The Patent Bazaar: Incentives, Motivated Agents and Bargaining in the Patent System*

William Matcham† Mark Schankerman†

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Abstract

We develop and estimate a dynamic structural model of the patent screening process. The model incorporates incentives, intrinsic motivation and bargaining structure. We estimate the model using novel negotiation-round-level data on examiner decisions and text data from 24 million patent claims. From the claim text data, we use modern natural language processing methods to develop a new measure of patent distance. Our model estimates imply substantial variation in examiners' intrinsic motivation relative to examiners' time costs, with senior examiners less intrinsically motivated than juniors on average. With the estimated model, we calculate changes to timeliness and examination quality resulting from changes to agents' incentives and the bargaining structure. We find that a reduction in the number of negotiation rounds would improve both timeliness and quality of the patent screening process.

Keywords: Patents, innovation, incentives, screening, bargaining, intrinsic motivation
JEL Classification: D73, L32, O31, O34, O38

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†Department of Economics, London School of Economics, Houghton Street, London WC2A 2AE, United Kingdom. Emails: w.o.matcham@lse.ac.uk, m.schankerman@lse.ac.uk

1 Introduction

Public institutions play a crucial role in promoting innovation. They allocate resources for R&D in health, energy, defense and other areas, grant patent rights to enhance innovation incentives and provide subsidies for private sector R&D. To give a sense of the scale of investment, in 2015, the U.S. federal government financed 54.3 percent of total R&D expenditures, or 120.9 billion dollars, and 34.1 percent of all university research. The aggregate economic impact of these R&D investments is magnified by the extensive knowledge spillovers they generate (Jaffe, 1989; Bloom, Schankerman, and Van Reenen, 2013). In 2020, the U.S. Patent and Trademark Office (USPTO, or the *Patent Office*) issued about 390,000 new patents. These patent rights underpin innovation by enhancing the private returns to R&D and facilitating access to capital markets and the market for technology, especially for small high-technology firms (Hall and Lerner, 2010; Budish, Roin, and Williams, 2015; Galasso and Schankerman, 2018).

It is important to analyze how public agencies allocate research funds and award patent rights. In particular, we need to understand how economic incentives, intrinsic motivation in public agencies, and the organizational design of these agencies shape the efficiency of resource allocation and property rights. There is extensive theoretical literature on the interaction between extrinsic and intrinsic motivation and how it shapes the optimal design of incentives and mission-oriented agencies (e.g., Benabou and Tirole (2003; 2006); Besley and Ghatak (2005); Prendergast (2007)). There is also extensive empirical literature and some experimental work on incentives and motivation in public agencies, but these studies are reduced-form analyses relying on various proxies for motivation. As such, while illuminating, this literature generally does not allow for counterfactual analysis of how incentives and motivation interact.

The aim of this paper, as part of a broader research program, is to show how structural models can be used to study the role of extrinsic incentives, intrinsic motivation and organizational design in public agencies. We study this topic in the context of the U.S. patent system by developing a dynamic structural model of the patent screening process, which incorporates incentives, intrinsic motivation and the institutional bargaining structure. We estimate the model using novel data covering around 24 million examiner decisions on patent claims. We conduct counterfactual analysis of how reforms to incentives, fees and the bargaining structure affect the quality and timeliness of patent screening.

Screening quality in the U.S. patent system is a hotly debated policy issue. There is growing concern among academic scholars and policymakers that patent rights are becoming an impediment rather than an incentive to innovation. These concerns have been prominently voiced in public debates (The Economist, 2015; Federal Trade Commission, 2011), recent U.S. Supreme Court decisions (eBay Inc. v. MercExchange L.L.C., 547 U.S. 338, 2006) and culminated in the Leahy-Smith America Invents Act of 2011, the most significant statutory change to the patent system in half a century. Critics claim that the problems arise in large part from ineffective patent office screening, with the Patent Office granting patents to inventions that do not represent a substantial inventive step – especially in emerging technology areas such as business methods and software (Jaffe and Lerner, 2004). The issue is important because granting "excessive" patent rights imposes static and dynamic social costs: higher prices and deadweight loss on patented goods, increased transaction costs of doing R&D and even retardation of cumulative innovation (Galasso and Schankerman, 2015).

Patent prosecution is an advantageous context for studying the effects of incentives and screening mechanisms for several reasons. First, the application process has a clear and well-documented structure that can be modeled. The model we construct involves an applicant who 'pads' their patent application, attempting to extract more property rights than their invention truly entails. It is important to note that in our model, the equilibrium level of padding is endogenous. This is because the applicant chooses how much to pad in light of the incentives and the bargaining structure that they and the examiner face. The examiner's role is to grant or reject the application based on existing judicial interpretation of statutory criteria.[1] If patent examiners have some degree of intrinsic motivation – i.e. if they are aligned with the mission statement to award inventors only the property rights accorded by existing statutory guidelines – it is natural to ask why screening might be ineffective and how it could be improved. Our model will highlight how – even in the presence of intrinsically motivated examiners – the existing structure of incentives can induce strategic behavior by both applicants and examiners that may lead to excessive

[1] The first is the size of the inventive step – or conversely, how close the invention is to existing patented inventions (*novelty* and *non-obviousness*). The second is the requirement that the patent application clearly lays out the relationship between the invention and the scope of rights claimed by the applicant (*indefiniteness*). In the model, we focus on the first criterion but discuss an extension that allows for the second.

scope of patent rights in equilibrium.

The interplay between applicant and examiner in the negotiation fits naturally into a *dynamic bargaining game*, which forms the basis of the model. The key tradeoff in the model for the applicant is between the benefits of increased patent scope and the costs of engaging in a lengthy and costly negotiation with the examiner. The tradeoff for the patent examiner is between the incentives to grant applications quickly and the punishments (both intrinsic and extrinsic) for awarding an inappropriate degree of patent scope. The patent examiner searches prior art to estimate the appropriate scope of patent protection for the invention, but this estimate contains two-sided error. Examiner error implies that negotiation between the applicant and examiner, while costly, may not always be socially wasteful.

Another advantage of the patent setting is that the patent office collects detailed and extensive data on all *applications*, not just granted patents. For this paper, we constructed a dataset covering around 24 million patent application claims between 2010–2015. For every application, we observe each examiner's decision on *every patent claim*, over *all rounds of the negotiation*. We also used modern methods from Natural Language Processing (NLP) to create distances between patent claims based on claim text data. Together with the characteristics of examiners and applicants, we use these data to estimate our model of the patent application process. Among other parameters, it allows us to identify the role of intrinsic motivation in patent screening, which in turn affects the impact of reforms, such as changing incentives for patent examiners at different stages of the patent screening process. We are the first paper to incorporate intrinsic motivation into a dynamic bargaining model of a public agency.[2]

In this paper, we view a patent as a collection of (independent) claims, each of which has its own inventive step and private value. This heterogeneity is a crucial feature of the model, and, as we will see, it is central to the negotiation in the screening process. Most literature treats patents as the unit of study, which is adequate for some purposes. However, in our context, this heterogeneity is a first-order feature and is necessary to develop counterfactual analysis of reforms to the patent examination process.

[2] Egan, Matvos, and Seru (2018) include intrinsic motivation in a model of arbitration with uninformed customers, but their setting precludes repeated negotiation between agents.

Our model estimates several novel parameters with four main implications. First, we find that junior examiners are more intrinsically motivated than senior examiners. Second, the distribution of examiners' intrinsic motivation is over three times more dispersed than the distribution of examiners' time costs of examination. Intrinsic motivation is the main factor explaining the variation in examiner-specific grant rates (examiner leniency), which several recent papers have used as an instrument for patenting (Gaule, 2018; Sampat and Williams, 2019; Farre-Mensa, Hegde, and Ljungqvist, 2019). Third, senior examiners face more significant time costs on average than junior examiners. Fourth, while senior examiners overestimate distances more than juniors, their errors on patent claim distances have a lower variance than those made by juniors.

Using the parameter estimates of the structural model, we evaluate counterfactual reforms involving incentives for the patent examiners, fees for the patent applicant, and the structure of the negotiation process (e.g., limiting the number of rounds allowed). We quantify the effects of the counterfactual reforms along two distinct dimensions. The first relates to the *accuracy of screening*, meaning the degree of alignment between the scope of property rights granted and the scope justified by the invention. We assess accuracy in terms of granting claims that are not justified and not granting claims that should be. Each of these errors carries its own social costs. The second dimension is the timeliness of patent examination, measured by the number of negotiation rounds that occurs in equilibrium.

Our counterfactuals show that different types of reforms imply trade-offs between both types of accuracy and timeliness in the patent screening process, and we quantify these trade-offs. In particular, faster resolution often coincides with more frequent abandonment of valid claims. By contrast, faster resolution of the patent application is typically accompanied by *fewer* cases where the examiner grants invalid claims. This counter-intuitive feature is driven by the applicant's decision on how much to pad and whether to apply in the first place. This endogeneity of padding is a crucial feature of our model.

Despite the fact that there is, in general, a trade-off between timeliness and accuracy, we find that there is one reform that represents an *unambiguous improvement* over the examination structure currently used by the Patent Office. In the current structure, there is no limit to the number of rounds that the applicant can negotiate, as long as they pay the required fees for additional Requests for Continued Examination (RCE). We find that imposing a limit of one RCE reduces the average number of negotiation rounds by

13 percent, and at the same time, reduces *both* grants to invalid claims by six percent *and* abandonment of valid claims by eight percent. A more radical counterfactual that prohibits all RCEs reduces the average number of negotiation rounds by 41 percent and decreases grants to invalid claims by 19 percent, but introduces a trade-off in that it increases abandoment of valid claims by four percent.

We organize the rest of the paper as follows. Section 2 reviews the related economics literature. Section 3 briefly describes the relevant features of the patent examination process which guide our modeling choices. In Section 4, we describe the various data sets, and Section 5 summarizes key features of the data revealed by descriptive analysis. In Section 6, we present the model. Sections 7 and 8 describe and justify our estimation methods, respectively. Sections 9 and 10 present our empirical results and the analysis of counterfactual reforms, respectively. Section 11 concludes.

2 Related Literature

2.1 Intrinsic Motivation and Organizational Design of Public Agencies

This paper contributes to the economic literature on intrinsic motivation and the design of incentives and mission orientation in public agencies. On the theory side, Benabou and Tirole (2003; 2006) study the interaction between (various forms of) intrinsic and extrinsic motivation and the conditions under which crowding out may occur. Besley and Ghatak (2005) emphasizes how intrinsic motivation—defined as the alignment of worker and agency objectives—can induce welfare-improving sorting of workers across entities with different objectives and how it affects the optimal design of incentives and authority.

There is also some literature using field experiments to study intrinsic motivation and public agency performance and productivity. To mention two leading examples: Ashraf, Bandiera, and Jack (2014) evaluates the effect of extrinsic rewards, both financial and non-financial, on the performance of agents in a public health organization in Zambia. Their findings suggest a kind of complementarity between extrinsic rewards and intrinsic motivation. In particular, both types of extrinsic rewards improve performance, but their effects are more substantial for 'pro-socially' motivated agents. In a related paper, Ashraf, Bandiera, Davenport, and Lee (2020) studies whether career benefits attract talent at the expense of ’prosocial’ motivation. Except for low skill levels, there is no apparent trade-off, and prosocial motivation is associated with more effort and better performance.

However, these papers do not estimate the magnitude of, or heterogeneity in, intrinsic motivation, and they cannot be used for counterfactual policy analysis. For that, one needs a structural approach. Our paper is the first to incorporate heterogeneous intrinsic motivation into a structural model and to estimate its distribution within a public agency.[3] In doing this, we follow Besley and Ghatak’s definition of intrinsic motivation – alignment of workers’ objectives and the public agency mission. In our context, the patent office’s mission is to award inventors property rights over their invention, consistent with statutory and judicial prescriptions. We model this as an inherent disutility that examiners incur if they award either more or less intellectual property rights than they believe the inventor deserves. We will show that patent examiners may not always award their assessment of the correct property rights due to strategic considerations or the extrinsic pay scheme they face from the Patent Office.

Finally, very few empirical papers study how organizational screening mechanisms affect the performance of public agencies. Leading examples are Li and Agha (2015); Li (2017) that analyze the allocation of research grants at the National Institutes of Health (NIH). They show that peer review increases the effectiveness of grants in terms of post-grant citations but that, while more experienced peer reviewers are better informed, they are also more biased about the quality of projects in their area of expertise, so there is a trade-off. Azoulay, Graff Zivin, Li, and Sampat (2018) studies the economic impact of these NIH grants. Our contribution is to quantify some of these forces – in particular, examiner seniority, incentives and motivation – in a structural model of a specific public institution, the patent office. Constructing this model enables us to quantify the equilibrium effects of changes to the regime allocating resources, which none of the existing descriptive studies can do.

[3] Egan, Matvos, and Seru (2018) estimates a distribution of intrinsic motivation (“fairness”, or “slant”) in the context of consumer arbitration.

2.2 Patents and Innovation

We contribute to the empirical literature on screening in the patent system. In one of the first papers on the topic, Cockburn, Kortum, and Stern (2003) shows that patent examiner characteristics affect the 'quality' of issued patents, measured by subsequent citations and litigation. Lemley and Sampat (2012) provide additional evidence. In an extension of this line of research, Frakes and Wasserman (2017) exploits detailed data on promotions of patent examiners (accompanied by lower incentives, in the form of fewer credits for each patent examined). They show that promotions are associated with sharp increases in grant rates, controlling for examiner experience, which they interpret as less rigorous screening and lower quality patents. While this is a striking finding, their reduced-form analysis cannot pin down whether this is driven by weaker extrinsic incentives or by an increase in the examiner's opportunity cost (senior examiners are given additional responsibilities). Our paper is the first attempt to build a structural model of patent examination with strategic interaction between the applicant and examiner in a dynamic negotiation process, rather than the incentives faced by examiners alone in a static process. This approach allows us to assess, at least in principle, the separate impacts of motivation, incentives and seniority-based productivity and opportunity costs.

The most closely related paper is Schankerman and Schuett (2022), which develops an integrated framework to study patent screening, encompassing the patent application decision, examination, licensing and litigation in the courts. They calibrate the model on microdata for the U.S. and use it to evaluate various counterfactual patent and court reforms. Their model takes the effectiveness of patent examination as exogenous and estimated, but they do not model the examination process. Our paper complements their analysis but is narrower in scope as we develop the first equilibrium model of patent examination itself, which allows us to explain how reforms to the incentives and structure of screening affect patent quality.

2.3 Empirical Models of Bargaining

Finally, we contribute to the literature on structural bargaining models. The final stage of our examination game is a bargaining model where the applicant and examiner make offers and counter-offers on narrowing the patent application's scope. In many environments where bargaining is present, researchers have adopted the Nash model of bargaining.[4] This is in part due to tractability. In Nash bargaining, the exact structure of the bargaining can be unspecified, which suits environments where the structure of bargaining may be unknown, very complicated or may differ between negotiation pairs.

We avoid this approach for two reasons. First, Nash bargaining cannot explain nor accommodate bargaining breakdown. Breakdown is an essential feature of our environment since over 50 percent of patent applications result in abandonment after some rounds of negotiation. Second, the exact method of bargaining in our environment is specified by the rigid process through which patent applications must take place. Therefore, we can incorporate this bargaining process directly into our model. Moreover, in typical empirical bargaining models, the size of offers is observed in each stage. However, in our environment, we observe only the discrete decisions by examiners and applicants over which claims to reject/accept and cancel/narrow, respectively. We can identify the extent of bargaining because we observe multiple rounds of negotiation on the patent claims.

3 The Patent Prosecution Process

Now we provide a very brief overview of the patent prosecution process. In what follows, we present the minimal detail necessary to understand our model. For a more detailed description of patents and the examination process, see Graham, Marco, and Miller (2018) and Harhoff (2016). Appendix A offers a short primer on patents, including how we view a patent as a collection (a *bundle*) of claims rather than a homogeneous quantum of intellectual property protection.

3.1 Pre-Application

Before the examination, an applicant and their patent attorney draft a patent document. Most of the legal fees applicants pay to their attorneys come in the drafting phase. The applicant and attorney organize the invention into a collection of independent claims. Dependent claims typically accompany independent claims, each of which elaborates what

[4]Recent examples in IO include Grennan (2013) on medical devices, and Gowrisankaran, Nevo, and Town (2015) on the hospital sector. For the microfoundations of this approach, see Collard-Wexler, Gowrisankaran, and Lee (2019).

the inventor is claiming in extra detail . After drafting, they send their patent to the Patent Office and pay the application fee. When preparing the document, they do not know which patent examiner the Office will assign to their patent application.

3.2 Examiner Assignment and Search

Once the Patent Office receives the application, they assign it to an examiner in the relevant technology area, known as an art unit. Interviews of senior patent examiners suggest that in many art units, applications are assigned randomly to examiners (Lemley and Sampat, 2012).[5] Upon receiving and reading the application, the designated examiner searches the existing patent and non-patent (e.g., scientific publications) literature and decides whether or not to grant a patent. The examiner does this by checking whether the claims meet the legal standards of patentability. The three main grounds examined for patentability are novelty (35 U.S.C. §102), obviousness (35 U.S.C. §103) and indefiniteness (35 U.S.C. §112).[6] Novelty requires that the claim has not been in use in any way for one year before filing. Obviousness requires that the claim makes an inventive step beyond the closest existing invention that would not be immediate to anyone skilled in the relevant area. Indefiniteness requires that the claim is precise and clear on the exact boundaries of claimed property rights.

3.3 Negotiation

If the examiner chooses to grant a patent, the application process ends. The Office issues a patent once the applicant finalizes the document and pays the finalizing fee. If the examiner does not grant, they must respond to the applicant with a "non-final" rejection. This correspondence informs the applicant which of the claims the examiner rejected and

[5] Feng and Jaravel (2019) provide statistical evidence on the art units for which this is the case.

[6] There is another ground for rejection, (35 U.S.C. Section 101) – subject matter ineligibility. The main requirement for patent eligibility is that the claimed invention falls into one of four categories – process, machine, manufacture or composition of matter, as these categories have been interpreted by the courts. The Courts have identified laws of nature, natural phenomena and abstract ideas as ineligible. Section 101 rejections account for 4.5 percent of all rejections, and are concentrated in software and business methods, though not exclusively. The main governing Supreme Court decisions are Bilski v. Kappos (2010), Mayo v. Prometheus (2012), and Alice Corp. v. CLS Bank International (2014). Because they only represent a moderate amount of all rejections, we do not build them into our baseline economic model.

the grounds for rejection.

In response to the rejection, the applicant can change the patent document and resubmit it to the Office. Then, the examiner responds to the redrafted application in the same manner as before, except this time, the Office describes the rejection as 'final.' Despite the name, the applicant can respond indefinitely to 'final' rejections, the only difference being that the applicant must pay additional fees for Requests for Continued Examination (RCE) beyond the 'final' rejection. This back-and-forth negotiation lasts until the applicant abandons or the examiner grants a patent. In the U.S. patent system, the examiner cannot issue a truly final rejection to end the process. The examiner can only conclude the process by issuing a patent.

Examiners receive *credits* for their decisions during patent examinations. These credits contribute towards targets (mainly annually, though also quarterly and biweekly) set by the Patent Office. The credits are adjusted by a seniority factor, with senior examiners receiving fewer effective credits for the same amount of work. The Office also change credits according to the complexity of the examiner's technology area .[7] Credits decline over the examination process, with fewer credits for equivalent actions in RCEs relative to non-final and final rejection periods. The Office assesses examiners on their productivity (number of credits), examination quality, docket management and, less critically, their stakeholder interaction (such as customer service) (Foit, 2018).

3.4 Post-Grant

If the examiner grants the patent and the applicant pays the finalizing fees, they officially receive the patent rights. To maintain the enforceability of the patent, they must pay renewal fees in the fourth, eighth, and twelfth years after issuance. Patent protection expires 20 years after the applicant *files* the patent.

[7] See Foit (2018) for further details and Appendix section C.2 for the way that we specify credits in our economic model.

4 Data

In this section, we describe our several data sources. We focus the discussion on our datasets yet to be used for empirical economic analysis of patents and the patent system.

4.1 Distance Metric

Our first novel data source is a unique measure of independent claim distance. We use modern Natural Language Processing (NLP) methods to compute numerical representations of patent distances by calculating the closeness of the patent claim text to all other granted independent claims. We provide a complete description of the methodology in Appendix B. Below, we summarize the method and give evidence of its performance.

To construct claim distances, we use the *U.S.PTO Patent Application Claims Full Text Dataset* and the *Granted Patent Claims Full Text Dataset.*[8]. The first dataset contains the full text for all U.S patent application claims published between 2001 and 2014, alongside an indicator for whether the claim is independent. We focus on independent claims since this is the closest interpretation to distance in our model and for computational reasons. The Granted Patent Claims Full Text Dataset records the full text for all U.S. patent claims granted between 1976 and 2014, alongside an indicator for whether the claim is independent. Again, we keep only independent claims. We also require patent application data to identify the application date and, for granted patents, the grant date. We describe these data further in section 4.3. We merge these datasets, standardize the text across claims and finally compute the distances.

To work out the distance between a patent application claim and the closest in the prior art, we take a patent application independent claim, work out its distance to every existing granted independent claim, and take the minimum (or some small percentile) of the smallest distances. The approach works out the distance by representing patent claims' text as a numerical vector and calculating a metric on that vector space. After representing a patent claim's text as a vector, we use cosine similarity and angular distance, both of which are standard in the text matching and the NLP literature. We compute the cosine

[8]The data are available at `https://www.uspto.gov/learning-and-resources/electronic-data-products/patent-claims-research-dataset`, last accessed 31 August 2022.

similarity (CS) between claim text vectors x and y as

$$CS(x,y) = \frac{\sum_i x_i y_i}{\sqrt{\sum_j x_j^2 \sum_j y_j^2}}.$$

Then, we calculate the angular distance (AD), which is a proper distance metric:

$$AD(x,y) = \frac{\arccos(cs(x,y))}{\pi}.$$

Finally, we double AD to obtain a normalized distance in the interval $[0,1]$.

The standard method for representing the patent claim text as a vector uses the *bag-of-words* approach.[9] However, bag-of-words approaches have two major weaknesses: they ignore the *ordering* and the *semantics* of words (Le and Mikolov, 2014).[10] Instead of bag-of-words, we use the *Paragraph Vector* approach of Le and Mikolov (2014). This approach uses an unsupervised algorithm to "learn" the meaning of words by studying the context in which they appear and forming a vector representation for each word. It then aggregates these word vector representations to create a vector representation of the claim text. The approach allows for synonyms, antonyms and technical terminology with similar meanings, all of which are not accounted for by the bag-of-words method. The details are lengthy, and we refer the reader to Le and Mikolov (2014); Mikolov, Sutskever, Chen, Corrado, and Dean (2013b); Mikolov, Chen, Corrado, and Dean (2013a) for further information.

We created patent distances using the bag-of-words and paragraph vector approaches and found that the paragraph vector performed better. To provide one example of our trust in the distance measure, we bin independent claims into 20 five-percentile buckets of the distance measure and then calculate the proportion of claims rejected on novelty/obviousness grounds in each bin. Assume that, on average, examiners are more likely to reject claims with a small distance to existing claims based on of novelty/obviousness. Then, if our distance measure is accurate, there will be a relatively higher proportion of rejections for the smallest distances, and a lower proportion of first round rejections for the most consid-

[9] This is the approach featured in Bussy and Geiecke (2021), which applies various dimension reduction techniques to the document term matrix from the bag-of-words approach. See Appendix B for a definition of the document term matrix.

[10] As Le and Mikolov (2014) give as an example, the words "powerful", "strong" and "Paris" have equal distance.

erable distances. Figure 3 confirms this, displaying a clear negative relationship between distance and probability of novelty/obviousness rejection.

4.2 Round Data

Since we estimate a model of the patent prosecution process over multiple rounds, comprehensive and reliable *round-level* data on the patent process are essential. We create a dataset on examiner decisions by rounds using the *Transactions History* data in the *Patent Examination (PatEx) Research Dataset* (Graham, Marco, and Miller, 2018).[11] The transactions dataset includes 275,606,097 observations covering 9,204,051 unique applications. For every patent application, these data record the type and date of every communication between examiner and applicant during the examination process. From the full set of 1,873 event codes, we extract the codes corresponding to examiner non-final and final rejections, applicant responses, requests for continued examination (RCE), applicant abandonment notification, acceptance and issuance. Using these, we construct a dataset recording the round-by-round evolution of utility applications between 2007 and 2014.[12]

4.3 Sources Matched to Round Data

We match the round-level data described in section 4.2 to five other datasets on patent applications. The first is the *Application Data*, which is also a part of the *PatEx Research Dataset* mentioned in section 4.2.[13] The Application Data contains information on features of the patent application, such as the applicant's and examiner's identity, the patent art unit and an indicator for firm size. We use these data to obtain the distribution of applications across art units and technology centers, the final resolution of the patent examination (granted or abandoned), and the match between applications and examiners.

[11] The data are available at https://www.uspto.gov/ip-policy/economic-research/research-datasets/patent-examination-research-dataset-public-pair, last accessed 31 August 2022.

[12] Part of these data are available in the *U.S.PTO Office Action Research Dataset*, which we describe below. However, the Office Action Research Dataset only collects data for non-final and final rejections—typically only the first two rounds—thereby missing some RCE rounds. Second, since the Office Action Research Dataset is collected through textual analysis that searches to specifically identify *rejections*, those data cannot exactly pinpoint what happens to claims that are not rejected.

[13] The data are available at https://www.uspto.gov/ip-policy/economic-research/research-datasets/patent-examination-research-dataset-public-pair, last accessed 31 August 2022.

Since we only model independent claims, we require data on the dependency of claims across all applications. We obtain this from the *Patent Claims Research Dataset* (Marco and Toole, 2016). The authors use an algorithm to "identify individual claims as well as the dependency relationship between claims".[14] In essence, their algorithm exploits the predictable and structured form of patent claim text, wherein dependent claims explicitly refer to an independent claim in a predictable structure. Independent claims make no such structured reference to another claim.

Third, we match our data to renewal decisions using the *U.S.PTO Maintenance Fee Events Dataset*.[15] These data record the fee status of every granted patent since 1981, from which we calculate the renewal decisions of each granted patent. To estimate our model, we only require the proportion of patents renewed at each stage, which is readily available from the entire distribution of renewal decisions.

Since our baseline model focuses on novelty/obviousness rejections, we require data on the *types* of rejections at each stage of the process. We obtain this from the *U.S.PTO Office Action Research Dataset for Patents* (Lu, Myers, and Beliveau, 2017).[16] An office action "is a written notification to the applicant of the examiner's decision on patentability and generally discloses the grounds for a rejection, the claims affected, and the pertinent prior art." (Lu, Myers, and Beliveau, 2017). These data are particularly instrumental since they report all the grounds for rejection for each rejected claim. From this, we calculate the overlap between the different grounds for refusal, which motivates our focus on novelty/obviousness rejections in the baseline model.

Finally, we obtain data on examiner seniority from Frakes and Wasserman (2017).[17] They provide a panel of General Schedule (GS) grades for examiners, including each examiner's

[14] The data are available at `https://www.uspto.gov/ip-policy/economic-research/research-datasets/patent-claims-research-dataset`, last accessed 31 August 2022.

[15] These data have been used by others, including Bessen (2008) for example. The data are available at `https://developer.uspto.gov/product/patent-maintenance-fee-events-and-description-files`, last accessed 31 August 2022..

[16] The data are available at `https://www.uspto.gov/ip-policy/economic-research/research-datasets/office-action-research-dataset-patents`, last accessed 31 August 2022.

[17] The data are available at `https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/ABE7VS`, last accessed 31 August 2022.

promotion dates. Using this, we can work out the seniority of the examiner for each application.

4.4 Attorney Fees

The ideal dataset would include the attorney fees paid by the inventor at every stage of the negotiation process across all examinations. We do not have access to this. Instead, we use data from the *2017 American Intellectual Property Law Association (AIPLA) Report of the Economic Survey*.[18] Collected biennially, this survey explores "the professional characteristics of intellectual property attorneys and patent agents." In our version, approximately 450 intellectual property legal firms report their hourly fees for preparation and filing, issuing, paying maintenance and amendment/argument. The survey includes the mean, median and 10^{th}, 25^{th}, 75^{th} and 90^{th} percentile of the reported fees. The survey also splits the distributions by the complexity of the application, including disaggregated distributions for simple, biotechnology/chemical, electrical/computer, and mechanical subgroups. We use these moments to estimate inventors' application and fighting costs in our model after adjusting for inflation to match the period for which we have application data.

4.5 Technology Complexity Correction

As described in section 3.3, patent examiners' credits for their actions in the examination process are adjusted based on their seniority grade and the technical complexity of their application. We obtained the three-digit United States Patent Classification (U.S.PC) level technology credit adjustments from the Patent Office. We aggregated these to the technology center level to create an art-unit level technology complexity correction, which we provide in Table 11.[19]

[18]See `https://www.aipla.org/detail/journal-issue/economic-survey-2017`, last accessed 8 September 2022

[19]Though this doesn't exactly match the process used by the Patent Office in applying technology complexity corrections, it fits the model we estimate.

5 Stylized Facts and Model Justification

In this section, we report sources of variation in the data we explain through our model. We also provide empirical evidence for some of the modeling choices in section 6.

5.1 Effects of Examiner Seniority and Technology Center

We show that the examiner's seniority and technology center affect the applicant's outcomes. We focus on two outcomes for applicants: their grant probability and the probability of requiring negotiation with the examiner. To study the effect of examiner seniority and technology center on applicants' outcomes, we run linear regressions of dummies for grant and negotiation on dummies for GS grade, technology center and year.

Table 4 column (1) reports the regression coefficients and standard errors when the outcome is a dummy for patent issuance. Holding year and examiner seniority constant, grant rates vary between the reference technology center 16 (Biotechnology and Organic Fields), which has a grant rate of 51 percent, and technology center 28 (Semiconductors, Electrical and Optical Systems and Components.), where the grant rate is 23 percentage points higher. Grant rates increase across seniorities, with GS-14 examiners 19 percentage points more likely to grant, holding technology center and year fixed. Table 4 column (2) reports similar results for the case where the outcome variable is a dummy for negotiation. There is subtantial variation in the length of negotiation across technology centers, and negotiation is less likely with more senior examiners.

These results align with Frakes and Wasserman (2017), which follows individual examiners over the course of their promotions. The paper shows that when examiners become more senior, there are reductions in examination scrutiny and increases in granting tendencies. We explain this variation in our model by letting examiners' intrinsic motivation and time cost vary by seniority and by including differences in the credit structure for examiners across seniority and technology centers.

5.2 Distribution of Examiner Leniency

The previous results show stark differences in mean grant rates when computed across all examiners in technology centers and examiner seniority grade groups. Next, we investigate the variation in examiner-specific mean grant rates *within* seniority grade and technology center groups. Several papers show that mean grant rates for examiners also vary, even when controlling for art units and year (Gaule, 2018; Sampat and Williams, 2019; Farre-Mensa, Hegde, and Ljungqvist, 2019).

For our model, it matters whether this variation persists when looking within a technology center *and* seniority group. Indeed, we find substantial variation in examiner-specific mean grant rates (and round one examiner-specific mean grant rates) within these groups. Figures 4 and 5 plot the examiner mean grant rate distribution for two specific technology center and GS grade groups, showing variation.[20] To explain the variation in examiner-specific grant rates *within* the technology center and seniority groups, our model includes group-specific *distributions* of examiner intrinsic motivation and examiner time cost rather than constant values for each group.

5.3 Concurrence of Rejection Types

Finally, we analyze the overlap between novelty/obviousness and indefiniteness rejections. We take the Office Action Research Dataset described in section 4.3 and calculate the empirical joint distribution of novelty/obviousness (102/103) and indefiniteness (112) office action rejections for those that contain 102/103 or 112 rejections. Table 5 contains the results. First, the table reveals that, across all office actions with either a 102/103 or a 112 rejection, only 18 percent include a 112 rejection. Further, 73 percent of office actions containing a 112 rejection also contain a 102/103 rejection. These statistics imply that obviousness/novelty rejections cover most of the observed indefiniteness rejections, suggesting that omitting indefiniteness from the baseline model is a profitable abstraction.

6 Model of the Patent Process

Now we present a model of the patent application process. We model the patent application process as a dynamic game in technology center T, between an inventor, a, and an examiner, e. The game has four potential stages: (1) Application Decision and Patent Drafting, (2) Examiner Search, (3) Negotiation and (4) Renewal. Figure 8 presents a timeline of the model, and Figure 9 depicts the extensive form of the game. Also, in Appendix

[20]Similarly, the distribution of examiner average grant rates in just the first round shows even more variation. Figures 6 and 7 provide a couple of examples.

C, we discuss extensions to the model, which include examiner learning, indefiniteness rejections and dependent claims.

6.1 Application Decision and Patent Drafting

6.1.1 Inventor Type

An inventor with fighting type f has an invention they are considering patenting. They organize their invention into M_0 initial independent claims $C_1, ..., C_{M_0}$.[21] Each independent claim C_j is a pair (D_j^*, v_j^*) where v_j^* denotes the initial returns from the true version of claim j (once commercialized) and D_j^* is the distance of the correct version of claim j to the nearest *existing* invention.[22] The returns v_j^* are relative to the inventor's outside option.

6.1.2 Inventor Decision

First, the inventor decides whether to apply. If they do not, the game ends. If they do, they become an *applicant*, and the game continues. The inventor, a risk-neutral expected utility maximizer, chooses to apply if the expected utility of the game that follows applying is positive.

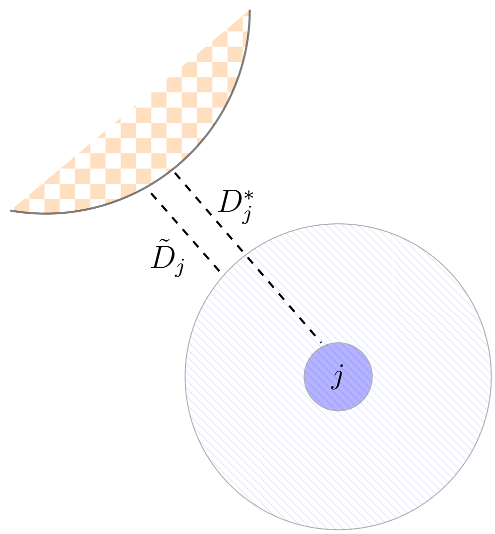
6.1.3 Padding

After deciding to apply, the applicant chooses the amount by which to exaggerate the claims on their patent application. We refer to this as the initial choice of *padding*, denoted p_0. Padding obfuscates the true metes and bounds of the invention, thereby concealing the inventive step and expanding the property rights claimed. Padding allows the patent owner to extract potentially more licensing revenue. However, greater padding also entails some obfuscation in defining the relationship between the actual invention, and the boundaries of the patent rights claimed and necessarily moves the inventor closer to the prior art. Figure 1 illustrates the concepts of independent claims and padding.

[21] We imagine that decisions on patent design and wording are made by the applicant's patent attorney, rather than the applicant. We want to avoid the intricacies of patent design and instead focus on the economic incentives for applicant.

[22] In order to cover rejections on *novelty* as well as *obviousness*, we consider an invention as existing if anyone (including the applicant) has been using it for over a year.

Figure 1: Distances and Padding



Notes: This Figure provides a visual representation of independent claims and padding. The Figure is situated in the intellectual property "space". In the image, the orange semicircle in the top left corner represents the closest existing invention to the independent claim j, which is the small full blue circle in the bottom right corner. The applicant pads the true independent claim to create the larger cross-hatched circle. The distance between the true independent claim and the nearest existing invention is D_j^*, whereas the distance between the padded claim and nearest point is $\tilde{D}_j$.

There is a tradeoff for the applicant in the choice of padding. The advantage of padding is that it increases the initial returns of claim j for the applicant from v_j^* to $\tilde{v}_j^0 = \mathcal{V}(v_j^*, p_0)$, where the padded value function $\mathcal{V}(\cdot, \cdot)$ is increasing in both arguments. On the other hand, padding increases the likelihood of examiner rejections during the examination process on the grounds of nonobviousness and indefiniteness. Padding shrinks independent claim distances from D_j^* to $\tilde{D}_j^0 = \mathcal{D}(D_j^*, p_0)$. The padded distance function $\mathcal{D}(\cdot, \cdot)$ is increasing in the distance argument and decreasing in the padding argument. For larger padding values, claims are more likely to be rejected for being too close to existing inventions, all else equal. Finally, there is a direct cost of padding through the application fee. The application fee is proportional to padding because heavily padded applications require more time to craft.

6.1.4 Applicant Expected Utility

The applicant decides the initial level of padding without knowledge of the identity of the examiner the Patent Office will assign. This feature is relevant because examiners differ in types (seniority, productivity and intrinsic motivation) and therefore in their actions. As a result, applicants make initial padding decisions with consideration of the distribution of examiner types. The applicant chooses initial padding to maximize their expected utility, where the expectation is taken first over the roster of potential examiners, then over examiner error and probability of potential obsolescence of their invention (all described later).

6.1.5 Decision to Apply and Patent Drafting: Summary

To summarize the first stage: there is an inventor who has an invention they may wish to patent. First, they decide whether to apply for a patent or not. If they apply, the applicant chooses how much to pad, trading off increased returns with an increased probability of rejection. The applicant decides how much to pad before the Patent Office assigns an examiner. Resultantly, the applicant must take into account the distribution of examiners that could be given the application, along with the cost they will face in negotiating over rejected claims.

6.2 Examiner Search

With the application submitted, the Patent Office assigns an examiner to the application in the second stage. This examiner searches the existing patent and non-patent literature (prior art) before making their first decision.

6.2.1 Examiner Assignment

The patent office assigns the application randomly to an examiner within the relevant art unit of the technology center. We characterize an examiner by the tuple (S, θ, π). Examiner seniority S is a pair of General Schedule grades ranging from GS-5 to GS-14 and a signatory authority level. For GS grades 5 to 12, examiners cannot have signatory authority. For GS-13, the signatory authority level can be "none" or "partial," and for GS-14, signatory authority can be "partial" or "full." Each GS grade and signatory authority level pair corresponds to a seniority factor S, used to calculate an examiner's production goal.[23] The type θ corresponds to the level of intrinsic motivation. More intrinsically motivated workers place a higher cost on awarding patent rights that differ from their best estimate of the true scope embodied in the invention. We let the distribution of θ depend on seniority S. Finally, π corresponds to the examiner's time cost of putting in work to the application. Examiners will differ in their productivity, and they also face other tasks to complete at work besides patent examination.

6.2.2 Examiner Grounds for Rejection

Once assigned, the examiner learns the applicant's identity and observes f. Next, the examiner reads the application and conducts an independent search of the existing prior art to assess the grounds for rejection throughout the negotiation process. We focus on the *obviousness/novelty* ground for rejection (35 U.S.C. §102/103).[24] After searching the prior art, the examiner assesses the obviousness/novelty of each claim j, denoted $\hat{D}_j$, equal to

$$\hat{D}_j = \mathcal{D}(D_j^*, p) \cdot \varepsilon_j,$$

with ε_j denoting examiner error in assessing obviousness/novelty. This error is independent of D_j^*. The distribution of search error depends on the seniority of the examiner, and it may also depend on the technology center since literatures across technology fields vary in complexity and denseness. The distribution of search error also depends on the intrinsic motivation of the examiner. We specify that the *mean* of the search error satisfies two criteria. The first is that the mean of the error tends to one as $\theta \to \infty$. The second is that for all $\theta < \infty$, the mean of the search error distribution is greater than one. We specify the second feature because examiners who aren't perfectly intrinsically motivated may not scour the literature thoroughly, thereby missing relevant prior art. When they miss relevant prior art, they perceive distances to be larger than they are and hence have errors greater than one. However, these requirements do not force one-sided examiner error since some draws may still be below one, even if the mean is well above one.

The examiner has *grounds* for an obviousness rejection if $\hat{D}_j$ is less than an obviousness threshold τ. Having grounds for rejection will not necessarily mean the examiner will

[23] See Foit (2018) for further details.

[24] See section 5.3 for an empirical justification on why we abstract from indefiniteness (35 U.S.C. §112) and (35 U.S.C. §101). We describe an extension that includes indefiniteness in section C.1.2.

reject the claim. The examiner's decision will be the one that maximizes utility taking into account pecuniary incentives and intrinsic motivation.

6.2.3 Summary and Additional Comments

To summarize the Examiner Search stage: the Office assigns an examiner randomly, and upon reading the application and searching the literature, the examiner error ε_j realizes. With this, the examiner calculates the initial grounds for rejection, after which he is ready to enter the negotiation phase. Before describing the final part of the model, there are a couple of important points worth noting.

First, the model we lay out distinguishes explicitly between grounds for rejection and decisions to reject. As we just mentioned, having grounds for the rejection does not mean that the examiner definitely will reject it. An overarching point of the model is that examiner decisions are made based on examiner payoffs and not necessarily on legal grounds. This feature means that examiners' decisions in the data may not align with decisions made solely on legal grounds.

Second, examiner errors are constant throughout the negotiation stage. In this sense, there is no updating of examiner error. However, the grounds for rejection will be recalculated at every negotiation round, as the applicant changes their padding.

6.3 Negotiation

The Negotiation Stage is a finitely repeated version of the stage game shown in the "Negotiation" section of Figure 9.[25] The applicant and examiner discount each stage at rates β_a and β_e, respectively. We detail the actions and payoffs obtained at the two decision nodes in turn, supposing we have reached round r.

6.3.1 Examiner Grant/Rejection

First, the examiner obtains updated assessments $\hat{D}_j^r = \mathcal{D}(D_j^*, p_0\eta^{r-1})$, where η is the narrowing proportion defined in section 6.3.2. Based on their updated assessment, the

[25] In principle, there is no limit of the number of repetitions allowed, around 95 percent of applications last at most three rounds of negotiation and the modal number is two. In the computation of the model that we estimate, we limit the number of rounds to six

examiner recalculates the grounds for rejection. Then they make their decision on whether or not to grant the patent.

Granting

Granting a patent ends the negotiation game and moves the applicant into the renewal stage. Let $\mathcal{R}_r \in [0, 1]$ denote the proportion of claims the examiner thinks they should reject on obviousness/novelty grounds. Then the immediate payoff to the examiner from granting is

$$g^r_{GR}(S, T) - \theta\mathcal{R}_r.$$

Here $g^r_{GR}(S, T)$ is the credit received by the examiner for granting at stage r. We explicitly denote its dependence on both seniority and technology center here. The Patent Office expects more senior examiners to deal with more applications per quarter. Therefore, the effective number of credits for each action is lower. We provide the full schedule of examiner credits in Appendix C. The term $\theta\mathcal{R}_r$ captures the intrinsic penalty to the examiner. For intuition on this term, consider the extreme cases. When $\mathcal{R}_r = 0$, the examiner believes there are no independent claims on which they have grounds to reject, hence feels no intrinsic disutility from granting the application. On the other hand, when $\mathcal{R}_r = 1$, the examiner believes they should reject every independent claim, so the examiner is very much going against the organization's mission statement in granting a patent. The examiner's intrinsic penalty from premature granting is the product of the proportion of strategically incorrect claim acceptances and their intrinsic motivation.

Regarding the applicant's payoff, if the examiner grants the patent, they must pay the finalizing fee ϕ, and then they enter a renewals model, described in subsection 6.4.

Rejecting

If the examiner chooses not to grant, they get credits $g^r_{REJ}(S, T)$, and the stage game continues. The examiner follows this choice by rejecting any claim on which there are §102/3 grounds to reject. Hence, the examiner rejects any independent claim j if $\hat{D}^r_j < \tau$. After this, the application moves back into the hands of the applicant, who decides whether to abandon or continue the application.

6.3.2 Applicant Abandonment/Continuation

Upon receipt of a rejection, the applicant has two choices. One option is to abandon. Abandoning gives the applicant a period payoff of zero, and the examiner $g^r_{ABN}(S,T)$ credits. The applicant obtains a period payoff of zero because the Patent Office reveals their invention through publishing their patent, so their potential for intellectual property protection has vanished.

Instead of abandoning, the applicant can choose to continue the application. Continuing involves narrowing rejected claims, and we model this by a reduction in padding p by proportion η.[26] Hence for all **rejected** claims j, the padding becomes $p_{j,r+1} = \eta p_{j,r}$. The padding level remains the same for all accepted claims.

Continuing involves a fighting cost to the applicant. This cost is equal to $fp_0\eta^{r-1}$ for each rejected claim. In the case of a Request for Continued Examination (continuing beyond round two), the applicant faces a direct monetary cost along with the indirect costs. Continuation involves further work for the examiner, which comes in at cost π. Continuation to an RCE gives the examiner the credits $g^r_{RCE}(S,T)$

With probability $P_{obs,app}$ the applicant's invention become obsolete. In this case, all returns shrink to zero, and, trivially, the applicant abandons. After narrowing occurs, the applicant pays fighting costs and obsolescence realizes or not, we move to round $r+1$ and continue with another round of negotiation, discounted once more.

6.4 Renewal

We enter the renewals stage if the examiner grants the patent and the applicant pays the finalizing fee. Our renewals model adapts Schankerman and Pakes (1986) to the United States context, adding obsolescence.[27] The returns for granted claims j start at $\tilde{v}_{j,r} = \mathcal{V}(v^*_j, p_r)$ and depreciate at rate δ each period after grant. With probability $P_{obs,renew}$, the invention becomes obsolete, at which point the returns shrink to zero. To keep the patent rights, the applicant must pay renewal fees F_4, F_8 and F_{12} at years four, eight, and twelve

[26]In a richer model, the applicant could choose whether to narrow by the proportion η or not.

[27]Equivalently, it is the model of Lanjouw (1998) without learning and also it is similar to Bessen (2008), except with non-stochastic initial returns and obsolescence.

after grant. The patent life ends at 20 years, at which point the invention ceases to be the inventor's intellectual property. Since the fees increase over time non-stochastically and the patent value depreciates over time non-stochastically, there is an optimal ex-ante renewal length for the applicant, say T^*, and conditional on the invention not becoming obsolete, the applicant renews for T^* years. This value of optimal renewal length maximizes the applicant's expected utility from retaining patent rights.

7 Estimation

In what follows, we explain how we map our model to our data. We use three approaches to estimate the complete set of model parameters. The first is calibration, the second is *external estimation* (by which we mean estimation *outside* the model) and the third is simulated method of moments. We describe the estimation technique and the parameters we estimate from each one of the three in turn.

7.1 Calibration

The data lack some detailed information for identifying all parameters. Specifically, discount rates are traditionally difficult to identify, and we fix them to $\beta_a = \beta_e = 0.95$—similar to common choices in the literature (Pakes, 1986).

7.2 External Estimation

We take advantage of the fact that we can estimate most of the fighting costs and the distance threshold τ outside the model.

7.2.1 Distance Threshold

We estimate the distance threshold externally using observations on claim distances and examiners' grant and rejection decisions. For every examiner, we calculate the minimum of the distances among claims they grant. This number corresponds to their "personal threshold." Because examiners aren't perfectly intrinsically motivated, some examiners' personal thresholds will be below the actual threshold in cases where they knowingly grant patents with relatively small distances. However, the most intrinsically motivated examiner will have a personal threshold equal to the true threshold τ since they apply the rules laid down by the Patent Office perfectly and never grant a distance below the threshold the Office trains them to use. Hence, we estimate the distance threshold as a top percentile of the distribution of examiners' personal thresholds. We experiment with the maximum value and the first and second percentiles. We also remove examiners who have conducted fewer than a threshold number of examinations. We experiment with values of 50 and 100 for this threshold and find minor differences in each case.

7.2.2 Negotiation Fighting Costs

As described in section 4.4, we have data from the AIPLA on the distribution of the *amendment*, *maintenance* and *issuance* hourly fees charged by lawyers. We assume that all three costs are log-normally distributed, each characterized by two parameters $\mu_{f_{ammend}}$ and $\sigma_{f_{ammend}}$, for example. Since these moments directly correspond to the elements of applicant fighting cost, and these moments do not identify any other parameters in the model, we run a two-step generalized method of moments estimation procedure for each of the three negotiation-based fighting costs. All three cases are over-identified because there are two parameters of a log-normal distribution, yet we observe the mean, median, and 10^{th}, 25^{th}, 75^{th} and 90^{th} percentile of legal fees. We also observe different distributions for different technologies, so we estimate different in-negotiation fighting cost distributions for each technology center. Finally, on application fighting costs, though we have similar moments on lawyers' application drafting fees, because this is proportional to padding in the model its distribution is contaminated by the endogenous choice of padding (which is a function of all model parameters). As a functional form, we choose that application costs are equal to $f_{app} \cdot (1 + |p_0 - 1|)$. The motivation for this functional form is that it takes time to under-pad ($p_0 < 1$) and over-pad ($p_0 > 1$), and that writing down the truth $p_0 = 1$ is quickest. This feature means that we cannot estimate the distribution of application fighting costs outside the model: we must estimate these parameters as part of the simulated method of moments procedure described next.

7.3 Simulated Method of Moments

We estimate the bulk of the parameters using simulated method of moments. The model does not admit an analytic solution for endogenous variables as a function of all the model primitives. Hence, the goal is to choose the parameters that best match moments of the data with the corresponding moments computed from the model's numerical solution. We estimate the model using the data described in Section 4, assuming they are generated from the model's equilibrium. We estimate a pooled model across technology centers, though an extension estimating the model technology center by technology center is possible.

We require functional form choices for some model elements to estimate the model's parameters. Regarding functional form choices for initial true returns and distances $\mathcal{V}$ and $\mathcal{D}$, we choose $\tilde{v}_j^0 = p_0 \cdot v_j^*$ and $\tilde{D}_j^0 = D_j^*/p_0$. In this case, p_0 represents the proportion by which returns increases and distance decreases.

We denote the full vector of parameters to estimate as $\boldsymbol{\psi} = (\boldsymbol{\psi}_e, \boldsymbol{\psi}_a)$, composed of examiner and applicant parameter vectors $\boldsymbol{\psi}_e$ and $\boldsymbol{\psi}_a$, respectively. The vector of applicant parameters is $\boldsymbol{\psi}_a = (\alpha_D, \beta_D, \mu_v, \sigma_v, \mu_{f_{app}}, \sigma_{f_{app}}, \eta, P_{obs,app}, P_{obs,renew})$. The latter three parameters $\eta, P_{obs,app}$ and $P_{obs,renew}$ are as described in the model. The pair (α_D, β_D) are the parameters of a beta distribution for distances. We choose a beta distribution since we normalize distance to $[0, 1]$. We use a multivariate normal distribution copula to generate correlation among distances.[28] The parameters (μ_v, σ_v) are the parameters of the log-normal distribution for claim initial returns v_j^*, a parametric assumption motivated by Schankerman and Pakes (1986). Finally, as mentioned in the previous subsection, inside the model, we estimate the (again log-normal) parameters of the distribution of application drafting legal fees, $\mu_{f_{app}}$ and $\sigma_{f_{app}}$.

The vector of examiner parameters is $\boldsymbol{\psi}_e = (\boldsymbol{\mu}_\theta, \sigma_\theta, \boldsymbol{\mu}_\pi, \sigma_\pi, \boldsymbol{\sigma}_\varepsilon)$. The two parameters $(\boldsymbol{\mu}_\theta, \sigma_\theta)$ correspond to the log-normal parameters for the distribution of examiner intrinsic motivation. The mean is emboldened as a vector because we estimate different mean parameters for "junior" (pre-GS-14 grade and partial signatory authority) and "senior" examiners. The same conventions apply for examiner costs π. The examiner errors are normally distributed, and we estimate different parameters σ_ε for junior and senior examiners. As discussed in the model, we link the mean of each examiner's error distribution to their intrinsic motivation. For an examiner with intrinsic motivation draw θ, we specify

[28]Specifically, in the simulation, for each application, we draw a vector of size M_0 from a standard multivariate normal with correlation coefficient ρ. We apply the quantile function of the normal to the draws to create correlated uniform random variables. Then for the estimation guess $(\tilde{\alpha}_D, \tilde{\beta}_D)$, we apply the inverse CDF of a beta distribution with these parameters to the uniform draws to generate correlated beta distributed initial distances. See Nelsen (2007); Wicklin (2013) for more detail.

$\mu_\varepsilon = 1 + \dfrac{1}{\theta}$.

We estimate $\boldsymbol{\psi}$ using a minimum-distance estimator that matches key moments of the data with the corresponding moments implied by the model. More specifically, for any value of $\boldsymbol{\psi}$, we solve the model for several simulated draws from the distributions of exogenous variables. This generates moments for the endogenous variables over simulated observations. We calculate two sets of moments: one corresponding to outcomes for examiners $\boldsymbol{m}_e$ and another for applicants $\boldsymbol{m}_a$. In the next section, we describe the moments we use and how they link to model identification.

Obtaining outcomes from the model requires calculating the value of initial padding p_0. Since there is no closed form for initial padding, for each parameter guess and each simulation, we solve for the applicant's initial padding choice by maximizing their expected payoff over all examiners and their potential errors. Then we select p_0 as the value which maximizes the applicant's expected payoff.

The final parameter we are yet to describe is the renewal depreciation parameter δ. We do not estimate this parameter. Instead, we apply the estimated value from Bessen (2008) to our context. Bessen (2008) estimates a composite value of depreciation that contains both depreciation and the probability of obsolescence. Hence, for each parameter guess of $P_{obs,renew}$, we extract the implied pure depreciation value by inverting the definition of Bessen's composite term to obtain the pure depreciation. [29]

The minimum-distance estimator minimizes the simulated method of moments (SMM) objective

$$\hat{\boldsymbol{\psi}} = \arg\min_{\psi} \left(\boldsymbol{m}(\psi) - \boldsymbol{m}_{\mathcal{S}}\right)' \Omega \left(\boldsymbol{m}(\psi) - \boldsymbol{m}_{\mathcal{S}}\right)$$

where $\boldsymbol{m}(\psi) = (\boldsymbol{m}_e(\psi), \boldsymbol{m}_a(\psi))$ is the vector of simulated moments computed from the model when the parameters are ψ, $\boldsymbol{m}_{\mathcal{S}}$ is the vector of corresponding sample moments, and Ω is a symmetric, positive-definite weight matrix.[30] We use Julia's `BlackBoxOptim` global optimization command to solve for the estimates. We describe further computational

[29] See Schankerman and Schuett (2022) for more details.

[30] As weight matrix we use a diagonal matrix that scales moments to a uniform scale. We cannot use the optimal two-step weight matrix since we do not have available corresponding data on fighting costs that can allow us to compute the correlation between these moments and others.

details in Appendix D

For a sample size n of the data on which we calculate moments, the estimator $\hat{\psi}$ is $\sqrt{n}$ consistent and asymptotically normal for all choices of the number of simulations (Gourieroux and Monfort, 1996). Since we do not have data on fighting costs at the application level, we cannot estimate the asymptotic variance-covariance matrix, so we bootstrap our standard errors.

8 Moments and Intuition for Identification

In this section, we describe how we choose the moments to include in $\boldsymbol{m}_{\mathcal{S}}$ for our simulated method of moments estimation and explain how these moments aid in identifying the parameters we estimate. The model is highly nonlinear, which means that (almost) all parameters will affect all outcomes. This feature makes explicit statements on the precise sources of parameter identification practically impossible. However, in what follows, we provide intuition on how key moments in the data aid in identifying some parameters.

8.1 Available Moments

We split our available moments into seven groups and describe these groups in turn.

Our first group of moments corresponds to examiners' issuance and applicants' abandonment decisions. For each round in the model and each seniority level, we calculate the proportion of applications examiners grant and the proportion that applicants abandon. Since there are nine seniority grade-signatory authority pairs, and we observe at least six rounds, this implies at least 108 moments on grants and abandonments.

Second, we observe the distribution of the proportion of claims rejected, both by round (six) and by seniority grade-signatory authority pair (nine). These observations generate another 54 moments.

Third, we observe the proportion of granted patents that renew at four, eight and twelve years after issuance. These observations generate four moments on patent renewals (don't renew at four, renew at four but not eight, renew at eight but not twelve and renew at twelve).

Fourth, we calculate the distribution of claim distances by round. We calculate the mean and standard deviation of the distance distribution by round for at least six rounds, implying at least 12 moments on distance. Another moment comes from the within-application distance correlation.

Fifth, at each of the nine seniority grades, we calculate each examiner's *leniency*, which is their average rejection rate across all the applications they examine. Hence for each seniority grade-signatory authority pair, we obtain a distribution of examiner rejection rates, for which we can calculate the mean and standard deviation of the distribution of examiner fixed effects. From this we obtain another 18 moments.

Next, given that we can identify the distance threshold externally, we calculate the proportion of granted patents containing at least one invalid claim (that is, a claim whose distance is below the distance threshold). Hence, for each round and each seniority, we calculate the proportion of patents granted containing an invalid claim, implying another 54 possible moments.

Finally, as described in section 7.2.2, we observe the distribution of application fighting costs. We have six moments on the distribution of legal application fees for four technology categories (simple, chemical, electrical and mechanical), which we match to the technology centers on which we estimate the model. This implies another 24 possible moments.

8.2 Chosen Moments

We have hundreds of data moments that we can calculate from endogenous variables in the model. Since we have 24 model parameters, in principle, we are over-identified. However, not all moments will aid the estimation procedure in identifying the parameters, so we assist by pruning the set of moments for estimation.

We followed a rigorous, data-driven methodology to create a subset of the moments that best estimate the parameters. To do this, we calculated the sensitivity matrix described in Andrews, Gentzkow, and Shapiro (2017). As the authors explain, "sensitivity gives a formal, quantitative language in which to describe the relative importance of different moments for determining the value of specific parameters." Further, as described in Jalali, Rahmandad, and Ghoddusi (2015), for each parameter and moment, we plot the value of the moment for different values of the parameter, fixing the other parameters at their estimates. If this curve is flat, this parameter does not influence on the value of the moment. For a given moment, if the curve is flat across all parameters, it suggests that the moment offers no useful variation to identify the parameters. We provide examples of successful and unsuccessful moment plots in Figures 10 and 11.

For each parameter, we also plot the value of the SMM objective across all values of the parameter, fixing other parameters at their estimates. Ideally, the SMM will be U-shaped in each parameter to ensure a well-defined global minimum exists. By doing this, we learn how well we pin down parameters based on the set of moments we have available. Figures 12 and 13 show some examples of these plots.

By combining the sensitivity matrix with moment and SMM plots, we pruned the set of moments down to those that offer some assistance in estimating the parameters. Since we split many parameters into two seniority groups (junior and senior), we split some of our moments into the same seniority categories. We converged to the following set of moments, which we split into those that relate to examiner and applicant outcomes separately. The selected moments corresponding to outcomes for examiners are:

(i) The proportion of applications granted in each round for juniors and seniors, for rounds one, two, three, and all rounds after four combined [eight moments]

(ii) The standard deviation of the distribution of examiner rejection rates for six seniority categories (GS levels 7, 9, 11, 12, 13 and 14) [six moments]

(iii) The proportion of patents granted containing an invalid claim (for juniors and seniors) for rounds one and two [four moments]

The moments corresponding to outcomes for applicants are:

(i) The proportion of abandonments in each round, when the assigned examiner is junior and senior, for rounds one and two [four moments]

(ii) The proportion of granted patents not renewed, renewed at year four but not eight, renewed at year eight but not twelve and renewed at year twelve [four moments]

(iii) The mean and standard deviation of the distribution of granted claim distances for rounds one, two and three [six moments]

(iv) The within-application correlation of distances on granted patents [one moment]

(v) Mean and median of legal application fees for four technology areas [eight moments]

In total, this yields 41 moments. Of course, since there is some leeway in the choice of moments we use, we conduct multiple robustness checks and have available a set of external moments that we can use to assess the model fit. We discuss this further in the results section.

8.3 Identification

A model is either identified or not, and technical conditions on the required variation in exogenous variables determine whether a model is identified (Keane, 2010; Andrews, Gentzkow, and Shapiro, 2017). Due to our model's complicated and nonlinear nature, we cannot calculate these conditions. However, there is some value in explaining which moments aid in pinning down specific parameters of the model.

We start with the parameters relating to the applicant. The renewal rates, together with moments on applicants' abandonment decisions, aid in identifying the parameters of the distribution of ex-ante values μ_v, σ_v. This is because, all else equal, an applicant with higher returns is less likely to abandon and more likely to renew, conditional on being granted. The renewal moments also aid in identifying the post-grant obsolescence probability $P_{obs,renew}$. Similarly, the ex-post claim distribution of padded distances, as calculated using the distance between text vectors, aids in identifying the parameters of the distribution of ex-ante distance, i.e., α_D, β_B. The ex-post correlation of granted distances helps identify the within-application correlation of actual distances D_j^*. Moments on application fighting costs directly pin down the distribution of application fighting costs, $\mu_{f_{app}}$ and $\sigma_{f_{app}}$. Regarding application obsolescence, $P_{obs,app}$, the only case in which an applicant abandons in the interim rounds two to four is when they become obsolete. Therefore, interim round abandonments offer sharp variation to identify the obsolescence probability in the application process. Changes in the value of η change moments on ex-post distance so η is picked up by residual variation in these moments.

Regarding the examiner, intuition for identification is more complicated. We identify the distribution of examiner intrinsic motivation $(\mu_\theta, \sigma_\theta)$ and examiner time costs (μ_π, σ_π) in part through the variance in examiner rejection rates by seniority group. Since examiners are randomly assigned to applications, the factors that explain differences in examiner-specific rejection rates for a given seniority level and technology center are examiner intrinsic motivation and time costs. Furthermore, each examiner has the same time cost across all applications and rounds, but faces varying intrinsic motivation costs at each round of every application (because $\mathcal{R}_r$, the proportion of invalid independent claims varies across rounds and applications). Resultantly, variation in within-examiner decisions across rounds aids in identifying the distributions of intrinsic motivation and time costs.

It remains to discuss examiner error. Suppose examiner-specific rejection rates pick up both intrinsic motivation and time costs. In that case, the distribution of overall examiner grant rates by round and the distribution of examiner errors by round are free to pin down examiner error parameters. Otherwise, these moments combine to pin down examiner error alongside intrinsic motivation and examiner time costs. It is difficult to tease apart these parameters from these moments, but these moments' combined variation assists in identifying the parameters' values.

9 Estimates and Fit

At this point, we present and interpret our parameter estimates. We split the discussion, naturally, into the applicant and examiner parameters. After presenting the estimates, we discuss model fit and robustness. For all parameters, standard errors are negligible, and all parameters are statistically significant.

9.1 Applicant Parameters

Table 6 presents the estimates and standard errors of the parameters relating to the applicant. In what follows, we interpret the set of parameters, with all values and fighting costs measured in 2013 U.S. dollars.

We estimate the proportion of narrowing by round as $1 - \eta = 0.23$. Shaving 23 percent of the padding in each round is substantial. Still, this value includes the effect of cancellations (which we do not feature in the baseline model) and the fact that some applicants will refute the examiner's request for narrowing entirely. As a result, the amount of narrowing by round, *conditional on narrowing*, is bounded above by 23 percent.

We estimate two probabilities of obsolescence: one in the application and one post-grant in renewals. We estimate that the applicant has a 13 percent probability of becoming obsolete in each negotiation round,. We know of no other estimates of this value in the literature. The likelihood of obsolescence after grant, estimated at 4 percent, is similar to those already available in the literature.[31] The value is higher during the application process for two reasons. First, applicants are more likely to discover that their invention is obsolete earlier in the invention life cycle. Second, the prosecution stage contains applications that are eventually granted and those who abandon and many of those who abandon do so precisely because they become obsolete.

Figure 14 plots the distribution of *application*, unpadded initial returns for independent claims as implied by a log-normal distribution with parameters $\mu_v = 9.556$ and $\sigma_v = 0.645$. The median unpadded initial returns from an independent claim is \$14,129.22, but the modal value of independent claims' unpadded initial returns is \$9,321. To understand the distribution of initial returns on the *application*, we take the distribution of the number of independent claims and use it to construct sums of draws from the distribution of claim returns. For example, the first patent application in our dataset has two independent claims. Hence we draw two values from the distribution of claim initial unpadded returns and add them to get the total initial unpadded returns on that application. Figure 15 plots the distribution of application initial unpadded returns. The mean is \$45,070, and the median is \$36,814.[32]

Bessen (2008) estimates the net present value of *patents* using U.S. renewals data. After adjusting for inflation, Bessen (2008) estimates the mean net present value of patents for all U.S. patentees as \$78,168 and \$113,067 for just U.S. public firms in manufacturing. Putnam (1996) estimates that the mean patent value for those also filed abroad is \$312,749. It is difficult to compare our estimates of initial returns to existing estimates in the literature on total patent returns since we estimate the distribution of initial returns for (a) all *applications* and (b) *unpadded* claims. Applications that become patents are likely to be

[31] Using data from 1953-1988, Lanjouw (1998) estimates a range of 7 percent to 12 percent for the renewal obsolescence probability. Based on French data between 1951-1979, Pakes (1986) calculates values of 6 percent, 4 percent and 1 percent for the likelihood of obsolescence in the first, second and third year after grant, respectively.

[32] The sum of log-normals is approximately log-normal (Dufresne, 2004), as our figure suggests.

positively selected on value, and the median value of padding is 2 percent, implying that padded initial returns for those granted will have a median of at least \$36,814.

Next, we discuss the implied distribution of initial unpadded distances. Figure 16 plots the distribution of initial distances from by a beta distribution with parameters $\alpha_D = 3.368$ and $\beta_D = 6.120$. The mean distance is 0.35, and the distribution is approximately symmetric. The Figure includes a vertical dashed line at the mean distance threshold (averaged over technology centers). From this, it is apparent that most claims start with a distance *below* the Patent Office threshold. Despite this, many applications are eventually granted because of narrowing and examiners sometimes granting invalid claims.

We compute statistics on the model's endogenous variables by simulating the model at our estimates. From this, we estimate the percentage of granted patents with at least one invalid claim at 16 percent. We also calculate the distribution of optimal initial padding choices for applicants. Some applicants *under*-pad, owing to their significant negotiation fighting costs. However, most applicants do pad, with a median padding proportion equal to 2 percent and 70^{th} and 90^{th} percentiles equal to 9 percent and 24 percent, respectively.

Finally, Figure 17 shows the distribution of *unpadded* application legal fees for the four technology categories we have data on (simple, chemical, electrical and mechanical). As expected, the median fees for simple applications are lower than all other categories. Using the median padding value of 1.02 implies a median application drafting fee of \$7,531 and a mean drafting fee of \$8,542 for simple applications. Chemical (the technology category with the highest median drafting fees) demands a median application drafting fee of \$11,002 and a mean of \$13,187.

9.2 Examiner Parameters

Table 7 presents the estimates and standard errors of the examiner parameters. To understand examiner time costs and intrinsic motivation, we require a slight digression on the units of examiner payoffs in the model, which we call "normalized credits."[33] The Office applies adjustments to each examiner's credits based on their seniority and the technological complexity of their applications. We also use the same corrections to examiners'

[33] Appendix section C.2 offers a detailed derivation of the examiners' credit structure.

credits in the model payoffs for examiners. For example, in the model, an examiner receives two credits for granting a patent in the first round of negotiation. We adjust these two credits by dividing by a seniority factor (for example, by 1.25 for a GS-14 examiner with partial signatory authority) and multiplying by a technology correction (say, 29 for the relatively complex category of computer networks).[34] Therefore, a GS-14 examiner with partial authority in technology center "computer networks" receives 46.4 normalized credits for granting a patent in the first round. These normalized credits are the unit of examiner payoffs; therefore, we interpret intrinsic motivation costs $\theta\mathcal{R}_r$ and time costs π in normalized credits.

We start by interpreting the parameters of intrinsic motivation. We know of no structural, quantifiable estimates of intrinsic motivation in a public agency to which we can compare these estimates. We estimate σ_θ as 0.48, which implies, by the properties of the log-normal distribution, a coefficient of variation of 0.51. Figure 18 plots the distribution of intrinsic motivation for junior and senior examiners as implied by the log-normal assumptions. We estimate $\mu_{\theta,junior} = 4.135$ and $\mu_{\theta,senior} = 3.059$. These estimates implies that, on average, junior examiners are more intrinsically motivated than senior examiners. At least two countervailing forces could influence the relationship between seniority and intrinsic motivation. We may expect intrinsic motivation to fall with seniority as examiners become jaded after conducting hundreds of patent examinations. However, we may expect intrinsic motivation to rise with seniority since the least intrinsically motivated examiners are more likely to change careers. This would leave only the more intrinsically motivated examiners to qualify for promotions. Given that junior examiners are more intrinsically motivated, the former appears to dominate the latter.

To interpret the values of the implied intrinsic motivation, we calculate the intrinsic motivation cost (in terms of credits) for a median intrinsically motivated GS-12 (junior) examiner in the technology center 36. For this examiner, the seniority correction is one, and the technology correction is 22.4. Recall that the intrinsic motivation cost (in terms of normalized credits) is $C_{IM} = \theta\mathcal{R}_r$, where θ is the intrinsic motivation and $\mathcal{R}_r$ is the proportion of claims the examiner believes to be invalid. We divide C_{IM} by 22.4 to change the units back to pure credits. Hence, in terms of credits, this examiner's intrinsic motivation

[34] Tables 10 and 11 report the values across all seniorities and technology centers.

cost is $2.79\mathcal{R}_r$, which means that this particular examiner faces a cost of 2.79 credits (just below the credits from two first-round non-final rejections) for granting a patent with 100 percent of its claims as invalid. Alternatively, the examiner faces a cost of 0.93 (around half the credits from a first-round non-final rejection) for granting a patent with one out of four invalid independent claims. We can do the same calculations for the median intrinsically motivated GS-14 with partial signatory authority (senior) examiner in technology center 36. In terms of credits, their intrinsic motivation cost function is $1.189\mathcal{R}_r$, implying a small cost of just over half the credits from a first-round grant if they grant an *entirely* invalid patent application. Table 8 provides quantiles other than the median of intrinsic motivation in terms of normalized credits.

Next, we move to the parameters of examiner time costs. The coefficient of variation of examiner costs is 0.15, over three times smaller than the equivalent for examiner intrinsic motivation. Figure 19 plots the distributions of examiner time costs implied by the log-normal assumption. Senior examiners' time costs are much higher ($\mu_{\pi,s}$ is over 10 times larger than $\mu_{\pi,j}$). To go an extra round, the GS-12 (junior) examiner in technology center 36, with a median time cost, pays 0.06 credits to go an extra round. On the contrary, a GS-14 partial signatory authority examiner in the same technology center with a median time cost pays 0.55 credits (equivalent to one-quarter of their credits gained from granting a patent in the first round).

These estimates imply that, despite their experience, senior examiners face much higher opportunity costs for further rounds of negotiation. Senior examiners, by our definition, must also oversee the performance of junior examiners and conduct several other duties as part of their job, which leaves less time for them to focus on examinations (Foit, 2018). When an examiner starts, their main job is examination, which explains their lower opportunity cost of negotiation. Both senior examiners' lower intrinsic motivation and more significant time costs explain their larger grant rates and faster resolutions, as shown in section 5.1.

Finally, we discuss examiner error. Figure 20 plots the distribution of examiner errors for the median intrinsically motivated junior and senior examiners. Recall that the distribution of examiner errors by seniority is normally distributed, with an estimated standard deviation and mean equal to $\mu_\varepsilon = 1 + \dfrac{1}{\theta}$, where θ is intrinsic motivation. The error that an examiner draws multiplies padded distances to create the examiner's assessment of distance. Since junior examiners are more intrinsically motivated on average, the mean of the junior examiners' error distribution is closer to one. However, we estimate the standard deviation of senior examiner errors as 0.01, five times smaller than the junior equivalent of 0.05. Though their distribution of errors is upward biased, senior examiners, perhaps owing to their experience, are more *consistent* in their assessments of distances across applications.

9.3 Fit

Figure 21 plots the model moments computed from the estimates alongside their equivalent data moments. As expected, we match most of the internal moments very well. The main exception is the second round grant rate. This is difficult to match with our model because examiners have incentives to wait to the third round and obtain RCE credits if they do not choose to grant in the first round. In reality, since examiners have across-application incentives and targets, they are more likely to grant in the second round than our model can explain.

10 Counterfactual Analysis

In the final part of our analysis, we run counterfactuals to estimate changes to applicants' padding, prosecution timeliness and examiner quality resulting from changes to examination structure and agents' incentives. In total, we conduct six counterfactuals, which fall into three categories.

In each counterfactual, we fix the estimated parameter values and proceed in three steps. First, we change the examination structure or players' incentives. Second, we simulate the model on a new set of applications. Third, we measure changes in endogenous variables. We calculate three kinds of endogenous variables. The first is the distribution of grants and abandonments across rounds, which includes the proportion who choose not to apply. We refer to this as "timeliness." The second set is four measures of patent application "error," which are the percentage of granted patents with at least one invalid independent claim, the percentage of granted claims that are invalid, the percentage of abandoned applications with at least one valid independent claim and the percentage of abandoned claims that are valid. The third set of reported endogenous variables is the distribution of initial padding by applicants.

10.1 Removing Negotiation Rounds

In our first set of counterfactuals, we change the structure of the patent examination by removing negotiation rounds. We consider three versions. First, we limit the applicant to one request for continued examination (RCE). We implement this in our model by forcing the applicant to abandon if the examiner does not grant in the final rejection stage of the first RCE. This change effectively allows for three negotiation rounds between applicant and examiner. Second, we remove RCEs entirely, forcing the process to end after one negotiation between the applicant and examiner. Third, we move to a single-round process, where the examiner makes a single decision on whether to grant or not, with no opportunity for negotiation.

Columns (1) to (3) in panel A of Table 9 report the distribution of round outcomes under these three changes to prosecution structure. As the opportunity for negotiation diminishes, the proportion of early resolutions rises, with increases in the proportion of first-round grants and abandonments increasing under all scenarios relative to the baseline. The expected length of the application, in rounds, moves from 2.66 in the baseline to 2.31 when only one RCE is allowed, 1.58 when no RCEs are allowed, and 1 when negotiation is removed. Further, the proportion of inventors choosing not to apply increases substantially from 20 percent in the baseline to 31 percent with one RCE, 59 percent with no RCEs and 80 percent when we remove all negotiation. When we remove negotiation, patenting becomes unprofitable for many more applicants.

Across all three counterfactuals, as reported in columns (1) to (3) in Panel B of Table 9, the distribution of padding shrinks, with the median padding proportion changing from 1.02 in the baseline to 0.95 when RCEs are removed and 0.91 when all negotiation is removed. These results show that when negotiation is removed, the median applicant slightly understates their inventions to ensure they receive some intellectual property rights. Many inventors still pad, even with no negotiation: the 90^{th} percentile changes from 1.24 in the baseline to 1.20 with no RCEs and 1.13 when negotiation is outlawed.

Finally, we turn to changes to patent prosecution "error," reported in Panel C, columns (1) to (3) of table 9. Across all three scenarios, the proportion of type-1 errors decrease. By type-1 error, we refer to the case when the examiner grants the patent even though it has at least one invalid claim. For example, in the baseline, 16 percent of granted patents contain at least one invalid claim. If negotiation was outlawed entirely, and the examiner made a single decision on whether to grant or not, only 2 percent of granted patents would contain at least one invalid claim. If RCEs were removed, the same proportion would fall to 13 percent. These errors decrease because applicants pad less, so claims are far more likely to be valid, yet examiners' within-round incentives are more or less unchanged by the counterfactual change. The increase in timeliness and the fall in type-1 errors are improvements to the patent prosecution procedure. The downside of removing negotiation (along with the number of valid inventions choosing not to apply for patent rights) comes in the sharp increase in type-2 errors: cases where applicants do not receive a patent despite having some quantum of valid intellectual property. In the baseline, 48 percent of abandoned applications have at least one valid claim, whereas when negotiation is removed entirely, this rises to 96 percent. However, when RCEs are removed, the increase is a mere two percentage points, with exactly half of all abandoned applications containing at least one valid independent claim.

Put together, we observe minimal changes to outcomes when only one RCE is allowed. This result occurs because almost all applications resolve before two RCEs in the baseline. On the other extreme, removing all opportunities for negotiation (1 round process) has an extreme effect on the patent prosecution process, with a 60 percentage point (300 percent) increase in the proportion choosing not to apply for patent rights and a reduction in applicants' initial padding choice. Though timeliness and type-1 errors improve, even amongst the highly selected set of applicants who choose to apply, almost all abandonments contain some valid claims. Moving to a system with one round of negotiation (a two-round process) strikes a balance between the two types of errors, with a modest increase in type-2 errors and a modest decrease in type-1. Further, with two rounds, the padding distribution moves closer to one.

10.2 Increasing Applicants' Fees

Next, we consider two changes to applicants' negotiation fees. First, we increase the RCE fee. Currently, the cost for the first RCE is $1,360, which is halved for small entities and halved again for micro entities. Second and subsequent RCEs cost the applicant $2,000. We try three increases and report the results for the case where we increase the first RCE fee to \$20,000 and subsequent RCEs to \$40,000.[35] In our second scenario, we introduce a flat fee of \$10,000 to the applicant for *every* round of negotiation, even before RCEs.

Columns (4) and (5) of panel A in table 9 report the proportion of grants and abandonments by round under these changes to applicant fees. With the increased fees, the percentage of inventors choosing not to apply increases from 20 percent to 34 percent when RCE fees increase and 35 percent when we introduce a round cost. Examiner grant rates increase in rounds one, two and three and the average number of rounds decreases from 2.66 in the baseline to 2.34 with increased RCE fees and 2.33 with round fees. In summary, when applicant fees increase, fewer inventors apply, and patents are resolved faster. Another contributing factor to faster resolution is a decrease in padding. As reported in columns (4) and (5) of panel B in Table 9, the 80^{th} percentile of padding falls from 16 percent in the baseline to 11 percent in both counterfactuals, and the median padding value falls from 2 percent in the baseline to 0 percent in the counterfactuals. Finally, type-1 errors slightly decrease, with the percentage of granted patents with invalid claims changing from 16 percent in the baseline to 15 percent in the counterfactual. On the contrary, the percentage of abandoned applications with at least one valid claim increases slightly from 48 percent in the baseline to 49 percent when we increase the RCE cost and 51 percent when we introduce the round cost. Overall, the change in patent examination errors is modest.

10.3 Changes to Examiner Credit Structure

Finally, we change the structure of examiner credits. We increase the credits for examiners in the second RCE so that they equal credits in the first RCE. We ran this counterfactual to understand the impact of the decreasing credit structure as negotiation rounds continue. Column (6) of Table 9 reports the endogenous variables after this change. Across all endogenous variables, there is no substantial change to any endogenous variable. The lack of change happens for two reasons. First, the increase in the credits we employ is relatively minor as the gap between first and second RCE credits was already small. Second, this happens because, as mentioned above, second RCEs are so rare in the baseline, changes to their structure will have minimal effects on applicants and, therefore, examiners.

[35]Results for similar, but less pronounced increases to RCE fees are qualitatively similar, but likewise less pronounced.

10.4 Tradeoffs Between Type-1 error, Type-2 Error and Timeliness

Considered together, what do we learn from our counterfactual changes about the patent prosecution process? First, across all our counterfactuals and the baseline model, there is a trade-off between type-1 and type-2 errors. Figure 22 plots the type-1 and type-2 error probabilities across the six counterfactuals and the baseline.[36] The relationship is generally downward sloping: scenarios with low type-1 error have high type-2 error probability. As a result, among the regimes we consider, type-1 and type-2 cannot both be small. However, from Figure 22, in terms of errors, the **baseline** and three counterfactual scenarios are *dominated* by the counterfactual where applicants are allowed only one RCE.

Second, there is a trade-off between type-2 errors and timeliness. Figure 23 plots the type-2 error probability against the average number of rounds, and the relationship is generally downward sloping. When there are fewer rounds of negotiation on average, there are generally more cases in which applicants with valid claims abandon, either because they run out of negotiation rounds or because the incentives for continuing to fight are too small. Similar to before, among the regimes we consider, there is no way to minimize type-2 errors and the number of negotiation rounds. However, once again, we see that the **baseline** and three counterfactuals are dominated by the counterfactual where applicants are allowed one RCE.

Finally, Figure 24 shows that type-1 errors increase in the average number of rounds. When applicants are charged for (or banned from) negotiation, they either do not apply or pad less and resultantly examiners grant fewer invalid patents.

11 Conclusion

To be added.

[36] Only six points are visible in the plot because the sixth counterfactual, in which we change RCE credits, led to no changes.

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Appendices

A Patent Background

This short section provides a primer on the essential details of patents necessary to understand our analysis. For extensive detail on patents, see Merges and Duffy (2002).

A patent is a grant of the right to stop others from making, using or selling an invention in a given country for a limited period. In that sense, a patent delivers temporary monopoly power to the inventor. In exchange for these monopoly rights, the inventor must make public the precise details of the invention through the patent document. Amongst other elements, the patent document contains an abstract, a description, citations and figures. The most important feature of the patent document, however, is the list of claims. Claims delineate the "metes and bounds" of the patentee's intellectual property (Merges and Duffy, 2002). The central part of the examination process involves assessing the patentability of each entry in the list of claims. Claims are either dependent, meaning they refer directly to one of the other claims, or independent. Independent claims are the primary expression of the boundaries of patent rights, and are the main source of value to the applicant. Dependent claims act more as clarifying devices, identifying successively narrower interpretations of the independent claim. They also re-interpret claims using different wording, in case particular wordings are more appealing to the examiner assigned to the application.

Several recent papers have studied patent rights, where a patent is a homogeneous object.[37] In this paper, we view a patent as a collection of claims of heterogeneous scope and value and incorporate this heterogeneity as a critical feature in the model. We believe this heterogeneity is a first-order feature necessary to develop accurate statements about the potential effects of regime changes to the patent examination process. We add heterogeneity to our model by endowing the inventor with multiple independent claims of varying distance and private value.

[37] Examples include Gaule (2018); Sampat and Williams (2019); Farre-Mensa, Hegde, and Ljungqvist (2019).

B Additional Details on Distance Measure

In this section, we provide full detail on our patent distance metric. We describe our first approach based on the bag-of-words method alongside the paragraph vector approach. There are four steps involved: (1) standardizing the independent claim text, (2) turning the text into a numerical vector, (3) calculating the distances between a focal patent claim on an application to all existing granted patent claims and (4) calculating the distance to the closest existing independent claim. The bag-of-words and paragraph vector approaches differ only in step (2), since they differ only in how they turn the text into a vector, rather than how they standardize the text or in what distance metric they use.

B.1 Standardizing Text

An important first step before converting text into a text vector is text standardization. This involves performing the following basic changes to the content of the text and removing words that carry no informational content:

1. Convert all words to lowercase.
2. Narrow all sequences of words (e.g Random Access Memory) to their acronyms (RAM). [38]
3. Remove all numbers in the text.
4. Expand contractions, such as "I've" to "I have".
5. Remove all punctuation.
6. Remove all stop words such as "the", "a', "for' etc. .
7. Convert all words to their base form. For example "compromising" to "compromise", "played" to "play" etc. .
8. Remove any punctuation within words, for example hyphens.

Table 1 provides an example of an independent claim that has been standardized. To understand why this step improves the accuracy of the text similarity, consider two patent claim texts, where one contains "Random Access Memory" and the other contains "RAM". Without converting "Random Access Memory" to RAM, the algorithm will miss that

[38]To get data on acronyms and their meanings we scrape a website list of 250 common acronyms used in technology.The list of acronyms we use is available upon request.

the two texts are referring to the same concept, and will resultantly underestimate the similarity between the two claims. Once we standardize the text, we drop any claims which have less than two words or include illegible text.

Table 1: Example of standardization of text

Claim text	**Standardized text**
A sequential value multi-point recorder for recording variable analog data on a heat sensitive recording sheet material comprising, a thermal print head, a motor drive circuit connected to a print head motor for moving the print head unidirectional and in a continuous sweep across the sheet material between ”0” and ”100” percent marginal positions on the sheet material, first sensing means for sensing the position of the print head in a first marginal position, second sensing means for sensing the position of the print head in the ”0” percent position, third sensing means for sensing the position of the print head in said ”100” percent position for deactivating or reversing the print head motor, means for sensing a plurality of variable analog data signals representing instantaneous values of physical parameters, an analog to digital converter unit for updating said variable analog signals for storing said updated signals, a central processing unit for storing and for tabulating said variable analog data in a memory circuit, said central processing unit subsequentially tabulating said stored signals in order of magnitude and storing said tabulated data in said memory circuit, a motor and a printer control logic for controlling the print head activator and said motor drive circuit, said print head activator controlling the print head for sequentially marking the tabulated variable analog data, as a function of time, and at their value representative of said physical parameters and in their order of magnitude on said sheet material, and a drive motor for driving said sheet material at a constant speed and as a function of time.	sequential value multipoint recorder record variable analog data heat sensitive record sheet material comprise thermal print head motor drive circuit connect print head motor move print head unidirectional continuous sweep across sheet material percent marginal position sheet material first sense mean sense position print head first marginal position second sensing mean sense position print head percent position third sense mean sense position print head say percent position deactivate reverse print head motor mean sense plurality variable analog data signal represent instantaneous value physical parameter adc unit updating say variable analog signal store say updated signal cpu store tabulating say variable analog data memory circuit say cpu subsequentially tabulate say store signal order magnitude storing say tabulate data say memory circuit motor printer control logic control print head activator say motor drive circuit say print head activator control print head sequentially mark tabulate variable analog data function time value representative say physical parameter order magnitude say sheet material drive motor driving say sheet material constant speed function time

Notes:

Table 2: Example of document term matrix

a	card	computer	component	cooling	graphics	of	the	memory
1	0	1	1	0	0	0	0	0
1	0	1	1	1	0	0	0	0
1	1	1	1	0	1	0	0	0
1	0	1	1	0	0	1	1	1

Notes: The document term matrix for the example in text.

B.2 Turning Patent Text into a Vector

B.2.1 Bag-of-words

We describe how to turn a collection of patent claim texts into a collection of patent claim numerical vectors through the bag-of-words approach. The key component to construct is the document term matrix (DTM) D. The idea is to take all words across all standardized texts and let each word represent a column j of D. Then, letting row i of the DTM represent a particular patent claim text i, the (i, j) element of the DTM D is one if the patent claim text i contains the word j, and zero otherwise. Then each row of the DTM corresponds to one numerical vector representation of the corresponding patent claim text. For an example, suppose we had four claims. The first reads "A computer component", the second "A computer cooling component", the third "A computer graphics card component", and the fourth "A component of the computer's memory". Removing punctuation and converting all words to lower case the entire text can be represented by the DTM in Table 2

We follow Bussy and Geiecke (2021) in dropping all words (and thus columns in the matrix) which appear in 15 percent or more of the 24 million independent claims, and words which do not appear in at least five of the 24 million independent claims. Further, we also divide the vector representation of each independent claim by its total number of words. The resulting DTM has a dimensionality of around 24 million rows by 550 thousand columns. Bussy and Geiecke (2021) continue by reducing the dimensionality of the matrix using truncated singular value decomposition (tSVD), explained in Strang (2016). We do not do this, and we explain why below. Instead we work with the full DTM representation.

We do not use tSVD for the following three reasons. The first is because of computing memory requirements. We could not run the Python implementation of tSVD on the entire DTM. Given the size of our DTM, with 24 million rows, the memory requirements to successfully run this code are so high that even with 64GB of RAM we could not find a way to get the code to complete. The second is that, unlike in Bussy and Geiecke (2021), who only have around four million rows, the truncation handicaps us, rather than helps us, in terms of the memory required to store a dense matrix, which the tSVD will output, with 300 columns. In our case, a 24 million by 300 column dense matrix requires around 40GB of RAM, so it is more memory efficient to work with the entire DTM, which is very sparse and therefore requires 11GB of RAM. Finally, we were not convinced with the performance of tSVD when we experimented with it on subsamples of the rows. When working with subsamples, reducing the dimensionality resulted in a loss of around 40 percent of the variation in the DTM.

B.2.2 Paragraph Vector Approach

To be added.

B.3 Calculating All Distances

The step above converts all patent claims, including those on applications and those granted, into a numerical vector. The next step involves taking every focal application patent claim vector and calculating its distance to every *existing* granted claim at the point of application. We now describe the computational method for this step.

1. We split the DTM into two matrices. One contains the patent claims sorted by their grant date and id. The other contains the application claims sorted by their application date and id. We sort on id to ensure a unique sorting each time, since dates can clash.
2. In the full data we generate a date column where, for granted patent claims the date is the day the patent was granted, and for the focal application claim, the date is the application day.
3. We sort the full data by the date column and the claim id. We assign the ids so that claims granted on the same day as an application is filled are ordered before the application. This means that applications are compared to all claims granted up

to and including their application date.

4. We remove the applications along with their index in the full data. From this index, we subtract the number of prior applications. This gives a list informing us, for each application in the application DTM, where to cut off the grant DTM so that we only compare the application claims to the prior granted claims.
5. We loop through the application DTM, filtering the grant claim DTM accordingly and calculating the cosine similarity and then angular distance to each prior granted claim.

In Table 3, we provide two examples of the distances computed by the bag-of-words approach.

Table 3: Example of closest claims and distance

Claim text	Closest match	Distance
A method for transmitting and receiving information using an electromagnetic wave, comprising: simultaneously transmitting a first information channel and a second information channel multiplexed together, each information channel being associated with a combination of a carrier frequency and a rotation frequency, the first information channel combination being different from the second information channel combination, the rotation frequency of each combination being greater than zero and less than the carrier frequency of that combination; and simultaneously receiving the first information channel and the second information channel.	A method for receiving information using an electromagnetic wave, comprising: receiving an electromagnetic wave having a first information channel and a second information channel combined together, each information channel being associated with a combination of a carrier frequency and a rotation frequency, the first information channel combination being different from the second information channel combination, the rotation frequency in a given unique combination being greater than zero and less than the carrier frequency in a given combination, the received electromagnetic wave having at least one wave component for each of the information channels that are combined; and splitting the two information channels.	0.27
A method of operating a voltage generator to provide a reference voltage to at least one memory array, said method comprising: associating a driver circuit to each memory array; generating control signals from a periphery of the at least one array, the control signals for respectively controlling each voltage driver; outputting the control signals to each voltage driver; generating at each voltage driver the reference voltage based on the respective control signals; and outputting the reference voltage to circuitry within each array associated with each voltage driver.	A method of operation in a semiconductor memory device wherein the memory device includes an array of memory cells and a voltage divider coupled to a first output driver, the method comprises; driving, from an output terminal coupled to the first-output driver, a first voltage level onto an external signal line to produce an amount-of voltage swing on the external signal line; generating a control voltage using the voltage divider, wherein the control voltage is based on the amount of voltage swing; comparing the control voltage with a reference voltage; and adjusting the amount of voltage swing produced by the first output driver based on the comparison between the control voltage and the reference voltage.	0.43

Notes:

B.4 Calculating the Distance to the Nearest Prior Art

With all distances computed, it is a simple step to take the closest 50 claims for each application. At points in the analysis, we experiment with different choices on which percentile of the closest 50 distances to use. We also experimented with taking an average of the five closest distances for example, and the closest distances were similar.

C Model Extensions and Details

C.1 Extensions

C.1.1 Dependent Claims

Now we show how to extend the model to include dependent claims. There are m_j^0 dependent claims associated with independent claim j. Dependent claim k is distance $\tilde{d}_{jk}$ from the nearest existing point in the intellectual property space. Independent claims mark the boundaries of the different aspects of the invention, and dependent claims identify successively narrower interpretations of the independent claim. Figure 2 shows how to visualize dependent claims, similar to Figure 1.

Padding now changes the distances of dependent claims, as well as independent claims. Padding determines the values of dependent claim distances $\tilde{d}_{jk}$ by splitting up the interval $[\tilde{D}_j, D_j^*]$ into m_j^0 blocks:

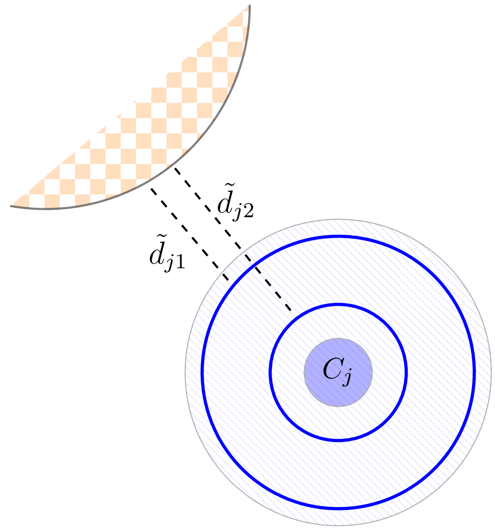
$$\tilde{d}_{jk} = \tilde{D}_j^0 + \frac{k}{m_j^0 + 1}\left(D_j^* - \tilde{D}_j^0\right) \qquad k = 1, \ldots, m_j^0.$$

On rejections, if an independent claim is rejected, so are all the associated dependent claims. In order to reduce padding on rejected claims, the applicant cancels any dependent claims k such that $\tilde{d}_{jk} < \tilde{D}_j^{t+1}$. Finally, the applicant's payoff if the examiner grants the payoff is the same as in the baseline model, except for the addition of the term

$$\lambda \sum_{j=1}^{M^{GR}} \omega_j^{GR} m_j^{GR},$$

where M^{GR} is the number of granted independent claims, m_j^{GR} is the number of granted dependent claims associated with independent claim j, and ω_j^{GR} are weights. Hence the value of dependent claims is given by a weighted sum of the number of dependent claims

Figure 2: Dependent Claims



Notes: The Figure illustrates the notion of dependent claims. These are represented through the thick rings inside the padded claim. We see two dependent claims here, with dependent claim 1 broader than dependent claim 2. The two dependent claims are distances $\tilde{d}_{j1}$ and $\tilde{d}_{j2}$ from the nearest point in the intellectual property space.

associated with independent claim j The weights ω_j^{GR} could be $\frac{\tilde{v}_j}{\sum_k \tilde{v}_k}$, in which case they represent the value of padded claim j relative to the total value of the padded claims. One way to interpret this is as a monetary equivalent of insurance against losing some scope of the independent claims in litigation after issuance. Interviews with legal scholars confirmed this interpretation of the value of dependent claims.

C.1.2 Indefiniteness Rejections

We can extend the model by defining claims as a triple $C_j = (v_j^*, D_j^*, I_j^*)$. The first two terms are as described in the baseline model. The new term I_j^* is the true ambiguity of the description of claim j. Now padding p increases claim indefiniteness from I_j^* to $\tilde{I}_j = \mathcal{I}(I_j^*, p)$, where the indefiniteness function $\mathcal{I}(\cdot, \cdot)$ is increasing in both arguments. The examiner now obtains an assessment $\hat{I}_j$ of the indefiniteness of claim j, given by

$$\hat{I}_j = \mathcal{I}(I_j^*, p) \cdot u_j,$$

where u_j is the examiner's indefiniteness error. The examiner has *grounds* for an indefiniteness rejection if $\hat{I}_j$ exceeds an indefiniteness threshold τ^I, that is $\hat{I}_j > \tau^I$. Again, this does not necessarily mean the examiner will reject, instead they just know that they have legitimate reasons to reject, should they want to.

The rest of the model remains the same. The extension is more attractive in the sense that assessments of indefiniteness are claim specific beyond the examiner error. Whether it is beneficial to include this extension depends on whether the data can identify a distribution of true indefiniteness I_j^*. One option is to use algorithms that estimate the readability of patent claims text as in Kong, Dulleck, Jaffe, Sun, and Vajjala (2020); Ashtor (2022).

C.1.3 Examiner Learning

There are two ways we could add examiner learning. The first would have the examiner *partially* learn with probability one. For example, the assessment in round r would become

$$\hat{D}_j^r = \mathcal{D}(D_j^*, p_j^r) \cdot \varepsilon_j^r,$$

where

$$\varepsilon_j^r = \varepsilon_j^{r-1} - (\varepsilon_j^{r-1} - 1)\ell_\varepsilon$$

and $\ell_\varepsilon \in [0, 1]$ is the rate of examiner learning on distance.

An alternative way to model learning would have the examiner *fully* learn with some probability. In that case, ε becomes 1, after the examiner discovers all the relevant prior art that they were missing. A very detailed model could have both forms of learning.

C.2 Examiner Credit Structure

Here we provide expressions for $g_{GR}^r(S,T)$, $g_{ABN}^r(S,T)$, $g_{RCE}^r(S,T)$ and $g_{REJ}^r(S,T)$. For $y \in \{GR, ABN, REJ, RCE\}$, we write $g_y^r(S,T) = \nu_y^r \cdot \kappa(S,T)$, and give expressions for ν_y^r and $\kappa(S,T)$ separately.

C.2.1 Credits

Granting in the first round gives the examiner a payoff of $\nu_{GR}^1 = 2$ credits. Rejecting in the first round gives $\nu_{REJ}^1 = 1.25$. If the applicant abandons in round one, the examiner obtains $\nu_{ABN}^1 = 0.75$. Granting in the second round gives $\nu_{GR}^2 = 0.75$ credits. Rejecting in the second round gives $\nu_{REJ}^2 = 0.25$ credits, with an extra $\nu_{ABN}^2 = \nu_{RCE}^2 = 0.5$ credits whether the applicant abandons or continues to an RCE. Ultimately, the examiner obtains two credits irrespective of what happens in the first two rounds. The only difference is whether they obtain the credits immediately (say, from an immediate grant) or spread out over the two rounds.

The structure of the payoffs in the first RCE are exactly the same, except $\nu^3_{REJ} = 1$ and $\nu^3_{GR} = 1.75$. In this case, irrespective of what happens in the RCE, the examiner will obtain 1.75 credits. The difference comes from whether they receive all 1.75 credits at once by granting, or 1 credit from their non-final rejection and $\nu^4_{REJ} = 0.25$ plus $\nu^4_{ABN} = \nu^4_{RCE} = 0.5$ credits from the applicant's response.

In the second and any subsequent RCEs, the structure of the payoffs is still the same, except $\nu^{2r+1}_{REJ} = 0.75$ and $\nu^{2r+1}_{GR} = 1.5$ ($r > 1$). As before, the examiner will receive 1.5 credits from second and subsequent RCEs. The difference comes from whether they receive all 1.5 credits at once from granting, or 0.75 credits from their non-final rejection and $\nu^{2r+2}_{REJ} = 0.25$ plus $\nu^{2r+2}_{ABN} = \nu^{2r+2}_{RCE} = 0.5$ credits from the applicant's response.

C.2.2 Seniority and Technology Complexity Adjustments

The seniority and technology complexity adjustment term is

$$\kappa(S,T) = \frac{\kappa_{TECH}(T)}{\kappa_{SEN}(S)}.$$

Table 10 gives the values of $\kappa_{SEN}(S)$ across the GS categories. We see that higher seniority factors imply larger values of κ_{SEN}, and therefore lower values of credits. Table 11 gives the values of $\kappa_{TECH}(T)$ we created across the technology centers we use to estimate the model.

D Computational Details

D.1 Logic of Structural Estimation Code

The economic model has four stages. First, an applicant chooses whether to apply. Then if they apply, they set an initial level of padding p_0 for their application, not knowing the identity of the patent examiner they will deal with. They do this by maximising the expected payoff that results from the choice of padding. To solve this, they must compute the payoff that would result from the game for *every* examiner type, and then take expectations over the distribution of examiner types. Second, an examiner is assigned, who obtains errors. Third, the examiner and applicant play a finite game to negotiate over the outcome of the patent examination process. Finally, if the applicant receives a patent, they decide how long to renew the patent for, in a model similar to Schankerman and Pakes (1986).

Here is the basic logic of the code for estimating the structural model:

1. Draw values for the fundamental shocks (e.g. application type and realized examiner types), used for *all* simulations $s = 1, \ldots, \mathcal{S}$ and *all* parameter guesses

2. **Outer loop optimization (Julia `BlackBoxOptim`)**:
   PURPOSE: SOLVING FOR THE PARAMETER VECTOR
   Fix a value of the parameter vector ψ:

   (a) **Inner loop:**
   PURPOSE: CALCULATING THE MODEL MOMENTS FOR A GIVEN VALUE OF ψ.
   For each simulated draw $s = 1, \ldots, \mathcal{S}$:

      i. **Optimal initial padding**:
      PURPOSE: CALCULATING EXPECTED PAYOFFS FOR EVERY CHOICE OF p_0
      Use the `GoldenSection` univariate optimization method to solve for the applicant's optimal initial level of padding

      ii. With that choice of initial padding :

         A. Solve the game for the *realized* examiner type that the applicant is actually given

         B. Work out if the applicant will choose to apply

      iii. If the applicant does apply, store the vector of endogenous variables for this simulation, $\mathbf{m}_s(\psi)$, for which we will compare moments

   (b) Calculate the simulated moments $\bar{\mathbf{m}}(\psi) = \frac{1}{\mathcal{S}} \sum_{s=1}^{\mathcal{S}} \mathbf{m}_s(\psi)$

   (c) Compute the value of the objective $(\bar{\mathbf{m}}(\psi) - \mathbf{m}_{\mathcal{S}})' W (\bar{\mathbf{m}}(\psi) - \mathbf{m}_{\mathcal{S}})$ where $\mathbf{m}_{\mathcal{S}}$ is the vector of empirical moments from the data

D.2 Optimization Details

We use Julia's `BlackBoxOptim` library to estimate the model parameters. The optimization routine has four main options, which we choose as follows:

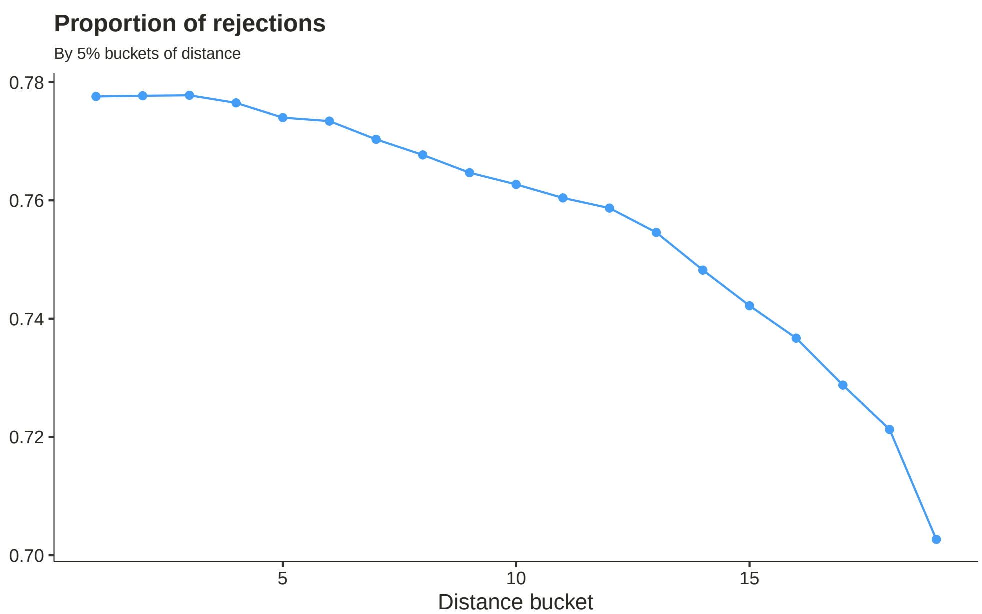
1. *Search Range*: See Table 12 for the parameter bounds we search over
2. *Maximum Function Evaluations:* We use a limit of 120,000 evaluations of the objective function in our search
3. *Method*: We use the default "adaptive_de_rand_1_bin_readiuslimited" method. This is an Adaptive Differential Evolution optimizer with radius limited sampling.
4. *Population Size*: We set the initial population size at 100.

We optimize over initial padding choices using Julia's `Optim` library. We use the `GoldenSection` method, which is a special method for univariate optimization without derivatives. We set an absolute tolerance of 0.02.

E Figures and Tables

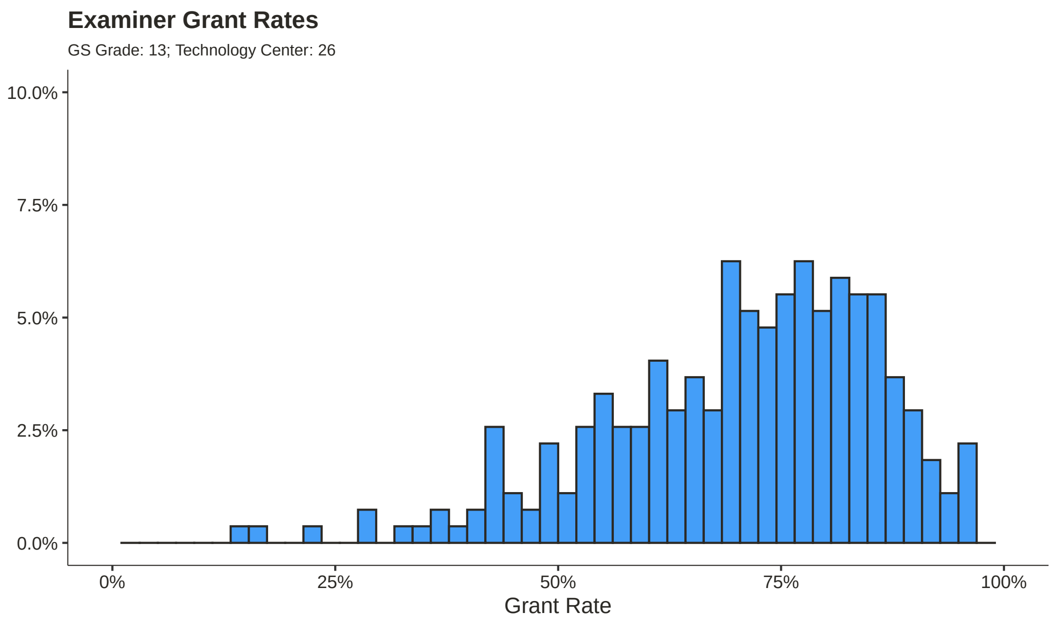
E.1 Figures

Figure 3: Check of distance metric



Notes: Each point represents a bucket of claims of a certain distance from the nearest existing independent claim.

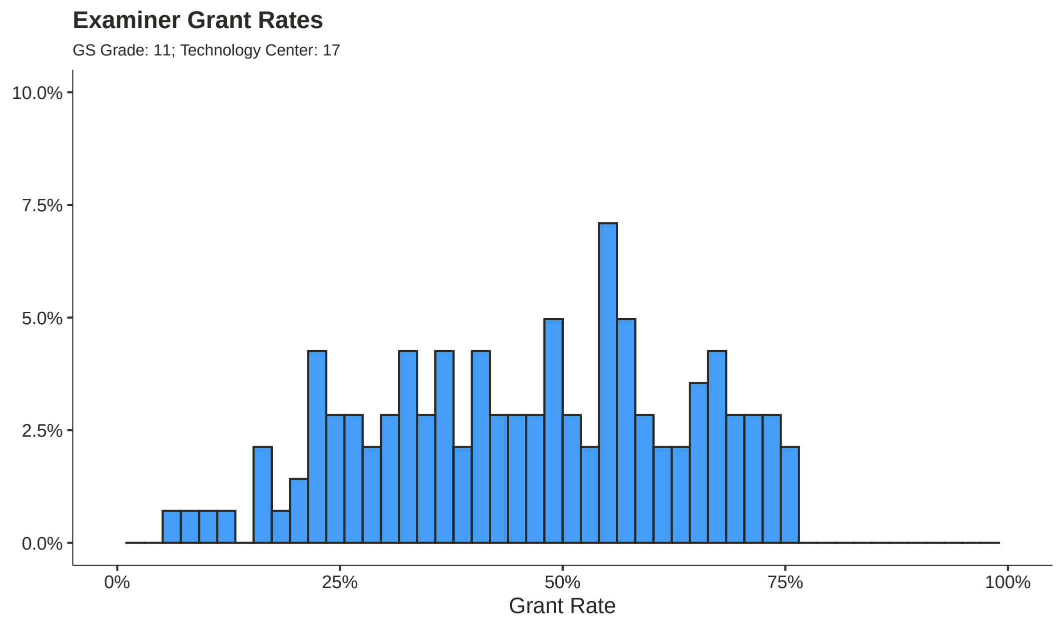
Figure 4: Distribution of examiner grant rates across all rounds: GS-13; Technology Center 26



Notes:

Back to discussion in empirical evidence section 5.

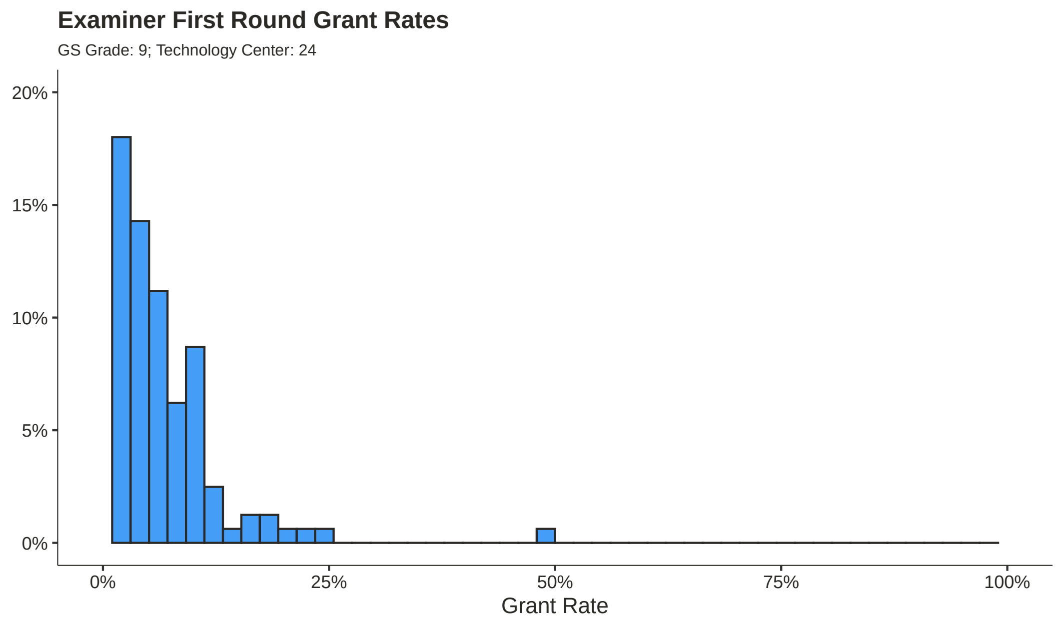
FIGURE 5: Distribution of examiner grant rates across all rounds: GS-11; Technology Center 17



Notes:

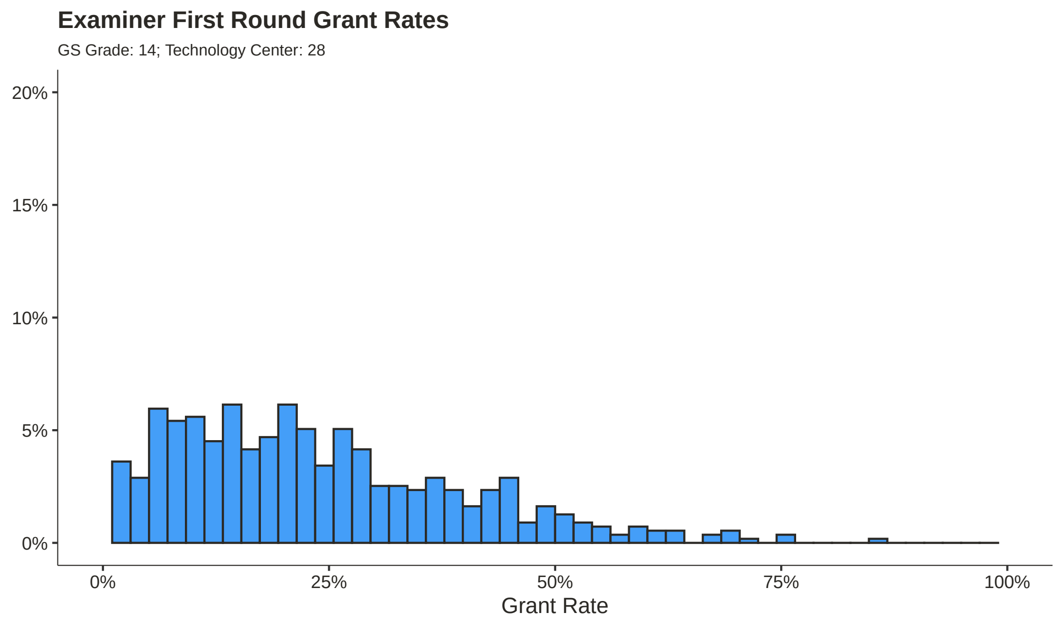
Back to discussion in empirical evidence section 5.

FIGURE 6: Distribution of examiner grant rates in the first round: GS-9; Technology Center 24



Notes:

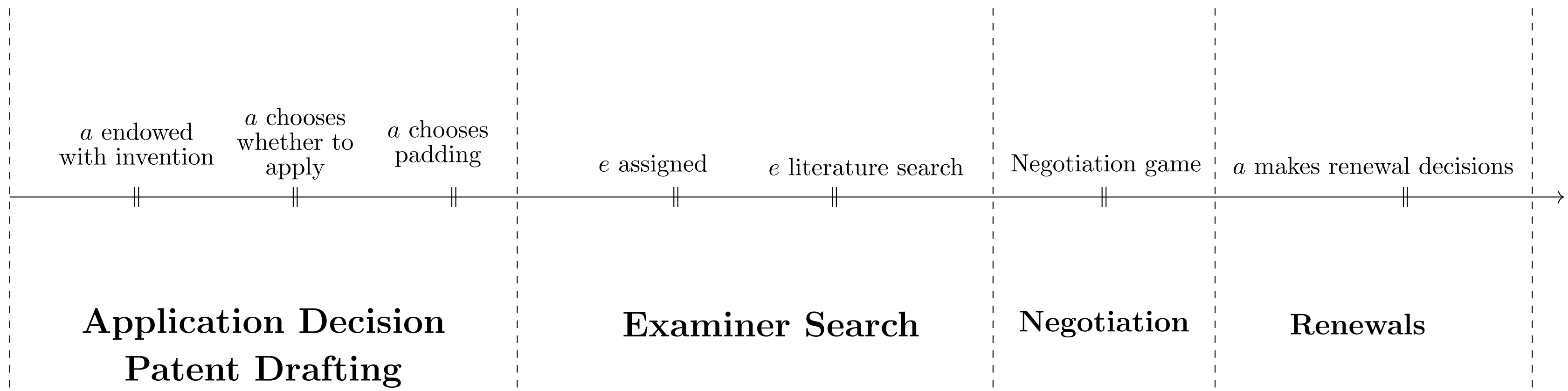
FIGURE 7: Distribution of examiner grant rates in the first round: GS-14; Technology Center 28



Notes:

Back to discussion in empirical evidence section 5.

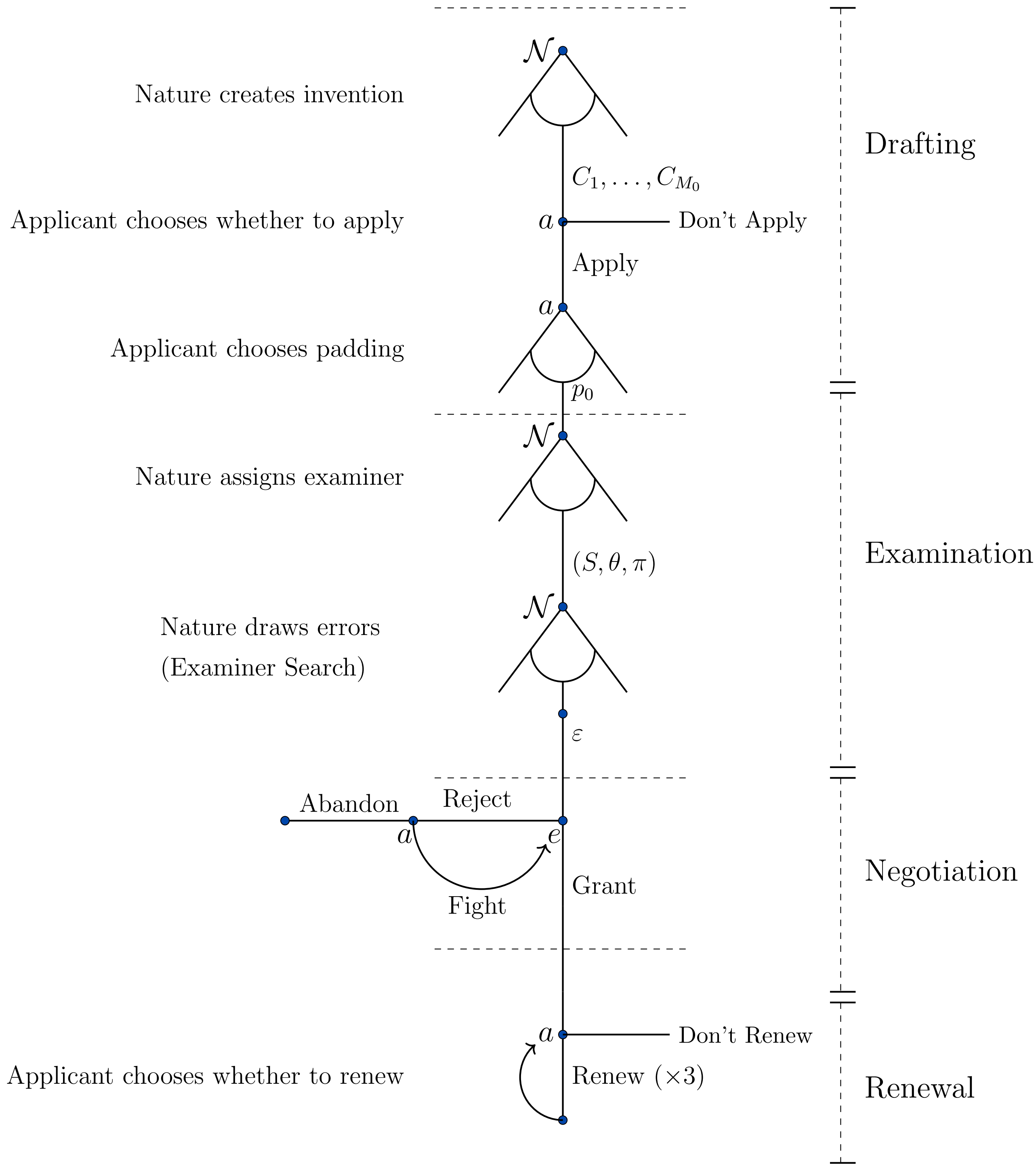
Figure 8: Model Timeline



Notes:

Back to model in section 6

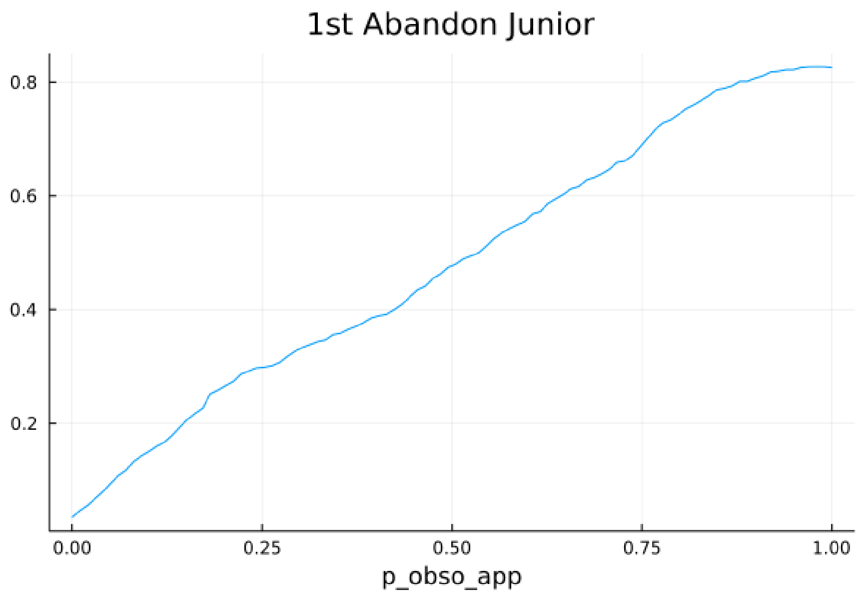
Figure 9: Model Extensive Form



Notes:

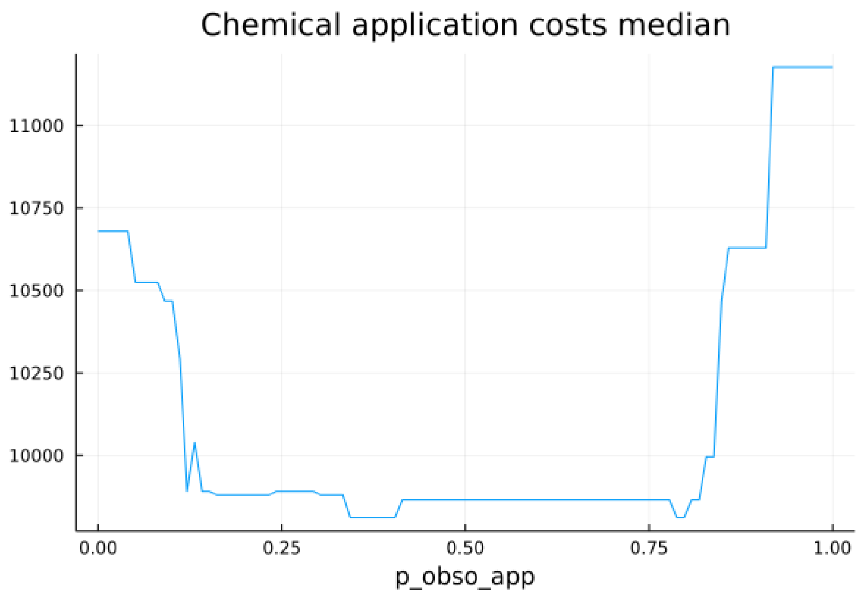
Back to model in section 6

Figure 10: Plot of moment against parameter: example one



Notes: The moment for first round abandonment for applications with junior examiners is monotone increasing in the probability of obsolesence in the application stage. This implies that the probability of obsolescence in the application stage changes the moment for first round abandonment. Since obsolescence drives value to zero, which makes the applicant abandon, it is intuitive that higher a probability of obsolescence yields higher abandonment probabilities.

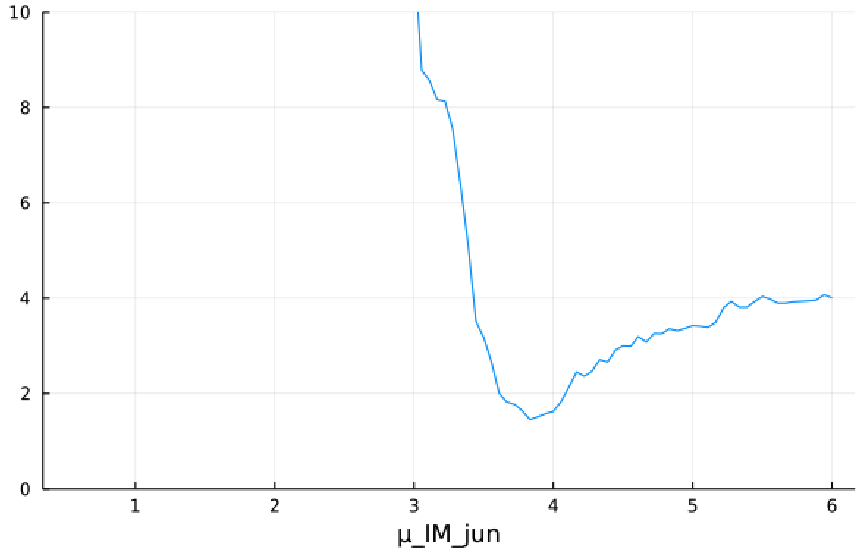
FIGURE 11: Plot of moment against parameter: example two



Notes: Very low values of obsolescence probability imply high application costs because applicants pad more when obsolesence is low. Similarly, when obsolescence is highly likely, applicants vastly underpad, since they desire a quick resolution before they become obsolete. In the interim values of obsolescence probability, there is little change in the padding value and therefore the application costs. As a result, this moment is less valuable in pinning down the obsolescence probability.

Back to discussion in identification section 8.

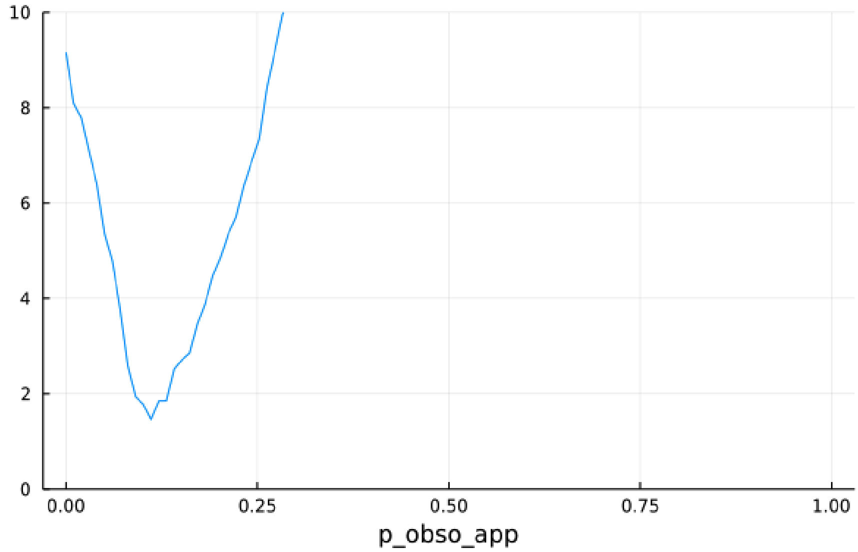
FIGURE 12: Plot of simulated method of moment objective against parameter: example one



Notes: This figure plots the SMM objective as a function of $\mu_{IM,junior}$, fixing all other estimates. At low values of intrinsic motivation, the objective is large, since the model overestimates the proportion of early grants and proportion of early grants containing invalid claims. At high values of intrinsic motivation, the objective is large, since the model underestimates the proportion of early grants and the fact that there are grants containing invalid claims. In between, there exists a value of $\mu_{IM,junior}$ which matches the moments best.

Back to discussion in identification section 8.

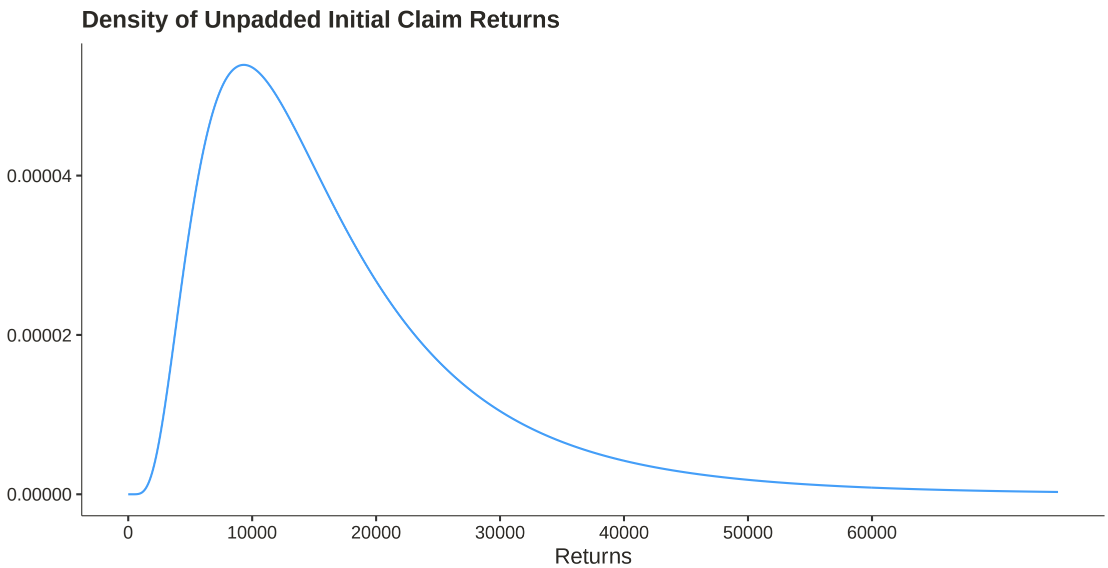
Figure 13: Plot of simulated method of moment objective against parameter: example two



Notes:

Back to discussion in identification section 8.

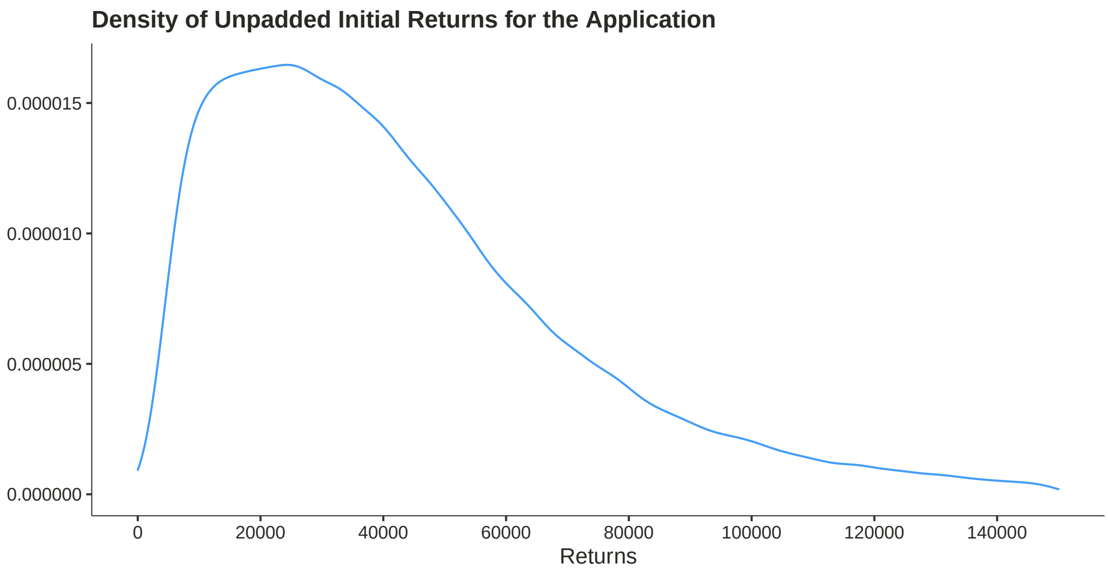
Figure 14: Density of initial unpadded claim values



Notes:

Back to discussion of applicant estimates in section 9.1.

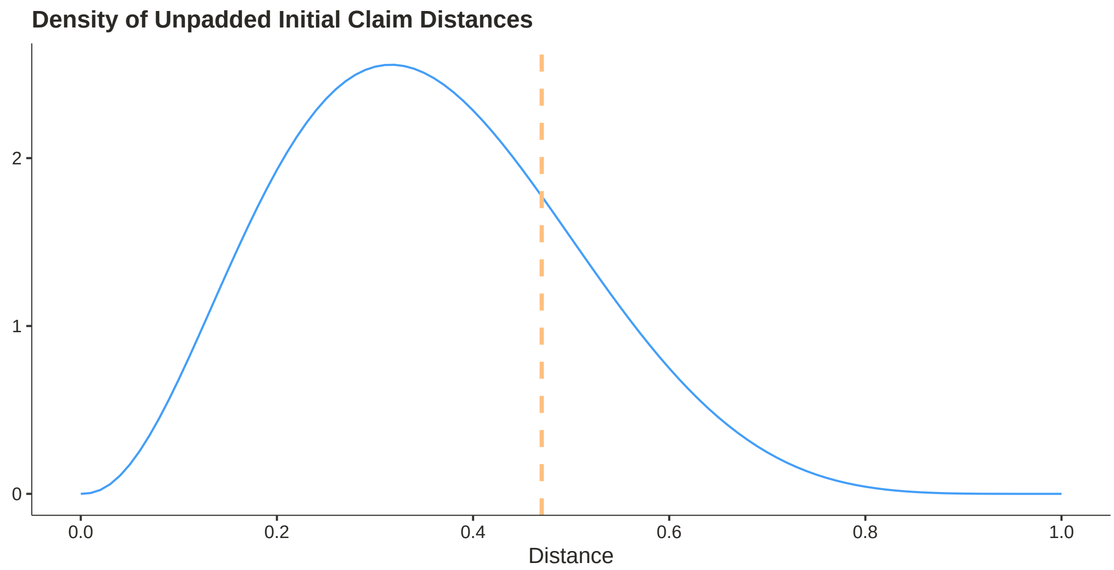
Figure 15: Density of initial unpadded application values



Notes:

Back to discussion of applicant estimates in section 9.1.

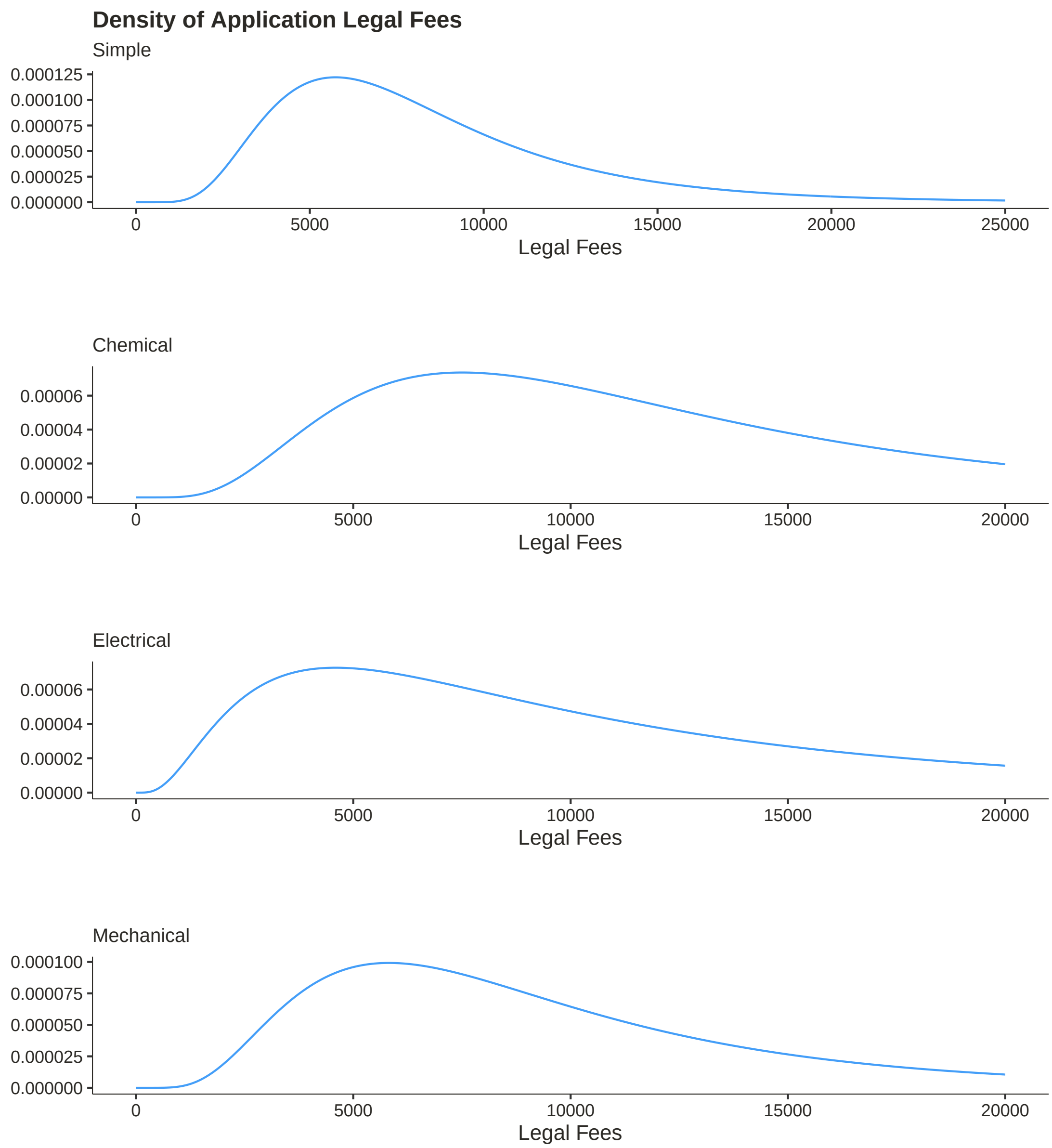
Figure 16: Density of initial unpadded claim distances



Notes: Vertical line represents the average of distance thresholds across technology centers.

Back to discussion of applicant estimates in section 9.1.

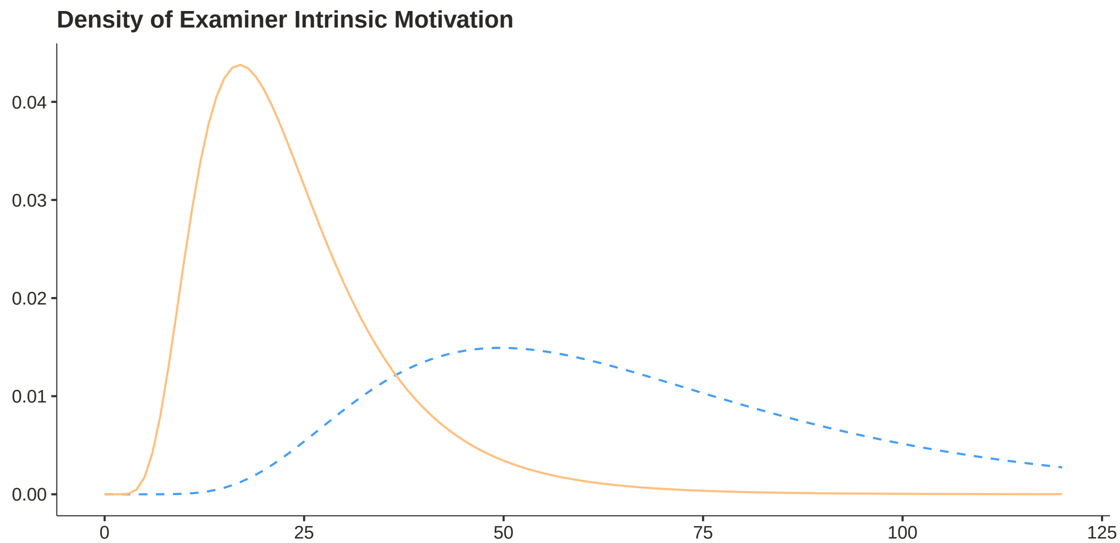
Figure 17: Density of unpadded application drafting legal fees



Notes:

Back to discussion of applicant estimates in section 9.1.

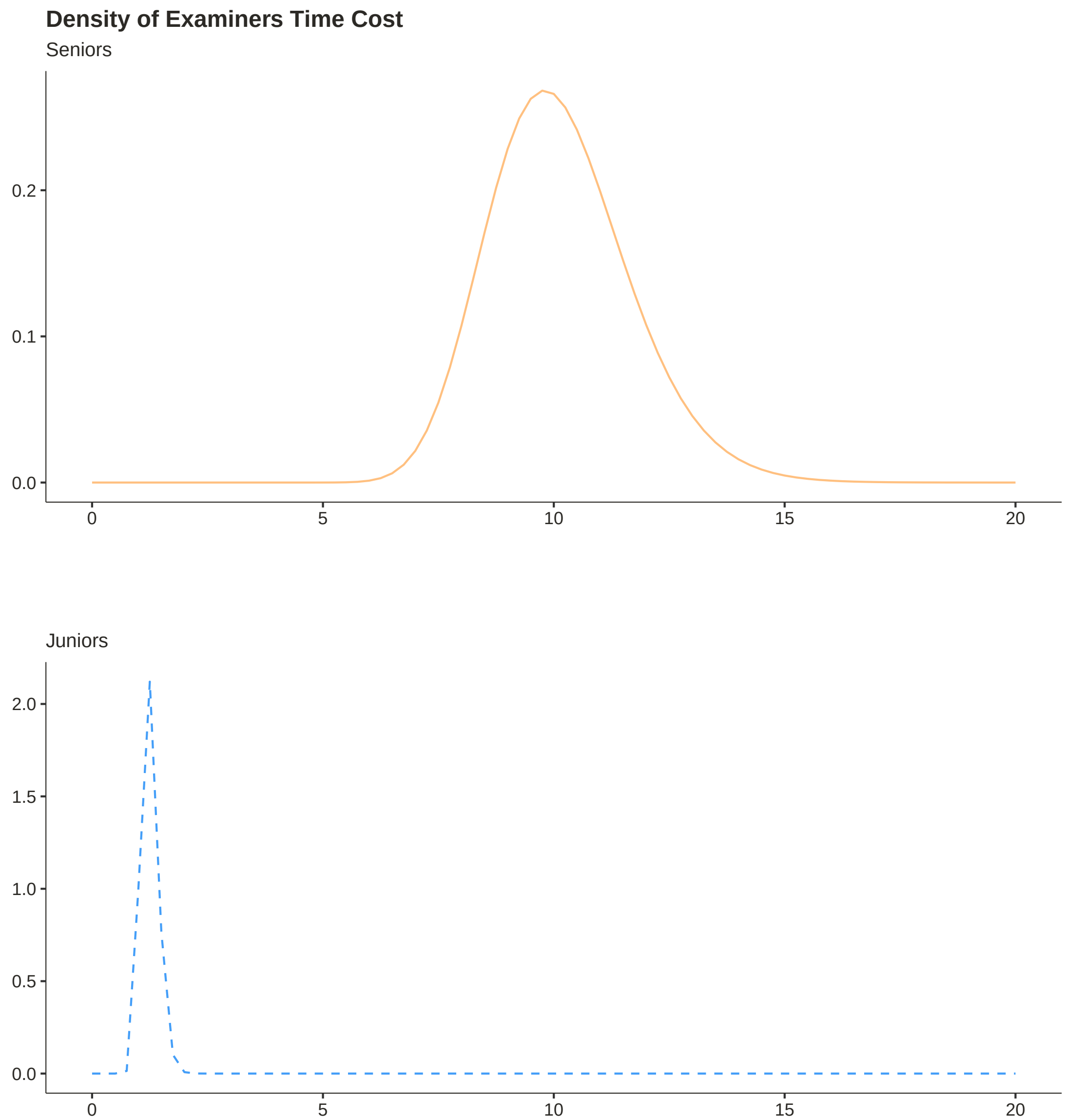
FIGURE 18: Density of examiner intrinsic motivation



Notes: Orange solid curve represents the distribution for senior examiners; blue dashed curve represents the distribution for junrior examiners. To interpret the x-axis, consider an examiner in technology center 36, where the technology correction is 22.4. Dividing the values on the x-axis by 22.4 yields the number of credits the examiner pays as an intrinsic motivation cost for granting a patent for an application on which every claim is invalid.

Back to discussion of examiner estimates in section 9.2.

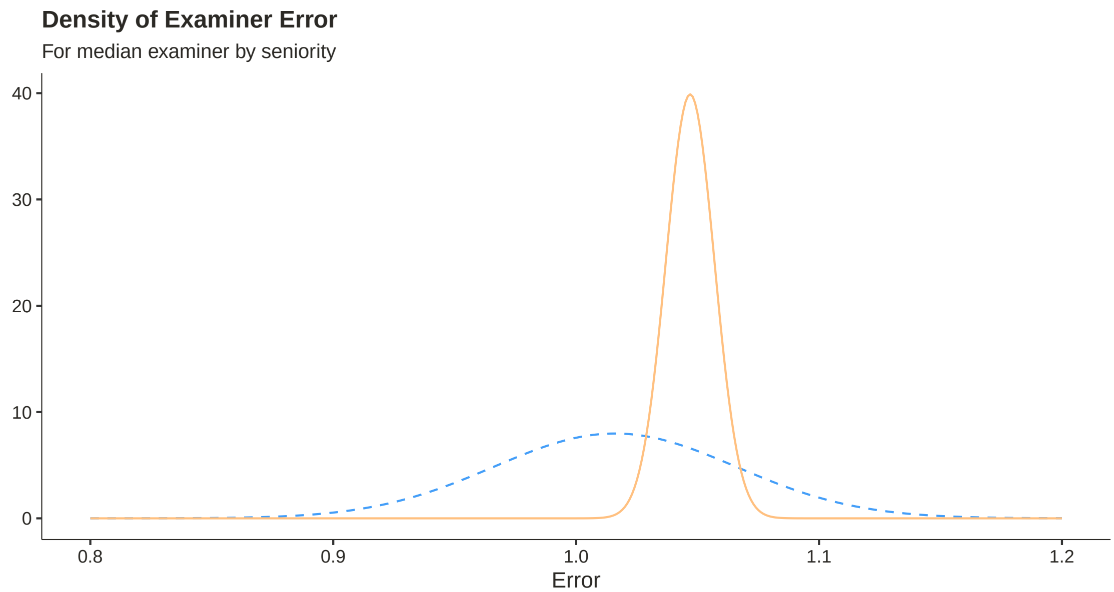
Figure 19: Density of examiner time costs



Notes: Orange solid curve represents the median intrinsically motivated senior examiner; blue dashed curve for junior examiners. To interpret the x-axis, consider an examiner in technology center 36, where the technology correction is 22.4. Dividing the values on the x-axis by 22.4 yields the number of credits the examiner pays for each round of extra negotiation.

Back to discussion of examiner estimates in section 9.2.

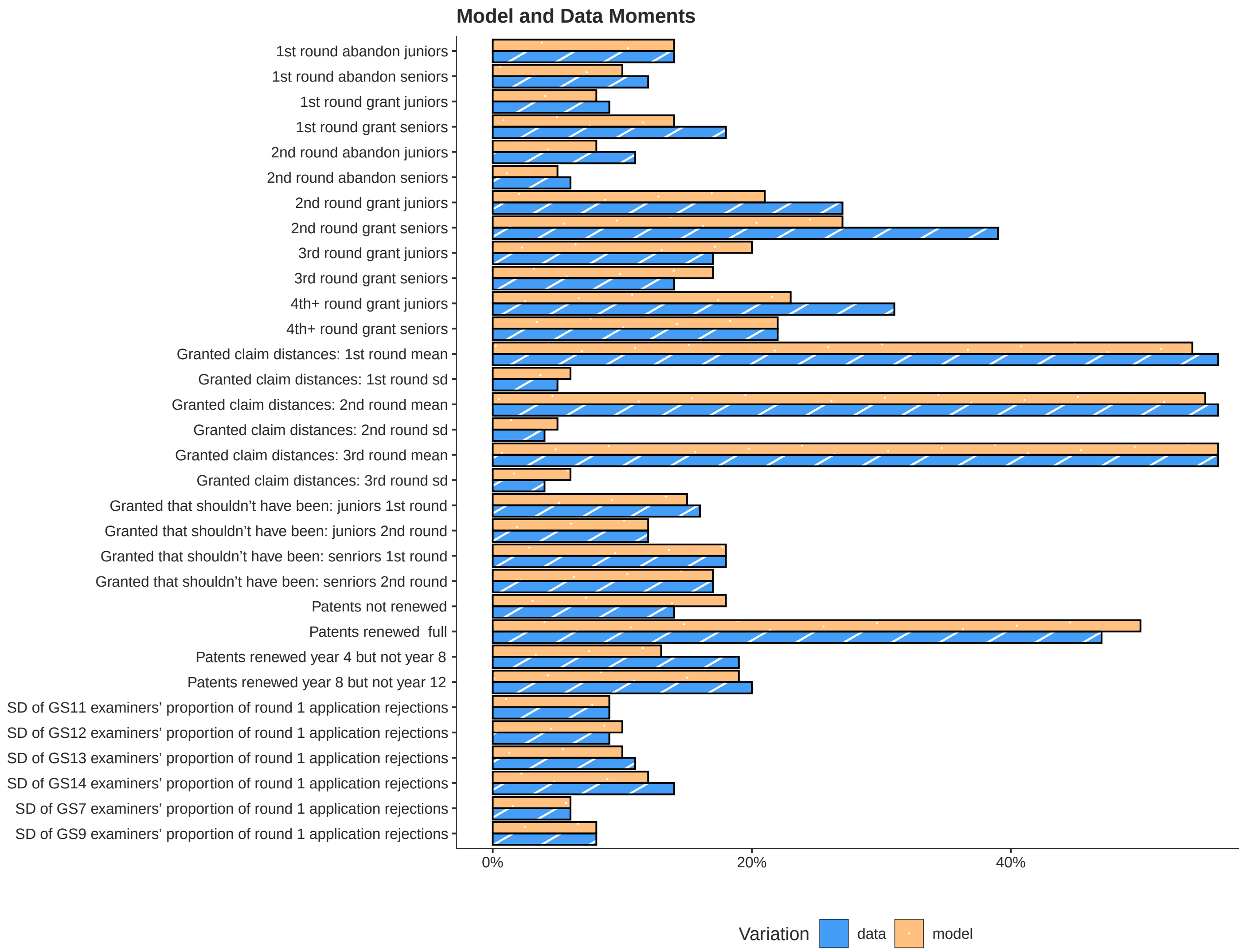
Figure 20: Density of examiner error



Notes: Orange solid curve represents the median intrinsically motivated senior examiner; blue dashed curve represents the median intrinsically motivated junior examiner.

Back to discussion of examiner estimates in section 9.2.

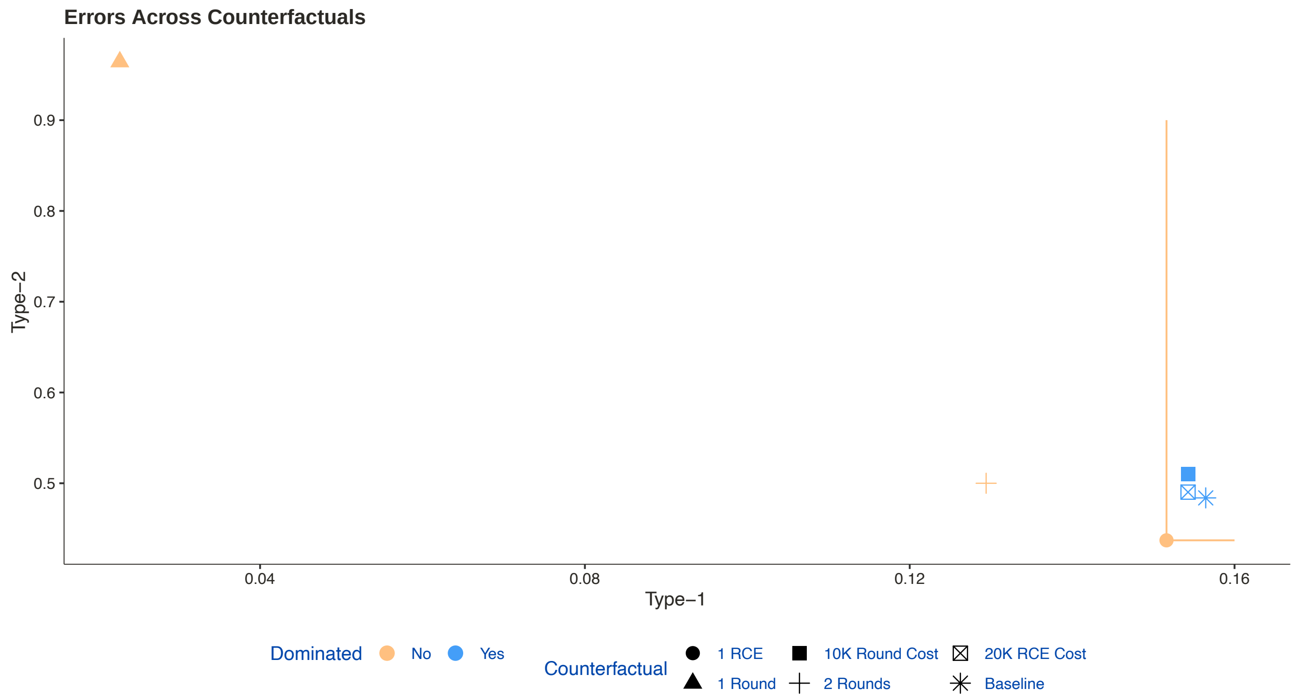
Figure 21: Match of data and model moments



Notes:

Back to discussion in fit section 9.3.

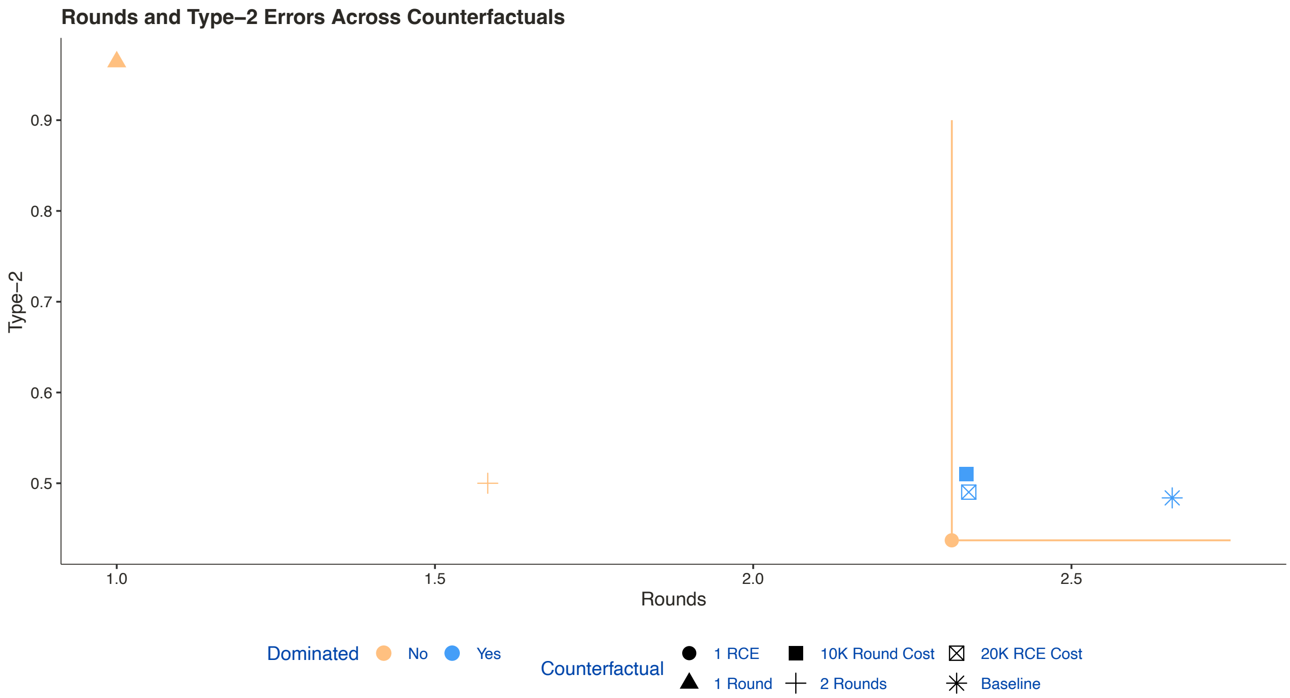
FIGURE 22: Tradeoff between Type-1 and Type-2 errors across counterfactuals



Notes:

Back to discussion in counterfactual section 10.4.

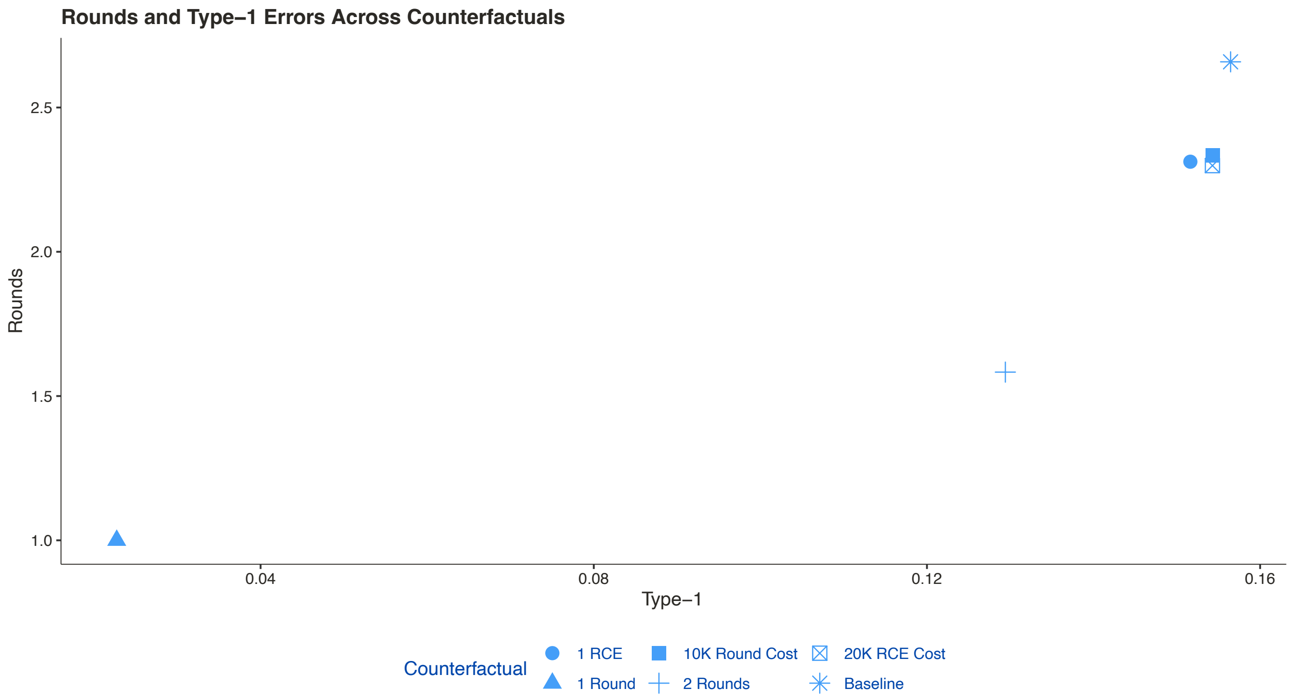
Figure 23: Tradeoff between rounds and Type-2 errors across counterfactuals



Notes:

Back to discussion in counterfactual section 10.4.

FIGURE 24: Rounds and Type-1 errors across counterfactuals



Notes:

Back to discussion in counterfactual section 10.4.

E.2 Tables

Table 4: Regression Results

Variable	(1) Issue	(2) Negotiation
GS-9	0.012 (0.003)	-0.012 (0.002)
GS-11	0.049 (0.002)	-0.012 (0.002)
GS-12	0.069 (0.002)	-0.015 (0.002)
GS-13	0.129 (0.002)	-0.015 (0.002)
GS-14	0.186 (0.002)	-0.047 (0.002)
Chemicals (17)	0.065 (0.002)	0.058 (0.002)
Comp. Software (21)	0.205 (0.002)	0.144 (0.002)
Comp. Networks (24)	0.226 (0.003)	0.139 (0.002)
Communications (26)	0.209 (0.002)	0.096 (0.002)
Electronics (28)	0.229 (0.002)	0.021 (0.002)
Other (36)	0.076 (0.002)	0.044 (0.002)
Mech Engineering (37)	0.098 (0.002)	0.026 (0.002)
N	937,929	937,929

Notes: Omitted grade is GS-7 and omitted technology center is Biotechnology and Organic Fields. Technology center "Other" refers to Center 3600, which is "Transportation, Electronic Commerce, Construction, Agriculture, Licensing and Review." We report heteroskedasticity robust standard errors in parentheses.

Back to seniority and technology center discussion in section 5.1.

Table 5: Conditional Distribution of 102/103 and 112 Rejections

102/103 112	No	Yes	Total
No	-	12,307,888	12,307,888
Yes	753,862	2,033,192	2,787,054
Total	753,862	14,341,080	15,094,942

Notes: This table displays the count of rejections in office actions by the rejection type. The figure in text is 2,033,192/2,787,054 = 73 percent, which is the proportion of office action rejections with a 112 rejection that also have a 102/103 rejection.

Back to rejection type discussion in section 5.3.

TABLE 6: Applicant Parameters

Parameter	Symbol	Estimate	Standard Error
Initial returns mu	μ_v	9.556	0.037
Initial returns sigma	σ_v	0.645	0.011
Initial distance alpha	α_D	3.368	0.014
Initial distance beta	β_D	6.120	0.038
Narrowing probability	η	0.766	0.007
Application obsolescence probability	$P_{obs,app}$	0.132	0.002
Renewal obsolescence probability	$P_{obs,renew}$	0.040	0.000
Simple application fighting cost mu	$\mu_{f,simple}$	8.907	0.032
Simple application fighting cost sigma	$\sigma_{f,simple}$	0.502	0.022
Chemical application fighting cost mu	$\mu_{f,chem}$	9.286	0.027
Chemical application fighting cost sigma	$\sigma_{f,chem}$	0.602	0.016
Electrical application fighting cost mu	$\mu_{f,chem}$	9.138	0.029
Electical application fighting cost sigma	$\sigma_{f,chem}$	0.840	0.050
Mechanical application fighting cost mu	$\mu_{f,mech}$	9.009	0.028
Mechanical application fighting cost sigma	$\sigma_{f,mech}$	0.583	0.012

Notes: This table provides the model parameters relating to the applicant. Standard errors are bootstrapped.

Back to applicant estimates in section 9.1.

Table 7: Examiner Parameters

Parameter	Symbol	Estimate	Standard Error
Junior IM mu	$\mu_{\theta,junior}$	4.135	0.015
Senior IM mu	$\mu_{\theta,senior}$	3.059	0.036
IM sigma	σ_{θ}	0.480	0.007
Junior cost mu	$\mu_{\pi,junior}$	0.211	0.005
Senior cost mu	$\mu_{\pi,senior}$	2.295	0.027
Cost sigma	σ_{π}	0.150	0.003
SD error junior	$\sigma_{\varepsilon,junior}$	0.050	0.001
SD error senior	$\sigma_{\varepsilon,senior}$	0.010	0.000

Notes: This table provides the model parameters relating to the examiner. Standard errors are bootstrapped.

Back to examiner estimates in section 9.2.

Table 8: Quantiles of Examiner Intrinsic Motivation Distribution

Quantile	Junior IM	Senior IM
10	33.780	11.517
20	41.722	14.225
30	48.584	16.565
40	55.334	18.867
50	62.490	21.306
60	70.570	24.061
70	80.376	27.405
80	93.595	31.912
90	115.601	39.415

Notes: This table provides the quantiles of the intrinsic motivation distribution for junior and senior examiners.

Table 9: Counterfactual Results

Counterfactual	Baseline	(1) 1 Round	(2) 2 Rounds	(3) 1 RCE	(4) 20K, 40K RCE Costs	(5) 10K Round cost	(6) Constant RCE Credits
Panel A: Timeliness							
% that would not apply	20%	80%	59%	31%	34%	35%	20%
Average # Rounds	2.66	1.00	1.58	2.31	2.34	2.33	2.66
Round 1 Grants	10%	86%	22%	11%	13%	15%	10%
Round 1 Abandoments	13%	14%	19%	16%	14%	13%	13%
Round 2 Grants	23%		58%	26%	29%	27%	23%
Round 2 Abandoments	7%		0%	5%	5%	6%	7%
Round 3 Grants	19%			23%	20%	21%	19%
Round 3 Abandoments	4%			2%	3%	3%	4%
Round 4 Grants	12%			16%	12%	10%	12%
Round 4 Abandoments	2%			0%	0%	0%	2%
Round 5 Grants	7%				3%	5%	7%
Round 5 Abandoments	1%				0%	0%	1%
Round 6 Grants	4%				1%	1%	4%
Round 6 Abandoments	0%				0%	0%	0%
Panel B: Padding							
minimum	0.78	0.78	0.78	0.78	0.78	0.78	0.78
10th percentile	0.86	0.82	0.84	0.86	0.86	0.84	0.86
20th percentile	0.91	0.84	0.86	0.89	0.89	0.89	0.91
30th percentile	0.93	0.86	0.91	0.93	0.91	0.91	0.93
40th percentile	0.98	0.89	0.93	0.98	0.96	0.95	0.98
50th percentile	1.02	0.91	0.98	1.02	1.00	1.00	1.02
60th percentile	1.05	0.95	1.02	1.05	1.05	1.05	1.05
70th percentile	1.09	1.00	1.05	1.09	1.07	1.07	1.09
80th percentile	1.16	1.05	1.09	1.16	1.11	1.11	1.16
90th percentile	1.24	1.13	1.20	1.24	1.24	1.24	1.24
maximum	1.55	1.48	1.52	1.55	1.52	1.55	1.55
Panel C: Errors							
% grants with $\geq$ 1 invalid claim	16%	2%	13%	15%	15%	15%	16%
% granted claims invalid	7%	1%	6%	7%	7%	7%	7%
% abn apps with $\geq$ 1 valid claim	48%	96%	50%	44%	49%	51%	48%
% abn claims valid	30%	98%	33%	30%	32%	32%	30%

Notes:

Back to counterfactuals in section 10.

Table 10: Seniority Corrections

Seniority Grade	**Signatory Authority**	$\kappa_{SEN}(S)$
GS-5	None	0.55
GS-7	None	0.7
GS-9	None	0.8
GS-11	None	0.9
GS-12	None	1.0
GS-13	None	1.15
GS-13	Partial	1.25
GS-14	Partial	1.25
GS-14	Full (primary examiner)	1.35

Notes: This table provides the seniority factors for credit adjustment. A pair of seniority grade-signatory authority values defines a seniority S in the model.

Back to examiner credit discussion in section C.2

Table 11: Technology Center Corrections

Technology Center T	$\kappa_{TECH}(T)$
17	22.2
21	31
24	29
26	26.5
28	21.4
36	22.4
37	19.9

Notes: This table provides the technology complexity factors for credit adjustment

Back to examiner credit discussion in section C.2

Table 12: Parameter Bounds

Parameter	**Symbol**	**Lower Bound**	**Upper Bound**
Junior IM mu	$\mu_{\theta,junior}$	0.05	5
Senior IM mu	$\mu_{\theta,senior}$	0.05	5
IM sigma	σ_{θ}	0.1	2
Junior cost mu	$\mu_{\pi,junior}$	0.1	4
Senior cost mu	$\mu_{\pi,senior}$	0.1	4
Cost sigma	σ_{π}	0.1	2
SD error junior	$\sigma_{\varepsilon,junior}$	0.01	0.3
SD error senior	$\sigma_{\varepsilon,senior}$	0.01	0.3
Initial returns mu	μ_{v}	5	10
Initial returns sigma	σ_{v}	0.5	5
Initial distance alpha	α_{D}	1	8
Initial distance beta	β_{D}	1	8
Narrowing probability	η	0	1
Application obsolescence probability	$P_{obs,app}$	0	1
Renewal obsolescence probability	$P_{obs,renew}$	0	1
Simple application fighting cost mu	$\mu_{f,simple}$	5	10
Simple application fighting cost sigma	$\sigma_{f,simple}$	0.5	5
Chemical application fighting cost mu	$\mu_{f,chem}$	5	10
Chemical application fighting cost sigma	$\sigma_{f,chem}$	0.5	5
Electrical application fighting cost mu	$\mu_{f,chem}$	5	10
Electical application fighting cost sigma	$\sigma_{f,chem}$	0.5	5
Mechanical application fighting cost mu	$\mu_{f,mech}$	5	10
Mechanical application fighting cost sigma	$\sigma_{f,mech}$	0.5	5

Notes: This table provides the bounds on parameters in estimation.