Patent Quality and Incentives at the Patent Office*

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Abstract

The purpose of patent examination is to ensure that patents are granted only for true inventions. This paper models examination as a problem of moral hazard followed by adverse selection: patent examiners must have incentives to exert effort, but also to truthfully reveal the evidence they find. The model can explain the puzzling compensation scheme in use at the U.S. patent office, where examiners are essentially rewarded for granting patents, as well as variation in compensation schemes and patent quality across patent offices. It also has implications for the retention of examiners and for administrative patent review.

Keywords: innovation, patent examination, soft information, intrinsic motivation, delegated expertise

JEL classification numbers: D73, D82, L50, M52, O31, O38

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1 Introduction

Patent examiners at the U.S. Patent and Trademark Office (USPTO) receive a bonus that depends on the number of applications processed. But because a rejection is more time-consuming than a grant, the bonus introduces a bias towards granting patents.\(^1\) Such a compensation scheme is puzzling. Apart from biasing the grant decision, it does not seem to give examiners good incentives to exert effort. Rejecting an application requires the examiner to come up with evidence that the claimed invention already exists or would have been obvious to someone skilled in the art. Granting a patent is much less demanding: the examiner can simply report not having found such evidence. If anything, shouldn’t we expect examiners to be rewarded for rejecting applications?

The objective of patent examination is to separate the wheat from the chaff. Good applications – those satisfying the patentability criteria, particularly novelty and non-obviousness – should be accepted, while bad applications should be rejected. How must incentives for examiners be designed to further this objective? In this paper I develop a theoretical model of patent examination to address this question. I argue that examination can be described as a problem of moral hazard followed by adverse selection: the examiner must be given incentives to exert effort (looking for evidence to reject, within the prior art), but must also be given incentives to truthfully reveal the evidence he finds (or lack thereof). I show that the model can explain the puzzling compensation scheme in use at the USPTO, as well as variation in compensation schemes and patent quality across patent offices. It also has important policy implications.

In the U.S., concerns about patent quality have given rise to intense policy debate.\(^2\) Observers bemoan that the USPTO is granting more questionable patents than other national patent offices, in particular the European Patent Office (EPO). Given that the EPO does not use any performance-based compensation (its examiners are paid a fixed wage only), the USPTO’s compensation scheme is a natural candidate for criticism and has often been cited as one of the main causes of the quality issues (Jaffe and Lerner, 2004; Merges, 1999; Lemley and Shapiro, 2005). My analysis, however, suggests that the scheme may be a symptom rather than a cause of the problem.

To see why it can sometimes be optimal to reward a patent examiner for granting, consider the following situation. Suppose the examiner has de facto discretion over the decision to accept or reject an application and wants to avoid mistakes. Ignore for a moment the decision

\(^1\) For details of the compensation scheme in use at the USPTO, see Section 5.

\(^2\) Both the Federal Trade Commission (2003) and the National Academy of Sciences (2004) have authored reports voicing concerns about poor patent quality, eventually leading to the patent reform bill that Congress is expected to pass in September 2011.
how much effort to provide and focus on the grant decision. If the examiner believes that a large proportion of applications is bad, he will have little confidence that an application is good when a shallow search for evidence turns up nothing. Absent monetary incentives, his desire to avoid mistakes will then lead him to reject the application despite the lack of evidence. Inducing him to truthfully reveal the result of his search requires rewarding him for grants.

In this situation, the adverse-selection problem is in conflict with the moral-hazard problem: the examiner may have to be rewarded for granting patents even though effort is positively correlated with producing evidence for rejection. Incentives are directed primarily towards inducing truthful revelation and can only play a limited role in inducing effort. Note however that they succeed in inducing at least some effort. In fact, ensuring truthful revelation is a prerequisite for effort provision: if the examiner anticipated not truthfully revealing the result of his search, there would be no reason for him to exert effort searching in the first place.

This argument rests on two premises. First, for the examiner to have discretion over the grant decision, the signal that an application is bad must be soft information, i.e., unverifiable by the principal and third parties. This makes sense because of the technical complexity of patent applications, the vagueness of patentability criteria, and because there is little information on the quality of an examiner’s decisions in the short run. While more information becomes available in the long run (e.g., through court decisions on patent validity), this information is difficult to include in a contract. Soft information means that the examiner is privately informed about the result of his prior-art search, creating the adverse-selection part of the incentive problem. Second, examiners must have a desire to avoid mistakes that is unrelated to short-term monetary compensation. Such a desire might stem from long-term implicit incentives within the organization (promotion, dismissal, etc.), but also from recognition by peers or a concern for social welfare. With a slight abuse of language, I will refer to the desire to avoid mistakes as intrinsic motivation. ³

In the model presented below, the government delegates patent examination to an examiner motivated by both extrinsic rewards (i.e., monetary transfers) and intrinsic rewards (i.e., utility gains from making correct decisions). The examiner must expend effort to obtain a signal about an applicant. If the applicant’s claimed invention is not truly new, the examiner can come up with a signal demonstrating the lack of novelty (defeating prior art); I assume

³ Intrinsic motivation, in the sense of a person being genuinely concerned with the outcome of his actions, has been identified as an important characteristic of many bureaucracies (Wilson, 1989; Dixit, 2002); see Prendergast (2007) for a recent contribution focusing on the role of intrinsic motivation in the public sector. The public administration literature refers to a similar concept as “public service motivation” (Perry and Wise, 1990). For the case of patent examination, a survey by Friebel et al. (2006) documents the intrinsic motivation of EPO examiners.
that the signal is soft information.

Potential applicants draw on a stock of technologies to submit applications. Some of these technologies, which I refer to as known, are already in the public domain, while others, which I refer to as innovative, have yet to be developed. To develop innovative technologies firms must invest in R&D. After development, they can decide whether to keep the technologies secret or to apply for patents, leading to good applications. Firms also decide whether to apply for patents covering known technologies, leading to bad applications. Their decisions to file applications depend on the application fee set by the government and on the examiner’s effort, which determines the probability of detection for bad applications. Firms submit fewer bad applications when they expect greater effort. They submit fewer of both kinds of applications when the application fee is larger. Accordingly, the proportion of good and bad applications is endogenous. The government’s objective is to maximize social welfare. Apart from the application fee, it also chooses an incentive scheme for the examiner.

My analysis of the government’s choice of incentives and of the equilibrium of the examination game yields three main results. Proposition 1 shows that in the absence of intrinsic motivation, no examination effort can be sustained in equilibrium. The amount of effort that is implementable increases with the examiner’s intrinsic motivation. This result holds under quite general conditions. The other two results are derived under conditions ensuring that the patent system is socially desirable. Proposition 2 demonstrates that for low levels of intrinsic motivation, the optimal incentive scheme rewards the examiner for granting patents, provided the proportion of good applications is sufficiently small when applicants expect zero effort. Proposition 3 establishes a complementarity between intrinsic and extrinsic rewards: provided the proportion of good applications is sufficiently large at the first-best patent policy, for high levels of intrinsic motivation it eventually becomes optimal to reward the examiner for rejecting, which feeds back positively into effort provision.

For the model to be able to explain a difference in compensation schemes through variations in intrinsic motivation, Propositions 2 and 3 must apply simultaneously. This requires that the proportion of good applications is larger at the first-best patent policy than at the optimal policy absent examination. I identify sufficient conditions on the distribution of returns to innovation for this to be the case (Proposition 4), and I argue that the required distributional assumptions are empirically plausible.

Patent quality can be defined as the posterior probability that a patent issued by the patent office actually satisfies the criteria for patentability. The model predicts that intrinsic motivation should be positively related to patent quality and negatively related to the use of short-term monetary rewards for granting patents. This prediction allows me to establish a link between observable organizational features of patent offices and observable outcomes of
opposition and litigation involving patents issued by those offices.

I argue that intrinsic motivation is likely to be positively related to how long the examiner expects to stay at the patent office and to how timely information about the quality of his decisions becomes available. A comparison of the USPTO with the European Patent Office (EPO) shows important differences in examiner turnover and the availability of information on decision quality. The USPTO has greater problems retaining examiners and lacks an administrative review procedure comparable to the EPO’s opposition system that can provide information on quality in a timely manner. Both suggest that intrinsic motivation should be lower in the U.S. than in Europe. Thus, the model predicts that patents issued by the USPTO are of lower quality than EPO patents, and that U.S. examiners are more likely to be rewarded for granting through short-term compensation. The observation that, unlike their U.S. counterparts, examiners at the EPO receive a fixed wage is in line with these predictions. And while patent quality is hard to measure, the available evidence from opposition and litigation, as well as the perception in the patent community, tend to confirm the notion that problems with patent quality are indeed more acute in the U.S.

Why should we care about patent examination? To begin with, patents create (temporary) monopolies. Granting patents for non-inventions causes deadweight loss and litigation without providing any offsetting benefit to society. This would be less of a problem if the courts only enforced good patents. Courts, however, sometimes enforce bad patents, as highlighted by the near shutdown of BlackBerry in 2006. Moreover, many patent disputes never reach the courts. Challenging a bad patent is a public good and may therefore be under-provided (Chiou, 2006; Farrell and Shapiro, 2008). When patents are licensed, the royalties negotiated by the parties to the licensing agreement determine the severity of price distortions. Farrell and Shapiro (2008) show that “weak” patents, in the sense of having a low probability of being held valid by the courts, may well command higher royalties than strong patents. Disputes over weak patents may also be particularly likely to be settled out of court (Chiou, 2008). And when patent disputes do reach the courts, they entail substantial legal costs. Ford et al. (2007) estimate the total cost of bad patents to the U.S. economy at an annual $25.5 billion.

A small number of recent papers investigate patent examination. Langinier and Mar-

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4 The maker of BlackBerry mobile devices, Research In Motion (RIM), was sued by patent-holding company NTP, and settled for a reported $612.5 million. RIM appears to have been forced into the settlement by the court’s threat to issue an injunction, which would have shut down the BlackBerry. Apparently, the judge was unprepared to wait for the final result of the re-examination of NTP’s patents by the USPTO even though the office had indicated that it was likely to revoke all of the patents NTP had asserted against RIM. See Time Magazine, “Patently Absurd”, April 2, 2006, available online at http://www.time.com/time/magazine/article/0,9171,1179349,00.html.

5 Of this sum, they attribute $4.5 billion to litigation costs, while the remainder corresponds to the disincentive to future innovators that patents create. While methodologically controversial, Ford et al.’s (2007) calculations indicate that the costs of bad patents are likely to be significant.
coul (2009) and Caillaud and Duchêne (2011) start from the idea that patent examination resembles an inspection game and as such is plagued by commitment problems. Langinier and Marcol (2009) study inventors’ incentives to search for and disclose relevant prior art to the patent office. The focus in Caillaud and Duchêne (2011) is on the “overload problem” facing the patent office: when flooded with large numbers of applications, the average quality of examination declines, leading to a vicious circle by encouraging even more bad applications. Régibeau and Rockett (2007) examine the optimal duration of patent examination as a function of the importance of an innovation. They find that, controlling for the position in the innovation cycle, more important innovations should be examined faster, a prediction which is borne out by evidence from a sample of U.S. patents. All of these papers consider a benevolent patent office maximizing social welfare. Therefore, they are unable to make predictions about examiner compensation.

More generally, the paper contributes to the literature on the optimal design of the patent system (see, e.g., Gilbert and Shapiro, 1990; Denicolò, 1996; Cornelli and Schankerman, 1999; Scotchmer, 1999; Hopenhayn and Mitchell, 2001; Hopenhayn et al., 2006). Information asymmetries play a central role in this line of research, which builds on the observation that innovators are typically better informed about some dimensions of their innovation than the government. The literature has so far only been concerned with the cost and value dimension of innovation but ignored the novelty and non-obviousness dimension that is the focus of the present paper.

The paper is also related to the literature on delegated expertise (Demski and Sappington, 1987; Gromb and Martimort, 2007). In this literature, a principal contracts with an expert to produce an unverifiable signal that is informative about the optimal project to undertake. Transfers to the expert can condition on the reported signal and the outcome of the chosen project. My model differs from this literature in several respects. My information gathering technology confounds the case where the expert has exerted low effort with the case where the project is good – in both cases, the signal is empty. This technology fits the specificities of patent examination and is crucial for the result that it may be optimal to reward the examiner for reporting no signal. Moreover, I assume that transfers cannot be conditioned on outcome information. Instead, outcome information enters the expert’s utility through what I refer to as intrinsic motivation. Unlike in the literature on delegated expertise, the proportion of good projects (i.e., applications) is endogenous in my model.

Finally, the paper is to some extent reminiscent of Iossa and Legros (2004), who study auditing with soft information. They show that a necessary condition for the auditor to exert any effort is that he be given a stake in the audited project. Similarly, I show that positive effort will only occur if the examiner is intrinsically motivated – that is, if he has a “stake”
in the social consequences of his decision.

The remainder of the paper is organized as follows. Section 2 presents the model and discusses the main assumptions. Section 3 derives the optimal policy in the absence of patent examination. Section 4 studies the government’s choice of incentives and application fees and derives the equilibrium of the examination game. Section 5 identifies plausible empirical proxies for examiners’ intrinsic motivation, as defined in the model, and provides some evidence on patent quality and examiner compensation in Europe and the U.S. Section 6 summarizes the results of the model and comments briefly on policy implications. Proofs are relegated to Appendix C.

2 A model of patent examination

Consider the following setup. There are three types of players: a benevolent planner, a patent examiner, and firms. The planner delegates patent examination to the examiner. Firms make R&D investments and file applications which can be good (G), i.e., true inventions, or bad (B), i.e., non-inventions which already exist or would have been obvious to someone skilled in the art. Upon receiving an application, the examiner performs a prior art search and reports to the planner.

R&D investment and filing strategies. Firms can file applications by drawing on an exogenously given stock of n technologies. Some of the technologies have already been developed, while others have not. I will refer to the latter as innovative technologies and to the former as known technologies. Innovative technologies allow firms to file good patent applications. Known technologies only allow them to file bad applications. The number of innovative technologies is n_G, while the number of known technologies is n_B, with n_G + n_B = n. Technologies are indexed by a parameter \( \theta \). As in Cornelli and Schankerman (1999), I assume that for innovative technologies, \( \theta \) and a firm’s R&D investment \( z \) together determine the size of the innovation. Specifically, the potential revenue from a technology \( \theta \) is given by \( r(z, \theta) = \theta z \), where \( z \) is the firm’s R&D investment. Thus, technologies with larger \( \theta \) are more valuable, in the sense of yielding a larger revenue for a given amount of investment. For simplicity, I assume that the cost of investing \( z \) is \( \psi(z) = z^2/2 \).\(^7\)

\(^6\) The term “known technologies” should be understood as encompassing both existing technologies and obvious combinations of existing technologies that are in the public domain. The idea is that these are technologies that (a) firms can claim to have invented and which are not easily distinguishable from true inventions, and that (b), if awarded a patent, allow the patent holder to extract rents from users; a necessary condition is that such bad patents are enforced by the courts with positive probability.\(^7\) The specific functional forms assumed allow me to derive a closed-form solution for the optimal investment, which is useful for the remainder of the analysis. The qualitative properties of the solution would be unchanged under more general assumptions.
Once developed, an innovative technology can be protected either by a patent or by secrecy. Applying for a patent requires payment of an application fee \( \phi \geq 0 \), which is set by the planner. If patent protection is granted, the firm obtains the entire revenue \( r(z, \theta) \). Protection by secrecy is imperfect: with probability \( 1 - s \), the innovative technology leaks out and becomes commonly known, so that its revenue is dissipated. In expectation, a technology protected by secrecy yields the firm \( sr(z, \theta) \), where \( s \in (0, 1) \). Thus, \( s \) measures the effectiveness of secrecy.\(^8\) Known technologies do not generate any profit unless protected by a patent. Since they are known, they cannot be protected by secrecy.

A firm that anticipates patenting innovative technology \( \theta \) chooses its R&D investment \( z \) to maximize \( \theta z - z^2/2 - \phi \), yielding the optimal investment \( z_P = \theta \). The firm’s profit from the patented technology (gross of the application fee) is given by \( \pi = \theta z_P - z_P^2/2 = \theta^2/2 \). A firm that anticipates keeping technology \( \theta \) secret chooses \( z \) to maximize \( s\theta z - z^2/2 \), yielding the optimal investment \( z_S = s\theta \). The investment under secrecy is lower than under patent protection because secrecy is assumed to be less effective than a patent \((s < 1)\); this is a minimal assumption in this framework for any firm to be willing to patent an innovative technology. The firm’s expected profit from the technology kept secret is given by \( s\theta z_S - z_S^2/2 = (s\theta)^2/2 = s^2\pi \).

Known technologies have already been developed and do not require additional R&D investment. If a firm obtains patent protection on a known technology \( \theta \) and the patent is upheld by the courts, I assume that the firm’s payoff is \( \theta z_P \). The firm enjoys the benefits of R&D investment without bearing its costs; the amount of R&D it benefits from equals the one that would have optimally been invested to develop an equivalent innovative technology. I will refer to a known technology being patented as a bad patent. I assume that a bad patent is enforced by the courts with exogenous probability \( \beta \in (0, 1) \).\(^9\) Thus, in expectation, a bad patent transfers an amount \( \beta \theta z_P = 2\beta\pi \) from technology users to the patent holder.

Because there is a one-to-one relationship between \( \theta \) and \( \pi \), and the profits from secrecy and bad patents can be expressed as functions of \( \pi \), the rest of the analysis will use \( \pi \) instead of \( \theta \) to index technologies. I assume that \( \pi \) is independently drawn from a continuously differentiable cumulative distribution function \( F \) with density \( f \) on \([\bar{\pi}, \pi]\) with \( 0 \leq \bar{\pi} < \pi \).

Innovative technologies create social benefits while bad patents create social costs. The social benefits from innovative technologies depend on whether they are patented or kept secret. Innovative technology \( \pi \) generates social value \( v_P(\pi) \) if patented and \( v_S(\pi) \) if kept secret. I assume \( v_P(\pi) > v_S(\pi) > 0 \) for all \( \pi > \bar{\pi} \), and \( v_P(\pi) = v_S(\pi) \geq 0 \). That is, innovative technologies generate greater social value when they are patented than when they are kept

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\(^8\) This can be seen as the static version of a continuous-time model à la Denicolâ and Franzoni (2004); see Appendix A.

\(^9\) The probability that a patent on an innovative technology is enforced by the courts is normalized to one.
secret, except at the lower bound of the distribution, where both are equivalent. A bad patent on a known technology \( \pi \) causes a social cost of \( \beta D(\pi) + C \), where \( D(\pi) \geq 0 \) is the deadweight loss from monopoly pricing that arises if the patent is enforced by the courts, and \( C > 0 \) is a fixed cost which might include, e.g., the cost of the judicial resources used up by litigation.

It is the assumption that \( v_P \) exceeds \( v_S \) that (potentially) makes the patent system socially desirable in this model. There are at least two reasons why the assumption may be plausible. The first, which is outside of the model, is the disclosure function of the patent system: unlike a technology that is kept secret, patented technologies become publicly known and can be used as an input in other R&D projects to produce follow-on innovations. The second reason is the more conventional notion according to which patents provide incentives to invest in research. Because \( s < 1 \), patents induce greater R&D investment than secrecy, which is likely to outweigh the fact that expected deadweight loss may be lower under secrecy because secrets can leak out. The following example illustrates this.

**Example.** Consider a product innovation, and suppose the market created by the innovation is characterized by a linear demand function whose intercept is determined by \( \theta \) and \( z \). Specifically, assume \( D(p) = 2\sqrt{\theta z} - p \): the larger the innovation, the greater the demand for it. Assume also that the marginal cost of production is zero. When the innovation is protected by a patent, the innovator is a monopolist and charges \( p_M = \sqrt{\theta z} \), yielding revenue \( \theta z \). Total surplus (producer surplus + consumer surplus) is \((3/2)\theta z\). The social value of the innovation is given by the total surplus it creates minus the cost of R&D. Using \( z = z_P = \theta \), we have \( v_P(\pi) = 3\theta^2/2 - \theta^2/2 = 2\pi \). When the innovation is protected by secrecy, the price is \( p_M \) with probability \( s \) and drops to zero with probability \( 1 - s \). Expected total surplus is \( 3\theta z_S/2 + (1 - s)\theta z_S/2 \). Using \( z_S = s\theta \), we have \( v_S(\pi) = s\theta^2(4 - s)/2 - s^2\theta^2/2 = 2s(2 - s)\pi \). Because \( s(2 - s) < 1 \) for any \( s < 1 \), we have \( v_P(\pi) > v_S(\pi) \) for \( \pi > 0 \), and \( v_P(0) = v_S(0) = 0 \).

**Patent examination.** Suppose patent applications must first pass an examination, which is administered by a patent examiner. The examiner does not observe the type of an application but believes that a proportion \( p \) is good and a proportion \( 1 - p \) is bad. He conducts a prior-art search that allows him to receive a signal \( \sigma \) about an application. The distribution of the signal depends on the type of the application and on the examiner’s effort, which is unobservable. If the application is good (\( G \)), the examiner never obtains any signal \( (\sigma = \emptyset) \). If the application is bad (\( B \)), he obtains a perfectly informative signal \( \sigma = B \) with probability \( e \), and no signal with probability \( 1 - e \), where \( e \in [0, 1] \) is the effort that he puts into patent examination. Such an asymmetry in the information gathering technology is inherent in patent examination: it is conceptually impossible to find evidence that something is new, i.e., that it has never been done before. One can only search the stock of existing knowledge for evidence that
something (similar) has already been done. Since the stock of knowledge is large, the search can never cover its entirety (or only at prohibitive costs). Accordingly, in practice examiners have to search for prior art, i.e., previously published literature (patents, scientific articles, etc.) proving that the claimed invention was already known or would have been obvious to someone skilled in the art (so that it does not satisfy the patentability standards of novelty and non-obviousness). I make the following assumption on the nature of the signal:

**Assumption 1 (Soft information).** *Patent examination produces soft information: the signal \( \sigma = B \) is unverifiable by the planner or third parties.*

The examiner has utility

\[
U = t + \alpha y - \gamma(e),
\]

where \( t \) is the monetary transfer he receives from the planner, \( y \) is an intrinsic reward, \( \alpha \geq 0 \) is a parameter measuring the strength of intrinsic rewards, and \( \gamma(e) \) is the cost of effort (increasing and convex with \( \gamma(0) = \gamma'(0) = 0 \) and \( \gamma'(1) = \infty \)). I assume that the examiner is protected by limited liability (i.e., transfers must be non-negative). The intrinsic reward \( y \) takes different values depending on the type of application and the approval decision, as indicated in table 1.

<table>
<thead>
<tr>
<th>Decision</th>
<th>Application</th>
<th></th>
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</thead>
<tbody>
<tr>
<td>Grant</td>
<td>Good</td>
<td>( y_G )</td>
</tr>
<tr>
<td></td>
<td>Bad</td>
<td>0</td>
</tr>
<tr>
<td>Rejection</td>
<td>Good</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Bad</td>
<td>( y_B )</td>
</tr>
</tbody>
</table>

Table 1: Intrinsic rewards

**Assumption 2 (Intrinsic motivation).** *Intrinsic rewards satisfy \( y_G > 0 \) and \( y_B > 0 \).*

According to Assumption 2, the examiner derives an intrinsic reward from accepting good applications and from rejecting bad ones. Note that the expected intrinsic reward also depends on the examiner’s posterior belief that an application is good given the result of his prior-art search.

This reward structure formalizes the idea that the examiner cares about making the right decision. Several interpretations are possible. One is that some information about the quality

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10 This is reflected in the patent statutes and their interpretation by the courts. For example, title 35 of the U.S. code specifies in \( \S \)102 that “A person shall be entitled to a patent unless” the invention was previously known. The courts have interpreted this language as requiring the patent office to accept an application unless it can demonstrate that the claimed invention does not meet the patentability criteria (see Federal Trade Commission, 2003, Ch. 5, p. 8).

11 The fact that the top-right and lower-left fields are set to zero is a normalization. All that matters for the examiner’s decision is the comparison between the intrinsic rewards of granting and rejecting a given type of application.
of an examiner’s decisions may transpire over time. Although this information cannot be
correlated on, it can be used in subjective performance evaluation and thus be brought
to bear on promotion and dismissal decisions, which are part of the organization’s implicit
incentives. The information may also be learnt by the examiner’s peers, whose esteem he
may value. Alternatively, the examiner may have genuine intrinsic motivation, i.e., he may
care about the impact of his decisions on others (in this context, particularly consumers and
technology users).

The planner, whose objective is to maximize social welfare, has two instruments at her
disposal: the application fee $\phi$, and the incentive scheme for the examiner. The incentive
scheme consists of a transfer $t$ and a grant rule $x$ specifying whether a patent is granted
conditional on the examiner’s report. I assume that the shadow cost of public funds is zero,
so that transfers to the examiner and revenues from application fees do not directly enter the
social welfare function. (Transfers do affect welfare indirectly through the equilibrium level
of $e$, however.) Shadow costs of public funds cannot be the primary justification for charging
fees to patent applicants: there should be less distortive ways for the government to raise
revenue (in particular through the tax system). Whenever my results would be affected by
costly public funds, I point this out in the analysis below.

In addition, I restrict attention to deterministic grant rules, i.e., $x \in \{0, 1\}$. A justification
for this assumption is that probabilistic grant rules ($0 < x < 1$ for some report) are subject
to commitment problems, related to a well-known issue of time inconsistency associated with
the patent system: while ex ante, it is optimal to award patents to encourage innovation, ex
post (once the innovation has been developed), reneging on the promise to award a patent
saves deadweight loss. (This argument holds a fortiori for bad patents.) While this is true
regardless of whether grant rules are deterministic or probabilistic, the patent office can more
easily commit to deterministic grant rules. It is hard for an applicant to verify whether the
patent office adheres to a probabilistic grant rule. In contrast, under a deterministic grant
rule, deviations are easy to detect.\footnote{For similar arguments, see Khalil (1997) in the context of auditing, and Nocke and Whinston (2011) in
the context of merger review.}

**Timing.** The timing of the game is as follows (see Figure 1). At the beginning of the game,
the planner chooses an application fee and an incentive scheme for the examiner. Then, firms
invest in R&D to develop innovative technologies and decide whether to file for patents on
innovative and known technologies. The examiner decides how much examination effort to
provide. Finally, signals are drawn, acceptance and rejection decisions are made, and payoffs
are realized. The important assumption here is that the examiner cannot commit to a level
Planner chooses application fee and incentive scheme. Firms invest and apply for patents. Patent examiner chooses \( e \). Signal \( \sigma \in \{ B, \emptyset \} \) realized. Acceptance/rejection. Payoffs realized.

\[ t = 0 \quad t = 1 \quad t = 2 \quad t = 3 \]

time

Figure 1: Timing of the examination game

of examination effort \( e \) before firms decide on their filing behavior. This implies that the examiner does not take into account the effect of his effort on the proportion of good and bad applications.

**Discussion of the main assumptions.** The setup I have adopted – the signal being soft information and the examiner caring about making correct decisions – calls for some justification. Soft information is generally considered a reasonable description of situations involving complex scientific evidence (see, e.g., Shin, 1998). Patent applications are inherently technical and have increased in complexity over time. Moreover, patentability criteria, and the non-obviousness standard in particular, are often vague, somewhat ill-defined concepts. As noted by Jaffe and Lerner (2004, p. 172), “there is an essentially irreducible aspect of judgment in determining if an invention is truly new. After all, even young Albert Einstein faced challenges while assessing applications (…) in the Swiss Patent Office.” In an experiment carried out by the UK Patent Office in 2005, workshop participants were asked to evaluate whether a number of fictitious inventions satisfied different definitions of a “technical contribution” (Friebel et al., 2006). There was large disagreement among participants as to the conformity of the fictitious applications with any given definition. Because of ambiguity in patentability criteria and the technical complexity of applications, patent examiners are likely to have considerable discretion over the decision to grant or reject an application.

Moreover, little information about the quality of their decisions is available in the short run. While judicial and administrative review of patent validity, such as court hearings, re-examination (in the U.S.) or opposition (in Europe), provides such information, it occurs with a significant time lag. Another problem is that courts may differ in their “patent friendliness” across time and space. These considerations make it impractical to include information on decision quality in a contract. It seems more appropriate to model it as being part of the implicit incentives within the patent office, which is captured by the assumption that the examiner cares about making correct decisions.\(^{15}\)

\(^{13}\) The notion of “technical contribution” was part of a proposed EU directive dealing with software patents; see http://eur-lex.europa.eu/LexUriServ/site/en/com/2002/com2002_0092en01.pdf.

\(^{14}\) Observers have suggested that this was the case in the United States after the creation of a centralized appeals court for patent disputes, the Court of Appeals for the Federal Circuit (CAFC).

\(^{15}\) It seems inappropriate to treat this as a standard career-concerns setup. The main outside opportunity
3 Innovation and welfare in the absence of patent examination

Suppose first that there is no patent system so that firms can only rely on secrecy to protect their innovations. Social welfare under secrecy alone is

\[ W_S \equiv n_G \int_{\pi}^{\hat{\pi}} v_S(\pi) dF(\pi). \]

Now suppose that there is a patent system, but no possibility to submit bad applications (for example, suppose there are no known technologies, \( n_B = 0 \)). Firms will seek patent protection for innovative technologies if \( \pi - \phi \geq s^2 \pi \), and keep them secret otherwise. This defines a threshold \( \hat{\pi}_G = \min\{\pi, \max\{\pi, \phi/(1 - s^2)\}\} \) such that innovative technologies with \( \pi < \hat{\pi}_G \) will be kept secret, and technologies with \( \pi \geq \hat{\pi}_G \) will be patented. A welfare-maximizing planner chooses the application fee \( \phi \) to solve

\[ \max_{\phi} n_G \left[ \int_{\pi}^{\hat{\pi}_G} v_S(\pi) dF(\pi) + \int_{\hat{\pi}_G}^{\pi} v_P(\pi) dF(\pi) \right]. \]

Clearly, the optimal application fee is such that \( \hat{\pi}_G = \pi \), which can be achieved with any \( \phi \in [0, (1 - s^2)\pi] \). All innovative technologies are patented. Let me now introduce the possibility for firms to submit bad applications. Bad applications naturally create a demand for patent examination. Before considering examination, however, I first examine the welfare properties of merely having a registration system, in which all applications are granted.\(^{16}\) In a registration system, firms continue to apply for innovative technologies if \( \pi \geq \hat{\pi}_G \), but firms will also apply for patents on known technologies if \( 2\beta\pi - \phi \geq 0 \). This defines a threshold \( \hat{\pi}_B = \min\{\pi, \max\{\pi, \phi/(2\beta)\}\} \) such that all known technologies with \( \pi \geq \hat{\pi}_B \) are submitted to the patent office. When the application fee is optimally chosen, welfare in a registration system is

\[ W_R \equiv \max_{\phi} n_G \left[ \int_{\pi}^{\hat{\pi}_G} v_S(\pi) dF(\pi) + \int_{\hat{\pi}_G}^{\pi} v_P(\pi) dF(\pi) \right] - n_B \int_{\hat{\pi}_B}^{\pi} [\beta D(\pi) + C] dF(\pi). \]

Differentiating with respect to \( \phi \) yields

\[ -n_G [v_P(\hat{\pi}_G) - v_S(\hat{\pi}_G)] f(\hat{\pi}_C) + n_B [\beta D(\hat{\pi}_B) + C] \frac{f(\hat{\pi}_B)}{2\beta}. \]

The first term corresponds to the (marginal) welfare loss that is due to innovators shifting from patenting to secrecy as \( \phi \) increases, while the second term corresponds to the (marginal)

\(^{16}\) Note that this is not merely a theoretical possibility. As documented by Lerner (2005), many countries use (or have in the past used) a registration system, leaving the determination of validity entirely to the courts. For patent examiners is employment in law firms. But the value of former patent examiners for patent attorneys comes mainly from their inside knowledge of patent office procedures, rather than from the particular skills they demonstrated during their stay at the office. As a matter of fact, examiners often leave before any information about the quality of their decisions becomes available to the public. The signaling motive emphasized by career-concerns models seems to be largely irrelevant.
welfare gain due to fewer known technologies being patented. Thus, the optimal application fee trades off the gains from innovative technologies getting patented rather than kept secret against the losses from known technologies getting patented. Notice that a registration system in which the fee is optimally chosen always weakly dominates a system of secrecy alone: the planner can always choose \( \phi \) so large that nobody applies. The following lemma gives sufficient conditions for a registration system to improve on a system of secrecy in a strict sense; it also gives conditions for the optimal fee, denoted \( \phi_R \), to be interior, so that there are both good and bad applications at the optimum.

**Lemma 1.** Suppose \( 2\beta + s^2 < 1 \). Then, \( W_R > W_S \). Suppose moreover that \( \bar{\pi} > \pi(1-s^2)/(2\beta) \), \( f(\pi) > 0 \) for all \( \pi \in [\underline{\pi}, \bar{\pi}] \) and \( f(\bar{\pi}) = 0 \). Then, \( (1-s^2)\bar{\pi} < \phi_R < 2\beta\bar{\pi} \), implying \( \bar{\pi} < \bar{\pi}_B < \bar{\pi} \).

According to Lemma 1, a sufficient condition for a registration system to be strictly welfare-superior to a system of secrecy alone is that the courts do not enforce too many bad patents and that secrecy is not too effective as a protection mechanism. Both are intuitive: if the probability of being able to enforce a bad patent is low, filing applications on known technologies becomes less attractive; if protection by secrecy is relatively ineffective, the investment that can be induced by secrecy alone is low, so patents lead to a large increase in R&D investment.

While the condition \( 2\beta + s^2 < 1 \) is not necessary for \( W_R > W_S \), it is convenient because, as Lemma 1 shows, together with some mild conditions on the density function \( f \) and the bounds of its support, it also implies that the optimal fee is interior, a fact that will be used in parts of the analysis below. The fee being interior implies in particular that \( \bar{\pi}_B < \bar{\pi} \), so that the optimal registration system does not deter all bad applications. The intuition is that if \( f(\bar{\pi}) = 0 \), there are few technologies at the upper bound of the distribution. Reducing \( \phi \) slightly from the level that would deter all bad applications thus causes only second-order losses. At the same time, \( 2\beta + s^2 < 1 \) implies \( \bar{\pi}_G < \bar{\pi}_B \), so that \( f(\bar{\pi}_G) > 0 \). Hence, reducing \( \phi \) leads to first-order gains from innovators switching to patenting.

Note that introducing a shadow cost of public funds would make a registration system more likely to be desirable. In the presence of costly public funds, the patent system provides an additional source of revenue for the government. The revenue from application fees can be used to reduce the tax burden elsewhere in the economy. Fee revenue, given by \( \phi[n_G(1 - F(\bar{\pi}_G)) + n_B(1 - F(\bar{\pi}_B))] \), has the usual inverse-U shape of a Laffer curve. Provided that \( 2\beta\bar{\pi} \) lies beyond the maximum of this Laffer curve, the result that bad applications will not be completely deterred also becomes more likely.

In a registration system, the planner must rely on the application fee to discourage bad applications. The drawback of application fees is that they do not discriminate between
good and bad applications. Thus, higher application fees also discourage firms at the margin between secrecy and patenting from applying for patents on innovative technologies, which reduces R&D investment. This can provide a rationale for ex ante examination of applications by the patent office, to which I now turn.

4 Designing incentives for the examiner

In this section, I study the optimal design of incentives for the examiner. It is instructive to begin by considering what happens when, contrary to Assumption 1, the signal is hard information. The planner then faces a simple moral hazard problem for which standard results apply. She should pay the examiner for coming up with defeating prior art, i.e., \( \sigma = B \). The intuition is that \( \sigma = B \) is informative about the examiner’s effort, whereas \( \sigma = \emptyset \) is not. Risk neutrality and costless public funds also mean that the planner can achieve the first best (or an arbitrary approximation thereof), irrespective of the examiner’s intrinsic motivation.\(^\text{17}\) Of course, these are strong assumptions that bias the analysis in the planner’s favor. What the remainder of the analysis shows is that even under these favorable assumptions, soft information constrains what the planner can achieve and lends importance to intrinsic motivation.

When the signal is soft information, the planner faces a problem of moral hazard followed by adverse selection: the examiner’s effort determines the distribution of “types” (in this case, the distribution of signals). We can work backwards from the adverse-selection stage and invoke the revelation principle, according to which a direct revelation mechanism is without loss of generality. The planner offers a menu of contracts \((t_{\hat{\sigma}}, x_{\hat{\sigma}})\), where \( \hat{\sigma} \in \{B, \emptyset\} \) is the signal reported by the examiner. That is, the planner asks the examiner to report his signal \( \sigma \). If he reports \( B \), the planner pays \( t_B \) and grants a patent according to the rule \( x_B \). If he reports \( \emptyset \), the planner pays \( t_{\emptyset} \) and grants a patent according to the rule \( x_{\emptyset} \).

Consider the case where the examiner has exerted equilibrium effort \( e^* > 0 \) and come up with signal \( \sigma = B \). For him to prefer to report \( B \), it must be the case that

\[
t_B + (1 - x_B)\alpha y_B \geq t_{\emptyset} + (1 - x_{\emptyset})\alpha y_B.
\]

(2)

Given signal \( B \), he knows with certainty that the application is bad, but he only enjoys the intrinsic reward from rejection, \( \alpha y_B \), if \( x_{\emptyset} = 0 \). If, on the other hand, the examiner obtains

\(^\text{17}\) The only potential impediment to achieving the first best in this model relates to the time inconsistency characteristic of inspection games: ex ante the planner may want to implement an allocation such that all bad applications are deterred. But ex post, if there are no bad applications, the examiner has no incentive to search for \( \sigma = B \) no matter how powerful the incentive scheme is. In that case, the planner can achieve an allocation that is close to but not equal to the first best.
no signal ($\sigma = \emptyset$), he will prefer to report $\emptyset$ provided

$$t_B + \alpha[\hat{p}xB_yG + (1 - \hat{p})(1 - x_B)y_B] \leq t_\emptyset + \alpha[\hat{p}x\emptyset yG + (1 - \hat{p})(1 - x_\emptyset)y_B],$$

where $\hat{p} \equiv \Pr[G|\emptyset]$ is the examiner's posterior belief that the application is valid given that he has found no evidence to the contrary. His expected intrinsic reward from reporting $B$ is $\alpha[\hat{p}xB_yG + (1 - \hat{p})(1 - x_B)y_B]$, while that from reporting $\emptyset$ is $\alpha[\hat{p}x\emptyset yG + (1 - \hat{p})(1 - x_\emptyset)y_B]$. Adding up inequalities (2) and (3) and simplifying, we obtain $x_B \leq x_\emptyset$. Thus, a necessary condition for incentive compatibility is that an application for which the examiner finds defeating prior art has a weakly lower probability of acceptance than one for which he finds no signal.

Turning to the moral-hazard stage, suppose the examiner anticipates truthfully revealing the signal he finds. He then chooses $e$ to maximize

$$p[t_\emptyset + x_\emptyset \alpha yG] + (1 - p)[e[t_B + (1 - x_B)\alpha y_B] + (1 - e)[t_\emptyset + (1 - x_\emptyset)\alpha y_B]] - \gamma(e).$$

With probability $p$, the application is good, so that he cannot find any grounds for rejection. The transfer he receives is $t_\emptyset$, and the expected intrinsic reward is $x_\emptyset \alpha yG$. With probability $1 - p$, the application is bad, for which he finds evidence with probability $e$. He is paid $t_B$ and enjoys an expected intrinsic reward of $(1 - x_B)\alpha y_B$. With probability $1 - e$, the examiner finds no evidence. He receives a transfer of $t_\emptyset$ and an expected intrinsic reward of $(1 - x_\emptyset)\alpha y_B$. Differentiating with respect to $e$ leads to the first-order condition

$$(1 - p)[t_B - t_\emptyset - (x_B - x_\emptyset)\alpha y_B] = \gamma'(e).$$

This equation defines the examiner’s best-response function, determining his effort as a function of the proportion of good applicants. It follows from (4) that, for a given $p$, effort is increasing in $t_B - t_\emptyset$ and decreasing in $x_B - x_\emptyset$. Moreover, positive examination effort is only sustainable if the examiner expects there to be some bad applications ($p < 1$).

A final set of constraints comes from the possibility of double deviation: the examiner may deviate from both the equilibrium effort and truthful reporting. Two cases are relevant: always reporting $\emptyset$, and always reporting $B$.18 In both cases, choosing $e = 0$ is optimal (if the examiner anticipates that his report will not depend on his signal, there is no point in exerting effort). To rule out double deviation, the equilibrium utility with truthful reporting must be larger than the utility with zero effort and either report ($\emptyset$ or $B$). Letting $U^*$ denote the examiner’s equilibrium utility, we must have

$$t_\emptyset + \alpha[px_\emptyset yG + (1 - p)(1 - x_\emptyset)y_B] \leq U^*,$$

18 A third strategy, which would consist in always reporting the opposite of the signal found, leads to an optimal effort of zero under condition (2), and therefore reduces to the strategy of always reporting $B$. 

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15
and

$$t_B + \alpha[x_B y_G + (1 - p)(1 - x_B)y_B] \leq U^*$$

(6)

with

$$U^* = p[t_\emptyset + x_\emptyset \alpha y_G] + (1 - p)[e^* t_B + (1 - x_B) \alpha y_B + (1 - e^*)[t_\emptyset + (1 - x_\emptyset) \alpha y_B]] - \gamma(e^*).$$

(7)

I now relate the proportion of good and bad applications to $x_\emptyset$, $x_B$, and $e$. As previously, let $\hat{\pi}_G$ and $\hat{\pi}_B$ denote the cutoffs on $\pi$ above which firms file good and bad applications, respectively. The number of good applications is $N_G \equiv n_G(1 - F(\hat{\pi}_G))$ and the number of bad applications is $N_B \equiv n_B(1 - F(\hat{\pi}_B))$. In determining $\hat{\pi}_G$ and $\hat{\pi}_B$, I will assume that firms correctly anticipate that the examiner exerts effort $e$ and reports truthfully. The payoff from applying for a patent on innovative technology $\pi$ is given by $\pi - \phi$ if $x_\emptyset = 1$. Assuming that firms whose innovative technology gets rejected can still protect it through secrecy, the payoff from applying is $s^2 \pi - \phi$ if $x_\emptyset = 0$. The payoff from not applying and keeping the innovative technology secret is $s^2 \pi$ in both cases. Thus, we have

$$\hat{\pi}_G = \begin{cases} 
\min\{\pi, \max\{\pi, \phi/(1 - s^2)\}\} & \text{if } x_\emptyset = 1 \\
\pi & \text{if } x_\emptyset = 0.
\end{cases}$$

(8)

Again, no one applies if $x_\emptyset = x_B = 0$. Unlike $\hat{\pi}_G$, the cutoff $\hat{\pi}_B$ is a function of $e$.

$$\hat{\pi}_B = \begin{cases} 
\min\{\pi, \max\{\pi, \phi/(2\beta)\}\} & \text{if } x_B = x_\emptyset = 1 \\
\min\{\pi, \max\{\pi, \phi/[2\beta(1 - e)]\}\} & \text{if } x_B = 0 \text{ and } x_\emptyset = 1 \\
\pi & \text{if } x_B = x_\emptyset = 0.
\end{cases}$$

(9)

The expected payoff from applying for a patent on a known technology $\pi$ is given by $2\beta \pi[e x_B + (1 - e)x_\emptyset] - \phi$. Thus, we have

$$p(e, \phi, x_B, x_\emptyset) = \frac{n_G[1 - F(\hat{\pi}_G)]}{n_G[1 - F(\hat{\pi}_G)] + n_B[1 - F(\hat{\pi}_B)]}.$$
The welfare function the planner maximizes is

\[ W(e, \phi, x_B, x_{\emptyset}) \equiv n_G \left[ \int_{x_G}^{x_B} v_S(\pi) dF(\pi) + \int_{x_{\emptyset}}^{x_B} v_P(\pi) dF(\pi) \right] - n_B [ex_B + (1 - e)x_{\emptyset}] \int_{x_{\emptyset}}^{x_B} [\beta D(\pi) + C] dF(\pi) - (N_G + N_B) \gamma(e). \]  

Welfare is the sum of three terms: the social value of innovation, the social cost of bad patents, and the cost of patent examination, which is equal to \( \gamma(e) \) multiplied by the total number of applications. The planner solves

\[ \max_{\phi, (t_B, x_B), (t_{\emptyset}, x_{\emptyset})} W(e^*, \phi, x_B, x_{\emptyset}) \]

subject to (2), (3), (5), and (6), \( \phi \geq 0, t_{\sigma} \geq 0, x_{\sigma} \in \{0, 1\} \), and

\[ \gamma'(e^*) = (1 - p^*)[t_B - t_{\emptyset} - (x_B - x_{\emptyset})\alpha y_B] \]

\[ p^* = p(e^*, \phi, x_B, x_{\emptyset}). \]

Equations (11) and (12) state that \((e, p)\) must be an equilibrium of the examination game, i.e., examination effort \( e \) and firms’ filing strategies, as summarized by \( p \), must be best responses to each other. The examination game is well defined as long as the number of applications filed is strictly positive. The number of applications is zero if either \( x_B = x_{\emptyset} = 0 \) or \( \phi \geq \max\{1 - s^2\pi, 2\beta\pi\} \). As the following lemma shows, for values of \( x_B, x_{\emptyset}, \) and \( \phi \) such that the examination game is well defined, equilibrium exists and is unique.

**Lemma 2 (Existence and uniqueness).** Suppose the incentive scheme \( (t_B, x_B, (t_{\emptyset}, x_{\emptyset})) \) satisfies (2), (3), (5), and (6). Then, there exists a unique equilibrium \((p^*, e^*)\) of the examination game characterized by (11) and (12).

Constraints (2), (3), (5), and (6), together with the equilibrium conditions (11) and (12), determine which levels of \( e \) the planner can implement through an appropriate choice of application fee, transfers, and grant probabilities. The next lemma provides a simpler representation of the planner’s problem.

**Lemma 3.** The planner’s problem is equivalent to

\[ \max_{e \geq 0, \phi \geq 0} W(e, \phi, 0, 1) \quad \text{subject to} \quad g(e, \phi) \leq \alpha(y_G + y_B), \]  

**Note:** I have omitted the examiner’s individual-rationality constraint,

\[ p[t_{\emptyset} + x_{\emptyset}\alpha y_C] + (1 - p)[e[t_B + (1 - x_B)\alpha y_B] + (1 - e)[t_{\emptyset} + (1 - x_{\emptyset})\alpha y_B]] - \gamma(e) \geq y, \]

where \( y \) is the examiner’s outside opportunity. Since public funds are assumed to be costless and the examiner risk-neutral, this constraint does not play any role. The solution of the relaxed problem will determine \( t_B - t_{\emptyset} \); the absolute levels can be obtained by combining (IR) with the limited liability constraints.
where

\[ g(e, \phi) \equiv \left(1 + \frac{n_B[1 - F(\hat{\pi}_B)]}{n_G[1 - F(\hat{\pi}_G)]}\right)[(1 - e)\gamma'(e) + \gamma(e)] + \left(1 + \frac{n_G[1 - F(\hat{\pi}_G)]}{n_B[1 - F(\hat{\pi}_B)]}\right)\gamma'(e). \] (14)

Lemma 3 contains two results: first, it is as if the planner could choose \( e \) directly, but is limited by the constraint \( g(e, \phi) \leq \alpha(y_B + y_G) \), which implicitly defines the maximum effort as a function of \( \phi \) and \( \alpha \); second, it is without loss of generality to focus on incentive schemes such that \( x_B = 0 \) and \( x_\varnothing = 1 \). The key element in the proof of the first result is that constraint (6) imposes an upper bound on transfers, given by

\[ t_B - t_\varnothing \leq (x_\varnothing - x_B)\alpha(\bar{p}y_G - (1 - \bar{p})y_B) - \frac{\gamma(e)}{p + (1 - p)(1 - e)}, \] (15)

and thus limits the power of incentives. Intuitively, soft information gives the examiner discretion over the signal he reports. If we pay him too much for reporting \( B \), he will always report \( B \). If we pay him too much for reporting \( \varnothing \), he will always report \( \varnothing \). In both cases, it is not worthwhile for him to exert effort because he knows his report will not depend on his signal. To be willing to exert effort, he must anticipate truthfully revealing the signal he finds and obtaining a sufficiently large equilibrium utility. Monetary incentives can only induce additional effort to the extent that they do not make it too tempting to deviate.

Evaluating \( t_B - t_\varnothing \) at its upper bound given by (15), the examiner’s best response function can be used to determine the maximum level of effort that can be implemented for given values of \( p, x_B, \) and \( x_\varnothing \). This maximum effort is implicitly defined by

\[ \gamma'(e)[1 - e(1 - p)] + (1 - p)\gamma(e) = (x_\varnothing - x_B)p(1 - p)\alpha(y_G + y_B). \] (16)

This result is illustrated in Figure 2, where the blue curve corresponds to equation (16). Its inverted-U shape has an intuitive explanation. If \( p = 0 \) or \( p = 1 \), the examiner knows in advance whether he is facing a good or bad application. There is no point in exerting effort to acquire information that is redundant; thus, only \( e = 0 \) is implementable. Noticing that an equilibrium needs to be a best response for firms as well, and that the firms’ best response depends on \( e \) and \( \phi \), the maximum amount of effort that can be implemented for a given \( \phi \) is \( \bar{e}(\phi) \), which is found at the intersection of the blue curve with the \( p(e, \cdot) \) curve. The \( e(p, \cdot) \) curve in the figure corresponds to the examiner’s best-response function, implicitly defined by (4), evaluated at some feasible pair of transfers; it is shown for illustrative purposes.

The second result, according to which setting \( x_B = 0 \) and \( x_\varnothing = 1 \) is without loss of generality, can be explained as follows. The grant probabilities have an effect on welfare both directly and indirectly through the examiner’s incentives. The direct effect of setting \( x_B = x_\varnothing = 0 \) (which is equivalent to not having a patent system) can be replicated by setting the fee prohibitively high, i.e., \( \phi \geq \max\{(1 - s^2)\pi, 2\beta\pi\} \). The direct effect of setting
Figure 2: The maximum implementable effort

$x_B = x_\emptyset = 1$ can be replicated by setting $x_B = 0 = 1 - x_\emptyset$ and $e = 0$. As for the indirect effect, equation (16) shows that setting $x_B = x_\emptyset$ always leads to zero effort. Thus, there is no loss of generality in terms of either direct or indirect welfare of setting $x_B = 0$ and $x_\emptyset = 1$.

For a given $\alpha$, the maximum effort that the planner can implement, $\bar{e}$, depends on the application fee $\phi$ through its effect on $p$. Suppose, for example, that an increase in $\phi$ leads to a greater proportion of good applications, for any $e$. This would shift the $p(e, \cdot)$ curve in Figure 2 upward. In the particular situation shown in the figure, such a shift would decrease the maximum implementable effort. More generally, though, the effect may go either way, depending on the position of the $p(e, \cdot)$ curve with respect to the blue curve. What is unambiguous is that for levels of $\phi$ such that $p$ approaches either 0 or 1, the maximum effort tends to zero.

The set of $(e, \phi)$ that the planner can implement depends on $\alpha$. The constraints caused by soft information mean that extrinsic rewards can only play a limited role in inducing effort, thus assigning a crucial role to intrinsic motivation, as the following proposition shows.

**Proposition 1** (Importance of intrinsic motivation). *If $\alpha = 0$, no examination effort can be sustained in equilibrium. An increase in $\alpha$ weakly increases welfare and strictly increases the maximum implementable effort.*

Some amount of intrinsic motivation is essential for effort provision. If $\alpha = 0$, no effort is implementable, $e = 0$. It follows that in the absence of intrinsically motivated examiners, the patent system must be a registration system. The optimal application fee in that case is $\phi = \phi_R$. Thus, letting $(e_{\alpha}, \phi_{\alpha})$ denote the solution to the planner’s problem (13) for a given

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21 As I show in Proposition 4 below, this will be the case if $F$ has an increasing hazard rate.

22 This result is quite general; in particular, it would also hold if I allowed for random grant rules.
\(\alpha\), we have \((e_0, \phi_0) = (0, \phi_R)\). An increase in intrinsic motivation relaxes the constraint on \((e, \phi)\), which makes it possible to achieve more desirable outcomes. In particular, an increase in \(\alpha\) makes it possible to induce greater examination effort. An examiner who cares more about making the right decision can be induced to exert more effort, whatever the proportion of good and bad applications (as long as there is at least some uncertainty as to whether an application is good or bad).

An increase in \(\alpha\) only weakly increases welfare because it is not certain in general that a patent system is desirable. If the planner shuts down the patent system by setting a prohibitive application fee, the constraint \(g(e, \phi) \leq \alpha(y_B + y_G)\) is not binding, so (marginal) increases in \(\alpha\) have no effect on welfare. For the following propositions, which concern the compensation scheme, I impose an additional assumption which ensures that the patent system is desirable and that bad applications are not completely deterred at the optimum when \(\alpha = 0\).

**Assumption 3.** The parameters satisfy \(2\beta + s^2 < 1\) and \(\pi > \frac{\pi(1 - s^2)}{(2\beta)}\). The density function satisfies \(f(\pi) > 0\) for all \(\pi \in [\pi, \overline{\pi})\), and \(f(\overline{\pi}) = 0\).

A sufficient condition for the patent system to be desirable is that a registration system is desirable: patent examination adds an additional instrument to the planner’s arsenal, and since \(\gamma(0) = 0\), she cannot do worse than without it. The conditions for a registration system to outperform secrecy alone where derived in Lemma 1 and are restated in the assumption.

**Proposition 2** (Rewarding grants). Suppose

\[
y_B/(y_B + y_G) > p(0, \phi_R, 0, 1).
\]  
(17)

Then, for \(\alpha\) small but strictly positive, \(e_\alpha > 0\) and \(t_B < t_\emptyset\).

Because there is a one-to-one relationship between the examiner’s report and the decision to grant or reject, the decision can be interpreted as being his, which is what I will do in describing the following results. According to Proposition 2, when intrinsic motivation is low and \(y_B/(y_B + y_G) > p(0, \phi_R, 0, 1)\), the compensation scheme rewards the examiner for granting. Were he not compensated for granting by means of a monetary transfer, the examiner would reject all applications. The intuition is that in an equilibrium in which effort is low and the proportion of bad applications relatively large, the best the examiner can do to avoid mistakes is reject everything. If the planner wants to make the examiner truthfully reveal his signal, she must reward him for granting. Moreover, unless the examiner anticipates being truthful, he will not exert any effort. Because the patent system is desirable and welfare is increasing in \(e\) at \(e = 0\), the planner wants to induce strictly positive effort. By rewarding the examiner for granting, she gets him to exert positive (albeit low) effort.
Condition (17) says that rejecting bad applications needs to give the examiner a sufficiently high intrinsic reward, relative to allowing good ones. The ratio of intrinsic rewards must be large compared to the proportion of good applications in the absence of examination. Because \( p(0, \phi_R, 0, 1) < 1 \) by Assumption 3, there always exists values of \( y_B \) and \( y_G \) that satisfy this condition. For example, the condition always holds in the extreme case where the examiner’s intrinsic motivation stems from a “myopic” concern for social welfare. Ex post – once the R&D investment is sunk – there is little, if any, welfare gain from granting a patent even to good applicants. Unlike from an ex ante perspective, the patent does not affect incentives to do R&D and merely creates deadweight loss. In that case, \( y_G \) would be (close to) zero. In the absence of monetary incentives, the examiner would be tempted to behave opportunistically and deny patent protection even if \( p \) is large. On the other hand, if the relative intrinsic rewards are perfectly aligned with the planner’s objective (i.e., ex ante welfare), then condition (17) can never hold. Thus, if we interpret intrinsic motivation as being a concern for social welfare, then Proposition 2 requires that the examiner be more myopic than the planner.

Fixing \( y_B \) and \( y_G \), another way to look at condition (17) is as saying that the proportion of good applications must be sufficiently low at low levels of effort. If the distribution of \( \pi \) has an increasing hazard rate, then \( p \) increases with \( \phi \), as shown in Proposition 4 below. Thus, the condition is more likely to be satisfied if \( \phi_R \) is low. From (1), \( \phi_R \) tends to be lower if the benefit from innovative technologies being patented rather than kept secret \( (v_P - v_S) \) is larger, and if the cost of bad patents (determined by \( D \) and \( C \)) is smaller.\(^{23}\)

While Proposition 2 looked at the compensation scheme that prevails at low levels of intrinsic motivation, the next proposition considers what happens as intrinsic motivation becomes larger.

**Proposition 3 (Complementarity).** Let \((e^0, \phi^0) \equiv \arg \max_{e, \phi} W(e, \phi, 0, 1)\). Suppose

\[
y_B/(y_B + y_G) < p(e^0, \phi^0, 0, 1).
\]

(18)

Then, there exists \( \hat{\alpha} \geq 0 \) such that \( t_B > t_\emptyset \) for all \( \alpha > \hat{\alpha} \).

The model yields a complementarity between intrinsic and extrinsic rewards: higher intrinsic motivation increases the examiner’s effort not only by itself, but also by allowing the planner to use monetary incentives more effectively. Assuming \( y_B/(y_B + y_G) < p(e^0, \phi^0, 0, 1) \), for sufficiently large values of \( \alpha \) it is possible to reward the examiner for rejecting applications without impeding truthful revelation. When the proportion of good applications is large and

\(^{23}\) The effect of the other parameters on \( p(0, \phi_R, 0, 1) \) is ambiguous. Consider for example \( n_B \). Holding \( \phi \) constant, \( p \) decreases with \( n_B \). At the same time, however, the optimal fee increases with \( n_B \), which raises \( p \). Since these effects go in opposite directions, the net effect is indeterminate.
the examiner has more confidence in the result of his prior-art search, he is no longer tempted to reject everything. Rewarding rejection then has a positive feedback effect on effort.

As shown in the proof of Proposition 3, there exists a threshold level of \( p \) above which rewarding rejection is optimal. If the optimal patent policy \((e^o, \phi^o)\) leads to a value of \( p \) that is above the threshold, then for levels of intrinsic motivation exceeding some value \( \hat{\alpha} \), the planner will pay the examiner for rejecting. The threshold is bounded above by \( y_B/(y_B + y_G) \); thus, (18) ensures that the optimal patent policy yields a \( p \) exceeding the threshold. A sufficient condition for \( \hat{\alpha} \) to exist is that \( g(e^o, \phi^o) \) is finite. To establish this, the proof shows that the unconstrained maximum, \((e^o, \phi^o)\), is interior: at the optimal patent policy, there are always some bad applications, and there are some innovative technologies that are kept secret rather than patented.\(^{24}\)

Condition (18) can be interpreted as saying that the ratio of intrinsic rewards \( y_B/y_G \) must be sufficiently low compared to \( p \); appropriate values of \( y_B \) and \( y_G \) always exist. Alternatively, fixing \( y_B \) and \( y_G \), it can be interpreted as saying that \( p \) needs to be sufficiently large at the unconstrained optimum. In other words, what is required is that the cost of effort be sufficiently low relative to the cost of bad patents. If \( \gamma \) and \( \gamma' \) are small, the first-best level of effort will be such that \( p \) is close to 1, so that the condition holds for a broad range of \((y_B, y_G)\).

For an exogenous variation in \( \alpha \) to be able to explain a difference in the compensation schemes used by two patent offices operating under otherwise identical conditions, conditions (17) and (18) must be satisfied simultaneously, holding all other parameters constant. The following corollary formally states the condition for this to be the case. Below I examine what it implies in terms of the primitives of the model.

**Corollary.** If \( p(0, \phi_R, 0, 1) < y_B/(y_B + y_G) < p(e^o, \phi^o, 0, 1) \), then there exists \( \bar{\alpha} > 0 \) such that \( t_B < t_\varnothing \) as \( \alpha \to 0 \) and \( t_B > t_\varnothing \) as \( \alpha \to \bar{\alpha} \).

Under the conditions of the corollary, the optimal compensation scheme rewards granting when \( \alpha \) is small and rewards rejecting when \( \alpha \) is large. Note that if \( p \) were exogenous and constant, only one of the conditions (17) and (18) could hold (so that either Proposition 2

\(^{24}\) The proofs of Propositions 2 and 3 rely on costless public funds only to the extent that a positive cost of public funds might affect whether the solution is interior. See the discussion following Lemma 1. Quantitatively, of course, costly public funds would affect the optimal patent policy, but in a way that is complex and a priori ambiguous. First, costly public funds add a revenue-raising motive to the planner’s objectives. Depending on the elasticity of applications at the optimal fee absent costs of public funds, this may lead to either a higher or lower fee. Second, costly public funds make it more expensive to pay the examiner. If the number of applications affects the number of examiners the patent office needs to employ, this makes it more attractive to increase the fee. Third, if the examiner has limited liability, costly public funds may make it less attractive to give him a high-powered incentive scheme: it is more expensive and, if it increases examination effort, also leads to fewer applications and thus lower fee revenue.
or 3 would apply). They could not hold simultaneously, as required for the corollary, which relies on
\[ p(0, \phi_R, 0, 1) < p(e^o, \phi^o, 0, 1). \]
If (19) is satisfied, then there exist values of \( y_B \) and \( y_G \) such that the corollary applies. The next proposition gives sufficient conditions for this inequality.

**Proposition 4.** The proportion of good applications satisfies (19) if either of the following holds:

(i) \( \pi \) follows the Pareto distribution;

(ii) the distribution of \( \pi \) has an increasing hazard rate, and \( \phi^o \geq \phi_R \).

Although it may seem intuitive that \( p \) should increase as one moves from \((0, \phi_R)\) to \((e^o, \phi^o)\), formally proving it turns out to be less than straightforward. As \( \alpha \) increases, the planner tends to implement greater effort, but may increase or decrease \( \phi \). Moreover, while \( p \) unambiguously increases with \( e \), it may increase or decrease with \( \phi \). In general, therefore, the net effect of increasing \( \alpha \) on \( p \) is ambiguous. Proposition 4 identifies two particular cases in which the effect is clear. If \( \pi \) follows the Pareto distribution, a change in \( \phi \) leads to the same percentage change in the number of both good and bad applications; as a result \( p \) remains constant as we vary \( \phi \). Because \( e \) increases from 0 to \( e_\alpha > 0 \) as we move from \( \alpha = 0 \) to any \( \alpha > 0 \), the proportion of good applications goes up. If the distribution of \( \phi \) has an increasing hazard rate, \( p \) increases with \( \phi \). Thus, if \( \phi^o \geq \phi \), the change in the fee reinforces the effect of increased effort, so the proportion of good applications at \( \bar{\alpha} \) is greater than at \( \alpha = 0 \).

Both of these cases are interesting. Several empirical studies have found that the Pareto distribution fits the observed distribution of returns to innovation (Pakes and Schankerman, 1984; Silverberg and Verspagen, 2007).\footnote{Pakes and Schankerman (1984) exploit information from patent renewals to estimate the value of patented inventions. They find that the data from four of the five European countries they study is consistent with a Pareto distribution. Since the value estimates for the set of patents that are renewed to full term rely on assumptions and extrapolations from the set of patents that are not renewed to full term, their analysis can be interpreted as being informative mainly about lower-value innovations. Harhoff et al. (2003) assess the tail of the distribution using survey evidence for a sample of German patents. They conclude that the log normal distribution provides a better fit than the Pareto distribution. Silverberg and Verspagen (2007), however, argue that Harhoff et al.’s definition of the tail may not be based on an appropriate threshold. Applying extreme-value analysis to several data sets on innovation values, constructed using a variety of methods (citations, licensing revenues, and surveys), Silverberg and Verspagen find that the Pareto distribution captures the tail behavior more accurately than the log normal.}

Many other distributions with single-peaked densities are characterized by increasing hazard rates; see Bagnoli and Bergstrom (2005). In addition, the example below shows that it is not implausible that \( \phi^o \geq \phi_R \). Note also that the condition \( \phi^o \geq \phi_R \) is sufficient but not necessary. More generally, when the hazard rate is increasing, (19) will hold as long as \( \phi^o \) is not too much smaller than \( \phi_R \).
Patent quality in this model can be measured by the posterior probability that an issued patent is good, \( \hat{p} \equiv p/[p + (1 - p)(1 - e)] \). We have \( \partial \hat{p}/\partial p = (1 - e)/(p + (1 - p)(1 - e))^2 \geq 0 \) and \( \partial \hat{p}/\partial e = p(1 - p)/(p + (1 - p)(1 - e))^2 \geq 0 \), so \( \hat{p} \) is increasing in both \( e \) and \( p \). Thus, under condition (19), patent quality increases as \( \alpha \) goes from 0 to \( \bar{\alpha} \). The effect on the grant rate, given by \( p + (1 - p)(1 - e) \), is ambiguous. Totally differentiating the grant rate yields

\[
\text{d}[p + (1 - p)(1 - e)] = \left[ e \frac{\partial p}{\partial e} - (1 - p) \right] \text{de} + e \frac{\partial p}{\partial \phi} \text{d}\phi.
\]

The first term is positive if the elasticity of the proportion of good applications with respect to the examination effort is greater than 1, and negative otherwise. Thus, even under the distributional assumptions envisioned in Proposition 4, the effect of an increase in \( \alpha \) on the grant rate is indeterminate. The following example illustrates many of the insights from the model.

**Example.** I return here to the functional forms of the example in Section 2. That is, I assume \( v_P(\pi) = 2\pi, \) \( v_S(\pi) = 2s(1 - s)\pi, \) and \( D(\pi) = \pi. \) In addition, I assume that \( \bar{\pi} = 0, \pi = 1, f(\pi) = 2(1 - \bar{\pi}) \) for \( \pi \in [0, 1] \) and zero otherwise, and \( \gamma(e) = e^2/(1 - e). \) Fixing \( n_G = n_B = 10, s = 0.5, \beta = 0.3, C = 0.1, \) and \( y_B + y_G = 1 \) yields the configuration depicted in Figure 3. Note that \( s^2 + 2\beta = 0.85 < 1, \pi = 1 > \bar{\pi}(1 - s^2)/(2\beta) = 0, f(\pi) > 0 \) for all \( \pi < 1, \) and \( f(1) = 0, \) as required for Assumption 3. Note also that the hazard rate is increasing. The figure plots \( e \) on the horizontal and \( \phi \) on the vertical axis. It shows iso-welfare curves and the constraint \( g(e, \phi) \leq \alpha(y_B + y_G) \) for two different values of \( \alpha, \alpha' = 0.17 \) and \( \alpha'' = 0.45. \) It also shows the line \( \phi = 2\beta\pi(1 - e); \) as patent policy approaches this line, the number of bad applications tends to zero.

The lowest iso-welfare curve, which corresponds to a welfare level of \( W_R, \) is tangent with the vertical axis; at the point of tangency lies \( \phi_R \approx 0.09. \) When intrinsic motivation is given by \( \alpha', \) the optimal patent policy that can be implemented by the planner is \( (e_{\alpha'}, \phi_{\alpha'}) \approx (0.17, 0.1). \) When \( \alpha = \alpha'' > \alpha', \) the optimal policy is \( (e_{\alpha''}, \phi_{\alpha''}) \approx (0.32, 0.12). \) The unconstrained maximum is found at the point \( (e^o, \phi^o) \approx (0.49, 0.16). \) The thicker curve that connects these points corresponds to the path that the optimal patent policy follows as intrinsic motivation expands.

Figure 4 shows what the optimal policy entails in terms of the proportion of good applications and the transfers to the examiner. It plots \( \alpha \) on the horizontal axis, \( p \) on the left vertical axis, and \( \Delta t = t_B - t_\varnothing \) on the right vertical axis. The figure is based on \( y_B = 0.6 \) and \( y_G = 0.4. \) It shows the \( \overline{\Delta t} = 0 \) locus, which is bounded above by \( y_B/(y_G + y_B), \) as established in the proof of Proposition 3. Because the constraint is binding for the range of \( \alpha \) depicted, \( t_B - t_\varnothing = \overline{\Delta t}. \) Points to the northeast of the locus are thus associated with transfers such that \( t_B - t_\varnothing > 0. \) Points to the southwest are associated with \( t_B - t_\varnothing < 0. \) The \( \overline{\Delta t} = 0 \) locus
Figure 3: Effect of an increase in intrinsic motivation from $\alpha'$ to $\alpha''$ in the example

intersects the $p(e_{\alpha}, \phi_{\alpha}, 0, 1)$ curve at $\hat{\alpha}$, where $t_B = t_\emptyset$.

As required for the Corollary to Propositions 2 and 3, we have $p(0, \phi_R, 0, 1) \approx 0.52 < y_B/(y_B + y_G) = 0.6 < p(e', \phi', 0, 1) \approx 0.72$. At $\alpha'$, the proportion of good applications is relatively low, $p(e_{\alpha'}, \phi_{\alpha'}, 0, 1) \approx 0.54$. The examiner is rewarded for granting, $t_B - t_\emptyset < 0$. At $\alpha'' > \alpha'$, the proportion of good applications is relatively high, $p(e_{\alpha''}, \phi_{\alpha''}, 0, 1) \approx 0.59$. The examiner is rewarded for rejecting, $t_B - t_\emptyset > 0$. The value of $\alpha$ that allows the planner to achieve $(e^o, \phi^o)$ is $\bar{\alpha} \approx 1.28$.

The increase in intrinsic motivation from $\alpha'$ to $\alpha''$ is associated with an increase in patent quality, as measured by $\tilde{p}$, which rises from 0.58 to 0.68. It is accompanied by a decrease in the grant rate, $p + (1 - p)(1 - \epsilon)$, which falls from 0.92 to 0.87.

5 Intrinsic motivation, patent quality, and examiner compensation in the U.S. and Europe

According to the theory, higher intrinsic motivation should be associated with higher patent quality and should make it less likely that examiners are rewarded for granting. In this section I identify plausible determinants of examiners’ intrinsic motivation, as defined in the model, and provide some empirical evidence on patent quality and examiner compensation in Europe and the U.S. that is consistent with the theoretical predictions.
**Determinants of examiner motivation.** Although I am unaware of any study that has tried to directly measure the intrinsic motivation of examiners on both sides of the Atlantic, one component of an examiner’s motivation can be assessed indirectly: the strength of implicit incentives within the organization. If the examiner cares about correct decisions in part because they affect his future with the patent office, a case can be made that how much he cares depends on how long he expects to stay at the patent office. He is likely to care more if he expects to stay long-term because, in the long run, more information about the quality of his decision-making becomes available. He can be rewarded for good decisions through promotion and punished for poor decisions through dismissal. He is likely to care less if he perceives the patent office largely as a stepping stone to a career as a patent attorney. For the same reason, intrinsic motivation is also likely to depend on the precise meaning of “long run.” That is, how timely does information about the examiner’s decisions become available? If such information only becomes available after the examiner has left the patent office, it cannot be used within the implicit incentive system.

On both of those dimensions, the U.S. and European patent offices differ considerably. At the EPO, examiners usually stay for a long time, whereas at the USPTO, examiners often
leave after short periods of time, making long-term incentives largely irrelevant. Friebel et al. (2006) report that 25 percent of EPO examiners had been at the office for more than fifteen years, compared with only 10.2 percent of USPTO examiners. The USPTO’s problems in hiring and retaining examiners have been extensively documented; see, e.g., GAO (2007), finding that more than 1600 examiners left the USPTO from 2002 to 2006 (in 2006, the USPTO employed a total of about 4800 examiners), and that 70 percent of those that left had been at the agency for less than five years.26

The EPO also has the edge in terms of timely information about decision quality, thanks to its widely-used opposition system. Opposition allows private parties to mount a challenge against questionable patents through the patent office itself. It can be triggered within nine months after a patent grant. The opposition procedure produces faster results than judicial review through the court system. Although the USPTO has a similar procedure called re-examination, it is rarely used. According to (Graham et al., 2002), during the 1981-1998 period, only 0.2 percent of patents were re-examined in the U.S., whereas 8.3 percent were opposed in Europe.

Patent quality. Even though claims about how badly the USPTO performs compared to other national patent offices are legion and anecdotal evidence about questionable patents abounds, there is surprisingly little systematic empirical evidence about patent quality.27 The correct way to assess patent quality would be to subject a random sample of issued patents to a thorough (administrative or judicial) review. The problem is that the U.S. does not have a widely-used administrative procedure and relies on the courts for the revocation of

26 In a Milwaukee Journal Sentinel article, deputy commissioner for patent operations Margaret Focarino is quoted as saying “we lose most of our examiners in the first three years” (see JSonline, August 16, 2009, available at http://www.jsonline.com/business/53365652.html).

27 In the policy debate, grant rate comparisons such as Quillen and Webster (2001) have sometimes been used as quality indicators. As highlighted by the theoretical model, however, grant rates say little about patent quality because they do not control for the quality of applications. The practice was nevertheless popular because of the scarcity of evidence on patent quality, and because grant rate comparisons seemed to indicate that the USPTO was granting patents to a substantially larger proportion of applicants than the EPO and the Japanese Patent Office (JPO). For example, Quillen and Webster (2001) report allowance rates of up to 97 percent in the U.S. More recent research takes a more nuanced stance on this issue. A careful analysis by Katznelson (2007) shows that the USPTO grant rate rose from 60 percent in the early 1980s to 76 percent in 1998. Lemley and Sanupat (2008) arrive at a similar grant rate of about 70 percent for a sample of patent applications filed in January 2001. In comparison, grant rates at the EPO and JPO hovered around roughly similar levels of about 65 percent during the late 1990s; see Trilateral Statistical Report 2007, available at http://www.trilateral.net/statistics/tsr/2007/data.xls. The difference is small and can possibly be explained by the lower number of average claims per patent application in Europe and Japan (Katznelson, 2007): for a given probability of rejection of each claim, and if a patent is issued whenever at least one claim is allowed, the grant rate increases with the number of claims per patent application. This is not to say that grant rates contain no information about patent quality at all – for example, Schankerman (1998) reports a positive correlation between the grant rate of a patent office and the average value of a patent issued by that office. What the preceding discussion suggests, however, is that the evidence from grant rate comparisons is inconclusive.
improperly granted patents, whereas Europe, with its fragmented system of national courts, relies on the opposition system, which is the only procedure that can invalidate a patent in all countries where it is in force.\footnote{Note that the patent reform bill expected to be passed by the U.S. Congress in September 2011 would create a post-grant review similar to the European opposition procedure.} The available evidence from U.S. court decisions and the European opposition procedure cannot easily be compared and should be interpreted with caution. It nevertheless lends some support to the perception that U.S. patents are of lower quality than European ones.

The probability that a litigated U.S. patent survives a validity challenge is considerably lower than the probability that a European patent survives opposition. Allison and Lemley (1998) study the population of all 299 final validity decisions in district courts and the Court of Appeals for the Federal Circuit (CAFC) between 1989 and 1996. They find that 46 percent of patents were held invalid. Similarly, in a study of 182 validity decisions by the CAFC between 1997 and 2000, Cockburn et al. (2002) report that 50 percent of patents where found to be invalid. The European opposition procedure is studied by Graham et al. (2002) who use a sample of 2021 opposed patents that were granted between 1980 and 1997. They find that opposition results in revocation of the patent in 35.1 percent of the cases. Merges (1999) reports that 34 percent of the oppositions filed in 1995 led to revocation.

Obviously, both litigated and opposed patents are subject to selection bias. There is reason to believe, however, that selection bias would reinforce the picture painted by these figures. Litigation and opposition differ in one important respect – namely, the party that initiates it. Litigation is usually initiated by the patent holder, seeking to assert its patent against an alleged infringer. Economic theory suggests that only those disputes for which the patent holder’s probability of winning is relatively large will be litigated to trial (Meurer, 1989; Chiou, 2008). In contrast, opposition is initiated by competitors of the patent holder. It seems plausible that challengers will select patents whose probability of being valid is relatively low.

Jaffe and Lerner (2004, p. 143) also report a different kind of evidence on differences in patent quality, based on OECD data on inventions that are successfully patented in all three triadic patent offices (USPTO, EPO, and the Japanese Patent Office (JPO)). Such inventions tend to be more important than those patented in a single patent office. While the number of “triadic” patents originating in the U.S. increased by 51 percent between 1987 and 1998, the total number of patents granted by the USPTO to U.S. inventors increased by 105 percent over the same period. If all three patent offices were equally rigorous, we would expect both kinds of patents to grow at approximately the same rate.
Examiner compensation. The compensation scheme for examiners at the USPTO has both fixed and variable components. The variable components include a bonus that rewards examiners who exceed a target number of “counts” (GAO, 2007). A count is awarded for each “first office action” and each “disposal.” The first office action is an official letter notifying applicants about the patentability of their invention; disposal occurs either when the examiner allows the application, or when the applicant abandons the application, files a request for continued examination (RCE), or files an appeal to which the examiner responds.\(^{29}\) This means that the fastest way for an examiner to obtain two counts is to dispose of an application through a first-action allowance. Disposing of an application through an abandonment or RCE usually requires working through a series of responses and amendments by the applicant and issuing a second office action, none of which earns the examiner any counts.\(^{30}\) As a result, it is more time-consuming to earn the second count through a rejection than through a grant. Notice that the difference in the necessary amount of time stems from the administrative part of examination (i.e., writing office actions and responding to the applicant), rather than from the search part. For any given level of search effort, a rejection takes longer. As others have noted, the count system thus essentially rewards examiners for granting patents (Merges, 1999; Jaffe and Lerner, 2004; Lemley and Shapiro, 2005).

At the EPO, examiners receive only a fixed wage (Friebel et al., 2006). There are no explicit monetary incentives tied to performance (productivity or other), although the implicit incentive system includes a regular performance evaluation that is used for promotion decisions. Performance is evaluated on four dimensions: productivity, quality, attitude, and aptitude. The productivity dimension is evaluated based on the number of actions completed. EPO management recently modified the way productivity is measured; refusals now count twice as much as grants or withdrawals.\(^{31}\)

6 Conclusion

I have presented a model of patent examination in which a benevolent planner delegates patent examination to an examiner, who receives applications filed by firms. The planner chooses an application fee for firms and an incentive scheme for the examiner, consisting of a transfer and a grant rule that depend on the examiner’s report. An application can be good or bad, and the examiner needs to exert effort to obtain a signal about it. I have modeled


\(^{30}\) Recently proposed changes to the count system (see http://www.uspto.gov/web/offices/ac/ahrpa/opa/documents/briefing_for_corps-final_draft-093009-external-jrb.pdf) leave the essence of the system unchanged.

\(^{31}\) The change was pointed out to the author by EPO controller Ciaran McGinley. In correspondence with the author, McGinley justifies the move by the fact that “experience has shown that refusals take twice as long as other finalisation processes (grants or withdrawals).”
examination as a problem of moral hazard followed by adverse selection: the examiner must be induced to provide effort but also to reveal the signal he finds, the assumption being that the signal is soft information (unverifiable by third parties, including the planner). I have also assumed that the examiner has a desire to make the right decisions, which I have termed intrinsic motivation. Finally, I have modeled the proportion of good applications as endogenous, depending on the application fee and the effort that firms expect the examiner to provide.

I have shown that soft information severely constrains the design of incentives, so that intrinsic motivation becomes a crucial determinant of the equilibrium outcome. When intrinsic motivation is low, monetary incentives may be reduced to the role of ensuring truthful revelation, leading to a seemingly paradoxical compensation scheme that rewards examiners for granting. Yet this scheme succeeds in inducing the examiner to provide effort: if the examiner anticipated not being truthful, he would optimally choose zero effort. The model also generates a complementarity between intrinsic and extrinsic rewards. As intrinsic motivation increases, extrinsic (monetary) incentives can be used more effectively, reinforcing the provision of effort. Under plausible conditions on the distribution of returns to innovation, the proportion of bad applications falls, resulting in higher patent quality.

I have argued that the modeling assumptions I use (most notably soft information and intrinsic motivation) provide a reasonable description of how patent examination works in practice. Examining patents requires assessing complex scientific evidence. Moreover, there is little short-term information about the quality of the examiner’s decisions; such information only becomes available after a delay and is difficult to contract on. It may, however, be used in the organization’s promotion and dismissal decisions, which provide long-term implicit incentives. These implicit incentives tend to create a desire to make correct decisions on the examiner’s part, consistent with how I have defined intrinsic motivation.32

Examiners are likely to care more about making correct decisions the longer they expect to stay at the patent office, and the quicker information about their decisions becomes available. A comparison of examiner turnover and procedures for administrative review at the European Patent Office (EPO) and the U.S. Patent and Trademark Office (USPTO) reveals that EPO examiners generally have longer tenure than their US counterparts, and that the administrative review procedure at the EPO is much more widely used than the one at the USPTO.32

Appendix B presents an extension in which intrinsic motivation is replaced by a random review of the examiner’s decision. It is shown that the result about the optimality of rewarding the examiner for granting can be generalized to a setting in which information about the quality of the examiner’s decision is explicitly modeled, and transfers can be contingent on this information. What is required is that there are certain restrictions on contingent transfers.
In the light of these considerations, which suggest that intrinsic motivation, as defined in this paper, is higher at the EPO than at the USPTO, the model can explain why U.S. examiners are essentially rewarded for granting patents, but also why European examiners do not face a similar compensation scheme and instead receive a fixed wage. In addition, its predictions are consistent with the fact that the quality of patents issued is generally perceived to be lower in the U.S. than in Europe.

The main policy implications concern examiner retention and administrative patent review. Retaining examiners for more than a few years allows long-term incentives to become effective, and a functioning system of administrative review makes information on the quality of examiners’ decisions available in a more timely manner. Moreover, my results suggest that incentives could be improved by implementing a random internal review of examiners’ decisions (which would not be initiated by outside parties), and conditioning bonus payments on the outcome of the review.\(^3\) While retaining examiners probably requires increasing their salary to match their outside opportunity, the resulting improvement in the quality of examination may well reduce the number of bad applications filed. This would partially offset the effect of increasing salaries on costs.

The analysis suggests that retaining examiners and creating an administrative review are desirable for reasons beyond those typically mentioned in the patent-reform debate, which has focused on the fact that more experienced examiners perform better work and that private parties may be better informed about prior art than examiners. Rather, the argument here is that both measures improve examiners’ incentives to make correct decisions and increase the scope for reinforcing effort provision through short-term compensation.

Appendix A  Patents and secrecy in continuous time

The model of returns to innovation in Section 2, where secrecy yields a fraction of the return that patent protection does, can be interpreted as the static version of the following continuous-time model, based on Denicolò and Franzoni (2004). Suppose an innovation generates a monopoly profit of \(m\) per period of time, \(t\). A patent lasts for an exogenous duration of \(T\) periods and profit drops to zero as soon as the patent expires. If a firm obtains a patent, its total discounted revenue (which corresponds to \(r\) in the text) is

\[
r = \int_0^T e^{-\rho t} m \, dt = \frac{m (1 - e^{-\rho T})}{\rho},
\]

where \(\rho\) is the discount rate. If instead the firm decides to keep its innovation secret, a leak occurs according to a Poisson process with exogenous arrival rate \(\ell\). (Thus, the expected

\(^{33}\) I thank an anonymous referee for pointing out this implication.
duration of the secret is $1/\ell$.) Assume again that profit drops to zero as soon as the secret leaks out. Expected discounted revenue under secrecy (which corresponds to $sr$ in the text) is

$$sr = \int_0^\infty e^{-\ell t} e^{-\rho t} m \, dt = \frac{m}{\ell + \rho}.$$ 

Hence,

$$s = \frac{1}{1 - e^{-\rho T}} \frac{\rho}{\ell + \rho}.$$ 

For secrecy to be less effective than patent protection ($s < 1$), we need

$$\ell > \frac{\rho e^{-\rho T}}{1 - e^{-\rho T}}.$$ 

If $T = 20$ and $\rho = 0.05$, for example, this means $\ell > 0.029$, i.e., the average duration of a secret must be less than 34 years.

**Appendix B  Random review of the examiner’s decision**

Suppose there is no intrinsic motivation but that a random review of the examiner’s decision occurs with probability $q$. The review identifies the type of an application (good or bad) correctly with probability $\nu > 1/2$, and incorrectly with probability $1 - \nu$. Let $t_{\tilde{\sigma}}^R$ denote the transfer to the examiner conditional on the reported signal, $\tilde{\sigma} \in \{B, \emptyset\}$, and the outcome of the review, $R \in \{0, G, B\}$, where 0 corresponds to no review. The examiner’s expected utility when exerting effort $e$ and reporting truthfully is

$$U = p \left[ q \left( (1 - \nu) (t_{\tilde{\sigma}}^G - t_{\tilde{\sigma}}^B) + \nu (t_{\tilde{\sigma}}^B - t_{\tilde{\sigma}}^B) \right) + (1 - p)(1 - e) \left[ q \left( (1 - \nu) t_{\tilde{\sigma}}^G + \nu t_{\tilde{\sigma}}^B \right) + (1 - q) t_{\tilde{\sigma}}^0 \right] + (1 - p)e \left[ q \left( (1 - \nu) t_{\tilde{\sigma}}^G + \nu t_{\tilde{\sigma}}^B \right) + (1 - q) t_{\tilde{\sigma}}^0 \right] \right] - \gamma(e).$$

The first-order condition determining the examiner’s choice of effort is

$$(1 - p) \left[ q \left( (1 - \nu) (t_{\tilde{\sigma}}^G - t_{\tilde{\sigma}}^B) + \nu (t_{\tilde{\sigma}}^B - t_{\tilde{\sigma}}^B) \right) + (1 - q) (t_{\tilde{\sigma}}^0 - t_{\tilde{\sigma}}^0) \right] = \gamma'(e). \quad (B.1)$$

Letting $U^*$ denote the examiner’s equilibrium utility, the two double-deviation constraints (the analogue of constraints (5) and (6) in the main text) are

$$p \left[ q \left( (1 - \nu) t_{\tilde{\sigma}}^G + (1 - q) t_{\tilde{\sigma}}^B \right) + (1 - p)(1 - e) \left[ q \left( (1 - \nu) t_{\tilde{\sigma}}^G + \nu t_{\tilde{\sigma}}^B \right) + (1 - q) t_{\tilde{\sigma}}^0 \right] \right] \leq U^*$$

$$p \left[ q \left( (1 - \nu) t_{\tilde{\sigma}}^G + (1 - q) t_{\tilde{\sigma}}^B \right) + (1 - p) \left[ q \left( (1 - \nu) t_{\tilde{\sigma}}^G + \nu t_{\tilde{\sigma}}^B \right) + (1 - q) t_{\tilde{\sigma}}^0 \right] \right] \leq U^*.$$ 

Like in the basic model, these constraints imply the incentive compatibility constraints, which I omit here for brevity. After rearranging, the double-deviation constraints become

$$(1 - p)e \left[ q \left( (1 - \nu) (t_{\tilde{\sigma}}^G - t_{\tilde{\sigma}}^B) + \nu (t_{\tilde{\sigma}}^B - t_{\tilde{\sigma}}^B) \right) + (1 - q) (t_{\tilde{\sigma}}^0 - t_{\tilde{\sigma}}^0) \right] \geq \gamma(e) \quad (B.2)$$
and

\[
(1 - p)(1 - e) \left[ q \left( (1 - \nu) \left( t_B^G - t_G^B \right) + \nu \left( t_B^B - t_B^G \right) \right) + (1 - q) \left( t_B^G - t_G^B \right) \right] \\
\leq p \left[ q \left( (1 - \nu) \left( t_G^G - t_G^B \right) + \nu \left( t_G^B - t_G^G \right) \right) + (1 - q) \left( t_G^G - t_G^B \right) \right] - \gamma(e), \tag{B.3}
\]

respectively. By (B.1), the left-hand side of (B.3) must be strictly positive for \( e > 0 \). Thus, a necessary condition for the constraint to hold is that the term in square brackets on the right-hand side is positive. Combining both facts and recalling that \( \nu > 1/2 \), we must have \( t_B^G - t_G^B < 0 \) and \( t_B^B - t_B^G > 0 \); moreover, for a given \( e \), setting \( t_B^0 - t_G^0 = 0 \) relaxes the constraint.

The expected transfer to the examiner equals \( U^* + \gamma(e^*) \). If the planner wants to minimize the expected transfer for a given amount of effort, the optimal transfers are such that only \( t_B^0 \) and \( t_G^G \) are positive, while \( t_B^G = t_B^B = t_G^G = t_G^B = 0 \). The examiner is rewarded only when the review confirms his report, and receives a fixed wage otherwise.

This is true as long as the transfers that condition on the outcome of the review \( (t_B^B, t_G^G, t_B^G, t_G^B) \) can be freely chosen. Clearly, if there are exogenous constraints on these transfers, satisfying (B.3) may make it necessary to set \( t_B^0 - t_G^0 > 0 \). Thus, the results in the main text generalize to a setting with random review of the examiner’s decision provided there are certain restrictions on contingent transfers. For example, if the information generated by the review can be used only through career concerns (and not through explicitly contracted bonus payments), restrictions could stem from the fact that there might be a limited number of promotions available, dismissal may not be credible if there is a backlog and training new examiners is costly, and so forth.

A final remark is that in the absence of restrictions on transfers, the above model with random review would be formally equivalent to the model with intrinsic motivation in the main text if \( y_B \) and \( y_G \) were among the planner’s choice variables and \( \nu = 1 \). To see this, let \( \tau = t_B^R - t_G^R \). Using \( \nu = 1 \), \( U \) becomes

\[
U = p \left( t_B^0 + q \tau_G^B \right) + (1 - p) \left[ e \left( t_B^G + q \tau_B^G \right) + (1 - e) \left( t_G^G + q \tau_G^B \right) \right] - \gamma(e).
\]

Replacing \( q \) by \( \alpha \), \( \tau_G^G \) by \( y_G \), and \( \tau_B^B \) by \( y_B \), the only difference with the utility function in (7) is the term \( q \tau_G^B \). But from the above analysis, we know that the planner will choose \( \tau_G^B = 0 \), confirming that both are equivalent.

Appendix C  Proofs

Lemma 1. Suppose \( 2\beta + s^2 < 1 \). Then, \( W_R > W_S \). Suppose moreover that \( \bar{\pi} > \bar{\pi}(1 - s^2)/(2\beta), f(\bar{\pi}) > 0 \) for all \( \pi \in [\bar{\pi}, \bar{\pi}) \) and \( f(\bar{\pi}) = 0 \). Then, \( (1 - s^2)\bar{\pi} < \phi_R < 2\beta \bar{\pi}, \) implying \( \bar{\pi} < \hat{\pi}_B < \bar{\pi} \).
Proof: Suppose the planner sets the fee so as to deter all bad applications, i.e., \( \phi = 2\beta \pi \). Then, \( \hat{\pi}_G = 2\beta \pi/(1-s^2) < \pi \), where the inequality follows from the assumption that \( 2\beta + s^2 < 1 \). Welfare is

\[
W_n \left[ \int_\pi^{2\beta \pi/(1-s^2)} v_S(\pi) dF(\pi) + \int_{2\beta \pi/(1-s^2)}^\pi v_P(\pi) dF(\pi) \right] = W_S + n_G \int_{2\beta \pi/(1-s^2)}^\pi [v_P(\pi) - v_S(\pi)] dF(\pi) > W_S.
\]

If the planner chooses a lower fee, it must be because it improves welfare, so \( W_R > W_S \), as claimed.

Because \( \hat{\pi}_G = \pi \) for any \( \phi \in [0, (1-s^2)\pi] \), the planner will always choose \( \phi \geq (1-s^2)\pi \) when \( n_B > 0 \). Evaluating (1) at \( \phi = (1-s^2)\pi \), and using the fact that \( \pi > \pi(1-s^2)/(2\beta) \) implies \( \pi_B < \pi \), we have

\[
-n_G[v_P(\pi) - v_S(\pi)] \frac{f(\pi)}{1-s^2} + n_B \left[ \beta D \left( \frac{(1-s^2)\pi}{2\beta} \right) + C \right] \frac{f(\frac{(1-s^2)\pi}{2\beta})}{2\beta} > 0,
\]

where the inequality follows from the assumptions that \( v_P(\pi) = v_S(\pi) \) and \( f(\pi) > 0 \) for \( \pi < \pi \). Evaluating (1) at \( \phi = 2\beta \pi \), we have

\[
-n_G \left[ v_P \left( \frac{2\beta \pi}{1-s^2} \right) - v_S \left( \frac{2\beta \pi}{1-s^2} \right) \right] \frac{f(\frac{2\beta \pi}{1-s^2})}{1-s^2} + n_B [\beta D(\pi) + C] \frac{f(\pi)}{2\beta} < 0,
\]

where the inequality follows from the assumptions that \( \beta > 0 \), \( f(2\beta \pi/(1-s^2)) > 0 \), and \( f(\pi) = 0 \). Thus, welfare is strictly increasing at \( \phi = (1-s^2)\pi \) and strictly decreasing at \( \phi = 2\beta \pi \), implying that the optimal application fee satisfies \( (1-s^2)\pi < \phi_R < 2\beta \pi \). 

**Lemma 2.** Suppose the incentive scheme \((t_B, x_B), (t_\emptyset, x_\emptyset)\) satisfies (2), (3), (5), and (6). Then, there exists a unique equilibrium \((p^*, e^*)\) of the examination game characterized by (11) and (12).

Proof: The examiner’s strategy set is the unit interval, \([0,1]\), which is a nonempty, convex and compact subset of \(\mathbb{R}\). His payoff function is continuous in \((e, p)\) and concave in \(e\) (because \(\gamma'' > 0\)). Because \(F\) is continuous, firms’ filing strategies (given by the thresholds \(\hat{\pi}_G\) and \(\hat{\pi}_B\)) lead to an aggregate best-response function \(p\) that is continuous in \(e\) and also takes values on \([0,1]\). By the existence theorem for Nash equilibria in infinite games with continuous payoffs (see, e.g., Theorem 1.2 in Fudenberg and Tirole (1991)), equilibrium exists.

By equation (4), \(e\) is monotonically decreasing in \(p\): if \(t_B - t_\emptyset - (x_B - x_\emptyset)\alpha y_B \leq 0\), the examiner’s best response is \(e = 0\) for any \(p\); otherwise \(e\) is strictly decreasing in \(p\). The
examination game is not well defined for \( x_B = x_\phi = 0 \); we thus only need to consider two cases. If \( x_B = x_\phi = 1 \) or \( \min\{2\beta\bar{\pi}, (1 - s^2)\bar{\pi}\} \leq \phi < \max\{2\beta\bar{\pi}, (1 - s^2)\bar{\pi}\} \), \( p \) is constant with respect to \( e \). If \( x_B = 0 = 1 - x_\phi \) and \( \phi < \min\{2\beta\bar{\pi}, (1 - s^2)\bar{\pi}\} \), we have

\[
p = \frac{n_G [1 - F(\phi/(1 - s^2))] + n_B [1 - F(\phi/[2\beta(1 - e)])]}{n_G [1 - F(\phi/(1 - s^2))] + n_B [1 - F(\phi/[2\beta(1 - e)])]} \quad \text{for } e < 1 - \phi/(2\beta),
\]

and \( p = 1 \) otherwise. This implies that \( p \) is monotonically increasing in \( e \) as

\[
\frac{\partial p}{\partial e} = \frac{N_Gn_B\phi f(\phi/[2\beta(1 - e)])}{2\beta(1 - e)^2(N_G + N_B)^2} > 0
\]

for \( e < 1 - \phi/(2\beta) \). Therefore, the equilibrium is unique. ■

**Lemma 3.** The planner’s problem is equivalent to

\[
\max_{e \geq 0, \phi \geq 0} W(e, \phi, 0, 1) \quad \text{subject to} \quad g(e, \phi) \leq \alpha(y_G + y_B),
\]

where

\[
g(e, \phi) \equiv \left(1 + \frac{n_B[1 - F(\pi_B)]}{n_G[1 - F(\pi_G)]}\right) [(1 - e)\gamma'(e) + \gamma(e)] + \left(1 + \frac{n_G[1 - F(\pi_G)]}{n_B[1 - F(\pi_B)]}\right) \gamma'(e).
\]

**Proof:** Rewriting (3) and (6) as

\[
t_B - t_\phi \leq (x_\phi - x_B)\alpha[\hat{p}y_G - (1 - \hat{p})y_B] \quad \text{(C.1)}
\]

\[
(t_B - t_\phi)[p + (1 - p)(1 - e)] \leq (x_\phi - x_B)\alpha[py_G - (1 - p)(1 - e)y_B] - \gamma(e), \quad \text{(C.2)}
\]

respectively, and using \( \hat{p} = p/\{p + (1 - p)(1 - e)\} \) so that (C.2) becomes

\[
t_B - t_\phi \leq (x_\phi - x_B)\alpha[\hat{p}y_G - (1 - \hat{p})y_B] - \frac{\gamma(e)}{p + (1 - p)(1 - e)}, \quad \text{(C.3)}
\]

we see that (C.3) implies (C.1) (and thus that (6) implies (3)). Similarly, rewriting (2) and (5) respectively as

\[
t_B - t_\phi \geq (x_B - x_\phi)\alpha y_B \quad \text{(C.4)}
\]

\[
t_B - t_\phi \geq (x_B - x_\phi)\alpha y_B + \frac{\gamma(e)}{e(1 - p)}, \quad \text{(C.5)}
\]

it becomes apparent that (C.5) implies (C.4) (and thus that (5) implies (2)). Therefore, the relevant constraints are (5) and (6), while (2) and (3) can be neglected.

Combining (5) and (6) yields the inequality

\[
(x_B - x_\phi)\alpha y_B + \frac{\gamma(e)}{e(1 - p)} \leq (x_\phi - x_B)\alpha[\hat{p}y_G - (1 - \hat{p})y_B] - \frac{\gamma(e)}{1 - e(1 - p)}
\]
\[\Leftrightarrow \frac{\gamma(e)}{e} \leq (x_\varnothing - x_B)p(1-p)\alpha(y_G + y_B). \quad (C.6)\]

As \(p\) is a function of \(e\) and \(\phi\), inequality (C.6) describes the set of \((e, \phi)\) for which there exist some transfers simultaneously satisfying both constraints, given \((x_B, x_\varnothing)\). Denote this set \(\Omega\).

Not every element in \(\Omega\) is implementable as an equilibrium. Since effort is increasing in \(t_B - t_\varnothing\), the maximal implementable effort, for a given \(p\), is obtained by substituting for \(t_B - t_\varnothing\) in (4) using the right-hand side of (C.3), yielding

\[
\gamma'(e) = (1-p)\hat{\rho}[(x_\varnothing - x_B)(y_G + y_B) - \gamma(e)/p]. \quad (C.7)
\]

Denote the set defined by this upper bound \(\Omega'\). What needs to be shown is that \(\Omega'\) is a subset of \(\Omega\). Rewrite (C.7) as

\[
\gamma'(e)[1 - e(1-p)] + (1-p)\gamma(e) = (x_\varnothing - x_B)p(1-p)\alpha(y_G + y_B). \quad (C.8)
\]

The left-hand side is nondecreasing in \(e:\)

\[
\frac{\partial}{\partial e}[\gamma'(e)[1 - e(1-p)] + (1-p)\gamma(e)] = \gamma''(e)[1 - e(1-p)] \geq 0,
\]

where the inequality follows from the convexity of \(\gamma\). A necessary and sufficient condition for \(\Omega'\) to describe a subset of \(\Omega\) thus is

\[
\gamma'(e)[1 - e(1-p)] + (1-p)\gamma(e) \geq \gamma(e)/e \Leftrightarrow \gamma'(e) \geq \gamma(e)/e.
\]

This inequality is satisfied for all \(e\) since by assumption \(\gamma\) is an increasing and convex function with \(\gamma(0) = 0\), hence its marginal is always above its average.

The next step is to show that setting \(x_B = 0\) and \(x_\varnothing = 1\) is without loss of generality. Since we must have \(x_B \leq x_\varnothing\) for incentive compatibility, there are two alternatives to consider:

(a) \(x_B = x_\varnothing = 0\), and (b) \(x_B = x_\varnothing = 1\). In both cases, (C.8) implies that \(e = 0\). Under (a), we have from (8) and (9) that \(\hat{\pi}_G = \hat{\pi}_B = \pi\), so that \(W = W_S\). The planner can achieve an equivalent outcome when \(x_B = 0 = 1 - x_\varnothing\) by setting \(\phi \geq \max\{2\beta\pi, (1 - s^2)\pi\}\). Under (b), assuming \(\max\{2\beta\pi, (1 - s^2)\pi\} < \phi < \min\{2\beta\pi, (1 - s^2)\pi\}\), we have \(\hat{\pi}_G = \phi/(1 - s^2)\) and \(\hat{\pi}_B = \phi/(2\beta)\), so that

\[
W = n_G \left[ \int_{\Xi} \phi(1-s^2)^{v_S(\pi)dF(\pi)} + \int_{\Xi} \pi^{v_P(\pi)dF(\pi)} - n_B \int_{\phi/(2\beta)}^{\pi} [\beta D(\pi) + C]dF(\pi). \right]
\]

The planner can achieve an equivalent outcome when \(x_B = 0 = 1 - x_\varnothing\) by setting \(t_\varnothing - t_B = \alpha y_B\), which, by (4), induces \(e = 0\). A similar argument applies for \(\phi \notin (\max\{2\beta\pi, (1 - s^2)\pi\}, \min\{2\beta\pi, (1 - s^2)\pi\})\).
Replacing \( x_B = 0 \) and \( x_\phi = 1 \) in (C.8), and using \( p = N_G/(N_G + N_B) \), I conclude that \( \Omega' \) is the set of \((e, \phi)\) satisfying
\[
\gamma'(e) \left(1 - \frac{e N_B}{N_G + N_B}\right) + \gamma(e) \frac{N_B}{N_G + N_B} \leq \frac{N_B N_G}{(N_G + N_B)^2} \alpha(y_G + y_B).
\]
Using the definitions of \( N_G \) and \( N_B \) and rearranging yields (14). ■

**Proposition 1.** If \( \alpha = 0 \), no examination effort can be sustained in equilibrium. An increase in \( \alpha \) weakly increases welfare and strictly increases the maximum implementable effort.

**Proof:** If \( \alpha = 0 \), the planner’s program is
\[
\max_{e \geq 0, \phi \geq 0} W(e, \phi, 0, 1) \text{ subject to } g(e, \phi) \leq 0.
\]
In equation (14), defining \( g \), the terms in parentheses are always strictly positive and \( \gamma(e) \), \( \gamma'(e) > 0 \) for all \( e > 0 \). Therefore, \( e = 0 \) is the unique solution satisfying \( g(e, \phi) \leq 0 \) for any \( \phi \).

Let \((e_\alpha, \phi_\alpha)\) denote the solution to program (13) for a given \( \alpha \), and let \( \mu_\alpha \) denote the Lagrange multiplier associated with the constraint \( g(e, \phi) \leq \alpha(y_B + y_G) \). By the envelope theorem,
\[
\frac{dW(e_\alpha, \phi_\alpha, 0, 1)}{d\alpha} = \mu_\alpha (y_B + y_G) \geq 0.
\]
For the claim that the maximum implementable effort increases with \( \alpha \), it further needs to be shown that \( \partial g/\partial e > 0 \). Letting
\[
G(e, q) \equiv (1 + q)[(1 - e)\gamma'(e) + \gamma(e)] + (1 + 1/q)\gamma'(e),
\]
and
\[
q = \frac{n_B[1 - F(\hat{\pi}_B)]}{n_G[1 - F(\hat{\pi}_G)]},
\]
we have
\[
\frac{\partial q}{\partial e} = \frac{\partial G}{\partial e} + \frac{\partial G}{\partial q} \frac{\partial q}{\partial e}.
\]
Furthermore,
\[
\frac{\partial G}{\partial e} = (1 + q)(1 - e)\gamma'' + (1 + 1/q)\gamma'' > 0,
\]
where the inequality follows from the convexity of \( \gamma \), and
\[
\frac{\partial q}{\partial e} = -\frac{(\partial \hat{\pi}_B/\partial e) f(\hat{\pi}_B)}{n_G[1 - F(\hat{\pi}_G)]} \leq 0
\]
where the inequality follows from the fact that \( \partial \hat{\pi}_B/\partial e \geq 0 \) by (9).
Being a ratio, \( q \) can take values on \([0, \infty)\). We have
\[
\frac{\partial G}{\partial q} = (1 - e)\gamma' + \left( 1 - \frac{1}{q^2} \right) \gamma,
\] (C.11)
which is positive as \( q \to \infty \) and negative as \( q \to 0 \). For \( \partial G/\partial q \leq 0 \), \( \partial g/\partial e > 0 \) follows immediately.

For \( \partial G/\partial q > 0 \), consider \( \bar{e} \equiv \max\{ e | g(e, \phi) = \alpha(y_B + y_G) \} \), which is the maximum value of \( e \) consistent with the constraint, given \( \phi \). Alternatively, \( \bar{e} \) can be defined as the largest value of \( e \) that solves the system \( \{ G(e, q) = \alpha(y_B + y_G) \} \). Equations (C.10) and (C.11) imply that the implicit function defined by \( G(e, q) = \alpha(y_B + y_G) \) giving \( e \) as a function of \( q \) is first increasing and then decreasing in \( q \). Let \( \rho \) denote its inverse defined on the decreasing part (where \( \partial G/\partial q > 0 \)), implying
\[
\rho'(e) = -\frac{\partial G/\partial e}{\partial G/\partial q}.
\]
By the definition of \( \bar{e} \), it must be the case that \( \rho'(\bar{e}) < \partial q(\bar{e}, \phi)/\partial e \). Thus, for \( \partial G/\partial q > 0 \),
\[
\frac{\partial g(\bar{e}, \phi)}{\partial e} = \frac{\partial G}{\partial q} \left( \frac{\partial q(\bar{e}, \phi)}{\partial e} - \rho'(\bar{e}) \right) > 0. \quad \blacksquare
\]

**Proposition 2.** Suppose
\[
y_B/(y_B + y_G) > p(0, \phi_R, 0, 1). \tag{17}
\]
Then, for \( \alpha \) small but strictly positive, \( e_\alpha > 0 \) and \( t_B < t_\phi \).

**Proof:** Denote \( \bar{\Delta t} \) the upper bound on transfers. From (15) and the fact that, by Lemma 3, \( x_\phi - x_B = 1 \), we have
\[
\bar{\Delta t} \equiv \alpha [\hat{p} y_G - (1 - \hat{p}) y_B] - \gamma(e) \hat{p}/p.
\]
Suppose \( \alpha = 0 \). By Proposition 1, we then have \( e = e_0 = 0 \) and \( \phi = \phi_0 = \phi_R \), so \( t_B - t_\phi \leq \bar{\Delta t} = 0 \) and \( p = p(0, \phi_R, 0, 1) \). Compute
\[
\frac{d\bar{\Delta t}}{d\alpha} = \frac{dp}{d\alpha} \alpha [y_G + y_B] + \hat{p} y_G - (1 - \hat{p}) y_B - \frac{\hat{p}}{p} \frac{de}{d\alpha} \gamma'(e) - \frac{\gamma(e)}{p^2} \left( \frac{dp}{d\alpha} p - \frac{dp}{d\alpha} \hat{p} \right).
\]
Evaluating this expression at \( \alpha = 0 \), noting that \( \hat{p} = p \) for \( e = 0 \) and \( \gamma(0) = \gamma'(0) = 0 \), we obtain
\[
\frac{d\bar{\Delta t}}{d\alpha} \bigg|_{\alpha=0} = p(0, \phi_R, 0, 1) y_G - (1 - p(0, \phi_R, 0, 1)) y_B < 0.
\]

By Lemma 1, \( 2\beta + s^2 < 1 \) guarantees that the optimal fee is interior \( ((1-s^2)\bar{\pi} < \phi_R < 2\beta \bar{\pi}) \) for \( \alpha = 0 \) and, by continuity, in its vicinity. Moreover, the constraint must be binding at
\((e, \phi) = (0, \phi_R)\) because
\[
\frac{\partial W(0, \phi_R, 0, 1)}{\partial e} = n_B \left[ \int_{\hat{\pi}_B} \left[ \beta D(\pi) + C \right] dF(\pi) + \frac{\phi_R}{2 \beta} (\beta D(\hat{\pi}_B) + C + \gamma(0)) f(\hat{\pi}_B) \right] \\
- (N_B + N_G) \gamma'(0) > 0.
\]

Thus, in the vicinity of \(\alpha = 0\), \((e_\alpha, \phi_\alpha)\) solves the first-order conditions for an interior solution of program (13), given by
\[
\frac{\partial W}{\partial e} - \mu \frac{\partial g}{\partial e} = 0 \\
\frac{\partial W}{\partial \phi} - \mu \frac{\partial g}{\partial \phi} = 0 \\
\alpha(y_B + y_G) - g(e, \phi) = 0,
\]
where \(\mu\) denotes the Lagrange multiplier. By the implicit function theorem,
\[
\begin{align*}
\frac{\partial e_\alpha}{\partial \alpha} &= \mu \frac{\partial^2 g}{\partial e \partial \alpha} \\
&= \frac{\mu \partial^2 g}{\partial e \partial \alpha} \left( \frac{\partial g}{\partial \phi} \right)^2 + \left( \frac{\partial^2 W}{\partial e \partial \phi} - \mu \frac{\partial^2 g}{\partial e \partial \phi} \right) (y_B + y_G) \frac{\partial g}{\partial \phi} - \left( \frac{\partial^2 W}{\partial e^2} - \mu \frac{\partial^2 g}{\partial e^2} \right) (y_B + y_G) - \mu \frac{\partial^2 g}{\partial e \partial \alpha}.
\end{align*}
\]
(C.12)

Clearly, \(\partial^2 g / \partial e \partial \alpha = \partial^2 g / \partial \phi \partial \alpha = 0\). Letting \(q(e, \phi) \equiv n_B[1 - F(\hat{\pi}_B)] / n_G[1 - F(\hat{\pi}_G)]\), at \((0, \phi_R)\),
\[
\frac{\partial g(0, \phi_R)}{\partial \phi} = \frac{\partial q}{\partial \phi} \left[ \gamma(0) + \gamma'(0) \left( 1 - \frac{1}{(q(0, \phi_R))^2} \right) \right] = 0,
\]
which follows from the fact that \(q(0, \phi_R) > 0\) by Lemma 1, and \(\gamma'(0) = \gamma(0) = 0\). By the same argument, \(\partial^2 g / \partial \phi^2 = 0\) at \((0, \phi_R)\) as well. Moreover,
\[
\frac{\partial g(0, \phi_R)}{\partial e} = (1 + q(0, \phi_R)) \gamma''(0) > 0.
\]

After simplifying, we obtain
\[
\left. \frac{\partial e_\alpha}{\partial \alpha} \right|_{(e, \phi) = (0, \phi_R)} = \frac{y_B + y_G}{\partial g(0, \phi_R) / \partial e} > 0.
\]

Hence, for small positive values of \(\alpha\), we have \(e_\alpha > 0\) and \(t_B - t_\phi < 0\). □

**Proposition 3.** Let \((e^o, \phi^o) \equiv \arg \max_{e, \phi} W(e, \phi, 0, 1)\). Suppose
\[
y_B / (y_B + y_G) < p(e^o, \phi^o, 0, 1) \tag{18}
\]

Then, there exists \(\hat{\alpha} \geq 0\) such that \(t_B > t_\phi\) for all \(\alpha > \hat{\alpha}\).
Proof: I start by establishing that $0 < e^o < 1$ and $(1 - s^2)\pi < \phi^o < 2\beta\pi(1 - e^o)$. Differentiating $W$ with respect to $e$ and $\phi$ yields

\[
\frac{\partial W}{\partial e} = n_B \left[ \int_{\pi_B}^{\pi} [\beta D(\pi) + C]dF(\pi) - \frac{\phi}{2\beta(1 - e)} \left( \beta D(\hat{\pi}_B) + C + \frac{\gamma(e)}{1 - e} \right) f(\hat{\pi}_B) \right] - (N_B + N_G)\gamma'(e)
\]

and

\[
\frac{\partial W}{\partial \phi} = -n_G \left[ v_P(\hat{\pi}_G) - v_s(\hat{\pi}_G) - \gamma(e) \right] \frac{f(\hat{\pi}_G)}{1 - s^2} + n_B \left[ (1 - e)(\beta D(\hat{\pi}_B) + C) + \gamma(e) \right] \frac{f(\hat{\pi}_B)}{2\beta(1 - e)}.
\]

By Lemma 1, $\arg \max_e W(0, \phi, 0, 1) = \phi_R \in ((1 - s^2)\pi, 2\beta\pi)$. Clearly, $\partial W(0, \phi_R, 0, 1)/\partial e > 0$ and $\gamma'(1) = \infty$ imply $0 < e^o < 1$. I claim that the optimal fee given $e^o$ is such that $\hat{\pi}_B < \pi$, which is equivalent to $\phi^o < 2\beta\pi(1 - e^o)$, and that $\hat{\pi}_G > \pi$, which is equivalent to $\phi^o > (1 - s^2)\pi$. Suppose otherwise, starting with the first case, $\hat{\pi}_B = \pi$. We have $\partial W(\pi, 2\beta\pi(1 - e), 0, 1)/\partial e \leq 0$ for any $e$, implying $e^o = 0$, a contradiction. Next, suppose $\hat{\pi}_G = \pi$. We have $\partial W(e, (1 - s^2)\pi, 0, 1)/\partial \phi > 0$ for any $e$, contradicting the optimality of $\phi^o = (1 - s^2)\pi$.

It follows from $0 < e^o < 1$ and $\hat{\pi}_G < \hat{\pi}_B < \pi$ that $g(e^o, \phi^o)$ is finite. Hence, there exists $\bar{a} > 0$ such that $g(e^o, \phi^o) < \alpha(y_B + y_G)$ if and only if $\alpha > \bar{a}$. By construction, when the constraint is binding, $t_B = t_\varnothing = \Delta t$. Let us find the locus in $(\alpha, p)$ space such that $\Delta t = 0$, that is,

$$\alpha[\hat{p}y_G - (1 - \hat{p})y_B] = \gamma(e)p/p.$$  \hspace{1cm} (C.13)

Using the definition of $\hat{p}$, and solving for $p$, we obtain

$$p = \frac{\gamma(e)/\alpha + (1 - e)y_B}{y_G + (1 - e)y_B}.$$  \hspace{1cm} (C.13)

From the first-order condition of the examiner’s problem (4), we have, for $t_B - t_\varnothing = 0$ and $x_\varnothing - x_B = 1$,

$$\gamma'(e) = (1 - p)\alpha y_B.$$  \hspace{1cm} (C.13)

By the convexity of $\gamma$, therefore $\gamma(e) \leq e(1 - p)\alpha y_B$, which we can use to obtain an upper bound on $p$ in equation (C.13):

$$p \leq \frac{y_B}{y_G + y_B}.$$  \hspace{1cm} (C.13)

Note that this upper bound is independent of $e$ and $\alpha$. For any $p$ that exceeds $y_B/(y_G + y_B)$, the associated $\Delta t$ is positive.

As $\alpha$ becomes sufficiently large, the constrained solution tends to the unconstrained solution, $\lim_{\alpha \to \bar{a}}(e_\alpha, \phi_\alpha) = (e^o, \phi^o)$. By assumption, $y_B/(y_G + y_B) < p(e^o, \phi^o, 0, 1)$. Hence, $\Delta t > 0$ as $\alpha \to \bar{a}$, proving that there must exist $\hat{\alpha} \geq 0$ as claimed in the proposition.
Proposition 4. The proportion of good applications satisfies (19) if either of the following holds:

(i) \( \pi \) follows the Pareto distribution;

(ii) the distribution of \( \pi \) has an increasing hazard rate, and \( \phi_o \geq \phi_R \).

Proof: Using the previous definition of \( q \), we can write \( p = 1/(1 + q) \). Thus, \( \partial p/\partial e = -\partial q/\partial e (1 + q)^{-2} \) and \( \partial p/\partial \phi = -\partial q/\partial \phi (1 + q)^{-2} \). We have

\[
\frac{\partial q}{\partial e} = -\frac{n_B \phi f(\frac{\phi}{2\beta(1-e)})}{n_G \left[ 1 - F(\frac{\phi}{1-s^2}) \right]} < 0,
\]

implying \( \partial p/\partial e \geq 0 \). The strict inequality follows from \((e_o, \phi_o)\) being interior, as established in the proof of Proposition 3. Furthermore,

\[
\frac{\partial q}{\partial \phi} = -\frac{n_B n_G f(\frac{\phi}{2\beta(1-e)})}{n_G \left[ 1 - F(\frac{\phi}{1-s^2}) \right]^2} \left[ 1 - F(\frac{\phi}{2\beta(1-e)}) \right] + \frac{n_B n_G}{1-s^2} f(\frac{\phi}{1-s^2}) \left[ 1 - F(\frac{\phi}{2\beta(1-e)}) \right] \frac{n_G}{1-s^2} \left[ 1 - F(\frac{\phi}{1-s^2}) \right]^2.
\]

Thus, \( \partial q/\partial \phi \leq 0 \) if and only if

\[
\frac{1}{2\beta(1-e)} h(\frac{\phi}{2\beta(1-e)}) \geq \frac{1}{1-s^2} h(\frac{\phi}{1-s^2}),
\]

where \( h(\pi) \equiv f(\pi)/(1-F(\pi)) \) is the hazard rate. Under condition (ii), \( h' \geq 0 \). Moreover, by Assumption 3, \( 2\beta(1-e) < 1 - s^2 \). It follows that \( \partial p/\partial \phi \geq 0 \). Hence, \( e_o > 0 \) and \( \phi_o \geq \phi_R \) imply (19).

Under condition (i), \( F(\pi) = 1 - (\pi/\overline{\pi})^a \) with \( a > 0 \), \( \overline{\pi} > 0 \), and \( \pi = \infty \). The hazard rate is \( h(\pi) = a/\pi \). It follows that \( \partial q/\partial \phi = \partial p/\partial \phi = 0 \). Hence, \( e_o > 0 \) implies (19). ■

References


