{\partial s} e^{-S} e^{g'} \frac{c}{r} + \frac{\partial g'}{\partial y} \left(\frac{\partial S}{\partial s} - 1 \right) e^{-S} e^{g'} \frac{c}{r} = 0.$$

Grouping terms we have

$$-\left(\frac{\partial S}{\partial s} - 1 \right) \left[\frac{\partial g}{\partial y} e^g \frac{c}{r} \left(1 + e^{-s} \right) - \frac{\partial g'}{\partial y} e^{-S} e^{g'} \frac{c}{r} + e^g \frac{c}{r} e^{-s} \right] - \frac{\partial S}{\partial s} e^{-S} v_L - \frac{\partial S}{\partial s} \left[e^{-S} e^{g'} + e^{-S} - e^g e^{-s} \right] = 0$$

We showed in the proof of Proposition 1 that: $e^{-S}e^{g'} + e^{-S} - e^{g}e^{-s} < 0$. Given that $v_L < 0$, to have the equation above satisfied, since we are deriving a property of the curve over which $\frac{\partial S}{\partial s} > 0$, it has to be that

$$-\left(\frac{\partial S}{\partial s} - 1\right)\left[\frac{\partial g}{\partial y}e^{g}\frac{c}{r}\left(1 + e^{-s}\right) - \frac{\partial g'}{\partial y}e^{-S}e^{g'}\frac{c}{r} + e^{g}\frac{c}{r}e^{-s}\right] < 0.$$

We also showed in the proof of Proposition 1 that $\frac{\partial g'}{\partial y} < 0$ and $\frac{\partial g}{\partial y} > 0$. So the above inequality implies that $\frac{\partial S}{\partial s} > 1$.

Step 5: Deriving the results.

Step 3 implies that if a crossing between $br_a(S)$ and $BR_p(s)$ occurs, it will be for values of (s, S) such that the properties of step 4 and 5 apply. Furthermore these properties imply both that the curves do cross and that the crossing is unique: when the curves cross, $\frac{\partial br^{-1}(s)}{\partial s} < 1$ and $\frac{\partial BR(s)}{\partial s} < 1$, so the curves cannot cross again.

Result 1. then follows from step 1.

Finally from Proposition 1.3, we know $S - br(S)$ is increasing in S, so since $S_N < S_a^*$ and $s_N = br_a(S_N)$, we have $S_N - s_N > S_a^* - s_a^*$. Similarly, using Proposition 2.3, we have $S_N - s_N > S_p^* - s_p^*$. This establishes result 3.

Proof Proposition 8

The lower best response for both the agent and the social planner is characterized by:

$$\beta_1(s, S)\ V_A^i = \beta_s(s, S)\ c/R$$

where

$$V_A^a = v_a$$

$$V_A^w = S(v_a + v_d^G) + (1 - S)(v_a + v_d^B)$$

We therefore have $V_A^a \geq V_A^w$ if and only if $S \leq \hat{q}_d$. Finally, according to earlier results, $S^{C_d} > S^{C_a} = \hat{q}_d$, so that we have $s_w^* < s^{C_a} < s^{C_d}$.

REFERENCES

Alonso, Ricardo, and Niko Matouschek. 2008. "Optimal Delegation." *Review of Economic Studies*, 75(1): 259–293.

Armstrong, Mark, and John Vickers. 2010. "A Model of Delegated Project Choice." *Econometrica*, 78(1): 213–244.

Bloom, Nicholas, Mark Schankerman and John Van Reenen. 2012. "Identifying Technology Spillovers and Product Market Rivalry." *Econometrica*, forthcoming.

Bolton, Patrick, and Christopher Harris. 1999. "Strategic Experimentation." *Econometrica*, 67(2): 349–374.

Bulow, Jeremy I., John D. Geanakoplos and Paul D. Klemperer. 1985. "Multimarket Oligopoly: Strategic Substitutes and Complements." *Journal of Political Economy*, 93(3): 488–511

Chan, Jimmy, and Wing Suen. 2011. "Does Majority Rule Produce Hasty Decisions?" Unpublished working paper.

Dahma, Matthias, Paula Gonzalez, and Nicolas Porteiro. 2009. "Trials, Tricks and Transparency: How Disclosure Rules Affect Clinical Knowledge." *Journal of Health Economics*, 28(6): 1141–1153

FDA. 2009. "Guidance for Industry Formal Meetings Between the FDA and Sponsors or Applicants "

Fernandez, Raquel, and Dani Rodrik. 1991. "Resistance to Reform: Status Quo Bias in the Presence of Individual-Specific Uncertainty." *American Economic Review*, 81(5): 1146–1155.

Gerardi, Dino and Luca Maestri. 2012. "A Principal-Agent Model of Sequential Testing." *Theoretical Economics*, 7(3): 425–463.

Grossman, Sandford J. 1981. "The Informational Role of Warranties and Private Disclosure about Product Quality." *Journal of Law and Economics*, 24(3): 461–483.

Gul, Faruk, and Wolfgang Pesendorfer. 2012. "The War of Information." *Review of Economic Studies*, 79(2): 707–734.

Halac, Marina, Navin Kartik, and Quingmin Liu. 2012. Optimal Contracts for Experimentation. Unpublished working paper.

Henry, Emeric 2009. "Strategic Disclosure of Research Results: The Cost of Proving Your Honesty." *Economic Journal*, 119(539): 1036–1064.

Holmstrom, Bengt. 1984. "On the Theory of Delegation." In: *Bayesian Models in Economic Theory*, eds. Marcel Boyer and Richard Kihlstrom. Amsterdam: Elsevier.

Horner, Johannes, and Larry Samuelson. 2012. "Incentives for Experimenting Agents." Unpublished working paper.

Junod, Suzanne White. 2008. "FDA and Clinical Drug Trials: A Short History," in: *A Quick Guide to Clinical Trials*, eds. Madhu Davies and Faiz Kerimani. Washington: Bioplan, Inc.

Kartik, Navin. 2009. "Strategic Communication with Lying Costs." *Review of Economic Studies*, 76(4): 762–794.

Kartik, Navin, Marco Ottaviani, and Francesco Squintani. 2007. "Credulity, Lies, and Costly Talk." *Journal of Economics Theory*, 134(1): 93–116.

Lewis, Tracy R. 2012. "A Theory of Delegated Search for the Best Alternative." *RAND Journal of Economics,* 3(1): 391–416.

Lewis, Tracy R. and Marco Ottaviani 2008. "Search Agency." Unpublished working paper.

Lizzeri, Alessandro, and Leeat Yariv. 2011. "Sequential Deliberation." Unpublished working paper.

Manso, Gustavo. 2011. "Motivating Innovation." *Journal of Finance,* 66(5): 1823–1860.

Milgrom, Paul R. 1981. "Good News and Bad News: Representation Theorems and Applications. *Bell Journal of Economics*, 12(2): 380–391.

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

Nundy, Samiran, and Chandra Gulhati. 2005. "A New Colonialism? Conducting Clinical Trials in India." *New England Journal of Medicine,* 352(16): 1633–1636.

Ocana, Alberto, and Ian Tannock. 2011. "When are 'Positive' Clinical Trias in Oncology Truly Positive?" *Journal of National Cancer Institute,* 103(1): 16–19.

Shavell, Steven. 1994. "Acquisition and Disclosure of Information Prior to Sale." *RAND Journal of Economics*, 25(1): 20–36.

Stokey, Nancy. 2009. "The Economics of Inaction. " *Princeton University Press.*

Strulovici, Bruno**.** 2010. "Learning while Voting: Determinants of Strategic Experimentation." *Econometrica*, 78(3): 933–971.

Taylor, Curtis, and Huseyin Yildirim. 2011. "Subjective Performance and the Value of Blind Evaluation." *Review of Economic Studies*, 78(2): 762–794.

Wald, Abraham. 1945. "Sequential Tests of Statistical Hypotheses." *Annals of Mathematical Statistics*, 16(2): 117–186.

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

Wald, Abraham, and Jacob Wolfowitz. 1948. "Optimal Character of the Sequential Probability Ratio Test." *Annals of Mathematical Statistics*, 19(3): 326–339.