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Patent Quality in the United States:

Findings and Suggestions for Policymakers

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Executive Summary

Background

Debates surrounding patent quality in the United States have historically focused on the notion that the United States Patent and Trademark Office (USPTO) is letting too many "bad patents" slip through. Yet the rejection of "good patents" is more widespread. The authors hope that by presenting a clearer, more nuanced picture of patent quality in the United States, this report will help facilitate a more balanced and fact-based policy dialogue.

Methodology

The definition of "quality" used in this report aligns with the statutory definition, as adopted by the USPTO. Under this definition, patents must satisfy four requirements codified in Title 35 of the U.S. Code. These are:

Section 101: to satisfy the criteria for patent subject matter eligibility

Section 102: to be novel

Section 103: to be non-obvious

Section 112: to be clearly and sufficiently claimed and described

The authors' analysis focuses on two types of errors. **Type 1** errors occur when a patent application is granted despite including invalid claims. **Type 2** errors occur when a patent application containing valid claims is improperly rejected.

The authors use three distinct methods to measure patent quality: analysis of the overall pool of patent applications, analysis of a random sample of patent applications, and analysis of patent applications submitted to multiple patent offices.

Key Findings

- The USPTO's Type 1 error rate is in the single digits (less than 9%), and low relative to other patent offices around the world.
- The USPTO's Type 2 error rate is significantly higher than its Type 1 error rate. The analysis suggests that the USPTO rejects valid claims more often than it grants invalid claims.
- Due to selection bias, patent invalidation rates at the Patent Trial and Appeal Board (PTAB) and at district courts do not accurately reflect patent quality in the United States.

Conclusion

Using three different methodologies and datasets, this report refutes the claim that there is a crisis of "bad patents" plaguing the U.S. patent system. Type 1 errors are rare, and the USPTO improperly grants patents at a lower rate than its counterparts around the world. Type 2 errors occur at a higher rate than Type 1 errors. Despite this fact, policy dialogue in the United States tends to focus primarily on Type 1 errors, when both kinds of errors are harmful and undermine innovation. Policy debates should account for these realities.

Recommendations

- Policymakers must recognize that there is a tradeoff between Type 1 and Type 2 errors. Efforts to reduce the prevalence of Type 1 errors would likely result in more Type 2 errors, and vice versa. Patent policy should seek to strike an effective balance between Type 1 and Type 2 errors, taking into account the impact on innovation.
- The USPTO should generate more data to inform policy decisions. This includes publishing more granular, claim-level data on its compliance metrics, including on Type 1 and Type 2 errors, segmented by technological areas.
- The USPTO should contract with an independent third party to execute random reviews on a representative sample of patent applications each year.
- The USPTO should support efforts at conducting comparative analysis across patent offices and evaluating patent quality worldwide.

Contents

Section 1

Patent Quality based on the Quality of Patent Examination

This report assesses patent quality in the United States by evaluating the effectiveness of patent examination at the United States Patent and Trademark Office (USPTO).

The analyses presented in this report take the statutory and judicial standards for patentability as given and estimate how frequently the patent office grants patents that do not meet the existing criteria for patentability, and how frequently the patent office fails to grant patents that do meet these criteria.

From the perspective of assessing the effectiveness of the USPTO, the relevant concept of quality used in this report is the statutory definition of patent quality, adopted by the USPTO. [1]

> ***"USPTO considers a quality patent to be one that is correctly issued in compliance with all the requirements of Title 35 as well as the relevant case law at the time of issuance."***

Under this definition, patent quality is the capacity of a granted patent to meet (or exceed) the four major statutory patentability requirements under U.S. law, codified at Title 35 of the U.S. Code. These include:

Section 101: to satisfy the criteria for patent subject matter eligibility.

Section 102: to be novel.

Section 103: to be non-obvious.

Section 112: to be clearly and sufficiently claimed and described.

A "low quality" patent, in contrast, would be one granted on an invention that does not meet one of these statutory standards.

It is important to note that there is a clear distinction between the quality of a patent, as previously defined, and its economic or social value, also labeled as quality by many studies. A policy paper by Organization for Economic Co-operation and Development (OECD) (Squicciarini et al. 2013), as an example, defines patent quality in terms of its technological and economic value, proposing a wide array of indicators to capture it, such as patent scope, family size, backward and forward citations, and renewals. A recent paper by Higham et al., (2021) presents a comprehensive list of indicators that the economics literature proposed capturing patent quality in terms of its value.

While one might expect a positive association between value and quality in patenting, these two concepts can be distinct and unrelated (Wagner, 2009; Schankerman and Schuett, 2022). This is due to the fact that the value of a patent depends on factors well beyond those of concern to patent law and the patent examination process, such as the size of the relevant market, stock market returns, patent renewals, and forward citations, among others.

[1] See https://www.uspto.gov/patents/quality-metrics, and USPTO Performance and Accountability Report Fiscal Year 2017, page 48.

Section 2

Measuring Patent Quality

To assess patent quality, this report evaluates the quality of patent examination. That is, how frequently does the patent office grant patents with claims that do not meet the existing statutory and judicial criteria for patentability (referred to also as invalid claims), and how frequently does the patent office fail to grant patents to claims that do meet this standard (referred to as valid claims).

Thus, the analyses presented in this section aim to estimate two types of errors:

> **Type 1 error** (false grants) occurs when an examiner grants a patent with invalid claims (referred to also as a low-quality patent).
>
> **Type 2 error** (false rejections) occurs when an examiner rejects a patent application, or an applicant abandons an application, that contains valid claims (also referred to as a potential high-quality patent).

Both types of errors create different kinds of economic costs. Type 1 errors impose welfare costs through higher prices and litigation costs associated with enforcing these (incorrectly granted) patents. Type 2 errors dilute incentives to innovate, discourage the development of new inventions that would contribute positive social value, and create costs for innovators. More discussion on the harms caused by Type 1 and Type 2 errors can be found in Section 4.

As will be explored later, the errors, though quantifiable, pose certain interpretive challenges. This is because the scope of an invention is captured in a patent by one or more claims, which are the main subject of examination before the patent examiner. These claims are often reworded to become more precise and overcome examiner objections. As will be illustrated later, the most effective method to measure compliance with each statutory provision is to conduct a claim-by-claim analysis.

This section presents findings of three distinct methods of measuring patent quality, which are based on three different datasets:

> **Section 2.1** analyzes patent quality based on the overall pool of patent applications, both granted and rejected, leveraging economic modeling, artificial intelligence, and statistical methods.
>
> **Section 2.2** analyzes patent quality based on a representative sample of patent applications, both granted and rejected, by conducting random reviews.
>
> **Section 2.3** analyzes patent quality based on patent applications submitted to multiple patent offices, both granted and rejected, using mathematical modeling and statistical methods.

Additionally, this report considers patent invalidation rates and shows that they are unsuitable for measuring patent quality (see Section 3).

Section 2.1

Patent Quality Based on the Overall Population: Estimating Errors using Economic Modeling and Machine Learning

Recent developments in Artificial Intelligence (AI) have made it possible to conduct assessment analysis on the entire patent application pool, which previously would have been extremely costly to conduct. While AI methods are new and require further validation, they open a promising avenue for generating insights on patent quality. This section presents the findings from ongoing work by economists William Matcham and Mark Schankerman, who developed a formal economic model, along with leveraging machine learning techniques, to estimate Type 1 and Type 2 errors based on detailed data from the USPTO.

Economic Model

Matcham and Schankerman (2023) developed a model of the U.S. patent screening process, which incorporates incentives that applicants and examiners face, intrinsic motivation on the part of examiners, and the actual structure of multi-round negotiation in the current system. They define intrinsic motivation as examiners' desire to ensure their decisions align with the USPTO's mission to award inventors property rights over their invention, consistent with statutory and judicial prescriptions.

Data and Methodology

The dataset consists of around 55 million patent application claim decisions covering 20 million independent claims on approximately 980,000 patent applications filed between 2011–2013. [2]

For applications, the examiners' decisions on patent claims are observed over multiple rounds of negotiation. Matcham and Schankerman (2023) use machine learning techniques, in particular modern Natural Language Processing (NLP), to measure the distance between different claims, which forms the basis for assessing patentability on the grounds of novelty and non-obviousness (35 U.S.C. § 102 and § 103). For that purpose, they construct a new measure of independent claim distance. To determine the distance between a patent application claim and the closest claim in existing patents, they compute the distance to every previously granted independent claim and then take the minimum. Following developments in computer science, the approach uses each patent claim's text to compute a similarity measure to other (prior) claims, based on the words and their placement in paragraphs (Le and Mikolov, 2014). The approach allows for synonyms, antonyms, and technical terminology with similar meanings.

The empirical analysis is based on calibrating the parameters of the economic model so that its predictions closely match key observed features of the data (e.g., grants, abandonments, and claim rejections at each round of the process). Among other things, Matcham and Schankerman (2023) are able to compute the underlying threshold distance for patentability by identifying the rejection rule used by the most intrinsically motivated examiners, who will use the threshold prescribed to them by the USPTO.

[2] The period 2011-2013 is used since these are the years where data are available from the USPTO on the outcomes of patent claims in examination across multiple rounds.

With the estimated threshold and the model, they estimate the extent of Type 1 and Type 2 errors.

Estimates of Type 1 and Type 2 Errors

Figure 1 presents the estimates of Type 1 and Type 2 errors from Matcham and Schankerman (2023). There are two such estimates: extensive margin and intensive margin. The extensive Type 1 error measures the proportion of granted patents with at least one estimated invalid claim. The extensive Type 2 error measures the proportion of abandoned patent applications with at least one estimated valid claim. The intensive Type 1 error measures the proportion of granted claims that are estimated to be invalid, and the intensive Type 2 error measures the proportion of abandoned claims that are estimated to be valid. This report focuses on intensive errors because, as will be explained, they provide a much more precise and accurate estimation of the extent of invalidity.

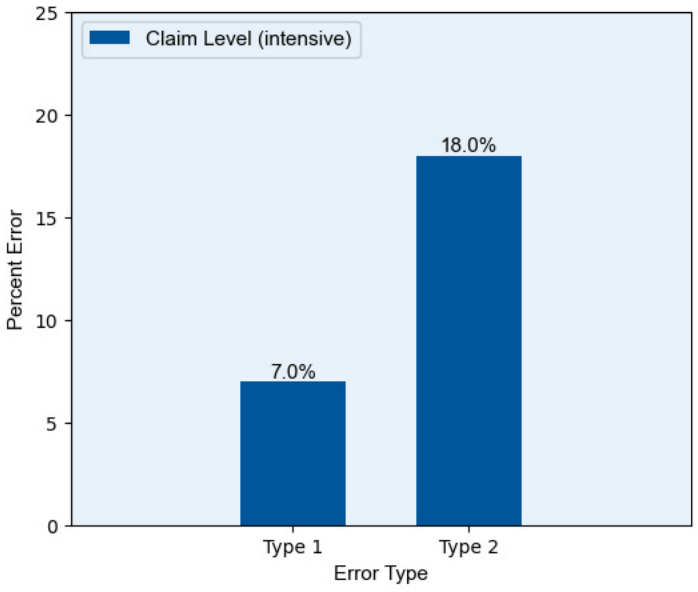

Figure 1: Estimates of Type 1 and Type 2 Error (Claim Level)

According to the estimates, among all granted claims, only 7% are estimated to be invalid, which reflects the fact that most "invalid" patents contain only a few invalid claims. Turning to Type 2 error, among all abandoned claims, 18% are estimated to be valid. These results show that Type 2 errors are more prevalent than Type 1 errors, even though most public policy discourse focuses on Type 1 errors.

Claim-level analysis offers a nuanced and more precise methodology for evaluating patent quality. Independent claims are the essential elements of patents, and examiners look at each claim on its own because each one can vary greatly in terms of its scope, detail, and overall quality. In contrast, patent-level analysis presents inherent challenges. Synthesizing claim-level insights into a whole assessment of a patent's quality requires aggregation with the potential for bias. Consider the dilemma posed by a patent comprising nine valid claims and one invalid claim: should it be regarded as a low-quality patent due to the presence of a single invalid claim, or should it be considered as a 90% high-quality patent? Either approach can be justified; however, focusing on the level of individual claims is preferable as a more straightforward and accurate assessment of a patent's quality.

Estimates of Type 1 and Type 2 Errors across Technology Centers

Technology Centers (TCs) are the administrative units the USPTO uses to separate examiners and patent applications by technological subject matter, with the aim of having patent applications in a particular subject be considered by a patent examiner with expertise in that subject. There are nine TCs in total. [3]

[3] See Patent Technology Centers Management, https://www.uspto.gov/patents/contact-patents/patent-technology-centers-management (last visited April 28, 2024). Note that the analysis presented in this report does not include analysis of TC 2900, which covers design patents. The analysis is limited to utility patents covered by the other Technology Centers.

Figure 2 and Figure 3 show the corresponding estimated errors for individual TCs. Both types of error vary across Technology Centers, although the variance appears greater for Type 2 error. Computer-related areas are at the lower end of Type 1 error but at the upper end of Type 2 error.

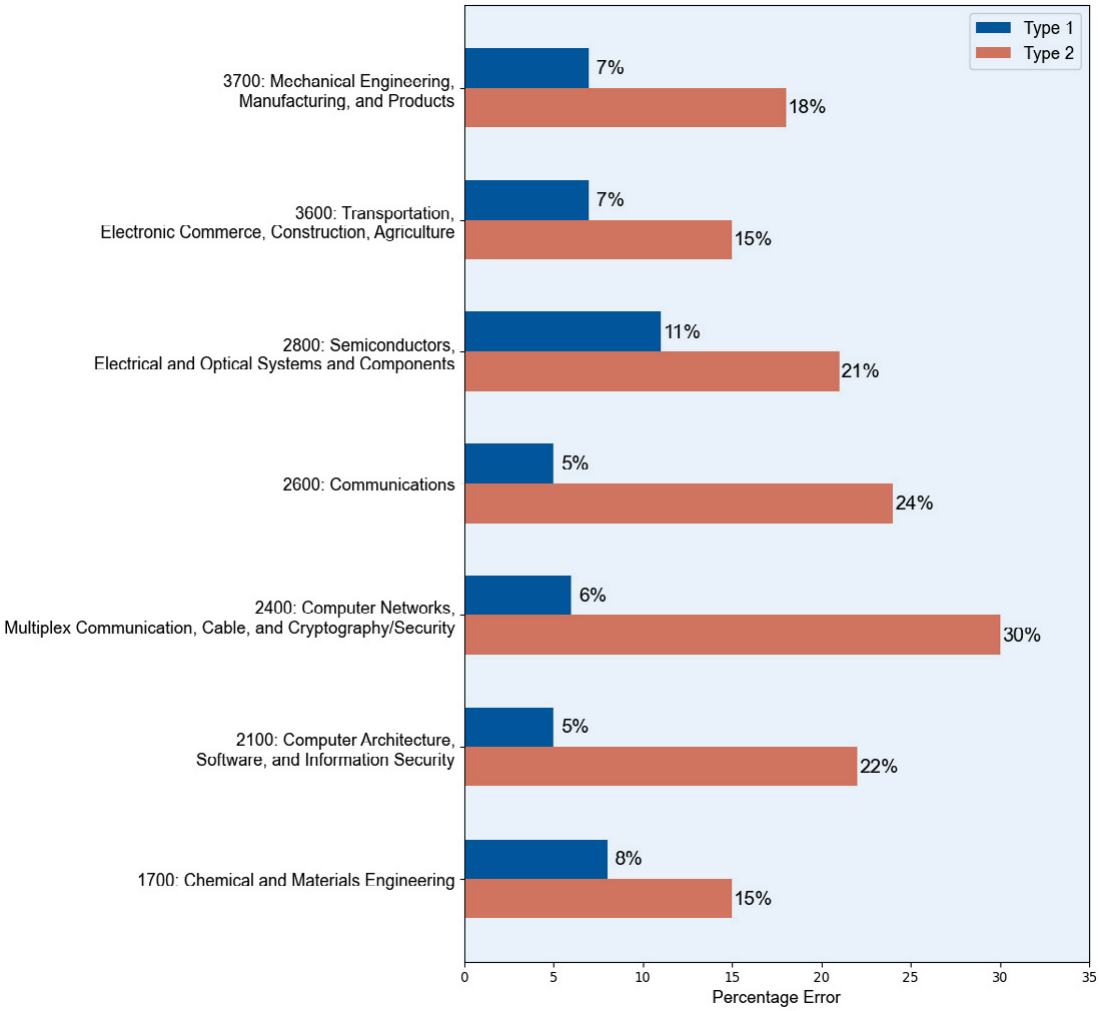

Figure 2: Estimates of Errors (Intensive) across TCs [4]

Points for Consideration

The detailed economic model of the patent screening process developed by Matcham and Schankerman (2023) is designed to correspond (as best as one can with any economic model) to the actual examination process in the USPTO. The model is constructed with careful consideration of the key elements and institutional features of the real-life process. The authors note that no model can capture the entire richness of reality (then, after all, it ceases to be a model and instead becomes reality), but is a serious attempt to be as realistic as possible while still being useful and sufficiently tractable for research and policy purposes. To illustrate this, the following describes two ways that the model and methodology are simplified to gain tractability.

[4] Note the analysis of Technology Center 1600 Biotechnology and Organic Chemistry is ongoing and has not been finalized.

First, it focuses on meeting the statutory standards of § 102 and § 103. If an applicant abandons an application that contains claims that satisfy the statutory requirements of § 102 and § 103, but does not satisfy § 101 or § 112, it will still be considered a Type 2 error according to the estimates. However, as Matcham and Schankerman (2023) show, there is significant overlap between § 102/103 rejections and § 112 rejections: 73% of Office Actions containing a § 112 rejection also contain a § 102/103 rejection, thus their inclusion would not be expected to greatly affect the robustness of the findings. Further, § 101 rejections account only for 4.5% of all rejections, and accordingly their inclusion would also not have significant effect on the estimates.

A second example is that their analysis focuses on independent claims. Independent claims are the primary expression of the boundaries of patent rights and the main source of economic value to the applicant. Dependent claims, on the other hand, act as clarifying devices, identifying successively narrower interpretations of the independent claim to which they refer. As a result, focusing on independent claims captures the key trade-offs for applicants and examiners. In short, these simplifications in the modelling make things empirically tractable and thus informative for policy analysis, without sacrificing essential detail.

Conclusion

The findings show that patent examination is relatively effective. Substantial assessment error remains, however; particularly Type 2 error. This is noteworthy because the policy debate focuses primarily on the costs associated with Type 1 error. The negative effects of Type 2 error on reduced innovation, innovator incentives, and innovator costs are not directly observed and thus easier for policymakers to overlook.

Section 2.1

Patent Quality Based on Random Reviews: Analysis of the USPTO's Quality Metrics

This section considers the USPTO's regular process for reviewing the quality of their examiners' work to assess its suitability for making inferences about patent quality. The USPTO's internal reviews are conducted by the Office of Patent Quality Assurance (OPQA). Their current quality metrics were developed in 2016 and focus on compliance with the main statutes governing patentability, namely Sections 101, 102, 103, and 112. [5]

Methodology

Each fiscal year, OPQA conducts statutory compliance reviews on a randomly selected sample of approximately 12,000 Office Actions. An Office Action is an official document prepared by a patent examiner that summarizes the examiner's review of a patent application. [6] There are three types of Office Actions:

Allowance: all the claims in the patent application are allowed to be patented.

Non-Final Rejection: an initial rejection of one or more claims of an application after which the applicant can either object to the rejection or amend the claims.

Final Rejection: a final rejection indicating the examiner finds insufficient justification to allow a patent. [7]

The reviewers at OPQA conduct a rigorous claim-by-claim analysis on selected Office Actions, using the Master Review Form (MRF), which contains over 330 questions through which claims related to an Office Action are scrutinized under all four statutes. To properly determine compliance, the reviewer checks for omitted rejections, incorrect rejections, improper rejections, and improperly omitted rejections.

The compliance rate for every statute is calculated in the following way:

$$\textit{Compliance rate} = \frac{\textit{number of Office Actions that properly evaluated all pending claims for the statute in question}}{\textit{total number of Office Actions reviewed}}$$

If a single claim is found non-compliant under a statute, the entire Office Action is determined as non-compliant for that particular statute, regardless of how many proper determinations were made. This approach amplifies the non-compliance rates compared to a claim-level approach, and the analysis would be more informative if they were based on total claims reviewed as compared to total Office Actions. [8]

[5] https://www.uspto.gov/patents/laws/examination-policy/patent-quality-assurance

[6] https://www.uspto.gov/patents/maintain/responding-office-actions

[7] The applicant may appeal to PTAB, and if the rejection is upheld, to the Court of Appeals for the Federal Circuit, or make a Request for Continued Examination (RCE) to be reconsidered for allowance.

[8] For example, a patent application that has only one claim, and that claim was improperly allowed or rejected, is counted the same way as a patent application with 20 claims, where only one of the dependent claims was improperly allowed or rejected. See also the discussion on patent level vs. claim level analysis in Section 2.1.

If all the claims in the Office Action are treated correctly under every statute, then the case is considered compliant. Any Office Action where there was at least one claim found to be non-compliant is verified by an OPQA supervisor and sent to the relevant TC for consideration. The receiving TC can disagree with the assessment; in that case, the OPQA has a process to reconsider the finding of non-compliance based on the arguments presented. The appropriate course of correction for work products ultimately finalized by OPQA as non-compliant is then left to the TC and may entail correction of the Office Action prior to allowing or rejecting a patent application.

The random sample is intended to be representative of the population of Office Actions by both the type of action and TC. To check the representativeness of the OPQA sample of Allowances across TCs, Sunwater Institute has conducted data analysis, dividing the number of reviewed Allowances by the total number of Allowances of a given fiscal year. The OPQA sample count across TCs is retrieved from the MRF summary data tables and the total allowance data is from USPTO's PatentsView data. In Fiscal Years (FY) 2021, 2022, and 2023, OPQA reviewed approximately 1.20, 1.26, and 1.22 percent respectively of patents granted in the same year, and as Figure 3 shows, the stratification across TCs has been done correctly.

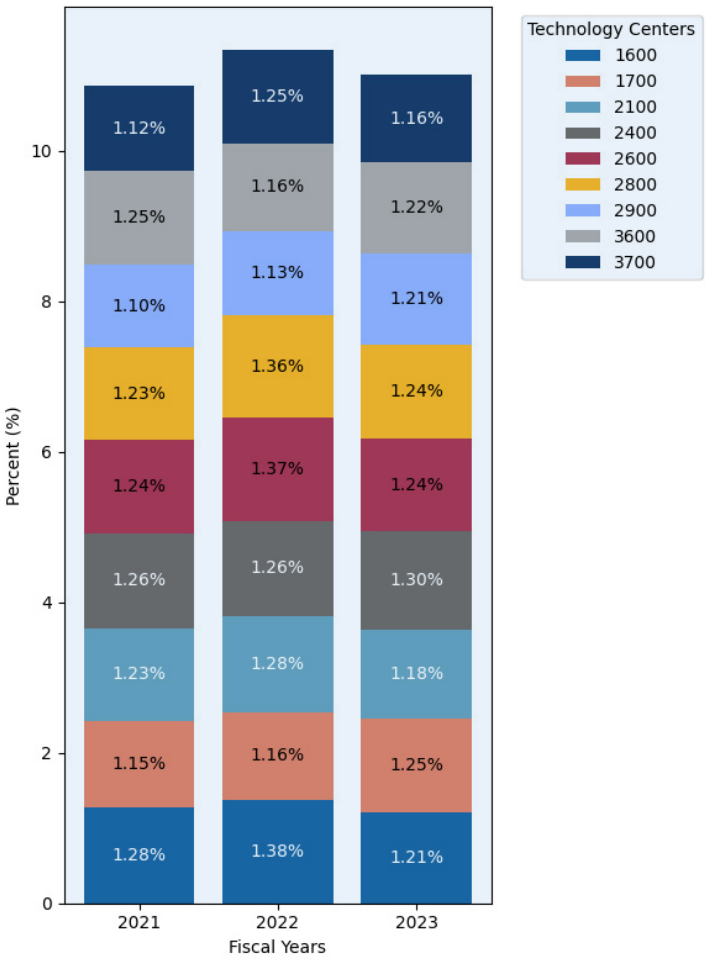

Figure 3: OPQA Review Sample of Allowances across TCs

Non-compliance Rates Over Time

Every year the USPTO releases a summary of its key performance indicator results in its Annual Performance Report, which also includes compliance rates for each statute. [9]

This report presents the non-compliance rates in Figure 4 for each statute from 2017, after the current quality metrics were introduced. The average non-compliance rates across all statutes and over all the years in this sample range from the single digits to at most 11%.

From 2017 to 2020, § 102, 103, and 112 non-compliance rates steadily increased and began to drop after 2020.

Non-compliance Rates by Office Action Types

The random sample of Office Actions reviewed by OPQA for statutory compliance generates an overall Compliance Metric for each statute, where the statutory Compliance Metrics are expressed as a percentage of Office Actions reviewed that properly handled all claims in the application and are further broken out by relevant statute.

[9] https://www.uspto.gov/about-us/performance-and-planning/uspto-annual-reports

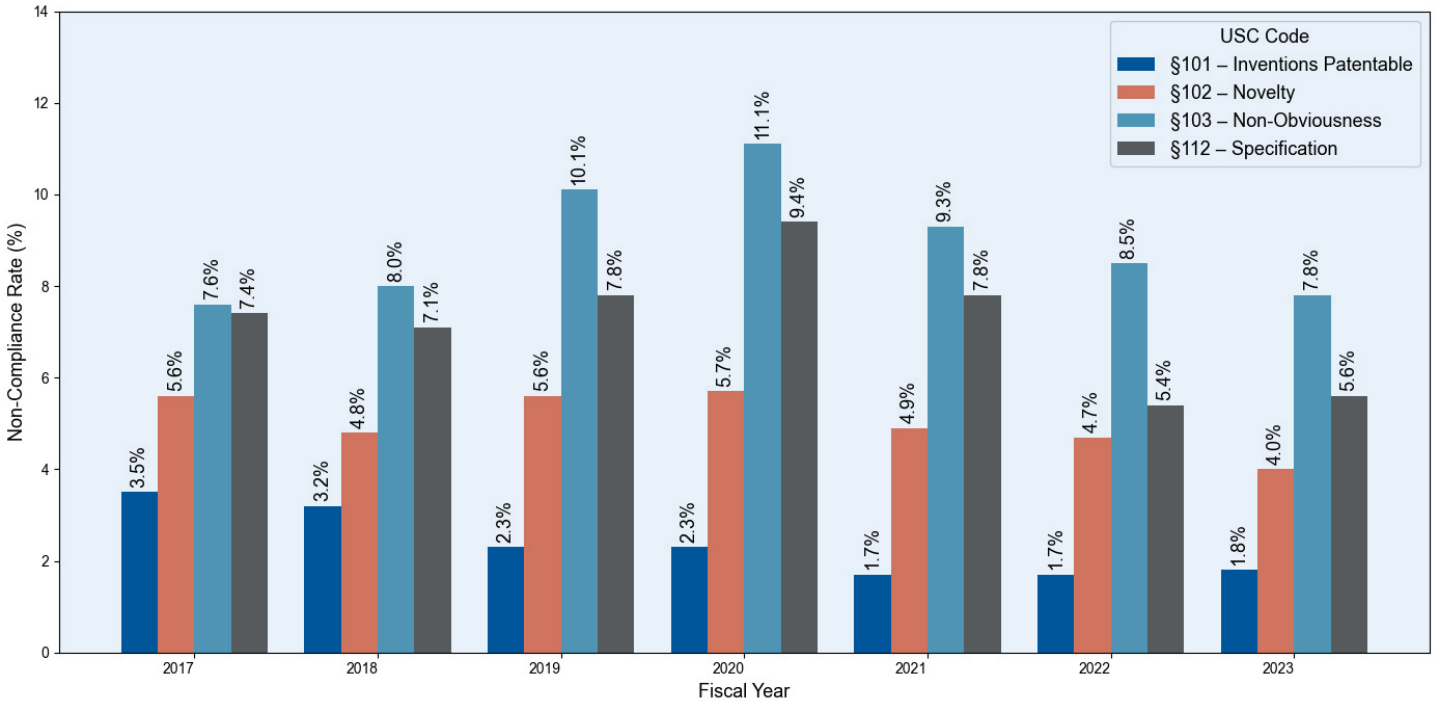

Figure 4: Non-Compliance Rates by Statutes

Based on the Compliance Metrics review results published by the USPTO for FY2023, FY2022, and FY2021, this report calculated the statutory non-compliance rates across Office Action types and for each statute. [10]

The results are presented in Figures 5, 6, and 7, where the last group of bars represents Office Actions that were found to be non-compliant under at least one of the four statutes.

Non-compliance rates have shown a consistent pattern over the observed years. The non-compliance rate of Allowances is about 7-8%. The same holds for non-compliance rates on Rejections, both final and non-final. However, the non-compliance rates of Rejections are consistently higher than the non-compliance rates of Allowances. The non-compliance rate of Final Rejections was about 20% in FY2023 and FY2022, and 25% in FY2021. Among the four statutes, the highest non-compliance rates were recorded for § 103 for about 10-15%.

[10] Compliance Metrics review results are available at https://www.uspto.gov/patents/quality-metrics. At time of the writing of this report, the USPTO made the review results publicly available only for the past three years.

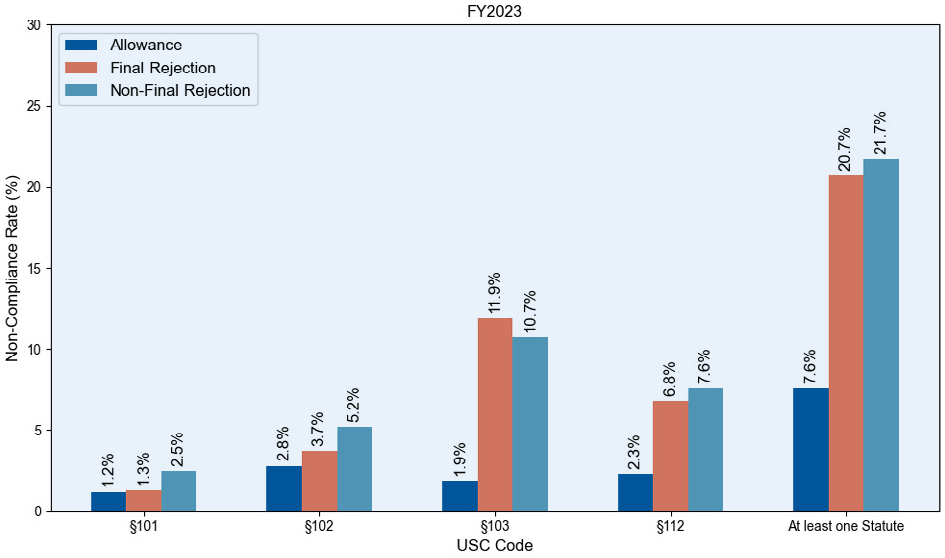

Figure 5: Non-Compliance Rates by Office Action Types in FY2023

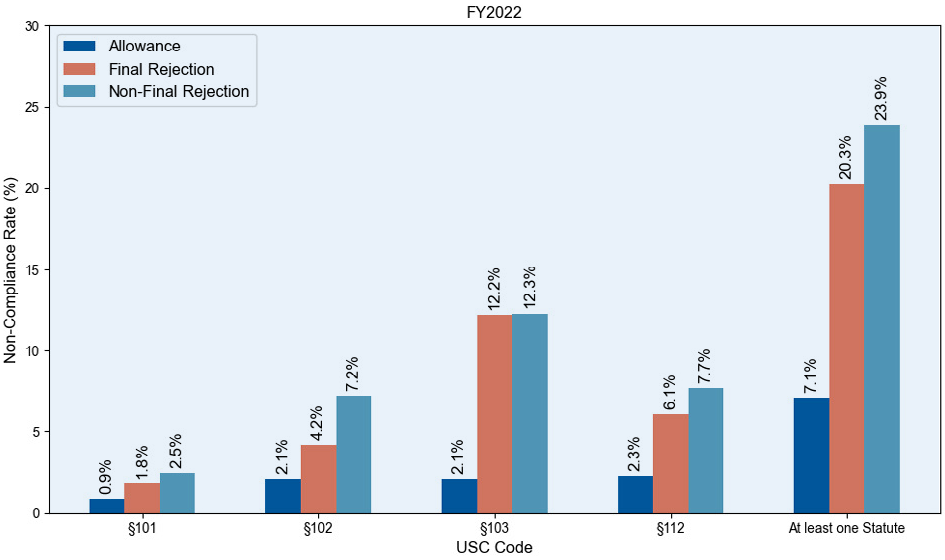

Figure 6: Non-Compliance Rates by Office Action Types in FY2022

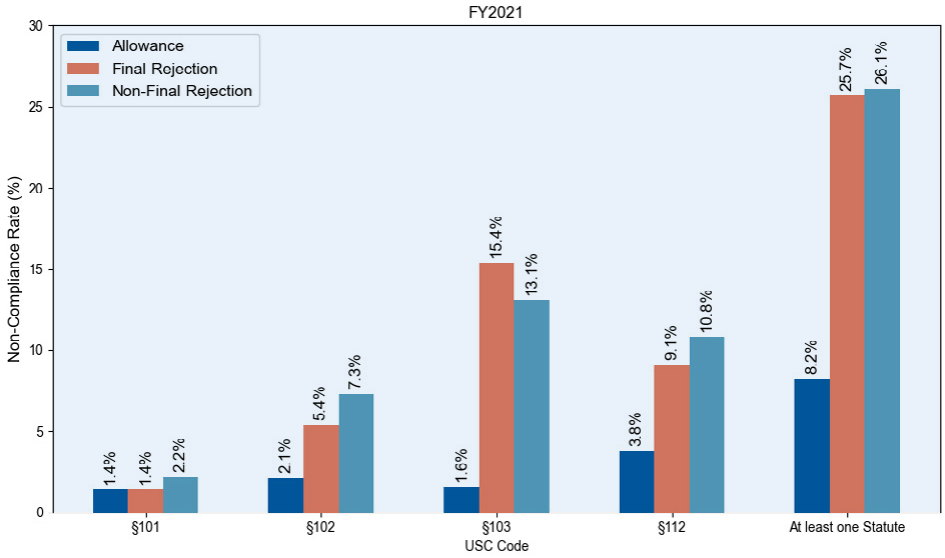

Figure 7: Non-Compliance Rates by Office Action Types in FY2021

Estimates of Type 1 and Type 2 Errors and Points for Consideration

The Office Actions "Allowances" only contain claims that have been allowed. Thus, Allowances are only reviewed to determine whether the allowance of the claims was proper. Therefore, its non-compliance rates provide estimates of Type 1 error.

The Office Actions "Rejections" both final and non-final, not only contain claims that have been rejected, but also claims that have been allowed. Rejections are reviewed both whether the rejection of any claim was proper and whether the indicated allowance of any claim was improper. While the non-compliance rates of Rejections contain Type 2 error, more disaggregated data on the reviewed claims would allow disentangling the type of errors made in the Rejections and provide accurate estimation of Type 2 error.

Conclusion

OPQA's Compliance Metrics analysis reveals that examiner error with respect to issuing a mistaken allowance or rejection on a claim over the past seven years remained the same or decreased and, on average, are in the single digits. The non-compliance rates for Allowances, that are the estimates of Type 1 error, are between 1–3% for each statute. The non-compliance rates for Rejections range from 2–15% depending on the statute. The comparison of non-compliance rates of Allowances and Rejections might be an indication that USPTO more frequently makes Type 2 error than Type 1 error; however, more detailed data are required to make such a comparison. Disaggregated claim-level data on the Compliance Metrics, which the USPTO has not made publicly available at the time of the writing of this report, would allow disentangling the reasons for errors within the Rejections and provide a more accurate estimation of Type 2 error.

Section 2.3

Patent Quality Based on Patent Applications Submitted to Multiple Offices: Comparative Study of Major Global Patent Offices

While it is acknowledged that patent offices universally are fallible, the magnitude of error rates gains significance primarily through a comparative perspective. The determination of whether a given office's error rate is "high" or "low" can be informed by benchmarking it against the performance of offices performing the same task in other countries. This report considers how the USPTO compares with the major global patent offices—those that handle approximately 80% of worldwide patent applications, the European Patent Office (EPO), Japan Patent Office (JPO), Korean Intellectual Property Office (KIPO), and the National Intellectual Property Administration of the People's Republic of China (CNIPA). [11]

Investigating such a research question presents a challenge due to differences among patent offices. An error rate quantified for one office may not serve as a reliable benchmark for another, given the differences in variables that influence these metrics.

One way to compare error rates is to track the patent applications for the same invention that is submitted to multiple patent offices. If a patent application is granted a patent in one office but refused in another, is that an indication of a mistake by one of the offices? The question is difficult to tackle since different offices have different patent grant standards.

De Rassenfosse et al. (2021) developed a methodology that estimates comparable error rates across offices, after estimating and controlling for the stringency of each office. To do so, they identified priority patent applications filed anywhere in the world over the period of 2000–2006 and tracked their one-to-one equivalents (those applications covering the same invention) in any of the five offices. The data consists of 408,133 inventions with linked patent applications that have been examined in at least two of the five major patent offices, covering a total of more than one million applications.

Though the article in consideration is a recent publication, the time period considered (patent applications filed between 2000–2006) may seem too dated to be currently relevant. However, patents issued from these applications can have a life of up to twenty years and would still be in force as of the writing of this paper. Importantly, the nature of these patents would likely have affected the perception of patent quality over the past decades until today, regardless of any changes (and there have been many) made during the intervening period. Moreover, there is a lag between when data is first observable (such as when a patent application is filed) and when enough time has passed for the relevant analysis to be conducted (such as allowing for applications to be filed in other countries and for the patent examination process to be completed). Additionally, there is also a delay caused by collecting and analyzing the often-considerable amounts of data.

Figure 8 shows the total number of twin applications that have been granted a patent in each office. Twin applications are defined as patent applications submitted to multiple jurisdictions that cover the same technical content. Figure 8 also shows the number of those twin applications that were granted a patent in each office but were refused in at least one other office.

[11] https://www.fiveipoffices.org/about

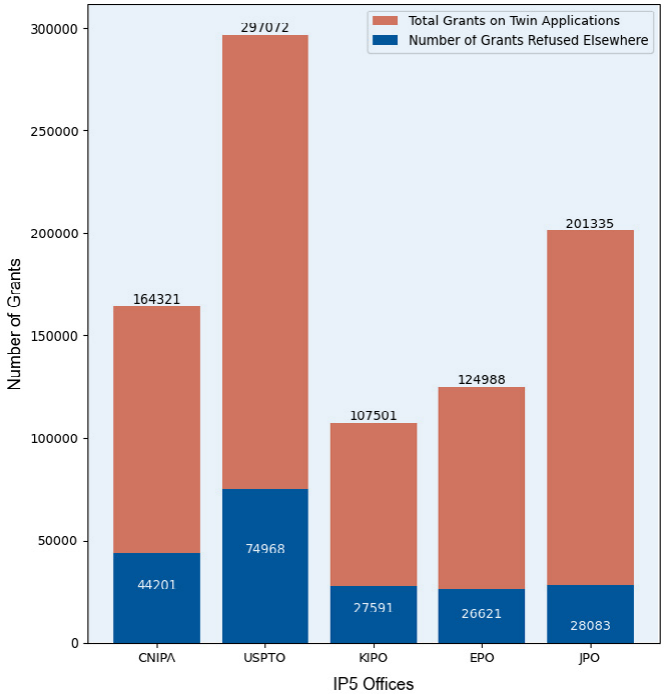

Figure 8: Total Number of Twin Applications Granted a Patent in Each Office, and the Total Number of which Refused in at Least One Other Office (Calculated Based on the Results of De Rassenfosse et al., 2021, Table 9)

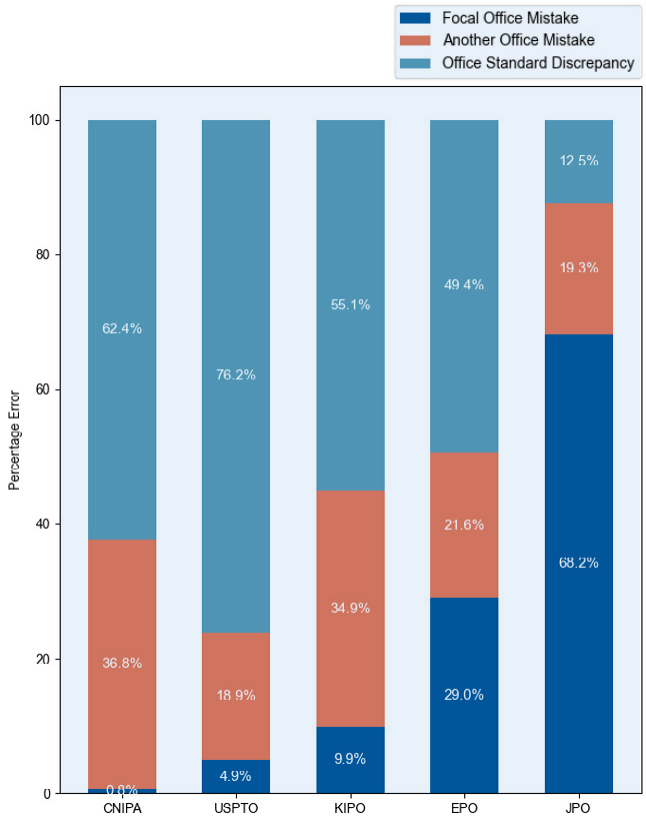

Figure 9: The Estimated Percentage of Why a Grant by One Office Was Rejected by Another Office (Calculated Based on the results of De Rassenfosse et al., 2021, Table 9

Comparable Estimates of Type 1 Error Across Global Offices

There are several reasons why a patent application that was granted a patent by office X might be rejected by office Y or Z. These include:

- Office X has a more lenient standard compared to other offices;
- Office X violates its own standard (makes an error by granting a patent);
- Office Y or Z violate their standards (make a mistake).

The methodology developed by De Rassenfosse et al. (2021) disentangles and quantifies the three reasons mentioned above.

Figure 9 presents the findings by estimated proportion for each reason.

Note that focal office mistakes here are estimates of Type 1 error rates – the percentage of patents granted in violation of the office's own patent grant standard. The findings show that JPO, EPO, and KIPO made more Type 1 errors than USPTO during the time period of the study.

Additional Results

By expanding the set of applications, including applications that were refused by each office (mixed-grant applications), the methodology also estimates total error rates for each office, after controlling for differences in office standards. Figure 10 presents the results and shows that USPTO's error rates are lower than the error rates of other global patent offices. [12]

[12] Note that the analysis of Figure 1 only includes applications that have been accepted by the focal office and rejected by at least one other office. The analysis of Figure 2 additionally includes applications that were rejected by the focal office. Thus, the results of the two figures are not comparable to each other.

By expanding the set of applications even further to all twin applications, including the ones allowed and rejected by all offices, the model developed by De Rassenfosse et al. (2021) allows estimates of Type 1 and Type 2 error rates for each office based on the discrepancy between data and model predictions, but without controlling for office standard differences. Thus, the results presented in Figure 11 are not comparable across offices, but they provide information on the differences between Type 1 and Type 2 error rates within offices.

Some offices make more Type 2 errors than Type 1 errors, such as the USPTO; while other offices, in particular EPO and JPO, make more Type 1 errors than Type 2 errors. This may be explained by JPO and EPO having high thresholds of patentability (stringent office standards); as a result, the probability of a grant not reaching their thresholds is high.

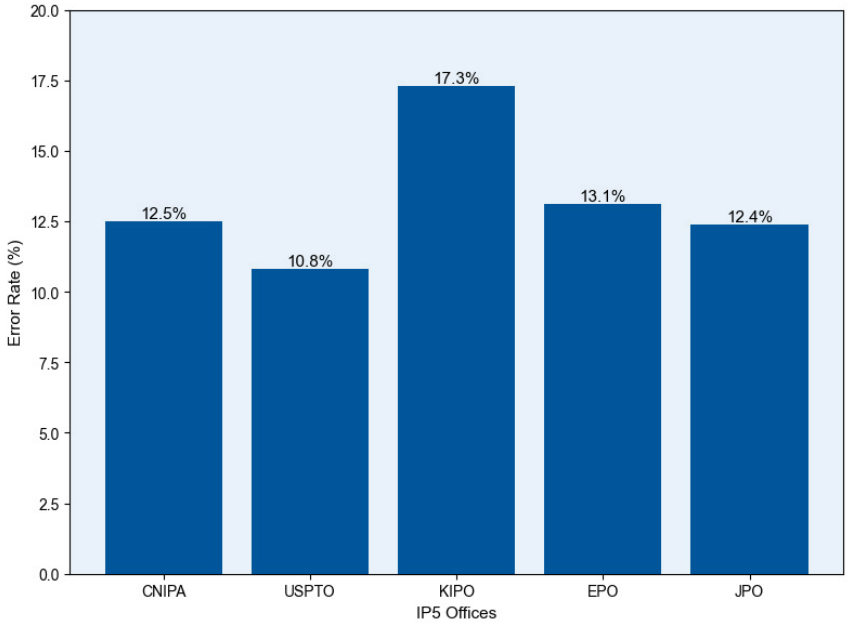

Figure 10: Estimated Error Rates across Global Patent Offices (Calculated Based on the Results of De Rassenfosse et al., 2021, Table 8)

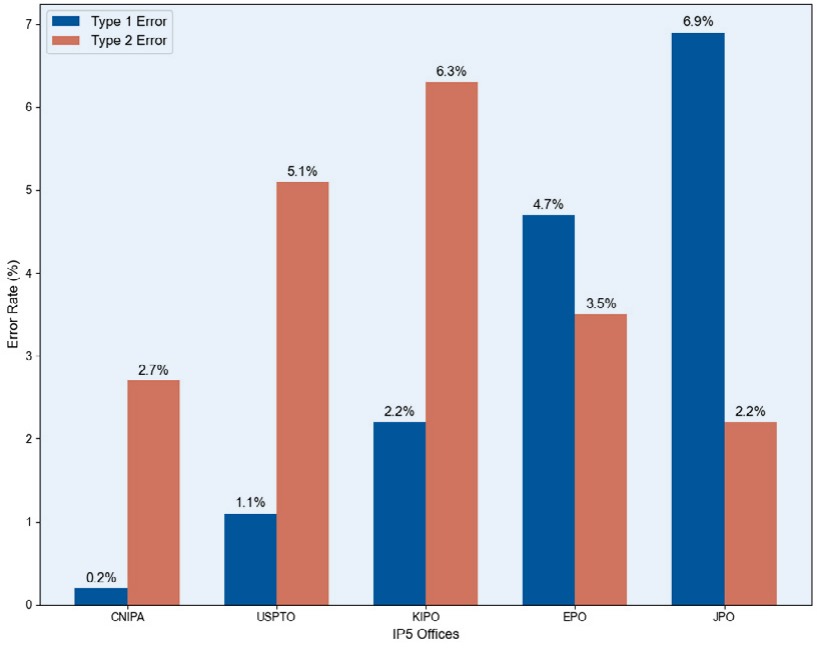

Figure 11: Estimated Error Rates across Global Patent Offices (Calculated Based on the Results of De Rassenfosse et al., 2021, Table 7)

Points for Consideration

Although the sample used in this analysis is very large, it is important to note that it is not randomly drawn. Patent applications that are examined in multiple international jurisdictions are likely to be of higher economic value than the average patent. The owners of valuable inventions may be incentivized to work harder on potentially high-value applications, which might reduce Type 2 errors, but it is not clear how this might affect Type 1 errors. On the other hand, the applicants' greater incentive to receive protection of a high-value invention might lead to increased Type 1 error. To the extent that this occurs, the estimates of Type 1 error rates found in this study may overestimate the corresponding rate for the larger population of patents.

The study by De Rassenfosse et al. (2021) provides useful findings regarding error rates across the major patent offices for the years 2000–2006. To provide relevant insights into current policy debates, the study needs to be updated to include analysis of more recent time periods. China's patent system was in its infancy during that time period and has since grown tremendously. The full impact of such growth on patent quality could not be fully assessed at that time. The patent system in the United States has also evolved since the early 2000s. The Leahy-Smith America Invents Act (AIA), for example, represented a landmark change in U.S. patent law. Enacted in 2011, and fully implemented in 2013, the AIA brought the United States patent system closer in line with the rest of the world and aimed to improve the quality of patents being issued. It would be useful to conduct comparative analysis across patent offices for the post-2011 time period to provide relevant insights regarding the changes in patent quality across the world.

Conclusion

The comparative study shows that the Type 1 error rate at the USPTO is in single digits and is among the lowest of the major global patent offices. The findings additionally show that USPTO makes more Type 2 errors than Type 1 errors, in contrast to other patent offices such as EPO and JPO, which make more Type 1 errors than Type 2 errors.

Section 3

Patent Quality Cannot Be Measured by Patent Invalidation Rates

This section examines the most widely cited indicators of patent quality in public discourse, patent invalidation rates. The analysis shows that invalidation rates do not reveal any useful information regarding patent quality.

Every year, a few hundred patents granted by the USPTO are fully or partially invalidated at the Patent Trial and Appeal Board (PTAB) [13] and district courts due to non-compliance with statutory requirements. According to the definition of this report and the USPTO, such patents are of low quality. How does the data on patent invalidation rates at PTAB or district courts inform the prevalence of low-quality patents in the overall pool of patents?

As the frequency of patent litigation fluctuates, together with the attention the media gives to such cases, a perception is created regarding the significance of patent litigation with respect to overall patent quality (Wagner, 2009). In fact, several publications in law journals have used data on adjudicated patents to draw implications about patent quality (Mann and Underweiser, 2012; Miller, 2013; Love et al., 2019; Ge, 2021; etc.). A 2016 Government Accountability Office (GAO) report on intellectual property found that most interviewed stakeholders tend to understand patent quality in terms of whether patents were upheld if challenged in a lawsuit or PTAB proceeding. The interviews conducted by the Sunwater Institute further confirmed that perceptions of patent quality are highly informed by court-based patent invalidation rates. Drawing conclusions on the overall quality of patents using data on adjudicated patents is also tempting, since such data is easier to collect and analyze than conducting analysis on the overall patent pool.

However, such data and analytics misrepresent patent quality, and they are not informative enough to make conclusions about the overall quality of patents for the reasons explained below.

Adjudicated Patents Are Not a Representative Sample of the Overall Population of Patents

In order to ensure that inferences or conclusions drawn from a sample are valid and applicable to an entire population, the sample needs to be representative of that population. A representative sample accurately reflects the characteristics of the population from which it is drawn. This means that estimates of the parameters of the overall population (like means, proportions, or variances) based on the sample are likely to be close to the true population values. To achieve representativeness, researchers often use random sampling methods, where every element of the population has an equal chance of being selected. This method helps to ensure that the sample accurately reflects the broader population's characteristics.

Patents selected for validity challenges are unlikely to be randomly selected; such patents are likely to cover innovation that has proven to be commercially valuable in the eyes of their owners. Validity challenges often follow litigation of those patents in district court, giving rise to strong selection effects governing which patents are litigated. Because adjudicated patents are not likely to be randomly selected, there is no reason to expect that they would

[13] The Patent Trial and Appeal Board (PTAB) is an administrative adjudicatory body of the USPTO which, inter alia, reviews the patentability of issued patents (referred to herein as invalidity). It was created by the Leahy-Smith America Invents Act, Pub. L. 112-29 (2011), and began accepting petitions on September 16, 2012.

be representative of the overall population of issued patents.

To check whether the adjudicated patents are representative of the patent population as a whole, Sunwater Institute examined patents challenged at PTAB through its inter partes review (IPR) proceedings and compared their characteristics to the overall pool of patents that were granted in the same time period.

Over the last decade, the PTAB proceedings have transformed the patent litigation landscape, becoming the forum hearing the single greatest number of invalidity challenges. While PTAB has jurisdiction over several types of proceedings, the IPR proceeding is the most utilized, accounting for 95–97% of total petitions. [14] It is for challenges of any patent from nine months after issuance through its remaining period of enforceability.

The analysis checks for representativeness across two patent characteristics: technology area and entity size. The data includes patents filed in the years 2011–2013 to allow sufficient time for a possible IPR challenge. The overall sample consists of approximately 765,000 granted patents and 2,072 IPR challenges.

Representativeness by Technology Areas

Figure 12 shows the distribution of IPR-challenged patents compared to all issued patents across TCs. If IPR-challenged patents were representative, the distribution of IPR-challenged patents would match the distribution across TCs for all issued patents, and the bars for each class in Figure 12 would look identical (or at least similar). The figure, however, shows that the distribution of IPR-challenged patents across TCs does not track the distribution across TCs for all grants. Technology Centers 1600 (Biotechnology), 2400 (Computer Networks), and 2600 (Communications) are overrepresented for IPR-challenged patents, whereas 1700 (Chemical and Materials Engineering), 2100 (Computer Architecture Software), and especially 2800 (Semiconductors) are underrepresented for IPR-challenged patents.

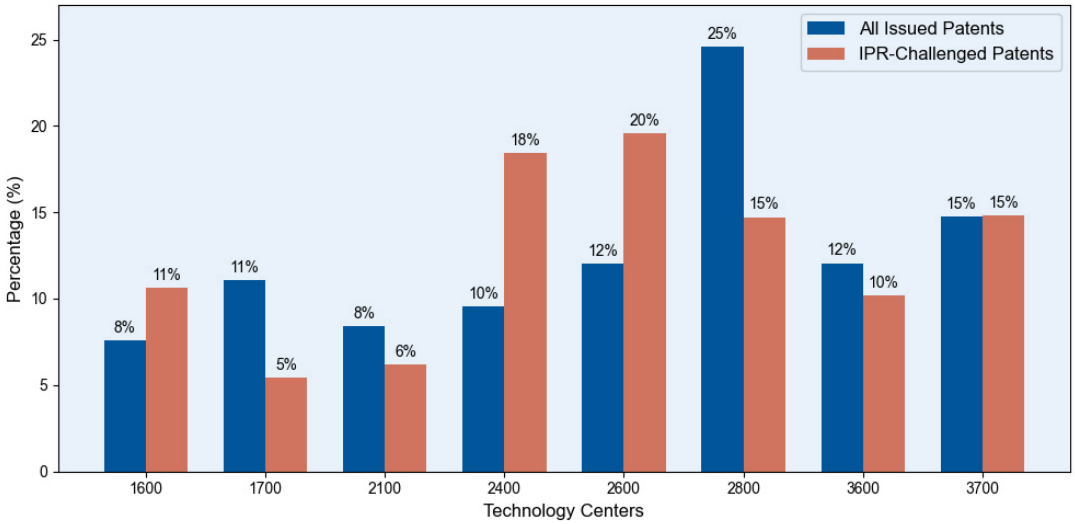

Figure 12: The Distribution of Patents Issued from Each Technology Center Compared to Those Subject to IPR Challenges

[14] PTAB's end-of-year outcome statistics for fiscal years 2019-2023 for AIA trials, accessible at https://www.uspto.gov/patents/ptab/statistics.

Representativeness by Entity Size

Next is the comparison of IPR-challenged patents to all issued patents based on the entity size that filed the patent application.

Entity size categorization of small entities is based on a reduced fee if an applicant entity meets the size limitation of having fewer than 500 employees.[15] This designation also includes qualified non-profit entities and universities, regardless of their size.[16] However, note that not all firms that qualify for this status necessarily seek this designation when they file for a patent.

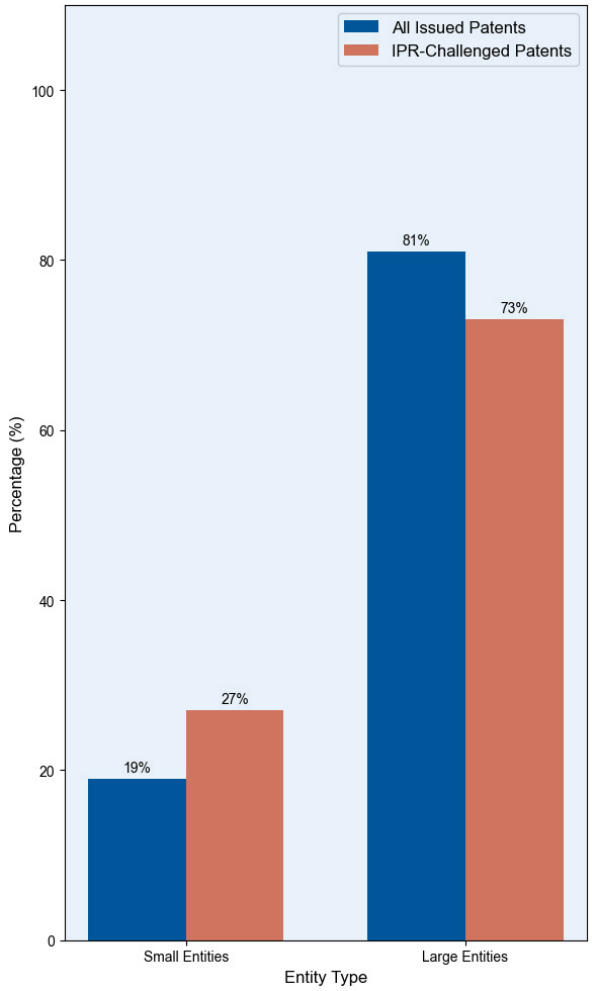

Figure 13: The Proportion of Patents Issued by Entity Type Compared to Those Subject to IPR Challenges

The analysis shows that patents subject to IPRs are also not representative of the overall pool of patents in terms of the status of the entity that filed for the patent: 27% of IPR-challenged patents were issued to small entities as compared to 19% for all issued patents. These differences are statistically significant.

Figure 13 shows that small entities are overrepresented as challenged parties at PTAB, while large entities are underrepresented.

These findings indicate that IPR-challenged patents differ from the rest of patents through several characteristics, and estimated parameters based on that sample cannot be generalized to the overall population of patents.

Similar findings, based on other dimensions of patents, such as the number of claims and forward citations, have been recorded in the literature regarding the sample of patents challenged at district courts compared to the overall pool of patents (Lanjouw and Schankerman, 2001).

The differences between the overall pool and the patents challenged at the courts are due to selection effects in patent validity adjudications. Recognizing this problem of selection effects, Miller (2013) attempts to correct for selection into an invalidity hearing, using a set of adjudicated patents and a set of control patents that have not been adjudicated to estimate a population-wide invalidity rate. However, in his research design, there were still two selection effects present that need to be accounted for: the selection of parties choosing trial over settlement and selection of the patents being disputed. These are not accounted for, suggesting that the estimates may still

[15] 35 U.S.C. § 41(h) (establishing fees for small entities); 37 C.F.R. § 1.27 (USPTO regulation defining small entities); 13 C.F.R. § 121.802 (Small Business Administration regulation establishing the 500 employee limitation).

[16] 37 C.F.R. § 1.27(a)(3).

be biased, and that the direction of the bias is unclear. Another study that tried to account for the presence of selection bias is by Henkel and Zischka (2019), who draw conclusions on the overall quality of patents in Germany using the invalidity rate of appeals at the German Federal Patent Court, but they did not identify statistically significant selection covariates (De Rassenfosse et al., 2021).

The presence of strong selection effects on the sample of patents challenged through PTAB or courts invalidates any attempt to draw conclusions about the overall pool of patents. However, do patent invalidation rates convey useful information for at least the sample of patents that are challenged? The following point illustrates that invalidation rates are not informative even for that small sample.

Patent Invalidation Rates Fundamentally Depend on Which Patents Get Challenged and Are Ultimately Adjudicated – the "Selection Problem" – and thus Reflect Plaintiff Win Rates Predicted by the Theories of Litigation and Settlement Rather than Conveying Any Useful Information on Patent Validity in General

Trials are costly — in terms of money, time, effort, and emotional toll. Patent validity challenges that reach a trial are not a random sample of the set of all validity challenges. Theories of litigation and settlement argue that litigated patents are highly selected for those with greater uncertainty about their validity. That is because cases that are clear-cut (where one side has a very high probability of winning, and the other side has a very high probability of losing) are more likely to be settled out of court. Since only the most uncertain disputes go all the way to a judgment in litigation, the outcomes in trials become just as uncertain as coin tosses.

The law and economics literature has long advanced theories of litigation and settlement, the most well-known of which is the Priest and Klein (1984) model, which predicts that, as settlement rates rise, plaintiff win rates approach 50%, *regardless of the fraction of plaintiff winners in the filed population.*

According to the Priest and Klein (1984) model, the plaintiff win rate will tend toward 50% under the assumption that neither the plaintiff nor the defendant has the informational advantage in litigation. To further develop this theory of divergent expectations, Hylton (1993) and Shavell (1996) incorporated asymmetric information in the model, showing that plaintiff win rates can be less than (greater than) 50% when defendants (plaintiffs) have the informational advantage in litigation.

Empiricists have tested the predictions from the theoretical literature, finding qualified support for the Priest and Klein model. Waldfogel (1998) showed that the empirical evidence supports the Priest-Klein model with deviations from 50% due to asymmetry in litigation stakes. Lanjouw and Schankerman (2001; 2004) were the first to focus on litigation rates and outcomes for patents and found that data strongly favor the Priest and Klein model for patent challenges.

For this report, the Sunwater Institute estimates the petitioner win rates calculated as the percentage of patents that have been instituted in PTAB among the patents that have been challenged in the past five years. Figure 14 shows the institution rates for the recent years are between 40-60%, consistent with the Priest and Klein model prediction that cases that are selected to have an institution decision at PTAB may indeed be the ones with the most uncertainty.

Instituted cases also undergo similar filtering before getting to trial at PTAB. Figure 15 shows the plaintiff win rates at PTAB trial - the invalidation rates, and they are around 40-60% as well.

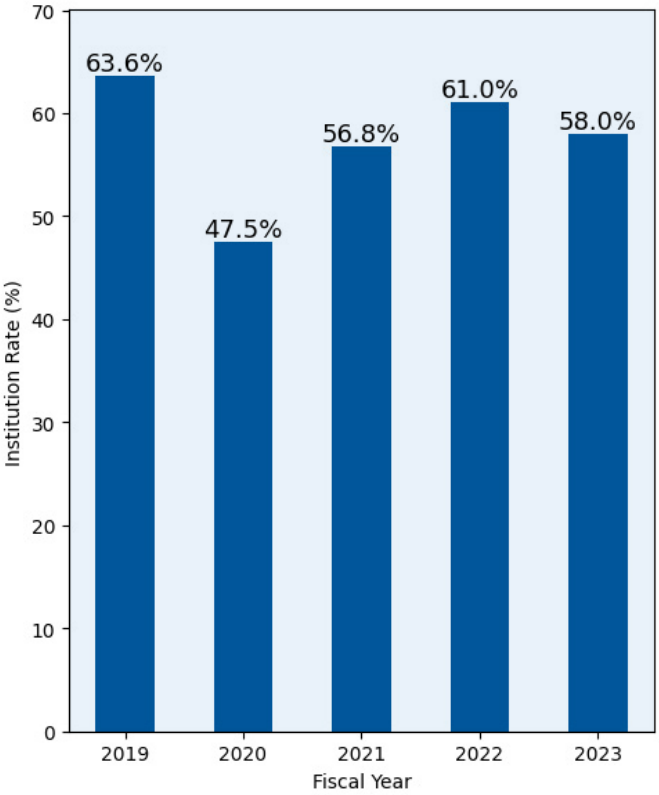

Figure 14: Percentage of Challenged Patents that Have Been Instituted

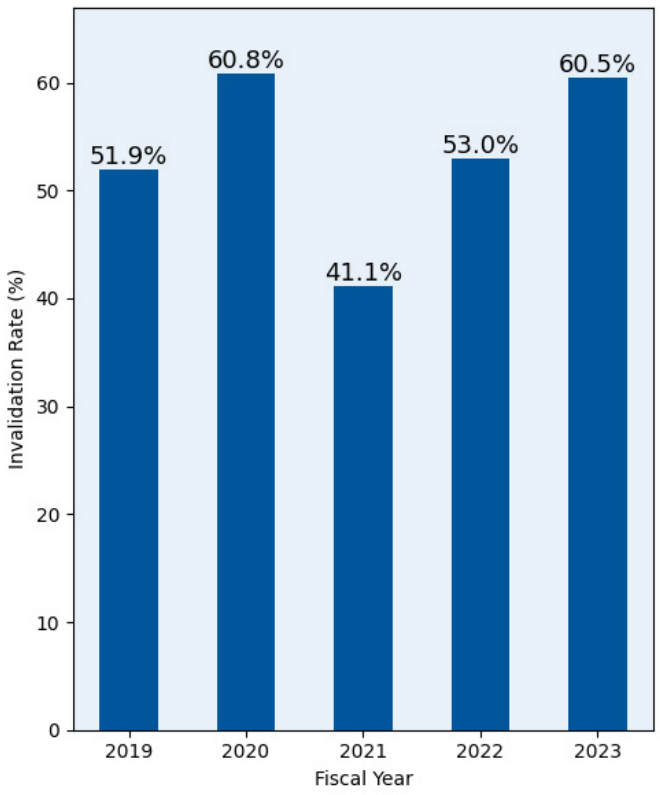

Figure 15: Percentage of Instituted Patents that Have Been Invalidated

Interestingly, 40–60% rates are typical not only to PTAB but also to district courts (Lanjouw and Schankerman, 2001, 2004; Allison et al., 2015) and European Patent Office Oppositions (EPO Annual Reports). [17]

The invalidation rates of approximately 50% align with the plaintiff winning rate predictions of leading theories of litigation and settlement and do not convey useful information on the validity of all patents.

Conclusion

The adjudicated patents are not a representative sample of all granted patents. Thus, conclusions about them cannot be generalized to the overall pool of patents. Patent invalidation rates are based on a small sample of the overall patents that get a validity challenge and then get to a trial after the challenge. Litigation and settlement theories predict that only the most uncertain disputes go all the way to a trial, which makes outcomes in trials just as uncertain as coin tosses, yielding approximately 50% invalidation rates. These predicted rates are reflected in the data and cannot convey useful information on the quality of all patents.

[17] See also this blog on outcomes at PTAB, district courts, and EPO at https://www.patentprogress.org/2018/05/a-little-more-than-forty-percent/.

Section 4

Conclusion

This report evaluates the quality of patents in the United States by assessing the effectiveness of patent examination, given the statutory standards of patentability. It measures how often the USPTO issues patents or patent claims that fail to meet the statutory standards of patentability (Type 1 errors) and how often it rejects patent applications or claims that do meet those standards (Type 2 errors). To measure these two types of errors, it utilizes three distinct methodologies and datasets, presented in Sections 2.1–2.3.

For Type 1 error rates, Section 2.1, which is based on ongoing work by Matcham and Schankerman (2023), estimated that 7.0% of all issued claims are invalid, based on the patent application filed between 2011–2013. Section 2.2, which is based on the USPTO's compliance metrics data, indicates that 7–8% of patent applications that have been granted a patent contain at least one claim that should have been rejected, based on patent applications reviewed between 2017–2023. Section 2.3, which is based on the data of patent applications submitted to multiple offices by De Rassenfosse et al. (2021) in the years 2000–2006, estimated that 4.9% of those patent applications were granted a patent by USPTO in violation of its patentability standards.

For Type 2 error rates, Section 2.1 reveals that Type 2 error rates are substantially higher than Type 1 error rates and those findings hold across all technology areas: 18.0% of abandoned claims are likely valid. In the case of Section 2.2, a much higher non-compliance rate for Rejections (20–26%) compared to non-compliance rates for Allowances (7–8%) is suggestive of a greater Type 2 error rate, subject to the caveats noted about bias in favor of overcounting non-compliance rates for Rejections. Section 2.3 also shows that the Type 2 error rates of the USPTO are higher than its Type 1 error rates.

The analyses of all three sections find that the USPTO's claim-level Type 1 error rates are in single digits, and Section 2.3 additionally shows that they are low relative to other major patent offices. The analyses further show that the USPTO appears to reject valid claims more than it issues invalid ones. While the presented analyses have limitations, the conclusions are strengthened given that three different methodologies and three different datasets arrive at similar results independently.

The report also considers patent invalidation rates at the PTAB and district courts and demonstrates their irrelevance to questions regarding patent quality. Despite being popular and easily obtainable numbers, the invalidation rates are not suitable proxies to measure the quality of issued patents: challenged patents are not representative of all issued patents and are subject to selection biases both in terms of which patents are challenged and which cases go to final adjudication rather than settlement or other resolution. In particular, the recorded patent invalidation rates of between 40–60% is consistent with long-advanced theories of litigation and settlement that predict outcomes of cases to be a virtual toss-up because, otherwise, parties have every incentive to settle.

When interpreting single-digit Type 1 error estimates, it is important to understand that patent quality should not be thought of in the same way as quality in other contexts, such as manufacturing parts for vehicles. In that manufacturing context, not only are there good reasons to keep errors as low as possible

for safety reasons, but errors can be driven to low rates because of these products' nature. Patents, in contrast, depend on words to capture new and even revolutionary concepts. This is an inherently fraught exercise, and there is likely to be a tradeoff between how quickly a patent system can accommodate new technologies and its stringency. In other words, even if the error rate could be driven down to zero (which is dubious), focusing on lowering the Type 1 error rate to this degree would undoubtedly lead to a system prone to improperly rejecting even more claims that are patentable (i.e., increasing the Type 2 error rate).

Accordingly, this report proposes to frame the patent quality dialogue in terms of the optimal balance between these two types of error, as estimated by appropriate methods and data. With this understanding, the patent system in the United States is already slanted towards having a lower Type 1 than Type 2 error rate. Given that public discourse focuses intently, perhaps even myopically, on Type 1 error rate, this may be surprising to some. Both types of error, however, have societal costs, and ignoring the costs of Type 2 error leads to an incomplete understanding of the innovation ecosystem. The next section discusses the implications of reframing the conversation about patent quality in terms of Type 1 and Type 2 error harms and provides policy recommendations.

Section 5

Discussion and Policy Recommendations

Harms from Type 1 vs, Type 2 Errors and the Policy Balance

There are several ways to view harms caused by estimates of Type 1 and Type 2 errors and their impact on public policy. Short-term economic harms to industry participants and consumers present the most obvious type of harm and where the economic, legal, and policy literature focuses its attention. Non-economic harms, also known as moral harms, are another important category of harms to consider. Finally, the distribution of these harms among the stakeholders should receive special attention.

Economic Harm

There are two sources of direct costs from Type 1 error: the deadweight loss associated with the royalties extracted by the patentee and the litigation costs associated with legal challenges involving invalid patents that are granted. Many invalid patents are not "exposed" to litigation because their private value is not large enough to justify litigation expense. The direct cost for invalid patents not exposed to litigation is only the deadweight loss from royalties, if any. Thus, the economic harm caused by most Type 1 errors is likely modest, to the extent that the (low-value) invalid patents are not subject to litigation. Many wrongly granted patents are of little or no economic value and are not asserted, challenged, or even noticed by anyone, including infringers. These errors do cause some harm to the reputation of the patent system if they are abundant or selectively cited. However, litigation costs on high-valued but invalid patents can be substantial, especially in the U.S. context. Litigation reform that lowers the cost of using the courts to resolve disputes — e.g., alternative dispute mechanisms — can be an effective way to reduce the costs of Type 1 errors.

Innovation has already occurred in the case of Type 2 error and the R&D cost is sunk. However, Type 2 error may lead to those innovations not being commercialized and therefore never reaching the public. Further, Type 2 error reduces the incentives for inventors to develop their ideas. Thus, the ultimate cost of Type 2 error includes the economic value of the inventions that are not developed and commercialized, but which would have been in the absence of Type 2 error. The economic harm caused by Type 2 errors, by contrast to Type 1 errors, proves much harder to conceptualize and assess. What innovations would have been commercialized that foundered because of Type 2 errors? How has the consumer been harmed by products that never appeared in the marketplace, and how much have consumers overpaid because cheaper alternatives would have been available? While efforts have been made to quantify these harms, doing so is a challenging and somewhat speculative task, as it involves constructing and contemplating counterfactuals.

Moral Harm

Contemporary elites prefer to focus exclusively on economic harms and view intellectual property as "a bundle of sticks." However, viewing the patent system as an economic utility-maximizing institution alone risks abandoning the notions of justice and natural rights on which the United States was founded and has thrived.

It is debatable whether all Type 1 errors result in moral harm to the inventor or society. Type 2 errors, however, always result in moral harms to innovators, denying them an earned property right. That property right has intrinsic value, regardless of the economic value of the innovation involved. The real property

equivalent of Type 2 error would be the government seizing an individual's land without providing compensation. It is worth noting the passion with which people have defended their rights to parcels of land that to many seem economically valueless.

Balancing Type 1 and Type 2 Errors

Providing patent examiners additional time, resources, and clearer guidelines via better statutes and judicial interpretation may simultaneously reduce both Type 1 and Type 2 errors. However, Type 1 and Type 2 errors ultimately exist in an equilibrium. Attempts to singularly reduce Type 1 error will likely increase Type 2 error. Efforts to reduce Type 2 error may also result in higher Type 1 error.

The question for policymakers is how to optimize the balance between these two types of errors given the resources allocated to the patent system to achieve long-term U.S. interests and protect the moral and economic rights of inventors as well as the public.

Vagueness and Uncertainty of the Governing Statutes and Case Law

Patent examination, upon which patent quality ultimately rests, depends on consistent judicial interpretation of the patent statues. Based on the expert interviews conducted for this report, a significant portion of industry participants believe these statutes are unclear, and that inconsistent judicial interpretation has made the situation for inventors even less clear. Further, judicial decisions have changed the interpretation of the patent laws, resulting in patents that previously would have been considered "high quality" becoming "low quality." These changes have significant negative impact on inventors and patent owners, their investors, and the innovation community. There may be positives from such changes, such as non-innovator firms benefitting from freedom to operate, but such changes should not be counted as evidence of the USPTO issuing low-quality patents.

Patent Quality in the United States: Policy Recommendations

Better conclusions about patent quality can only be drawn from better data and analytical studies based on it. The USPTO should generate this data to help it and the policy community adjust the patent system to achieve national goals and protect the rights of inventors and consumers alike.

The policy community, and the U.S. Congress in particular, should reframe its debate about patent quality as a balance between Type 1 and Type 2 errors, rather than a myopic focus on Type 1 errors. Policies aimed exclusively at reducing Type 1 errors lead to greater harm to innovators and potential consumers of noncommercialized innovations. It is possible that the much higher rate of Type 2 errors compared with Type 1 errors is a result of the imbalanced policy dialogue and is disproportionately harming resource-constrained innovators.

The USPTO should publish more granular, claim-level data on its compliance metrics, including on Type 1 and Type 2 errors, segmented by technological areas. This data is currently publicly released in aggregate form, which is a good first step towards transparency and accountability, but one that still leaves significant limitations that prevent the data from being useful to researchers. The USPTO should contract with an independent third party to execute random reviews on a representative sample of patent applications each year. This data should be made available to the public on a disaggregated basis for analysis. Using a third party to review patent application samples would increase transparency and trust and address potential conflicts of interest. The data should assess Type 1 and Type 2 errors on a claim level. The USPTO should encourage foreign patent offices to follow suit.

The USPTO should support efforts in conducting comparative analysis across patent offices and evaluating patent quality worldwide. Comparative data from different patent offices provides valuable insights from "comparing like to like," and USPTO should encourage the different offices to consider how they could jointly support efforts to facilitate this sort of data gathering and promote further research and analysis of the resulting information.

References

Allison, J.R. & Lemley, M.A. (1998). Empirical evidence on the validity of litigated patents. *AIPLA Quarterly Journal, 26*, 185.

Allison, J.R., Lemley, M.A. & Schwartz, D.L. (2015). Our divided patent system. *The University of Chicago Law Review, 1073-1154.*

De Rassenfosse, G., Griffiths, W.E., Jaffe, A.B. & Webster, E. (2021). Low-quality patents in the eye of the beholder: Evidence from multiple examiners. *The Journal of Law, Economics, and Organization, 37*(3), 607-636.

Henkel, J. & Zischka, H. (2019). How many patents are truly valid? Extent, causes, and remedies for latent patent invalidity. *European Journal of Law and Economics, 48*, 195-239.

Higham, K., De Rassenfosse, G. & Jaffe, A.B. (2021). Patent quality: Towards a systematic framework for analysis and measurement. *Research Policy, 50*(4), 104215.

Hylton, K.N. (1993). Asymmetric information and the selection of disputes for litigation. *The Journal of Legal Studies, 22*(1), 187-210.

Lanjouw, J.O. & Schankerman, M. (2001). Characteristics of patent litigation: a window on competition. *RAND Journal of Economics, 129-151.*

Lanjouw, J.O. & Schankerman, M. (2004). Protecting intellectual property rights: are small firms handicapped?. *The Journal of Law and Economics, 47*(1), 45-74.

Le, Q. & Mikolov, T. (2014). "Distributed representations of sentences and documents," in International conference on machine learning. *Proceedings of Machine Learning Research,* 1188–1196.

Lemley, M. A. (2001). Rational Ignorance at the Patent Office. *Northwestern University Law Review 1495, 95*(4). https://dx.doi.org/10.2139/ssrn.261400

Love, B. J., Miller, S. P., & Ambwani, S. (2019). Determinants of patent quality: Evidence from inter partes review proceedings. *University of Colorado Law Review, 90*, 67.

Mann, R. J., & Underweiser, M. (2012). A new look at patent quality: Relating patent prosecution to validity. *Journal of Empirical Legal Studies, 9*(1), 1–32.

Matcham, W. & Schankerman, M. (2023). 'Screening Property Rights for Innovation,' *CEPR Discussion Paper No. 18334.* CEPR Press, Paris & London.

Miller, S.P. (2013). Where's the innovation: An analysis of the quantity and qualities of anticipated and obvious patents. *Virginia Journal of Law and Technology, 18*, 1.

Priest, G.L. & Klein, B. (1984) The selection of disputes for litigation. *The Journal of Legal Studies, 13*(1), 1–55.

Schankerman, M. & & Schuett, F. (2022). "Patent Screening, Innovation, and Welfare," *The Review of Economic Studies, 89*, 2101–2148.

Shavell, S. (1996). Any frequency of plaintiff victory at trial is possible. *The Journal of Legal Studies, 25*(2), 493–501.

Squicciarini, M., Dernis, H., & Criscuolo, C. (2013). Measuring Patent Quality: Indicators of Technological and Economic Value. *OECD. Science, Technology and Industry Working Papers. 2013/03,* OECD Publishing.

Wagner, R.P. (2009). Understanding patent-quality mechanisms. *University of Pennsylvania Law Review, 157*(6), 2135–2173.

Waldfogel, J. (1998). Reconciling asymmetric information and divergent expectations theories of litigation. *The Journal of Law and Economics, 41*(2), 451–476.

You, G. (2021). A Closer Look at the PTAB Operation. *Southern California Law Review, 95*, 693.

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