# Patent Obfuscation and Reliance on External Financing

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We use large language models to decompose patent readability into fundamental and strategic components, introducing a novel measure of obfuscation as the gap between them. Exploiting variation in examiner strictness as an instrument, we show that obfuscation involves a tradeoff: it deters competitors and reduces litigation risk but restricts access to external finance by lowering patents' collateral value. In response to disclosure shocks, firms more reliant on external finance are less likely to attempt to offset the effect by changing their obfuscation approach. Our results underscore the strategic role of patent disclosure in shaping both innovation and financing outcomes.

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# 1 Introduction

Patents allow individuals and companies to monopolize technological innovations. However, the disclosure of the invention exposes the patent holder to potential negative outcomes such as infringement, imitation, and litigation. Thus, companies may describe their inventions with unclear or overly complex language, both to avoid rejection by the patent examiner for lack of novelty, and to deter competitors from developing a similar technology due to the unclear scope of the patent (Ireland et al., 2024; Figueroa and Lemus, 2024).

Prior literature has argued that firms deliberately obfuscate patents in order to deter others from producing related patents in related technology classes (Dyer et al., 2024). By making it difficult to understand, the probability of competitors entering the same market and/or understanding the technology is reduced (Bhattacharya and Ritter (1983)). However, this comes at a potential cost to the patent holder. The value of a patent is not only in its inherent productive capabilities but also as a valuable asset class to obtain financing (Mann, 2018). Patents are often an important asset class supporting external financing, and increasingly so in recent years. If the patent's content is obscure to a company's competitors, it will be even more so for investors, who have less subject matter expertise.[1] In this paper, we examine the tradeoffs firms make in determining the level of clarity or obfuscation in their patent applications (Anton and Yao, 2004).

The first challenge is to provide a measure of obfuscation. A number of papers have attempted to define obfuscation or clarity using large language models (LLM). Generally, the approach is to use standard readability measures on patent text, textual length or word counts of the application, or the classification of words that capture difficult to understand text. The primary drawback to these methods is the lack of a counterfactual. Patents may be deemed obscure because the technology itself is complex or it may be a strategic decision on the part of the patent writer. Disentangling the two is difficult. In this paper, we propose

[1]There is a large literature that shows that increased disclosure transparency can reduce a firm's cost of capital. (See Healy and Palepu, 2001, Leuz and Wysocki, 2016, and Goldstein and Yang, 2017 for reviews of the literature.

a novel LLM-based measure of obfuscation to disentangle these two potential components.

Our methodology is to compare the actual abstract to an alternate AI-generated version. To do so, we first instruct a leading LLM, Claude Sonnet v3.5, to provide the clearest possible restatement of the patent's abstract. We manually inspect a sample of the LLM-written abstracts and confirm that it maintains the information content of the original patents. This LLM-simplified abstract represents the fundamental information about the innovation that is inherent in the patent abstract.

Then, we compute measures of readability for both the original abstract and the alternate abstract provided by the LLM and take the difference between the two. This difference represents the readability gap between the two versions. If the difference is small, the abstract captures the technology without the use of extraneous, complex or obscure language. On the other hand, if the difference between the two is large, then we assume that the original abstract contains additional information that is unlikely to add to a reader's understanding of the technology.[2] We argue that this readability gap is a reflection of a firm's strategic obfuscation of the language of the patent abstract.[3]

The goal of the abstract is to give the reader a high-level overview of the patent's core technical contribution without going into extensive claims.[4] We focus on this section of the patent application not only because this shorter text is easier to handle computationally but also because abstracts allow for faster scanning and filtering, especially when dealing with millions of patents. With the advent of automated textual analysis, obfuscation thus serves as the first line of defense against infringement or imitation by competitors and patent

[2]Our approach is motivated by Bushee et al. (2018a) who decomposes managerial obfuscation in earnings calls into discussions that are unlikely to be obfuscated (those provided by analysts' discussion and the discussion of business complexity) and the residual.

[3]Alternatively, it could also reflect other non-strategic idiosyncratic components such as an inexperienced or low quality patent drafter. The former will be correlated with variables we predict are more likely to reflect strategic considerations, while the latter will not. Indeed, we find that the determinants of the readability gap is consistent with strategic obfuscation.

[4]According to the USPTO guidelines for preparing patent abstracts, the content of a patent abstract should be such as to enable the reader thereof, regardless of his or her degree of familiarity with patent documents, to determine quickly from a cursory inspection of the abstract the nature and gist of the technical disclosure and that which is new in the art to which the invention pertains. Source: https://www.uspto.gov/web/offices/pac/mpep/s608.html

litigators.

We begin by studying the characteristics of our measure of obfuscation both in the time series and in the cross-section of patents. We find significant time-series variation in obfuscation, including a sharp upward trend in the most recent years of the sample, validating concerns about growing obfuscation within patent documents (Figueroa and Lemus, 2024). In the cross section, we find that obfuscation is more common in firms with characteristics that are related to patent protection, for example those who have a larger market share in their industry and face greater competition with peers that have highly valuable patents, as measured by Kogan et al. (2017).

Moreover, we find that the financial condition of the firm is related to the extent of the obfuscation. Firms that rely more on external financing and are more likely to face financing constraints are less likely to obfuscate their application. Whether this is due to the value of patents as collateral for external financing or the type of firm is the focus of our analysis.

We validate our focus of the readability gap as a measure of obfuscation by examining the characteristics of the LLM-simplified abstract itself. First, we show that the LLM-simplified versions contain very similar content to the actual abstract by comparing the embeddings. Second, we find that readability of the LLM-simplified abstract is fairly stable over time and maintains a consistent rank-ordering across technology categories. Both of these are consistent with the notion that the LLM-simplified abstract successfully streamlines the fundamental content of the patented technology, while the readability gap captures the strategic dimension of obfuscation that depends more on firm conditions.

In order to disentangle the endogenous relationship between obfuscation and patent outcomes that may be due to unobservable firm characteristics, we use an instrumental variable for obfuscation that is based on the random assignment of patent examiners. The role of patent examiners, particularly their leniency in approving applications, in patent outcomes has been studied in the literature (Feng and Jaravel, 2020; Farre-Mensa et al., 2020). To do so, for each examiner, we measure the rate at which they issue initial rejections only

due to inadequate description of the technology based on Section 112 of the Patent Act ("§112 strictness"). As documented by Dyer et al. (2024), patent examiners' propensity to reject patent applications for disclosure-related reasons (i.e., §112) is modestly or negatively correlated with their propensity to do so for non-disclosure-related reasons.

To establish the relevance of our instrument, we begin by examining how an examiner's §112 strictness influences both obfuscation behavior and the responses of the market.[5] We find that assignment to a §112-strict examiner significantly reduces the degree of obfuscation. Such examiner strictness also predicts greater improvement in the readability of the application text from the initial to the final version. Moreover, stricter examiners are associated with more negative market reactions to patent grants (as measured by Kogan et al., 2017) and with lower subsequent market valuations of the patenting firm. These findings suggest that the examiner-induced clarification is, from the firm's perspective, value-reducing. Taken together, the results indicate that examiners exert a substantial influence on the disclosure strategies of firms.

Next, we analyze how obfuscation, instrumented by examiner strictness, influences outcomes at both the patent and firm levels. Consistent with prior work (Freilich, 2017; Ashtor, 2022), we find that obfuscated patents receive fewer citations from outside firms. As a novel contribution, we also show that obfuscated patents are less likely to be involved in infringement litigation. Both results align with the view that obfuscation discourages other firms from pursuing related technologies or filing related patents by creating uncertainty about the precise scope of protection. Taken together, these findings highlight the strategic benefits of obfuscation, which enables firms to secure a broader and less contested technological domain.

However, the benefits of obfuscation come with potential costs. When fewer competitors operate in adjacent technological areas, there are also fewer prospective acquirers for the firm's technology, or for the firm itself, should it face financial distress. This dynamic reduces the firm's pledgeable income and, in turn, its access to external finance. Consistent

[5]Following the literature, we include fixed effects for the examiner's art unit in our IV specifications.

with this mechanism, we find that obfuscated patents are significantly less likely to be sold or transferred after grant and are less likely to be pledged as collateral for loans.

We employ two additional identification strategies to corroborate these findings. The first exploits the enactment of the American Inventor's Protection Act (AIPA), which has been widely used in the literature as a disclosure shock because it requires patent applications to be published 18 months after filing rather than only upon being grant. Following the difference-in-differences approach of Ireland et al. (2024), we find that treated firms increased obfuscation in response to the AIPA, consistent with the view that firms attempt to counteract the effects of forced transparency. However, this response is substantially weaker among firms that rely on patent collateral for financing or that are highly leveraged, consistent with the notion that dependence on external finance dampens incentives to obfuscate patent filings.

The second additional strategy focuses on the Supreme Court's decision in Nautilus v. Biosig, which strengthened the standard for evaluating patent claim definiteness under §112. Prior to 2014, a claim could only be rejected if it was "insolubly ambiguous" (Ashtor, 2022). Under *Nautilus*, this standard was changed to improve claim clarity. We find that firms with higher exposure to the ruling significantly reduce their level of obfuscation afterward. However, the effect is smaller for firms that rely on external financing, consistent with the idea that such firms had already chosen an obfuscation level that protected the collateral value of their patents before the ruling, leaving less room for adjustment. Together with the AIPA results, these findings highlight that the cost of obfuscation is higher for firms dependent on external financing.

Our work contributes to two main strands of literature. First, we extend research on the determinants of disclosure in patent applications. For instance, Dyer et al. (2024) show that examiner leniency with respect to §112 is associated with disclosures containing less substantive content and receiving fewer follow-on citations. Ashtor (2022) demonstrates more broadly that examination procedures and policies can significantly affect claim clar-

ity. Freilich (2017) documents the rise of "clutter", claim language unrelated to the invention—which makes patents harder to search. Relatedly, Kong et al. (2023) find that university patents are more readable than corporate patents.

Second, we contribute to the literature on financial disclosure by proposing a novel measure of obfuscation, made possible by the advent of widely accessible AI tools (Gunning, 1969; Li, 2008; Loughran and McDonald, 2014; Bushee et al., 2018b to name a few). Instead of relying on traditional readability metrics, we construct counterfactual patent abstracts that improve clarity relative to the original text. In doing so, we add to the growing literature in natural language processing that develops new approaches to quantify textual complexity.

Finally, we highlight the financial implications of obfuscation. We show that patent obfuscation may hinder capital formation, underscoring the tradeoffs inherent in disclosure strategies. While obfuscation can expand a firm's uncontested technological space, it also reduces the salability and pledgeability of patents. Accordingly, firms that rely on external financing may find obfuscation costly. This suggests that financing needs can temper the incentives to obfuscate, illustrating a positive role for financial constraints and for the growing use of intellectual property assets in overcoming them.

# 2 Data

## 2.A Measuring Patent Obfuscation

Bushee et al. (2018a) was one of the first to recognize that complexity in natural language is not necessarily obfuscation. They note that the underlying fundamental characteristics of a firm may necessitate complex language that promotes, not hinders transparency. To address this point, they measure obfuscation by benchmarking the linguistic difficulty of the manager's discussion in earnings conference calls (using the Gunning-Fog index) against that of analysts, who are assumed to have no incentive to obfuscate.

With the advent of AI LLM tools, we are able to generate a reduced form counterfactual text from any raw input. In our case, we use patent abstracts with the goal of quantifying when patent language is unnecessarily difficult to understand. The first step is to identify where such language would occur. We suggest that most parties who need to understand a patent will focus on its abstract and summary, which are meant to summarize the patent's contribution. One benefit of focusing on these sections is that they do not carry the same legal weight as the claims section of the patent, which are notoriously difficult for even specialists to read (Mille and Wanner, 2008). The abstract and summary portion, therefore, allows the patent writer more room for discretion.

In addition, patent searches are often conducted using algorithmic textual analysis with a focus on the abstract of the patent to identify relevant technologies. Therefore, a competitor, acquirer, or investor who wants to quickly identify what is protected by the patent would focus on these sections, and the patent writer can thus influence how much they learn through their choice of wording.

At a high level, our approach leverages a large language model (LLM) to evaluate patent texts and propose revisions that would enhance clarity. In other words, we ask the LLM to simplify the abstract to its most fundamental content. To ensure computational tractability, we restrict attention to the patent abstract rather than the longer accompanying summary. We assume that firms engaging in obfuscation in one section would do so consistently across both. A violation of this assumption would bias our estimates toward zero, thereby reducing the likelihood of detecting statistically significant relationships.

To implement this idea, we begin downloading from PatentsView the abstracts and identifiers of the full sample of 2.6 million patents granted since 1976 through 2023 that have been matched with public firm identifiers in the KPSS+CCM link tables.[6] We provide each patent abstract to Claude Sonnet v3.5 (with the temperature parameter set to zero) and instruct it to generate a simplified version if possible. The exact prompt is: *Give me a simpler*

[6]Available at https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data. We use the October 2024 data release.

*and clearer version of this patent abstract. Reply with JUST your version, not any label, title, header, or comments.* We intentionally refrain from instructing the LLM to preserve technical or legal detail, as these are not critical in the abstract, and we keep the prompt deliberately brief to minimize token count.[7]

Table I provides two examples from this process. In the left column of the table are the abstracts of two patents that are often highlighted as potential examples of obfuscation. The first is patent number 8786366, Intel Mobile Communications' patent for its Amplifier circuit. The second is patent number 9547842, IBM's patent for an email autoreply feature. Both ideas seem relatively simple to describe, but the abstract in both cases is surprisingly complex with unnecessary information and ambiguous wording.[8]

[Insert Table I about here]

Next, we quantify the readability of both the original abstract and the LLM-simplified version using tools from the linguistics literature. Specifically, we calculate the Flesch, Flesch-Kincaid, Gunning-Fog, ARI, Coleman-Liau, LIX, RIX, and entropy scores. These scores use various approaches to estimate the difficulty or readability of reading a text, often expressed as a grade level. For example, we find the Gunning-Fog readability of the sample patent abstracts in Table III improves by four and seven grade levels, respectively after being rewritten by the LLM.

[Insert Table II about here]

To exploit all the available readability measures, we calculate the first and second principal components for the combined samples of original and LLM-simplified abstracts. We use

[7] In ongoing work we check robustness of our results to more token-intensive approaches applied to smaller subsamples of patents, including longer prompts and examining the patent summary in addition to the abstract.

[8] Indeed, recent literature finds strong evidence that the fidelity of the summarizations produced by LLMs is high (e.g., Huang et al., 2023). As can be seen in the second column, the LLM is able to explain the core idea of each patent much more clearly. We validate the information preserving nature of these summaries by computing the cosine similarity of the embeddings of the original and rewritten abstract. More than 80% of patents have a similarity above 70%, indicating that the rewritten abstracts contain the same content.

these two principal components (PCA1 and PCA2) as our primary measure of readability in the paper. In Table II, We find that PCA1 loads about evenly across all the indices except for entropy, while the second principal component, PCA2, loads mainly on entropy (the difficulty of predicting the next word in a sequence). This suggests that the indices capture a correlated notion of what makes a text easy or difficult to read, while entropy is a slightly different concept.

One can think of the readability of the LLM-simplified abstract as a measure of the fundamental ease of describing the technology. In order to assess the clarity of the original abstract, we take the difference between the readability (either the first and second PCs of the readability scores) of the original and LLM-simplified abstracts as follows:

$$\text{Obfuscation} = \text{Readability of LLM-simplified abstract} - \text{Readability of original abstract} \quad (1)$$

with a larger value corresponding to more obfuscation. Our primary results compute obfuscation using PCA1 as the measure of readability, but we show that our results are robust to using Gunning Fog and Entropy.

## 2.B Other Data Sources

The analysis in this paper combines data from many sources. We link our patent sample with data on citations within 10 years of the grant date and CPC technology classes (PatentsView), patents sold or pledged as collateral (USPTO Assignments database), infringement allegations (USPTO and the Stanford NPE litigation database), art-unit assignments (PatEx), competitor patenting, and firm-level financial data (Compustat).[9] We classify patent self-citations based on the identifiers in the KPSS link tables. Patent value estimates come from KPSS, and we obtain a proxy for breakthrough patents (*RETech*) from

[9]We determine which patents have been pledged and sold following Mann (2018) and Bowen III (2016), respectively. We use the general financial constraint proxy "delaycon" from Hoberg and Maksimovic (2015) and label it *HMConstrained*. *Market Share* is based on sales within SIC3 industries. *HHI (TNIC3)* is from Hoberg and Phillips (2016). *Peer Patent Value* is the KPSS value of competitors defined by TNIC3 industries. Firm-level data is merged using the application year to measure the firm's condition at the invention of the patent.

Bowen III et al. (2023). Finally, data used to estimate examiner strictness comes from USPTO Office Action Research Dataset and PatEx, and we describe the construction of these variables in detail in Section 4.B.

### 2.C Summary Statistics

Table III presents the summary statistics. Our full sample consists of 2,647,518 patents spanning 1976-2023 grants. The average value of *Obfuscation* is 2.51 with wide variation across the sample. *LLM Readability* has a tighter distribution than our measure of obfuscation. Data required to define examiner strictness is only available after 2008 and the average examiner gives a first-action rejection that only cites §112 for 4% of patents. The average citation for a patent is 3.8 with the median having none. The average KPSS value of a patent is almost $13 million (1982 dollars). In our sample, 15% of patents are pledged as collateral and 26% are sold. Patent infringement is rare with a little over 11,000 patents experiencing litigation. The remaining variables from Compustat have distributions that closely match studies over the same period of time.

[Insert Table III about here]

## 3 Attributes of Obfuscation

### 3.A Stylized Facts

In this section, we show how obfuscation varies over the time series and across patents.

[Insert Figure I and Figure II about here]

Figure I plots the time series of our obfuscation measure, constructed using PCA1 and PCA2 as readability indices (solid red lines). Obfuscation measured with PCA1 (Panel A) and PCA2 (Panel B) exhibits substantial time variation, and the two often trend in opposite

directions, suggesting that they capture distinct dimensions of readability. Nevertheless, both measures show a pronounced upward trend beginning around 2015, consistent with growing concerns about obfuscation in patent filings (Figueroa and Lemus, 2024).

The dashed black lines in Figure I display the fundamental readability of patent abstracts—that is, the readability of the LLM-simplified abstracts. Unlike the obfuscation measures, the readability of the rewritten abstracts exhibits relatively little time-series variation. This suggests that much of the variation in obfuscation reflects heterogeneity in the original writing style of the patent rather than shifts in the underlying technical content.

Importantly, the relative stability of LLM readability over time does not imply that all abstracts are rewritten to the same readability standard. LLM-simplified abstracts exhibit systematic differences in readability across technology classes, though these differences remain relatively stable over time within each class.

We further illustrate this point in Figure II, which plots the time series of our obfuscation measure across broad technology classes. Obfuscation does not follow identical trajectories across categories, indicating substantial cross-sectional variation. However, all categories exhibit an upward trend beginning around 2015, demonstrating that this is a pervasive phenomenon across industries rather than an artifact of any single technological domain.

[Insert Figure III about here]

Our last set of stylized facts relate obfuscation to key patent metrics. In lieu of correlations that hide non-linearities, Figure III presents binscatter plots relating patent value, citations, and RETech to *Obfuscation* and *LLM Readability*, the readability of the LLM-simplified abstract. Highly obfuscated patents have significantly lower patent valuations, receive fewer citations, and are less likely to use ideas that are rapidly evolving (i.e., creating or following breakthroughs). These results, while not causal, highlight potential benefits of clarity when inventors make strategic patent disclosure choices.

The bottom row in the figure relates the same outcomes to *LLM Readability*, which captures how clearly the patent can be conveyed. The relationships between *LLM Readability*

and the outcome metrics are also negative but make an importantly different point: Ideas that are fundamentally simpler are less valuable as measured by the stock market reactions or citations generated and lead to fewer breakthroughs.

## 3.B Determinants

We next examine the determinants of obfuscation using a regression framework and present the results in Table IV. The dependent variable in Column 1 is our main measure of obfuscation based on the first PCA of readability scores. Column 2 uses Gunning-Fog as the readability measure to compute obfuscation, while Column 3 uses entropy. Standard errors are clustered by firm-year to match the unit level of the independent variables.

To assess the relationship between financing and obfuscation, we regress obfuscation on leverage as a proxy for the firms reliance on debt financing, a direct measure of financing constraints (*HMConstrained*) available for part of the sample, and firm size as an always-available proxy for (lack of) financing constraints.[10]

The results in Table IV show that obfuscation is less prevalent among smaller firms, highly leveraged firms, and those that disclose financial liquidity problems. These findings suggest that obfuscation is less common among firms more reliant on external financing, potentially because patents may serve a valuable role in fundraising by acting as collateral. To explore this possibility formally, the next section develops an IV strategy to identify the causal effect of patent obfuscation on firm financing, and in the final section we reinforce the evidence by examining shocks from court rulings.

[10] *HMConstrained* is available for most firms from 1997 to 2015. To use the full sample, we fill missing values with zero and include a boolean variable equal to one for these observations, following the suggestion of Hoberg and Maksimovic (2015).

# 4 IV Analysis: Patent Examiner §112 Strictness

## 4.A Institutional Details on Patent Examination

To facilitate a causal interpretation of our baseline results, we implement an instrumental variable strategy leveraging the exogenous variation in patent obfuscation arising from the random assignment of examiners, who differ in their stringency when rejecting patents for disclosure-related reasons (i.e., Section 112). As described in more detail in Section 4.B, we measure examiner strictness as the fraction of applications that an examiner issues non-final rejections due only to a lack of disclosure under §112 and then use it as an instrument for patent obfuscation. In doing so, we build upon a growing literature leveraging the patent examination process in the USPTO (Gaulé, 2018; Sampat and Williams, 2019; Farre-Mensa et al., 2020; Melero et al., 2020; Ertugrul et al., 2024; Dyer et al., 2024). Below we briefly describe the institutional details of the patent examination process, with a focus on events that are crucial to the underlying rationale of our instrumental variable.

Upon arriving at the USPTO, patent applications are received by a central office that performs an initial review to ensure that applications are ready for examination. Then patent applications are assigned a filing date, patent class, and subclass codes, and allocated to an art unit specializing in certain technology areas (Lemley and Sampat, 2012; Gaulé, 2018). After an application arrives in an art unit, the supervisory patent examiner (SPE) of that unit assigns it to a patent examiner, who will have continuing responsibility for examining the application throughout the process until it is disposed of either through patent issue or abandonment (Cockburn et al., 2002; Carley et al., 2015). After receiving an assignment, the examiner evaluates the application and issues a preliminary determination of its validity—the 'first-action decision'—which is communicated to the applicant through an official letter.

The most frequent grounds for patent rejection are noncompliance with §101 (subject-matter eligibility), where the claimed invention does not fall within statutory categories or is directed to a judicial exception without additional inventive elements; §102 (novelty), where

the invention is already disclosed in prior art; §103 (non-obviousness), where the invention would have been evident to a person having ordinary skill in the art in light of existing knowledge; and §112 (written description and claim clarity), where the specification fails to adequately describe the invention or the claims are indefinite or ambiguous. For our identification strategy, we focus on examiners' rejection rates based solely on §112, excluding other grounds, which generates exogenous variation in the degree of patent obfuscation, independent of the underlying quality of the patented invention or the quality of the applicant.

Our instrument for patent obfuscation, examiner strictness with respect to disclosure-related reasons (§112), is motivated by the following. First, both the institutional details and the existing literature (see, e.g., Lemley and Sampat, 2012 and Sampat and Williams, 2019) suggest that the assignment of patent applications to examiners is quasi-random within an art unit and year. For example, interviews with patent examiners conducted by Lemley and Sampat (2012) document that applications are assigned based on the last four digits of the application number, docket flow management, or familiarity with certain technologies, none of which is related to the application or applicant (firm) quality.

Second, patent examiners exercise considerable discretion in the review process, and they differ significantly in their strictness regarding compliance with disclosure requirements. Therefore, a patent application reviewed by a stricter examiner is more likely to receive a first-action rejection on disclosure-related grounds and to be revised with less obfuscation in order to pass the review process.

The application of patent examiner strictness also applies to the abstract of the document. Patent examiners are required to ensure that patent abstracts comply with the USPTO guidelines. According to the Manual of Patent Examining Procedure(MPEP) 608.01(b), if an application lacks an abstract or the abstract does not meet the guidelines, the examiner must point out the defect and require correction.[11] This implies that examiners actively

[11]https://www.uspto.gov/web/offices/pac/mpep/s608.html "The Office of Patent Application Processing (OPAP) will review all applications filed under 35 U.S.C. 111(a) for compliance with 37 CFR 1.72 and will require an abstract, if one has not been filed. In all other applications which lack an abstract, the examiner in the first Office action should require the submission of an abstract directed to the technical disclosure in

enforce clarity and compliance in abstracts as part of the examination process.

## 4.B Data on Patent Examiners and Construction of IV

Our instrument for patent obfuscation, *Examiner §112 Strictness*, is computed as the fraction of total applications the examiner non-finally rejects in the first action only due to failure to meet disclosure clarity requirements under §112, excluding the focal application.

To construct our instrument, we first utilize the USPTO Office Action Research Dataset, which provides information on the first-action decisions for all patent applications filed between 2008 and 2023, irrespective of their ultimate disposition (granted, abandoned, or pending). Specifically, the Office Action data lists whether a patent application has been issued a §101, §102, §103, or §112 rejection. We then merge these records with the Patent Examination Research Dataset in order to compile the track record of rejection rate by reason for each examiner over the same period.

Specifically, we compute the instrument for obfuscation of a patent application $a$ that is reviewed by examiner $k$ as the §112 strictness of examiner $k$ faced by a patent application $a$ using the following:

$$\text{Examiner §112 Strictness}_{ka} = \frac{\text{Total §112 Rejections}_k - 1(\text{§112 Rejection}_a = 1)}{\text{Total Applications}_k - 1}. \quad (2)$$

In the above, Total §112 Rejections$_k$ and Applications$_k$ are the total number of §112 rejections that examiner $k$ issued at the first action and the total number of applications she reviewed. 1(§112 Rejection$_a$=1) is equal to one if patent application $a$ was issued a §112 rejection by examiner $k$ who reviewed it and zero otherwise. In doing this, we follow the existing literature (e.g., Gaulé, 2018; Melero et al., 2020) and calculate the examiner's §112 strictness faced by a patent application excluding this focal application.[12] In our IV regressions, we include

the specification."..."If the abstract contained in the application does not comply with the guidelines, the examiner should point out the defect to the applicant in the first Office action, or at the earliest point in the prosecution that the defect is noted, and require compliance with the guidelines."

[12]Following Dyer et al. (2024), we calculate examiners' §112 strictness using the full sample, as this

art unit–by–year fixed effects, as both institutional details and prior research indicate that the assignment of examiners to patent applications is quasi-random within an art unit and year. Our findings remain robust when we instead employ an art unit–adjusted measure of examiner §112 strictness, defined as an examiner's individual §112 strictness relative to the average §112 strictness within the same art unit—in place of art unit–by–year fixed effects.

As a way of validating our instrument, in Table A1 we focus on a subset of patent applications for which we can observe the text of the application evolving through the review process, from initial review and rejection to final acceptance. We find that patents assigned to stricter examiners indeed exhibit improved readability by the end of the review process.[13]

In Table V we regress examiner strictness on both the value of the patent (*KPSS*), and the firm's market-to-book ratio in the year following the application (*Q(t+1)*). Stricter examiners are associated with more negative valuations of patent grants (as measured by Kogan et al., 2017) and with lower subsequent market valuations of the patenting firm. These findings suggest that the examiner-induced clarification is, from the firm's perspective, value-reducing. Taken together, the results indicate that examiners exert a substantial influence on the disclosure strategies of firms.

## 4.C IV Results

We report the results of our IV analysis in Table VI. In Column 1, we report the first stage result. As expected, the coefficient of examiner §112 strictness is negative and significant at the 1% level. The first stage F-stat is 29.46, which is significantly greater than the critical value suggested in Stock and Yogo (2005). This demonstrates that the examiner §112 strictness is a strong determinant of patent obfuscation, confirming that the relevance condition required for a valid instrument is satisfied.

approach leverages more data and thus provides greater variation. This is also supported by existing evidence suggesting that examiners' strictness in issuing rejections is at least partly driven by examiner-specific, time-invariant attributes (e.g., Lemley and Sampat, 2012).

[13]This is consistent with Ashtor (2022), who shows that patents rejected on §112 grounds become more simplified during the review process.

[Insert Table VI about here]

The remainder of Table VI presents the second-stage results, examining the causal impact of patent obfuscation on financing outcomes and patent litigation.[14] Column 2 shows that obfuscated patents receive fewer citations overall, with the decline coming both from outside firms (Column 3) and the inventing firm itself (Column 4). The lower level of citations from other firms is consistent with the notion that obfuscation deters other firms from operating in related technological areas or pursuing related patents by creating ambiguity around the exact scope of patent protection. Moreover, obfuscated patents receive fewer citations from the inventing firm. This is consistent with the deterrent effect reducing their incentives to build defensive thickets of related patents. In Column 5, we identify a novel benefit of patent obfuscation that is also consistent with this deterrence-oriented view: obfuscated patents are less likely to be infringed upon, and less likely to be involved in patent litigation.

Most prior literature has focused on the benefits of obfuscation as summarized in the results above. Based only on this mechanism, one might expect that firms generally obfuscate as much as possible, and that strong enforcement is required to achieve the public good of disclosure that is core to the patent system.

However, the remaining results in Table VI demonstrate offsetting costs of obfuscation. In Column 6, we find that obfuscated patents are significantly less likely to be resold, which is consistent with the notion that obfuscation reduces the liquidity of patents. In Column 7, we find that obfuscated patents are less likely to be pledged as collateral for loans. This draws a direct connection between patent obfuscation and external financing.

Note that our IV analyses control for examiner strictness based on §101-103 grounds (usefulness, novelty, non-obviousness), which captures the extent to which examiners scrutinize substantive aspects of the patented invention in a patent application. This ensures that our main coefficient is identified from variation in how the invention is written. For five of the six outcome variables, the coefficient on *Examiner Other Strictness* is not statistically

[14] To be precise, the IV captures the effect of obfuscation for the subset of "complier" patents, that is, patents that actually exhibited lower levels of obfuscation due to the assignment to a strict examiner.

significant. We also include *LLM Readability* to control for the fundamental complexity of the ideas embedded in the patent. We find that patents that are fundamentally less complex and more readable receive more citations, are more likely to be resold, and are more frequently pledged as collateral.

[Insert Table VII about here]

Table VII repeats the tests but uses different readability scores to measure Obfuscation and LLM Readability. Results are reported using Gunning Fog for readability in Panel A and PCA2 in Panel B. The estimates are very similar to the main IV tests in both statistical and economic significance.

Overall, our findings in this section support a causal interpretation of the costs and benefits of patent obfuscation: while obfuscation deters competition and reduces the likelihood of patent infringement, it also hinders firms' access to external financing.

# 5 Exogenous Shocks to Patent Disclosure

To corroborate and extend our argument based on the patent examiner IV strategy, we conclude by studying two exogeneous shocks, using a difference-in-difference approach: the enactment of the American Inventors Protection Act (AIPA) and the decision in *Nautilus v. Biosig*, both of which affected the transparency of patent disclosure.

## 5.A The Enactment of AIPA

The first disclosure shock that we study is the American Inventors Protection Act (AIPA), which was enacted in 1999 and effective in 2000. Its most important new requirement is that patent applications must be published eighteen months after they are initially filed rather than when granted. The publication of the application occurs regardless of whether the patent was ultimately granted. However, applications for which patent protection is

not sought outside the US are able to opt out of the pre-grant publication. Thus, the Act differentially affect US and foreign firms.

We adopt the same difference-in-difference strategy of Ireland et al. (2024) to test whether the enactment of the Act changes the obfuscation behavior of the firm. We begin by confirming their main result using our sample and our obfuscation measure. Following their approach, we first classify patents according to whether they also sought foreign protection, based on family IDs available through Google Patents that connect patents with related applications in foreign jurisdictions. Family IDs that include foreign applications are considered to be treated by the new Act. As in Ireland et al. (2024), we assume that US domiciled patent applications opt out of the new disclosure requirement.

In Column 1 of Table VIII, we regress our obfuscation measure on an indicator variable if patent is filed in 2000 or later (*Post-AIPA*) and an indicator variable for whether the patent sought foreign protection (*Foreign*). We then interact the two.

The results in Column 1 show that obfuscation increased by 0.16 post-AIPA (which is 10% of the median obfuscation amount), for patents that sought foreign protection relative to other patents. This is consistent with the result in Ireland et al. (2024) in which the raw readability of patents decreases following the enactment.

We next note that the choice to seek foreign protection may itself be affected by the new regime post-AIPA. To avoid concerns about endogeneity, we next use a treatment exposure measure that is not whether *this* patent seeks foreign protection, but rather, what percentage of the filing firm's patents sought foreign protection in the pre-AIPA era (*Pct Foreign*). Column 2 shows that our qualitative result continues to hold. Obfuscation increases post-AIPA by 0.301 more for a firm where this percentage was 100% as opposed to zero.

Overall, Columns 1 and 2 confirm that AIPA forced treated firms to disclose more patents, and that they responded on average by obfuscating those patents more. This is again consistent with the perspective that greater disclosure may be costly to patent firms as it weakens their protection. Firms, therefore, counteract the intended effect of the Act by increasing

their obfuscation.

Our central hypothesis is that the benefits of greater protection may be outweighed by the lower probability that the patent can be pledged as collateral. Therefore, we examine whether the effect of the Act on disclosure is weaker for firms with high external financing needs.

In Column 3, we examine whether the AIPA had differential effects for firms that are more likely to rely on the collateral value of their patents for financing. We include an indicator variable for whether the filing firm pledged patents as collateral during the pre-AIPA period (*Pledged Patents*) and interact it with both the percentage of the filing firm's patents that sought foreign protection and the post-AIPA variable.

Even though treated firms have more obfuscation after the enactment of the AIPA, the triple interaction term shows that if these same treated firms have pledged patents, they are less likely to obfuscate. Hence, the incentives to obfuscate are much stronger for firms that do not depend on the collateral value of their intellectual property.

In Column 4, we further investigate whether the AIPA had a differential effect on firms that are more reliant on external finance. To capture this reliance, we use the firm's debt-to-asset ratio (*Debt/Asset*) as the primary variable of interest. Firms with higher debt-to-asset ratios are assumed to be more dependent on external financing. Confirming our prior result, treated firms with greater debt financing are less likely to obfuscate after the passage of the AIPA.

Overall, this section indicates that firms have an incentive to increase the obfuscation of their patents in order to mitigate the new disclosure requirements imposed by AIPA. Our results are also consistent with Saidi and Žaldokas (2021), who show that firms who are more affected by the new disclosure requirements of AIPA find it easier to establish new banking relationships. Enhancing transparency in patent applications, therefore, may facilitate access to capital markets.

## 5.B Nautilus v. Biosig

The second disclosure shock we analyze is *Nautilus v. Biosig* (2014), a U.S. Supreme Court ruling that tightened the standard for evaluating patent claim definiteness under 35 U.S.C. §112. The case involved Biosig Instruments, a medical equipment company that held a patent on a heart-rate monitor, and Nautilus, a fitness equipment manufacturer that challenged the patent on the grounds that its claims were ambiguous and too indefinite to enforce. In its decision, the Court established the "reasonable certainty" standard, replacing the Federal Circuit's "insolubly ambiguous" test and requiring patent claims to clearly define their scope.[15] Consistent with the ruling's objective of preventing unclear claim boundaries that could create legal uncertainty, Ashtor (2022) documents a significant increase in §112(b) rejections post-*Nautilus*. The Court's decision explicitly increases the standard of clarity in patent applications.

To examine how the ruling influences firms' obfuscation practices, we implement a difference-in-differences research design in Table IX using 513,606 patent applications filed three years before and after the decision date (6/2/2014). We require firms to have filed patent applications both before and after the ruling.

Across columns, the dependent variable is our obfuscation measure. Our treatment variable, *Exposure*, captures those firms that are more likely to be affected by the ruling and is defined as the median obfuscation level across patent applications filed in the period before the ruling. In other words, while the decision made patent disclosure requirement more stringent for all applicants, we firms that had a higher level of obfuscation will need to change their behavior more than firms with a lower level of obfuscation. *Post-Nautilus* is an indicator variable equal to one if patent application is filed after the decision date, and zero otherwise.

As shown in column 1, the interaction term of *Exposure* x *Post* is -0.180 and statistically significant at the 1% level. In terms of economic magnitude, a one standard deviation increase

[15] https://supreme.justia.com/cases/federal/us/572/898/

in pre-period exposure corresponds to a 5.9 percent reduction in obfuscation.[16] This finding is in line with Ashtor (2022), who reports a significant improvement in patent claim clarity following the ruling.

Next, we examine whether the *Nautilus* ruling had different effects for firms that are hypothesized to rely more heavily on external financing. As in Section 5.A, we consider firms that pledge their patents and those with high leverage as more likely to use external financing. In column 2, we interact an indicator variable that represents whether the firm had pledged patents as collateral during 2011-2013, *Pledged Patents*. The results show that while firms with higher pre-period obfuscation reduced obfuscation following the ruling (the coefficient of *Exposure* x *Post* is negative and significant), this reduction is smaller for firms that had previously pledged patents as collateral (the coefficient of *Exposure* x *Pledged patents* x *Post* is 0.420 and significant at the 1% level). These results are consistent with the view that firms relying on patent-based loans had more transparent disclosure that optimized the patent's collateral value before the ruling, reducing the need to adjust to the Court's mandate of increased clarity.

In a similar fashion, column 3, we interact an indicator variable that equals one if the firm was highly levered in the pre-period, *High Leverage*. Firms are classified as highly levered if their leverage exceeds the industry median. Medians are defined at the Fama-French 12-industry level based on firms' average leverage during 2011-2013.

We find that the reduction in obfuscation is less pronounced for firms that have higher leverage in pre-period: while the interaction term *Exposure* x *Post* remains negative and significant, the coefficient of the triple interaction term *Exposure* x *High Leverage* x *Post* is 0.183 and significant at the 1% level. These patterns echo our findings in column 2: firms with higher reliance on external capital in the pre-period react less strongly to the Court's ruling.

Together with the evidence presented in Section 5.A, we document a consistent and

[16]The standard deviation of pre-period *Exposure* is 0.8, and the mean of obfuscation is 2.44. It follows that -0.18*0.8/2.44 = -0.059, or -5.9%

notable pattern. Although firms respond differently on average to these patent disclosure shocks—increasing obfuscation after the AIPA and decreasing it following the *Nautilus* decision—the effect on obfuscation is smaller in both cases for firms that are more reliant on external financing. These findings are consistent with the assumption that these firms have more transparent disclosure strategies because of they reap the benefit of using the patent as collateral. Thus, their incentive to mitigate the court's ruling of improving clarity by obfuscation is lower than firms who do not rely external financing.

# 6 Conclusion

Courts and regulators have long sought to improve the clarity of patent applications. Yet many studies document that patent writers counter these efforts by employing increasingly obscure language. In this paper, we introduce a novel LLM-based approach to measuring obfuscation. The LLM extracts the core content of a patent abstract and restates it as clearly as possible, thereby isolating the fundamental information. We then define obfuscation as the difference in readability between the original and LLM-simplified versions, which captures the improvement in clarity achieved by rewriting.

Using this measure, we study the effects of obfuscation in patent abstracts, though the method is readily applicable in other settings. Our findings suggest that LLMs offer new opportunities for analyzing the role of misleading or opaque wording in financial and legal documents.

We document several novel patterns. Obfuscation has increased in recent years, consistent with concerns that firms seek to circumvent disclosure requirements that are central to the patent system. While obfuscation can deter competitors and reduce litigation risk, it also lowers the collateral value of patents when used in external financing. Accordingly, firms with greater reliance on debt or on patents as collateral engage in less obfuscation. We also find that patent writers respond to constraints such as stricter examiners or heightened

disclosure requirements imposed by laws and court decisions.

Overall, our results indicate that obfuscation is not uniformly desirable from the firm's perspective but instead entails a strategic tradeoff. In particular, external financing needs may discourage firms from obfuscating. These findings highlight mechanisms that regulators should consider when evaluating policies aimed at promoting disclosure and limiting obfuscation in the interest of the social goals of the patent system.

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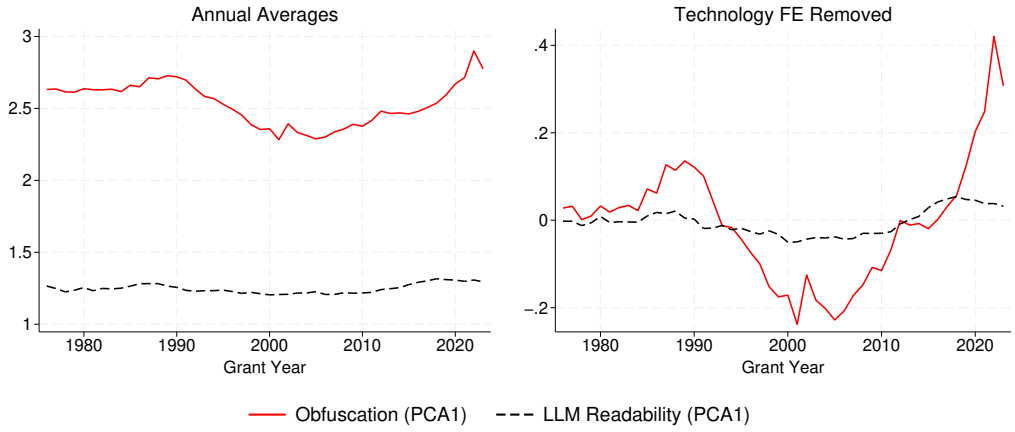
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**Figure I: Time Series of Obfuscation**

This figure plots the evolution of our measures of obfuscation from 1976-2023. Panel A shows the average level of our main measure of *Obfuscation* (red line) and the average readability of LLM-simplified abstract (gray dotted line), with both variables using readability defined as the first principle component of the readability measures listed in Table II. Panel B shows the average level of obfuscation (red line) and the average readability of LLM-simplified abstract (gray dotted line), where readability is based on the second principal component of the same set of readability measures. Left panels report raw annual averages and right panels show technology class-adjusted averages.

**Panel A: Obfuscation with PCA1 as Readability Measure**




**Panel B: Obfuscation with Entropy as Readability Measure**

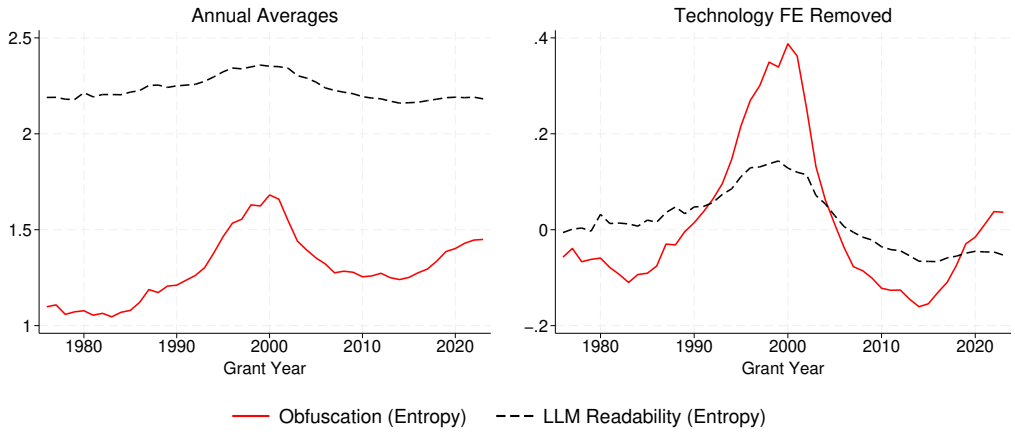


**Figure II: Time Series of *Obfuscation*, by Technology Category**
This figure plots the evolution of *Obfuscation* across the six largest technology sections in the CPC classification scheme from 1976 to 2023. Each subpanel reports in parentheses the fraction of patents over the entire sample belonging to that category.

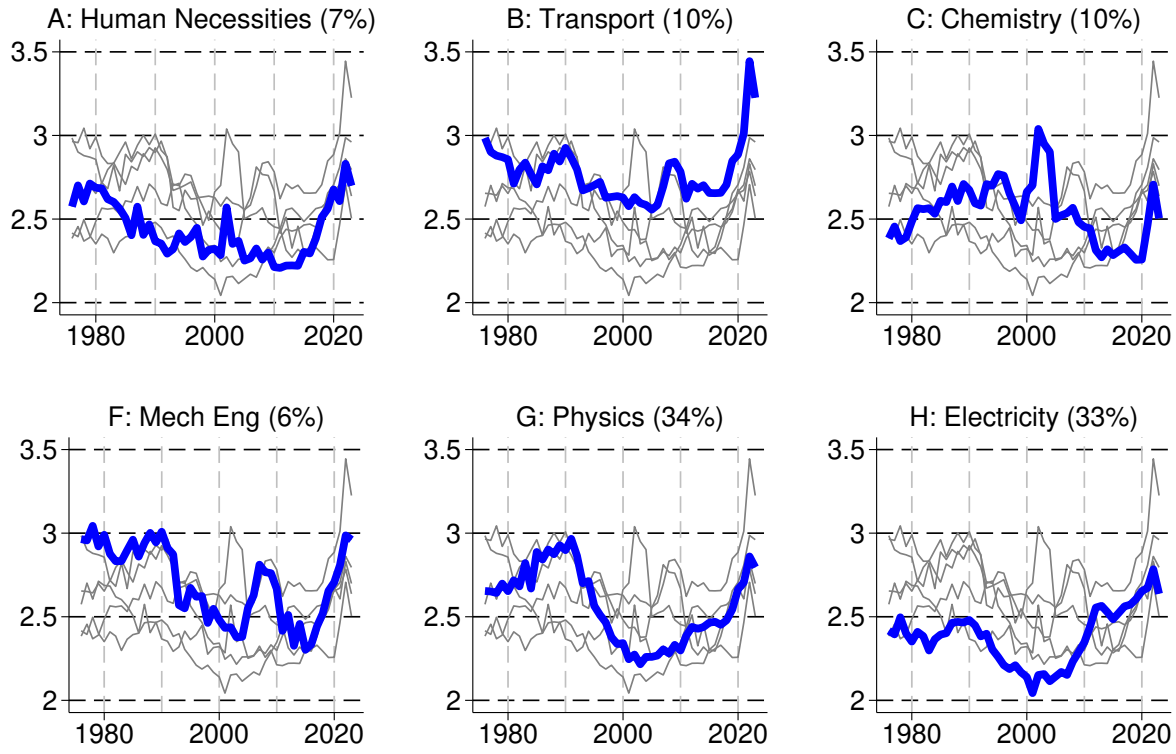


**Figure III: Relation with Key Patent Metrics**

This figure shows binned scatter plots illustrating the relation between *Obfuscation* and key patent metrics (top subpanels). As a benchmark, we also plot the relation between *LLM Readability* and key patent metrics (bottom subpanels). *Log(KPSS)* is the natural log of the patent value estimate from Kogan et al. (2017). *Log(1+Cite10)* represents the natural logarithm of one plus the number of forward citations received within 10 years of the grant date. *RETech* is a proxy for breakthrough patents from Bowen III et al. (2023). To facilitate interpretation, both *Obfuscation* and *LLM readability* are standardized. All plots control for application year fixed effects.

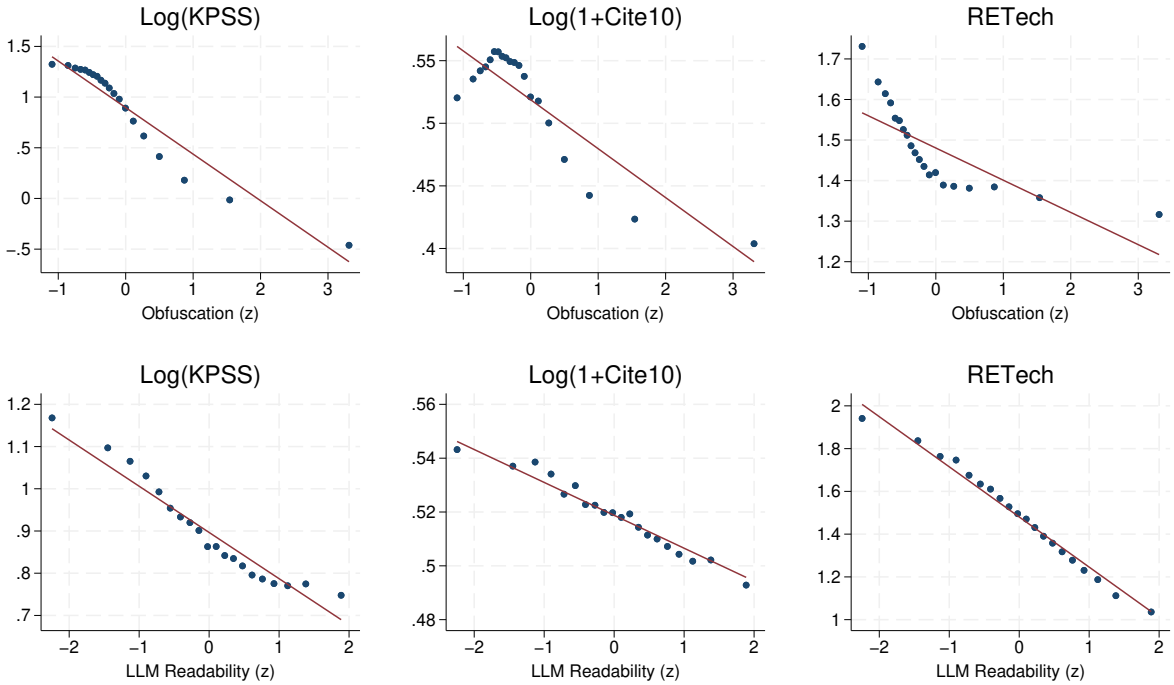


**Table I: Examples of Patents with Obscured Language**

This table shows two patent abstracts and the LLM rewritten version. Patent 8786366 is Intel Mobile Communications' "Amplifier circuit" patent, and patent 9547842 is IBM's "out of office" auto reply patent.

| Patent | Abstract | LLM Rewrite |
|---|---|---|
| 8786366 | An amplifier circuit is described comprising a first field effect transistor comprising a first source/drain terminal coupled to a first supply terminal, a second source/drain terminal coupled to an output of the amplifier circuit and a gate terminal; a second field effect transistor comprising a first source/drain terminal coupled to an input of the amplifier circuit, a second source/drain terminal coupled to the gate terminal of the first field effect transistor and a gate terminal; a third field effect transistor comprising a first source/drain terminal coupled to a first bias current source of the amplifier circuit, a second source/drain terminal and a gate terminal coupled to its first source/drain terminal and the gate terminal of the second field effect transistor; a fourth field effect transistor comprising a first source/drain terminal coupled to a second bias current source, a second source/drain terminal coupled to a second supply terminal and a gate terminal coupled to the second source/drain terminal of the third field effect transistor; and a control circuit coupled to the gate of the fourth field effect transistor configured to control the source drain voltage of the fourth field effect transistor by means of the gate of the fourth field effect transistor to be equal to a reference voltage. | This patent describes an amplifier circuit with four transistors and a control circuit. The first transistor connects to the power supply and the output. The second transistor links the input to the first transistor's gate. The third transistor connects to a bias current source and the second transistor's gate. The fourth transistor connects to another bias current source and the power supply. A control circuit regulates the fourth transistor's voltage to match a reference voltage. |
| 9547842 | A method, a system and a computer program product of transmitting availability information in an electronic mail system are disclosed. The system includes a first system including a sender, the first system is adapted to activate an availability indicator having a start date, wherein the activation is performed by the sender and extract availability indicator metadata from the availability indicator. The availability indicator metadata includes the start date, an end date, and at least one availability indicator message. If an e-mail has not been sent to a receiver since activation and if a current date is prior to the start date, the first system is further adapted to attach the availability indicator metadata to the e-mail, and send the e-mail to the receiver. The electronic mail system further includes a scheduling system functionally coupled to the first system, and is adapted to define the availability indicator. | This invention describes a way to share availability information through email. It involves a system where a sender can set up an availability indicator with start and end dates, along with a message. When the sender emails someone for the first time after setting this up, and before the start date, the system automatically adds the availability information to the email. The system also includes a scheduling feature that helps create these availability indicators. |

## Table II: Principal Components Analysis of Readability Factors

This table shows the loadings on the first three principle components of the readability scores. The loadings are estimated using the readability scores measured on both the granted abstracts and the LLM rewritten abstracts. The sample of patents are those granted from 1976 to 2023 that are linked to public firm identifiers by Kogan et al. (2017).

| | Comp1 | Comp2 | Comp3 |
|---|---|---|---|
| Component Loadings | | | |
| Flesch Reading Ease | -0.40 | 0.12 | -0.07 |
| Flesch Kincaid Grade | 0.40 | 0.07 | -0.13 |
| Gunning Fog | 0.40 | 0.06 | -0.12 |
| Automated Readability Index | 0.40 | 0.05 | -0.13 |
| Coleman Liau Index | 0.16 | -0.68 | 0.68 |
| LIX | 0.40 | -0.02 | -0.06 |
| RIX | 0.40 | 0.02 | -0.10 |
| Entropy | 0.12 | 0.72 | 0.69 |
| Principle Components | | | |
| Eigenvalues | 6.04 | 1.20 | 0.63 |
| CumulExplained | 0.76 | 0.91 | 0.98 |

## Table III: Summary Statistics

This table presents summary statistics at the patent level for patents granted from 1976-2023 to publicly traded firms. *Obfuscation* is the difference between the readability of the LLM rewrite of a patent abstract and the readability of the abstract in the patent grant, with readability defined as the first principle component of the readability measures listed in Table II. *Pledged*, *PatSold*, and *Infringed* are booleans equal to one if the patent is used as collateral, sold to another entity, or involved in litigation by year-end 2024. *KPSS* is the patent value estimate from Kogan et al. (2017). Examiner strictness variables are defined in Section 2.

| | N | Mean | SD | p10 | p50 | p90 |
|---|---|---|---|---|---|---|
| Obfuscation | 2,647,518 | 2.51 | 2.91 | 0.20 | 1.70 | 5.80 |
| LLM Readability | 2,647,518 | 1.25 | 0.83 | 0.20 | 1.29 | 2.28 |
| Examiner 112 Strictness | 936,551 | 0.04 | 0.06 | 0.00 | 0.02 | 0.11 |
| Examiner Other Strictness | 936,551 | 0.54 | 0.19 | 0.26 | 0.57 | 0.78 |
| Cite10 | 2,647,518 | 3.84 | 33.94 | 0.00 | 0.00 | 6.00 |
| Log(1+Cite10) | 2,647,518 | 0.52 | 0.96 | 0.00 | 0.00 | 1.95 |
| Log(1+NonSelf10) | 2,647,518 | 0.44 | 0.88 | 0.00 | 0.00 | 1.61 |
| Log(1+Self10) | 2,647,518 | 0.15 | 0.52 | 0.00 | 0.00 | 0.69 |
| KPSS | 2,647,518 | 12.98 | 35.56 | 0.08 | 3.94 | 30.32 |
| Log(KPSS) | 2,647,518 | 0.90 | 2.28 | -2.57 | 1.37 | 3.41 |
| RETech | 2,625,510 | 1.48 | 2.12 | -0.06 | 1.10 | 3.31 |
| Pledged | 2,033,284 | 0.15 | 0.36 | 0.00 | 0.00 | 1.00 |
| PatSold | 2,647,518 | 0.26 | 0.44 | 0.00 | 0.00 | 1.00 |
| Infringe | 2,647,518 | 0.00 | 0.07 | 0.00 | 0.00 | 0.00 |
| Leverage | 2,635,646 | 0.22 | 0.17 | 0.02 | 0.20 | 0.41 |
| Cash/AT | 2,647,450 | 0.18 | 0.16 | 0.03 | 0.13 | 0.40 |
| HMConstrained | 640,235 | -0.01 | 0.08 | -0.11 | -0.02 | 0.10 |
| Log(AT) | 2,647,513 | 9.74 | 2.08 | 6.94 | 10.10 | 11.93 |
| Profitability | 2,642,058 | 0.13 | 0.14 | 0.05 | 0.14 | 0.25 |
| Tangibility | 2,646,896 | 0.24 | 0.16 | 0.06 | 0.20 | 0.49 |
| R&D/AT | 2,647,518 | 0.07 | 0.07 | 0.01 | 0.05 | 0.13 |
| Log(Claims) | 2,647,518 | 2.64 | 0.69 | 1.79 | 2.83 | 3.33 |
| Market Share | 2,642,482 | 0.15 | 0.19 | 0.01 | 0.09 | 0.40 |
| HHI (TNIC3) | 1,587,116 | 0.28 | 0.26 | 0.08 | 0.17 | 0.73 |
| Log(Peer Patent Value) | 2,394,654 | 7.43 | 5.37 | 0.00 | 10.07 | 12.72 |

## Table IV: Firm Determinants of Obfuscation

This table examines how patent and firm characteristics are related to patent obfuscation. The sample is patents granted from 1976-2023 to publicly traded firms. The dependent variables use different constructions of "obfuscation," which is the difference between the readability of the LLM rewrite of a patent abstract and the readability of the abstract in the patent grant. Column (1) uses our main measure of "obfuscation," which is based on the first principle component of the readability measures listed in Table II. Columns (2) and (3) use Gunning Fog and Entropy, respectively, as the readability measure. Other variables are defined in Section 2. To facilitate interpretation, all independent variables are standardized. Standard errors are clustered by firm-year. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All models include technology-by-application year fixed effects.

| | (1) Obfuscation (z) (PCA1) | (2) Obfuscation (z) (Gunning Fog) | (3) Obfuscation (z) (Entropy) |
|---|---|---|---|
| Leverage (z) | -0.024* | -0.086* | -0.017*** |
| | (0.01) | (0.05) | (0.00) |
| HMConstrained (z) | -0.022*** | -0.094*** | -0.008*** |
| | (0.01) | (0.03) | (0.00) |
| Log(AT) (z) | 0.046*** | 0.227*** | 0.003 |
| | (0.01) | (0.05) | (0.00) |
| Cash/AT (z) | -0.037*** | -0.140** | 0.003 |
| | (0.01) | (0.06) | (0.00) |
| Profitability (z) | -0.114*** | -0.462*** | -0.010*** |
| | (0.01) | (0.05) | (0.00) |
| Tangibility (z) | 0.009 | 0.036 | -0.042*** |
| | (0.02) | (0.08) | (0.00) |
| R&D/AT (z) | -0.094*** | -0.372*** | -0.022*** |
| | (0.01) | (0.05) | (0.00) |
| Log(Claims) (z) | -0.076*** | -0.381*** | 0.059*** |
| | (0.01) | (0.02) | (0.00) |
| Market Share (z) | 0.054*** | 0.221*** | -0.009** |
| | (0.02) | (0.07) | (0.00) |
| HHI (TNIC3) (z) | -0.020 | -0.103** | -0.011*** |
| | (0.01) | (0.05) | (0.00) |
| Log(Peer Patent Value) (z) | -0.315*** | -1.339*** | -0.014*** |
| | (0.02) | (0.08) | (0.01) |
| Fixed effects: | | | |
| CPC-year | Y | Y | Y |
| Obs. | 2,620,832 | 2,620,832 | 2,620,832 |
| $R^2$ | 0.06 | 0.07 | 0.08 |

## Table V: Effect of Examiner Strictness

This table reports how examiner strictness is related to the value of patents and firms. The sample is patents granted from 2010-2023 to publicly traded firms where examiner strictness can be measured. *Examiner 112 Strictness* is the fraction of applications considered by an examiner that do not meet disclosure clarity requirements under §112 in the first review action but pass other requirements, excluding the focal application. *Examiner Other Strictness* is the fraction of applications considered by an examiner where the first action decision flags §101, §102, or §103, excluding the focal application. *KPSS* is the patent value estimate from Kogan et al. (2017). *Q(t+1)* is firm market-to-book, and is measured in the year following the application. Other variables are defined in Section 2. To facilitate interpretation, all independent variables are standardized. Standard errors are clustered by firm-year. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All models include technology-by-application year and art-unit-by-application year fixed effects.

| | (1) KPSS | (2) Log(KPSS) | (3) Q(t+1) | (4) Q(t+1) |
|---|---|---|---|---|
| Examiner 112 Strictness (z) | -0.105*** | -0.005*** | -0.004*** | -0.002* |
| | (0.03) | (0.00) | (0.00) | (0.00) |
| Examiner Other Strictness (z) | -0.092*** | -0.002* | -0.001 | -0.000 |
| | (0.03) | (0.00) | (0.00) | (0.00) |
| Log(at) (z) | | | | -0.337*** |
| | | | | (0.12) |
| Tangibility (z) | | | | 0.017 |
| | | | | (0.06) |
| Profitability (z) | | | | 0.141** |
| | | | | (0.07) |
| Leverage (z) | | | | 0.157*** |
| | | | | (0.06) |
| Cash/AT (z) | | | | 0.175*** |
| | | | | (0.04) |
| Q (z) | | | | 0.566*** |
| | | | | (0.15) |
| Fixed effects: | | | | |
| CPC-year | Y | Y | Y | Y |
| Art-unit-year | Y | Y | Y | Y |
| Firm-year | Y | Y | N | N |
| Firm | N | N | Y | Y |
| Obs. | 743,396 | 743,396 | 743,022 | 735,093 |
| $R^2$ | 0.69 | 0.95 | 0.73 | 0.79 |

## Table VI: Effects of Patent-Level Obfuscation

This table reports the effects of patent-level obfuscation estimated using an instrumental variables framework. The sample is patents granted from 2008-2023 to publicly traded firms where examiner strictness can be measured. Column 1 shows the first-stage regression result where *Obfuscation* is regressed on *Examiner §112 Strictness*, our instrument for *Obfuscation*, *Examiner Other Strictness*, and *LLM Readability*. The subsequent columns show second-stage regression results. *Log(1+Cite10)* is the natural logarithm of one plus the number of forward citations received within 10 years of the grant date. *Log(1+NonSelf10)* and *Log(1+Self10)* are defined in a similar manner, with the former measuring non-self citations and the latter measuring self citations. *Infringed*, *PatSold*, and *Pledged* are indicator variables equal to one if the patent is used as collateral, sold to another entity, or involved in litigation by year-end 2024, and zero otherwise, respectively. To facilitate interpretation, all independent variables are standardized. Standard errors are clustered by firm-year. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All models include technology-by-application year and art-unit-by-application year fixed effects.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | | Log(1+ | Log(1+ | Log(1+ | | | |
| | Obfuscation (z) | Cite10) | NonSelf10) | Self10) | Infringe | PatSold | Pledged |
| Examiner 112 Strictness (z) | -0.010*** | | | | | | |
| | (0.00) | | | | | | |
| Obfuscation (z) | | -2.255*** | -1.335*** | -1.595*** | -0.048*** | -0.399*** | -0.191** |
| | | (0.48) | (0.32) | (0.33) | (0.02) | (0.12) | (0.08) |
| Examiner Other Strictness (z) | -0.009*** | -0.007 | -0.005* | -0.003 | -0.000 | -0.001 | 0.001 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| LLM Readability (z) | 0.235*** | 0.506*** | 0.295*** | 0.363*** | 0.011*** | 0.092*** | 0.043** |
| | (0.00) | (0.11) | (0.08) | (0.08) | (0.00) | (0.03) | (0.02) |
| Fixed effects: | | | | | | | |
| CPC-year | Y | Y | Y | Y | Y | Y | Y |
| Art-unit-year | Y | Y | Y | Y | Y | Y | Y |
| Obs. | 747,341 | 747,341 | 747,341 | 747,341 | 747,341 | 747,341 | 747,341 |
| Cragg-Donald F | 29.46 | | | | | | |

## Table VII: Robustness of IV Estimates

This table repeats the IV tests in Table VI using different measures of readability to define Obfuscation and LLM Readability. The measures are based on Gunning Fog in Panel A and on PCA2 in Panel B. For brevity, we only report the coefficient on the main endogenous variable. Outcome variables are described in Table VI. To facilitate interpretation, all independent variables are standardized. Standard errors are clustered by firm-year. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All models include technology-by-application year and art-unit-by-application year fixed effects.

### Panel A: Gunning Fog instead of PCA1 as Readability Measure

| | (1) Log(1+ Cite10) | (2) Log(1+ NonSelf10) | (3) Log(1+ Self10) | (4) Infringe | (5) PatSold | (6) Pledged |
|---|---|---|---|---|---|---|
| Obfuscation (Gunning Fog) (z) | -1.996*** | -1.183*** | -1.410*** | -0.042*** | -0.352*** | -0.169** |
| | (0.39) | (0.27) | (0.27) | (0.01) | (0.10) | (0.07) |
| Fixed effects: | | | | | | |
| CPC-year | Y | Y | Y | Y | Y | Y |
| Art-unit-year | Y | Y | Y | Y | Y | Y |
| Obs. | 747,341 | 747,341 | 747,341 | 747,341 | 747,341 | 747,341 |

### Panel B: PCA2 as Readability Measure

| | (1) Log(1+ Cite10) | (2) Log(1+ NonSelf10) | (3) Log(1+ Self10) | (4) Infringe | (5) PatSold | (6) Pledged |
|---|---|---|---|---|---|---|
| Obfuscation (PCA2) (z) | -2.088*** | -1.237*** | -1.474*** | -0.044*** | -0.369*** | -0.177** |
| | (0.43) | (0.30) | (0.30) | (0.01) | (0.10) | (0.07) |
| Fixed effects: | | | | | | |
| CPC-year | Y | Y | Y | Y | Y | Y |
| Art-unit-year | Y | Y | Y | Y | Y | Y |
| Obs. | 747,341 | 747,341 | 747,341 | 747,341 | 747,341 | 747,341 |

## Table VIII: AIPA and Patent Obfuscation

This table examines how the enactment of the American Inventors Protection Act (AIPA) affected patent obfuscation, and how that effect was mediated by reliance on patent collateral and external financing. The identification strategy is a difference-in-difference approach following Ireland et al. (2024); see text for discussion. The regressions study all patents with application years from 1990 to 2010 that can be matched with public firm identifiers. *Foreign* is an indicator for a patent seeking foreign protection (that is, being in a family with an identical foreign patent). *Pct Foreign* is the percent of a filing firm's patents that sought foreign protection in the pre-AIPA era. *Post-AIPA* is an indicator for the patent application year being 2000 or later. *Pledge Patents* is an indicator for whether the firm pledge patents as collateral in the pre-AIPA era. *Debt/Assets* is the book value of debt to the book value of assets. Standard errors are clustered by the intersection of firm and grant year. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Obfuscation | Obfuscation | Obfuscation | Obfuscation |
| Post-AIPA | 0.0701 | -0.141* | -0.318*** | -0.289*** |
| | (0.0450) | (0.0721) | (0.0994) | (0.100) |
| Foreign | 0.701*** | | | |
| | (0.0514) | | | |
| Foreign X Post | 0.164*** | | | |
| | (0.0621) | | | |
| Pct Foreign | | 1.212*** | 0.285 | 0.781*** |
| | | (0.0887) | (0.182) | (0.134) |
| Pct Foreign X Post | | 0.301** | 0.889*** | 1.020*** |
| | | (0.122) | (0.245) | (0.214) |
| Pledged Patents | | | -0.245** | |
| | | | (0.104) | |
| Pledged Patents X Pct Foreign | | | 1.035*** | |
| | | | (0.206) | |
| Pledged Patents X Post | | | 0.183 | |
| | | | (0.127) | |
| Pledged Patents X Pct Foreign X Post | | | -0.580** | |
| | | | (0.279) | |
| Debt/Assets | | | | 0.300 |
| | | | | (0.306) |
| Debt/Assets X Pct Foreign | | | | 1.632*** |
| | | | | (0.451) |
| Debt/Assets X Post | | | | 1.026*** |
| | | | | (0.371) |
| Debt/Assets X Pct Foreign X Post | | | | -3.535*** |
| | | | | (0.782) |
| Intercept | 1.787*** | 1.671*** | 1.867*** | 1.624*** |
| | (0.0446) | (0.0584) | (0.0829) | (0.0867) |
| Obs. | 995163 | 1059935 | 1059935 | 1045808 |
| $R^2$ | 0.0217 | 0.0210 | 0.0224 | 0.0223 |

## Table IX: Nautilus v. Biosig and Patent Obfuscation

This table examines the impact of *Nautilus v. Biosig* (2014) on patent obfuscation. The sample is based on patent applications by public firms three years before and after the decision date (6/2/2014). Across columns, the dependent variable is obfuscation. *Exposure* is the median obfuscation level for a given firm across patent applications filed during the pre-period. *Post-Nautilus* is an indicator for patent applications after the ruling. *Pledged Patents* is an indicator for firms that pledged patents as collateral during 2011-2013. *High Leverage* is an indicator for firms with above-median leverage, where medians are defined at the Fama-French 12-industry level based on firms' average leverage during 2011-2013. To be included in the sample, firms should have filed patents in both the pre- and post-periods. Standard errors are clustered by the intersection of firm and grant year. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) | (3) |
|---|---|---|---|
| | Obfuscation | Obfuscation | Obfuscation |
| Exposure | 1.209*** | 1.039*** | 1.230*** |
| | (0.025) | (0.025) | (0.034) |
| Post-Nautilus | 0.435*** | 0.982*** | 0.465*** |
| | (0.068) | (0.090) | (0.095) |
| Exposure x Post-Nautilus | -0.180*** | -0.463*** | -0.211*** |
| | (0.042) | (0.049) | (0.057) |
| Pledged patents | | -0.286*** | |
| | | (0.067) | |
| Exposure x Pledged patents | | 0.226*** | |
| | | (0.039) | |
| Pledged patents x Post-Nautilus | | -0.786*** | |
| | | (0.105) | |
| Exposure x Pledged patents x Post-Nautilus | | 0.420*** | |
| | | (0.058) | |
| High leverage | | | 0.106 |
| | | | (0.084) |
| Exposure x High leverage | | | -0.0371 |
| | | | (0.049) |
| High leverage x Post-Nautilus | | | -0.285** |
| | | | (0.117) |
| Exposure x High leverage x Post-Nautilus | | | 0.192*** |
| | | | (0.070) |
| Intercept | 0.259*** | 0.464*** | 0.195*** |
| | (0.044) | (0.043) | (0.058) |
| Obs. | 513606 | 513606 | 512956 |
| $R^2$ | 0.110 | 0.114 | 0.112 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# Appendix

- Table A1 examines how changes to abstracts during the review process are related to examiner strictness on different review components.

## Table A1: Abstract Simplification During Patent Examination Process

This table examines the changes in patent abstract readability before and after the examination process. The sample is based on a subset of patent applications for which abstracts are observable both at filing and at grant. Across columns, the dependent variable is an indicator variable that equals one if the readability of the abstract improved during the examinatin process, and zero otherwise. *Examiner 112 Strictness* is the fraction of applications considered by an examiner that do not meet disclosure clarity requirements under §112 in the first review action but pass other requirements, excluding the focal application. Variables representing strictness for other sections are defined in a similar manner. *LLM Readability* is the readability of the LLM-simplified abstract, which uses the first principle component of the readability measures listed in Table II. When constructing strictness measures, we use examiners' raw rejection rates in columns 1-2 and unit-adjusted rejection rates in columns 3-4. In columns 1 and 3 (2 and 4), rejection rates are calculated based on all applications (only on eventual grants). To facilitate interpretation, all independent variables are standardized. Standard errors are clustered by firm-year. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All models include technology-by-application year and art-unit-by-application year fixed effects.

| Rej Rates Are: | Examiner Only | | Unit-Adjusted | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Rej Rates For: | Apps. | Grants | Apps. | Grants |
| Examiner 112 Strictness (z) | 0.649*** | 0.641*** | 0.471*** | 0.469*** |
| | (0.06) | (0.06) | (0.04) | (0.04) |
| Examiner 101 Strictness (z) | 0.774*** | 0.773*** | 0.362*** | 0.363*** |
| | (0.07) | (0.07) | (0.03) | (0.03) |
| Examiner 102 Strictness (z) | 0.207*** | 0.206*** | 0.179*** | 0.179*** |
| | (0.04) | (0.04) | (0.04) | (0.04) |
| Examiner 103 Strictness (z) | 0.160*** | 0.159*** | 0.152*** | 0.152*** |
| | (0.04) | (0.04) | (0.04) | (0.04) |
| LLM Readability (z) | -0.049 | -0.048 | -0.049 | -0.049 |
| | (0.04) | (0.04) | (0.04) | (0.04) |
| Fixed effects: | | | | |
| CPC-year | Y | Y | Y | Y |
| Art-unit-year | Y | Y | Y | Y |
| Obs. | 402,753 | 402,752 | 402,722 | 402,721 |
| $R^2$ | 0.06 | 0.06 | 0.06 | 0.06 |